

Predictability and Anomalies in Equity and Commodity Markets

Der Wirtschaftswissenschaftlichen Fakultät der
Gottfried Wilhelm Leibniz Universität Hannover
zur Erlangung des akademischen Grades

Doktor der Wirtschaftswissenschaften
- Doctor rerum politicarum -

genehmigte Dissertation

von

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geboren am 16.07.1989 in Halle (Saale)

2018

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Tag der Promotion: 22.01.2019

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Björn Tharann

Acknowledgements

I am indebted to the members of my disputation committee, Prof. Dr. Maik Dierkes and Prof. Dr. Marcel Prokopczuk, CFA, for their effort and guidance. I would like to express my thanks in particular to Marcel who gave me the opportunity to do my doctorate under his supervision. Beyond that, for his untiring assistance as a mentor and co-author in numerous papers, who gave me the opportunity to attend conferences in Boston, Oxford, and Zurich, and who encouraged me to deepen my knowledge in return predictability.

I also thank Fabian Hollstein for his inexhaustible assistance and advice over the years of my doctorate. Numerous conversations have never stopped him (and there were really many) from advising with his expertise for both professional and private purposes. I am also grateful to Chardin Wese Simen who, as a co-author, has contributed significantly to the development of the doctorate through his expertise. Also many thanks to Fabian Bätje who has always delivered good ideas and suggestions in numerous spontaneous talks.

In addition, I am grateful to Christel Köhler and Steffen Zimpel who have been supporting me, outside academia, as good friends for many years with their numerous advices.

Abstract

This thesis studies the predictability of stock and commodity returns. It also examines the sources of return anomalies in financial markets. Chapter 1 introduces the main concepts and delivers an overview of the subsequent chapters.

Chapter 2 begins with the analysis of stock return predictability around the globe. By studying more than 80 countries for a sample period of up to 144 years, we conduct the most comprehensive analysis of equity premium predictability that thus far exists. We find substantial evidence of in-sample and out-of-sample predictability for aggregate excess returns of countries in all regions. We detect predictability by examining price ratios, interest-related variables, and economic indicators, as well as forecast combination approaches. Investors in international markets can realize sizable utility gains. Analyzing the cross-section of countries, we find that markets that are more efficient are generally more predictable, while more variability in business cycles does not lead to better predictability.

Building on the analysis of return predictability based on historical measures in Chapter 2, Chapter 3 examines another strand in the literature and comprehensively analyzes the predictive power of several option-implied variables for monthly S&P 500 excess returns and realized variance. The correlation risk premium (*CRP*) and the variance risk premium (*VRP*)

emerge as strong predictors of both excess returns and realized variance. This is true both in- and out-of-sample. A timing strategy based on the *CRP* leads to utility gains of more than 5.03 % p.a. Forecast combinations provide stable forecasts for both excess returns and realized variance, and add economic value.

Inspired by the remarkable degree of predictability in stock markets, Chapter 4 extends the analysis to commodity spot markets. Using more than 140 years of data, we comprehensively analyze the predictive power of a broad set of macroeconomic variables for commodity prices and volatilities. We find some evidence for short-term predictability, while the predictability is much stronger in the long-term, at least in the case of predicting returns. The level of volatility and the degree of predictability are affected by the introduction of derivatives trading. A business cycle analysis shows that the degree of return predictability is independent of being in a recession or expansion. Volatility predictability is more pronounced in recessions.

Motivated by the findings in commodity spot markets in Chapter 4, Chapter 5 translates the analysis to futures markets and studies the predictability of metal futures returns. Additionally, it identifies years of high predictability. Generally, we find a substantial degree of predictability both in- and out-of-sample. Gold returns seem to be best predictable out-of-sample. A timing strategy leads to utility gains of 2.18 % p.a. In particular, the Aruoba–Diebold–Scotti (ADS) business conditions index incorporates relevant information for metal returns, and strongly predicts gold returns.

In the previous chapters, stock and commodity markets have been analyzed in isolation. Chapter 6 examines commodity futures markets to draw inferences about stock markets. The analysis is based on the insight that financial markets are populated by a large number of return anomalies. Our main objective is to provide evidence as to which of these are likely

behaviorally-based and which have a risk-based explanation. To do so, we examine return anomalies in commodity futures markets. These markets provide an ideal ground for such research since (i) they are populated mostly by institutional investors rather than retail investors and (ii) there are only small limits to arbitrage. We find that downside beta, idiosyncratic volatility, and MAX are likely due to behavioral reasons, while jump risk, momentum, and volatility-of-volatility have a risk-based origin.

Finally, Chapter 7 concludes and outlines possible future directions for research questions.

Keywords: Return Predictability, Volatility Predictability, Capital Market Anomalies, Stock Markets, Commodity Markets

Zusammenfassung

Diese Arbeit untersucht die Vorhersagbarkeit von Aktien- und Rohstoffrenditen. Außerdem werden die Quellen von Renditeanomalien in Finanzmärkten analysiert. Kapitel 1 stellt die Hauptkonzepte vor und liefert einen Überblick über die nachfolgenden Kapitel.

Kapitel 2 beginnt mit der Analyse der Vorhersagbarkeit von Aktienrenditen in einem internationalen Vergleich. Durch die Untersuchung von mehr als 80 Ländern über einen Zeitraum von bis zu 144 Jahren führen wir die umfangreichste Analyse der Vorhersagbarkeit der Marktrisikoprämie durch, die bisher existiert. Wir finden bedeutende Anhaltspunkte für eine in-sample und out-of-sample Vorhersagbarkeit von Aktienmarktüberrenditen für Länder in allen geografischen Regionen. Wir stellen Vorhersagbarkeit durch Preiskennzahlen, Zinssatz-bedingte Variablen, ökonomische Indikatoren sowie durch prognosekombinierte Ansätze fest. Investoren können in internationalen Märkten beträchtliche Nutzengewinne realisieren. Bei der Analyse des Querschnitts aller Länder finden wir, dass effiziente Märkte im Allgemeinen besser prognostizierbar sind, wohingegen eine größere Variabilität in Konjunkturzyklen nicht zu einer besseren Vorhersagbarkeit führt.

Aufbauend auf der Analyse der Vorhersagbarkeit von Renditen auf Basis von historischen Maßen in Kapitel 2, analysiert Kapitel 3 die

Prognosekraft von Options-implizierten Variablen für monatliche S&P 500 Überrenditen und realisierte Varianz. Die Korrelationsrisikoprämie (*CRP*) und die Varianzrisikoprämie (*VRP*) offenbaren sich als starke Prognosevariablen sowohl für Überrenditen als auch für realisierte Varianz. Dies zeigt sich sowohl in-sample als auch out-of-sample. Eine Handelsstrategie, die auf der *CRP* basiert, führt zu Nutzengewinnen von mehr als 5.03 % p.a. Prognosekombinationen liefern stabile Vorhersagen für Überrenditen sowie für realisierte Varianz, und liefern Nutzengewinne.

Inspiziert durch den bemerkenswerten Grad an Vorhersagbarkeit auf Aktienmärkten erweitert Kapitel 4 die Analyse auf Rohstoff-Spotmärkte. Mit mehr als 140 Jahren an Daten analysieren wir umfangreich die Prognosekraft zahlreicher makroökonomischer Variablen für Rohstoffpreise und Volatilitäten. Wir finden Anhaltspunkte für eine kurzfristige Vorhersagbarkeit, während die Vorhersagbarkeit auf langer Sicht viel stärker ist, zumindest für die Vorhersagbarkeit von Renditen. Das Level der Volatilität und der Grad der Vorhersagbarkeit werden durch die Einführung des Derivatehandels beeinflusst. Eine Konjunkturanalyse zeigt, dass der Grad der Vorhersagbarkeit von Renditen unabhängig von der Tatsache ist, ob sich die Wirtschaft in einer Rezession oder in einer Expansion befindet. Die Vorhersagbarkeit von Volatilitäten ist in Rezessionen ausgeprägter.

Motiviert durch die Ergebnisse von Rohstoff-Spotmärkten im Kapitel 4 überträgt Kapitel 5 die Analyse auf Terminmärkte und untersucht die Vorhersagbarkeit der Renditen von Metallterminkontrakten. Darüber hinaus werden Jahre hoher Vorhersagbarkeit identifiziert. Im Allgemeinen finden wir einen erheblichen Grad an Vorhersagbarkeit sowohl in-sample als auch out-of-sample. Goldrenditen scheinen out-of-sample am besten prognostizierbar zu sein. Eine Handelsstrategie führt zu Nutzengewinnen von 2.18 % p.a. Insbesondere der Aruoba–Diebold–Scotti (ADS) Business Conditions Index umfasst relevante Informationen für Metallrenditen, und

prognostiziert Goldrenditen in einem beträchtlichen Umfang.

In den vorhergehenden Kapiteln wurden Aktien- und Rohstoffmärkte isoliert analysiert. Kapitel 6 untersucht Rohstoff-Terminmärkte, um Rückschlüsse auf Aktienmärkte zu ziehen. Die Analyse basiert auf der Einsicht, dass auf Finanzmärkten eine große Anzahl von Renditeanomalien existieren. Unser Hauptziel ist es, Anhaltspunkte zu liefern, welche von diesen möglicherweise verhaltensbasiert sind und welche einen risikobasierten Erklärungsansatz haben. Um dies zu tun untersuchen wir Renditeanomalien auf Rohstoff-Terminmärkten. Diese Märkte liefern einen idealen Gegenstand für solch eine Forschungsfrage, da sie (i) hauptsächlich von institutionellen Investoren als von Kleinanlegern genutzt werden, und (ii) nur geringe Beschränkungen für Arbitrage aufweisen. Wir finden, dass Downside Beta, idiosynkratische Volatilität und MAX wahrscheinlich verhaltensbedingt sind, wohingegen Jump Risiko, Momentum und Volatilität-von-Volatilität einen risikobasierten Ursprung haben.

Abschließend zieht Kapitel 7 Schlussfolgerungen und zeigt mögliche Anregungen für zukünftige Forschungsfragen auf.

Schlagwörter: Vorhersagbarkeit von Renditen, Vorhersagbarkeit von Volatilitäten, Kapitalmarktanomalien, Aktienmärkte, Rohstoffmärkte

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Chapter 1

Introduction

Whether returns are predictable or not has been one of the most discussed issues in finance for decades. Initial attempts to predict stock returns were already performed by Dow (1920). Numerous studies have tackled the question of return predictability and provided evidence either in favor or against predictability.

Goyal & Welch (2008) re-drew attention to and stimulated that topic by their seminal paper, in which they re-examine previous studies and provide evidence against return predictability in the U.S. They argue that the so far observed predictability is mainly driven by the period of the oil crises and, to some extent, due to econometric issues of previous studies. They conclude that the historical mean is a tough benchmark to beat. Campbell & Thompson (2008) provide evidence in favor of return predictability when including two economically motivated restrictions. Cochrane (2008) shows that return predictability results from the time-variation of expected returns. Overall, return predictability is challenging and the answer of whether it is there is still inconclusive.

Chapter 2 accepts this challenge and extends the analysis of return predictability to an international setting. Most of the existing literature

has focused only on studying the return predictability in the U.S., using historical aggregated measures. Among others, the dividend–price ratio (Rozeff, 1984; Fama & French, 1988b; Hodrick, 1992), short-term interest rates (Campbell, 1987; Hodrick, 1992; Ang & Bekaert, 2007), the consumption–wealth ratio (Lettau & Ludvigson, 2001), and the earnings–price ratio (Campbell & Shiller, 1988, 1998) have been examined. There are also some recent studies that examine a small number of European countries (e.g., Ang & Bekaert, 2007; Henkel, Martin, & Nardari, 2011; Jordan, Vivian, & Wohar, 2014; Golez & Koudijs, 2018), or some Asian and European countries (e.g., Charles, Darné, & Kim, 2016). However, the focus of each of these studies is rather narrow.

Thus, in this chapter, we perform the most comprehensive analysis of market return predictability in terms of sample length and cross-section that, to the best of our knowledge, exists thus far. Our sample period extends from January 1871 to December 2015 and includes more than 80 countries. Moreover, the broad set of countries enables us to gain insights about the determinants of the predictability of the market risk premium. The countries in our sample are heterogenous in various dimensions. Making use of this heterogeneity in the cross-section of countries, we examine the sources of international return predictability.

Our empirical evidence suggests that stock market returns in America, Asia Pacific, and Europe are well predictable, whereas those in Africa and the Middle East are less well predictable. We detect better predictability in more developed and more open countries. Overall, aggregate market returns in more inefficient countries appear to be severely less predictable. Furthermore, we find that returns in countries with more business-cycle variability are less predictable than those in countries with relatively more stable business cycles.

Due to the notable degree of return predictability in an international

setting based on historical measures, Chapter 3 analyzes the predictive power of option-implied variables for monthly S&P 500 excess returns and realized variance. It makes use of recent developments in the literature, using option-implied measures. Among others, the variance risk premium (Bollerslev, Tauchen, & Zhou, 2009; Bollerslev, Marrone, Xu, & Zhou, 2014; Pyun, 2018), the correlation risk premium (Driessen, Maenhout, & Vilkov, 2009, 2013), implied variance (Jiang & Tian, 2005; Kourtis, Markellos, & Symeonidis, 2016), and implied skewness (Rehman & Vilkov, 2012; Stilger, Kostakis, & Poon, 2017) are examined.

To complement the existing literature, Chapter 3 provides a comprehensive analysis of the forecasting ability of variables separately proposed in the recent literature on option-implied variables. We do not only analyze return predictability, but also the predictability of variance at the same time. In doing so, we are able to draw inferences for an investor's portfolio choice.

We find that in particular the correlation risk premium (*CRP*) and the variance risk premium (*VRP*) strongly predict the monthly excess return of the S&P 500. This is true both in- and out-of-sample. Furthermore, we show that both variables predict not only the market excess return but also its realized variance. We note that most of the variables under study have strong predictive power for realized variance but not for market excess return. Moreover, we find that relative to an agent who assumes that the mean and the variance of the market return are unpredictable, a mean-variance agent with a risk-aversion coefficient of 3 who uses the information content of the *CRP* would realize utility gains of 5.03 % p.a.

Motivated by the remarkable degree of predictability in stock markets of both returns and variance, Chapter 4 studies analogously the predictability in commodity spot markets using historical measures. Commodities have drawn more attention in recent decades as stock and bond portfolios have

beneficial properties when commodities are included. Thus, investors have turned to commodities as a new investment class (e.g., Bessembinder & Chan, 1992; Gorton & Rouwenhorst, 2006; Kogan, Livdan, & Yaron, 2009). Due to the low correlation with stocks and bonds, commodities are useful to achieve a high degree of portfolio diversification and serve as a good hedge against inflation (e.g., Sadorsky, 2002; Gorton & Rouwenhorst, 2006; Lien & Yang, 2008; Symeonidis, Prokopczuk, Brooks, & Lazar, 2012). Moreover, commodities seem to be predictable by variables known from the equity literature (e.g., Bessembinder & Chan, 1992; Bailey & Chan, 1993; Chen, Rogoff, & Rossi, 2010; Pierdzioch, Risse, & Rohloff, 2016).

Chapter 4 extends the existing literature by providing the most comprehensive evidence on the predictive power of macroeconomic variables for commodity excess returns and volatilities. We analyze more than 140 years of data and use a comprehensive set of commodity markets and predictive variables. Our sample spans the period from January 1871 to December 2015 and covers 30 commodities and 16 predictive variables. Moreover, we do not only analyze the predictability of excess returns but also the predictability of volatilities. We analyze whether the introduction of derivatives trading systematically affected the degree of predictability, and we study the predictability over business cycle stages (Cujean & Hasler, 2017).

Our empirical results suggest that there is short- and long-term predictability for both commodity excess returns and volatilities. We observe, however, more predictability at longer horizons. These improvements are more pronounced for the predictability of excess returns rather than that of volatilities. In particular, we find that the growth of industrial production, the market risk premium, and the default return spread reveal themselves as the most reliable predictive variables in the short-term return predictability, whereas interest rate-related variables are the most reliable

predictive variables in the long-term. Analogously, the dividend–price ratio, the dividend yield, the inflation rate, and the long-term government bond yield are the most important predictive variables in the short-term volatility predictability, whereas for longer horizons, the earnings–price ratio, the default yield spread, and the term spread contribute to the predictability. Moreover, we find that the level of volatility and the degree of predictability are affected by the introduction of derivatives trading. The degree of return predictability is independent of being in a recession or expansion, whereas the volatility predictability is more pronounced in recessions.

Analyzing spot markets in Chapter 4 allows us to identify economic linkages over a very long sample period. Chapter 5, in turn, extends the analysis to commodity futures markets in order to study trading strategies. This chapter provides evidence on return predictability of metal commodity futures. Using 12 variables that seem to predict stock returns, we analyze several sample periods and identify years of high predictability. We study the effect of forecast combinations on return predictability, and whether investors might earn utility gains relying on predictive variables. We also analyze the Aruoba–Diebold–Scotti (ADS) business conditions index to examine the potential effects on metal futures returns and on the behavior over business cycles.

We find substantial in- and out-of-sample predictability for next year’s excess return. The best performing variable is the long-term government bond yield, indicated by an out-of-sample R^2 of 37.90 % in the case of gold. The findings provide evidence for stable forecasts using forecast combinations. Gold returns seem to be best predictable out-of-sample. A timing strategy leads to utility gains of 2.18 % p.a., when predicting gold returns. Moreover, the ADS index seems to incorporate relevant information for metal futures returns, and strongly predicts gold returns, indicated by an out-of-sample R^2 of 8.21 %.

Finally, Chapter 6 uses commodity futures markets to explain capital market anomalies. The literature has found numerous anomalies and factors in the cross-section of stock returns (Harvey, Liu, & Zhu, 2016). Anomalies may be explained by three main categories. First, they may be explained rationally as reflecting some underlying form of systematic risk (e.g., Fama & French, 1993; Berk, Green, & Naik, 1999; Johnson, 2002; Liu & Zhang, 2008; Fama & French, 2015). Second, by irrational behavior, mostly of individual investors (e.g., De Long, Shleifer, Summers, & Waldmann, 1990a; Daniel, Hirshleifer, & Subrahmanyam, 1998; Hong & Stein, 1999; Daniel, Hirshleifer, & Teoh, 2002; Diether, Malloy, & Scherbina, 2002; Baker & Wurgler, 2006; Hirshleifer, Subrahmanyam, & Titman, 2006; Baker, Coval, & Stein, 2007; Hirshleifer & Jiang, 2010). Finally, by limits to arbitrage (e.g., Jarrow, 1980; Mayshar, 1981; Shleifer & Vishny, 1997; Mitchell, Pulvino, & Stafford, 2002; Acharya, Amihud, & Litov, 2011; Baker, Bradley, & Wurgler, 2011; Ljungqvist & Qian, 2016).

Chapter 6 uses commodity markets as ideal testing ground to organize the set of anomalies, by examining the underlying causes of the anomalies that constitute, in our view, the most relevant issues. To do so, we examine whether the anomalies found in equity markets are also present in commodity futures markets.

Using portfolio sorts with a holding period of one month, our empirical results suggest distinct patterns in the anomalies. For many anomalies detected in the equity literature, we do not find significant return premia in commodity futures markets. Downside beta, idiosyncratic volatility, and the MAX measure reveal themselves as behaviorally caused, whereas jump risk, skewness, momentum, and volatility-of-volatility underly systematic risk-based explanations. Moreover, using cross-sectional Fama & MacBeth (1973) regressions, we reach very similar conclusions.

This thesis proceeds as follows. Chapter 2 analyzes return predictability

in an international setting. Chapter 3 examines return and variance predictability in the U.S. using option-implied variables. Chapter 4 studies return and volatility predictability in commodity spot markets. Chapter 5 extends the analysis to metal futures. Chapter 6 studies the economic sources of equity market anomalies using commodity futures. Finally, Chapter 7 summarizes the main findings of this thesis and suggests several directions for future research.

The thesis consists of several chapters, which are to be regarded as independent. Therefore, each chapter has its own notation of variables and acronyms. To facilitate readability, they are used consistently throughout the thesis, where possible.

Chapter 2

Predicting the Equity Premium: Comprehensive Evidence from a Large Sample*

2.1 Introduction

Whether the equity premium is predictable or not is an important question that has now been analyzed for at least a century. Initial attempts to predict stock returns date back to Dow (1920). Typically, the literature examines the predictability of stock market returns in the U.S. However, even though numerous studies have examined this issue, the empirical evidence about equity premium predictability is still inconclusive.

Studying return predictability is important from both a theoretical and a practical standpoint. For applications in practice, enhanced return predictability goes along with an improved investment performance. Inves-

*This chapter is based on the Working Paper “Predicting the Equity Premium: Comprehensive Evidence from a Large Sample” authored by Fabian Hollstein, Marcel Prokopczuk, Björn Tharann, and Chardin Wese Simen, 2018.

tors might better choose their portfolio allocations across different markets. Knowledge about country-specific market return predictability might also enable investors to establish profitable market timing strategies. For theorists, knowing about the sources and drivers of return predictability is important since we need to distinguish between rational predictability (e.g., Campbell & Cochrane, 1999; Bansal & Yaron, 2004) due to time-varying expected returns and irrational or frictions-based predictability that might be more concentrated in less efficient markets. Any predictability should be accounted for when aiming for realistic asset pricing models.

Several studies find that stock returns are predictable by macroeconomic variables (e.g., Fama & French, 1988b; Campbell, 1991; Cochrane, 1992). On the other hand, Goyal & Welch (2003, 2008) argue that most forecasting variables have limited predictive power out-of-sample. They conclude that overall the historical mean is the best predictor for the equity premium in the U.S.

Connecting to these findings, the main goal of this paper is to analyze whether the equity premium around the globe is predictable. In doing so, we make two contributions to the existing literature. First, we perform the most comprehensive analysis of market return predictability in terms of sample length and cross-section that, to the best of our knowledge, exists thus far. Indeed, our sample period extends from January 1871 to December 2015 and includes more than 80 countries.¹ Most of the literature has focused on either the U.S. stock market or a small number of developed countries. This narrow focus might raise issues about data snooping (Lo & MacKinlay, 1990a). With our data, we are able to directly address these concerns and provide *out-of-sample* evidence by extending the analysis to a framework covering numerous countries across the entire globe. Second, the broad

¹The exact sample length naturally differs across countries, and depends on data availability in the respective countries.

2.1. INTRODUCTION

set of countries enables us to gain insights about the determinants of the predictability of the market risk premium. The countries in our sample are heterogenous in various dimensions. Making use of this heterogeneity in the cross-section of countries, we examine the sources of international return predictability.

Our focus lies on analyzing the predictive power of variables for the future 12-month market excess return. We find evidence of substantial predictability of aggregate market returns for countries in all geographic regions. However, there is heterogeneity in the strength of predictability across regions and for different predictive variables. In-sample, we find that the dividend yield and the price–earnings ratio are very strong predictors of future aggregate excess returns for countries all over the world. While we find that, overall, market excess returns in Africa and the Middle East are the least predictable, these two variables also provide significant in-sample predictability there. Stock market returns in America, Asia Pacific, and Europe are very well predictable. In America, the dividend yield, the price–earnings ratio, and the inflation rate are the strongest return predictors. In Asia Pacific, the dividend yield and the price–earnings ratio are the best predictors, but there is also remarkable predictive power of the government bond yield, the inflation rate, and the unemployment rate. Finally, in Europe, the government bond yield and the unemployment rate appear to be the strongest predictors for future stock market excess returns.

Out-of-sample, we detect significant predictability for market risk premia in countries of all regions. The pattern for the regions is the same as in-sample. Returns are least forecastable in Africa and the Middle East. In these regions, the dividend yield and the inflation rate appear to be the best out-of-sample predictors. The same variables perform best in America, where aggregate stock market excess returns are better predictable out-of-sample than in Africa and the Middle East. In Asia

Pacific, the dividend yield, the price–earnings ratio, and the unemployment rate are the strongest predictors, while in Europe the inflation rate and the unemployment rate generally yield the best out-of-sample predictions. In total, also considering model selection approaches, we find that a mean forecast combination yields very good out-of-sample predictions. For the mean forecast combination approach, we obtain out-of-sample R^2 s ranging between -35.29% and 1.06% for Africa, -122.19% and 6.88% for America, -114.99% and 29.83% for Asia Pacific, -35.03% and 20.60% for Europe, and -18.12% and 31.68% for the Middle East.

We also analyze whether the observed return predictability can be used to generate economic utility gains, finding that it is possible to generate sizable utility gains across all regions and predictors. For the mean forecast combination (MFC) approach, we obtain annualized economic utility gains ranging between -0.96% and 2.06% for Africa, -17.97% and 1.22% for America, -1.10% and 3.02% for Asia Pacific, -4.12% and 2.56% for Europe, and -4.02% and 0.84% for the Middle East.

Having established predictability all over the globe, an important question relates to what drives this return predictability: market efficiency with time-varying expected returns, or mainly financial frictions? To address this question, we sort the countries according to proxies for market efficiency and the variability of the respective business cycles. In general, we detect better predictability in more developed and more open countries. Thus, aggregate market returns in more inefficient countries appear to be severely less predictable. We also find that returns in countries with more business-cycle variability are less predictable than those in countries with relatively more stable business cycles.

Finally, we perform several additional analyses. The economic sign restrictions of Campbell & Thompson (2008) generally slightly strengthen the return predictability. There is also predictive power of U.S. variables

2.1. INTRODUCTION

for aggregate market excess returns in other countries. However, the predictability is generally weaker than that based on local predictive variables. One remarkable exception is that the U.S. government bond yield seems to be a strong predictor of international market excess returns, often stronger than the domestic yield. Finally, examining U.S. Dollar (USD) returns, the results are largely very similar.

Our study naturally faces limitations. It is possible that different sample periods and heterogeneous definitions of the variables between the countries affect the return predictability. Moreover, the data quality might differ between countries, depending on the respective political and economic conditions. We try to address these issues by using the variables from the same database and taking into account the time-variation in variables by, e.g., using a rolling rather than an expanding window in the out-of-sample analysis. Additionally, we also test the robustness of our results for a substantially shorter post-1990 period, which, at the cost of reduced power of the statistical tests, substantially reduces the heterogeneity of the dataset in all dimensions. We obtain overall very similar results as for the full sample period.

This paper is related to the literature on the predictability of U.S. market excess returns, which mainly uses aggregate valuation ratios as return predictors. Variables which have been extensively examined in the existing literature are, e.g., the dividend–price ratio (Rozeff, 1984; Fama & French, 1988b; Hodrick, 1992), short-term interest rates (Campbell, 1987; Hodrick, 1992; Ang & Bekaert, 2007), and the consumption–wealth ratio (Lettau & Ludvigson, 2001). Campbell & Shiller (1988, 1998) show that the earnings–price ratio especially predicts long-term stock returns.

In recent years, several studies also have examined a wide-range of accounting-based valuation ratios (e.g., Rapach & Wohar, 2006; Rapach & Zhou, 2013). Goyal & Welch (2008) conduct a comprehensive analysis of

previously documented predictor variables and argue that, due to serious econometric issues, many existing methodologies yield unstable or spurious results. They conclude that previously documented predictability of the equity premium is not robust, and that the historical mean is the best predictor for the equity premium. Campbell & Thompson (2008) show that predictive regressions are able to beat the historical mean if economically motivated restrictions related to the sign of the slope coefficient and/or the equity premium forecast are imposed on the model. We extend their analysis to a large international sample studying international return predictability both with and without these restrictions.

Our study also adds to the literature on international stock return predictability. Most studies focus on a limited number of European countries. Ang & Bekaert (2007) analyze Germany, the U.K., and the U.S. and show the short-term predictive power of dividend yields in combination with short-term interest rates. Golez & Koudijs (2018) analyze return predictability for four centuries by combining Dutch, U.K., and U.S. data and provide evidence for a strong annual and multi-annual predictability, and show that expected returns are higher in recessions. Henkel et al. (2011) examine the G7 countries and find short-term predictability of macroeconomic variables only in recessions. Rangvid, Schmeling, & Schrimpf (2014) provide evidence for dividend growth predictability in an international setting. In addition, Jordan et al. (2014) consider 14 European countries and provide evidence for return predictability of the short-term interest rate and the historical stock return variance. Charles et al. (2016) analyze Asian and European countries and document a weak predictability of financial ratios, and a moderate short-term predictability of several macroeconomic variables. Rapach, Strauss, & Zhou (2013) show that lagged aggregate U.S. returns have predictive power for those of 10 non-U.S. industrialized countries.

2.2. DATA AND METHODOLOGY

The remainder of this paper proceeds as follows. Section 2.2 introduces the data and explains the variables used. Section 2.3 presents the main empirical results on predictability. Section 2.4 examines the sources of return predictability. Section 2.5 provides further results. Finally, Section 2.6 concludes.

2.2 Data and Methodology

2.2.1 Data

We obtain our data from several sources. We retrieve the monthly time series of equity market indices for 81 countries from the Global Financial Database (GFD).² All time series are directly available both in domestic currency and in USD. For the U.S. 3-month Treasury bill rate, we use the extended dataset of Goyal & Welch (2008).³ Our sample period extends from January 1871 to December 2015. Table 2.1 provides an overview of the countries under study and the number of observations for each market index. In order to put some structure on our analysis, we group countries according to their geographic regions, i.e., Africa, America, Asia Pacific, Europe, and the Middle East.

In addition, we obtain several measures characterizing the economic strength and the environment for investments in the respective countries. We collect the GDP per capita and the annual GDP growth rates (both in USD and base year 2010) from the World Bank as well as data on the stock market capitalizations (in USD), adjusted by the GDP implicit

²Due to a lack of data availability at GFD, we obtain the market indices of Ecuador (in USD) and Russia (in domestic currency) from Datastream. Due to a lack of data availability in Datastream, we use the index of Ecuador only denominated in USD.

³The dataset is available at <http://www.hec.unil.ch/agoyal/>.

CHAPTER 2. PREDICTING THE EQUITY PREMIUM: COMPREHENSIVE
EVIDENCE FROM A LARGE SAMPLE

Table 2.1: Summary Statistics – Market Risk Premia

This table summarizes key statistics about the individual market risk premia. We sample all data at the monthly frequency. We sort the countries according to geographic regions. The time series of the market indices are denominated in domestic currencies. Ecuador is denominated in USD. “Average”, “Std Dev”, “Skew”, “Kurt”, and “AR(1)” denote the (annualized) mean, (annualized) standard deviation, skewness, kurtosis, and the AR(1) coefficient, respectively. “First Obs” and “Nobs” denote the first observation and the number of observations, respectively.

	Country	Average	Std Dev	Skew	Kurt	AR(1)	First Obs	Nobs
Africa	Average	0.0364	0.1787	0.0916	9.0014	0.2185		
	Botswana	0.1006	0.1371	1.4744	11.6475	0.4366	06.1989	319
	Ghana	-0.0358	0.2556	1.0617	11.1113	0.4137	12.1990	236
	Kenya	-0.0253	0.1774	0.6305	11.9322	0.2301	02.1964	623
	Mauritius	0.0575	0.1544	-0.0481	6.2439	0.2664	08.1989	317
	Morocco	0.0959	0.1438	-0.0337	5.7870	0.0956	01.1988	336
	Namibia	-0.0002	0.2304	-1.3483	10.1760	0.1081	03.1993	274
	Nigeria	0.0704	0.2119	-0.6109	9.8161	0.2085	01.1988	336
	South Africa	0.0286	0.1656	-0.7580	7.8281	0.1357	02.1910	1271
	Tunisia	0.0361	0.1320	0.4571	6.4702	0.0715	01.1998	216
America	Average	0.1179	0.3360	-0.7303	47.5038	0.1803		
	Argentina	0.5647	0.6048	2.3631	14.2038	0.2605	01.1967	588
	Brazil	-0.0078	0.9870	-17.8075	422.1675	-0.0180	02.1955	731
	Canada	0.0426	0.1576	-1.0921	8.8685	0.1813	02.1915	1211
	Chile	0.1451	0.3234	1.0461	14.2134	0.2793	02.1960	661
	Colombia	0.0658	0.1991	1.8617	21.9943	0.2400	02.1927	1067
	Ecuador	-0.0002	0.2088	0.7363	12.8598	0.1317	01.1994	264
	Jamaica	0.0057	0.2363	0.8226	6.7070	0.3255	07.1969	558
	Mexico	0.0433	0.1718	-0.6579	9.2334	0.0442	02.1938	803
	Peru	0.2782	0.3854	3.6523	27.5458	0.3488	01.1933	996
	Trinidad and Tobago	0.0439	0.3247	-0.5074	5.5715	0.0685	02.1985	371
	United States	0.0615	0.1649	-0.4488	11.8389	0.1097	01.1871	1740
	Venezuela	0.1719	0.2686	1.2677	14.8412	0.1918	01.1937	948
Asia Pacific	Average	0.0539	0.2626	-0.1020	11.2091	0.1353		
	Australia	0.0781	0.1336	-2.2470	33.4600	0.0909	10.1882	1599
	Bangladesh	0.0566	0.2950	0.9264	11.5369	0.1903	07.1980	408
	China	0.0832	0.2922	-0.0375	4.2015	0.0605	01.1995	252
	Hong Kong	0.0920	0.3159	-0.7553	9.9577	0.0720	08.1964	617
	India	0.0399	0.1927	0.3294	7.6286	0.1273	07.1922	1110
	Indonesia	0.1096	0.2923	0.8647	16.7527	0.1866	01.1983	396
	Japan	0.0504	0.2070	0.5477	10.9253	0.1315	08.1914	1206
	Korea	0.1521	0.3820	1.5544	30.2861	0.0469	02.1962	647
	Malaysia	0.0423	0.2768	-0.5515	6.5627	0.1421	12.1972	517
	New Zealand	0.0092	0.1402	-0.9310	11.8695	0.1513	01.1931	1020
	Pakistan	0.0605	0.2289	-0.7932	11.4081	0.0772	08.1960	665
	Philippines	-0.0348	0.2816	0.1743	5.9244	0.1906	01.1953	756
	Singapore	0.0533	0.2267	-0.5080	6.8195	0.1520	08.1965	605
	Sri Lanka	0.0052	0.2136	0.4894	5.4698	0.1705	01.1963	516
	Taiwan	0.0514	0.3201	-0.3091	7.2557	0.0907	02.1967	587
	Thailand	0.0628	0.2979	-0.4396	6.3284	0.0755	05.1975	488
Vietnam	0.0046	0.3672	-0.0474	4.1674	0.3437	01.2001	180	

2.2. DATA AND METHODOLOGY

**Table 2.1: Summary Statistics – Market Risk Premia
(continued)**

	Country	Average	Std Dev	Skew	Kurt	AR(1)	First Obs	Nobs
Europe	Average	0.0256	0.2663	-0.2170	20.6059	0.2100		
	Austria	0.0488	0.2550	4.0091	63.0844	0.2721	02.1922	1071
	Belgium	0.0075	0.1759	0.1012	7.1514	0.0936	02.1897	1357
	Bulgaria	-0.2280	0.3843	-1.9165	11.9364	0.5209	10.1993	267
	Croatia	-0.0015	0.2888	-1.5123	12.2023	0.0667	02.1997	227
	Czech Republic	0.0051	0.2776	0.3542	8.6036	0.2619	10.1993	267
	Denmark	0.0153	0.1275	-0.1841	7.3464	0.2454	02.1893	1475
	Estonia	0.1309	0.3462	-0.5886	7.6367	0.2750	08.1995	245
	Finland	0.0687	0.2035	0.2875	8.2076	0.2432	11.1912	1238
	France	0.0288	0.1783	-0.1269	4.9375	0.1314	01.1898	1400
	Germany	0.0404	0.3392	-5.0350	187.8966	-0.0342	01.1871	1740
	Greece	0.0154	0.2777	0.5333	7.2474	0.2098	01.1954	744
	Hungary	-0.0049	0.2964	-0.2234	8.3953	0.1160	02.1991	299
	Iceland	-0.0223	0.3359	-8.5592	108.5430	0.2149	01.1993	276
	Ireland	0.0252	0.1619	-0.8334	8.9796	0.2431	02.1934	983
	Italy	0.0117	0.2356	0.9488	9.3258	0.1619	10.1905	1317
	Latvia	0.0603	0.3229	0.2900	11.7569	0.3114	05.1996	236
	Lithuania	0.0314	0.3030	1.4524	15.6386	0.1892	01.1996	240
	Luxembourg	0.0742	0.1679	-0.9036	9.7534	0.2388	01.1954	744
	Malta	0.0435	0.1714	1.0103	5.6374	0.3295	01.1996	240
	Netherlands	0.0110	0.1668	-0.5579	5.6680	0.1801	02.1919	1142
	Norway	0.0236	0.1718	-0.9661	9.6329	0.1825	02.1915	1211
	Poland	0.1071	0.4824	1.4191	15.3133	0.2902	02.1921	517
	Portugal	0.0517	0.2423	2.0347	22.0341	0.1687	01.1934	949
	Romania	0.1486	0.4918	1.4781	9.9794	0.2407	01.1931	410
	Russian Federation	-0.0784	0.5300	-1.4045	10.3650	0.1814	02.1995	251
	Slovakia Republic	-0.0120	0.2956	2.8791	29.8210	0.3013	10.1993	267
	Slovenia	0.0284	0.2512	1.1214	9.9935	0.2445	02.1993	275
	Spain	0.0284	0.1671	-0.4829	6.6801	0.1567	01.1915	1168
	Sweden	0.0586	0.1620	-0.6451	7.3069	0.1446	11.1901	1370
Switzerland	0.0256	0.1508	-0.5555	8.2437	0.1443	01.1914	1207	
Ukraine	0.0317	0.4241	-0.1290	4.3530	0.3128	02.1998	215	
United Kingdom	0.0452	0.1375	-0.2393	15.7176	0.0827	01.1871	1740	
Middle East	Average	0.0334	0.2397	0.0807	7.3695	0.1756		
	Bahrain	-0.0080	0.1290	-0.2114	3.9214	0.3079	07.1990	306
	Cyprus	0.0064	0.0957	1.4541	10.0501	0.1869	01.1984	384
	Egypt	0.0485	0.3046	-0.0933	4.5476	0.1647	01.1993	276
	Israel	0.1986	0.2275	0.0970	6.8117	0.2477	02.1949	803
	Jordan	0.0273	0.2181	0.0488	6.9907	0.0432	02.1978	455
	Kuwait	0.0482	0.2133	-0.2279	15.1681	0.2401	02.1973	431
	Lebanon	-0.0613	0.2523	1.1110	8.7831	0.1473	02.1996	239
	Oman	0.0375	0.1984	-0.5705	6.9893	0.2226	12.1992	277
	Qatar	0.0871	0.2747	-0.4805	5.1146	0.1053	10.1999	195
	Saudi Arabia	0.0228	0.2266	-0.8275	5.6805	0.2244	01.1993	276
	Turkey	-0.0398	0.4968	0.5877	7.0070	0.0411	02.1986	359

price deflator.^{4,5} Finally, we use the Chinn & Ito (2006) index, which the authors compute as the first principal component of several indicator variables measuring capital controls, as a measure for market openness. We employ the average of the standardized Chinn–Ito index as a classification criterion.^{6,7} Table A.1 in the Appendix to this chapter presents the tickers for all the time series used in this chapter.⁸

2.2.2 Variables

Market Excess Return We compute the market excess return as the difference between the log-return on the market index and the risk-free rate for the corresponding period, i.e.:

$$ER_{t+1} = \log\left(\frac{P_{t+1}}{P_t}\right) - rf_t, \quad (2.1)$$

where ER_{t+1} is the monthly excess return on the specific market index at the end of month $t + 1$.⁹ P_{t+1} and P_t denote the index price at the end of months $t+1$ and t , respectively. rf_t refers to the log risk-free rate observed at the end of month t .¹⁰ Following Ang & Bekaert (2007), Hjalmarrsson (2010), and Rapach et al. (2013), we measure returns in the respective national

⁴The datasets are available at <http://data.worldbank.org/indicator/NY.GDP.PCAP.KD?locations=CL> and <https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG>, respectively.

⁵We obtain the stock market capitalizations from the GFD, and the GDP implicit price deflator from the Federal Reserve Bank of St. Louis (FRED). The dataset is available at <https://fred.stlouisfed.org/series/GDPDEF>.

⁶The standardized Chinn–Ito index is defined between 0 (no market openness) and 1 (complete market openness).

⁷Due to limited data availability, the sampling windows for these measures differ slightly. For GDP per capita and GDP volatility, we have data starting from 1960. For market capitalization and market openness, the sample periods start in 1947 and 1970, respectively.

⁸To use the maximal number of observations, there are market indices that are combined from two subsequent indices. These time series are denoted by two tickers.

⁹The k -month excess return between time t and $T = t + k$ is simply the sum of all monthly excess returns occurring between t and T .

¹⁰We define the risk-free rate as follows: we use the subscript for the time when it is observed, thus, at time t even though it is realized at time $t + 1$.

2.2. DATA AND METHODOLOGY

currencies. Solnik (1993) notes that this approach yields returns that are approximately equal to currency-hedged excess returns an investor from any country can realize.¹¹ We use the 3-month Treasury bill rate of the respective country to proxy for the risk-free rate in domestic currencies.¹² Following Goyal & Welch (2008), we use the 3-month Treasury bill rate to proxy for the risk-free rate in USD.

Predictive Variables Rational return predictability requires time-variation in expected returns. Expected returns are typically deemed to be high in business cycle troughs and small in peaks. Accordingly, Cochrane (1999) argues that prices are driven down if future cash flows are discounted at a higher rate. Low prices indicate high expected returns, and vice versa. Thus, in principle all variables that have some correlation with the business cycle are potential predictors of returns. In particular price-related variables are natural candidates for forecasting variables. Both a high dividend-price ratio and a low price-earnings ratio imply that assets have high expected returns. Campbell & Cochrane (1999) and Cochrane (2007) argue that return predictability based on these variables could be, for example, generated by habits which react slowly to changes in consumption.

We base our main analysis on six predictor variables.¹³ We obtain the monthly time series for the predictor variables from the GFD.¹⁴ All

¹¹Solnik (1993) argues that this is due to interest rate parity, when the difference in interest rates equates to the forward premium. Furthermore, working with currency-converted returns raises the issue of a potential risk premium in exchange rates. Nevertheless, for robustness, we study the predictability for international returns in USD in Section 2.5.4.

¹²Due to a lack of data availability, we employ the 3-month Treasury bill rate rather than that with a 12-month maturity. When there is no risk-free rate available, the risk-free rate is set to zero. Please note that, because of this, the market risk premia for countries for which this occurs can be slightly biased upwards.

¹³Further variables used in previous studies are, among others, the dividend-payout ratio, the long-term Treasury yield, the consumption-wealth-income ratio, the default yield spread, the default return spread, and the term spread. Due to a lack of data availability for these variables in our international setting, we do not include these.

¹⁴For the unemployment rate of Ecuador, we obtain the time series from Datastream.

variables are country-specific.¹⁵ We use three stock market variables: the monthly dividend yield (*dy*) (e.g., Cochrane, 2008, 2011), the monthly price–earnings ratio (*pe*) (e.g., Campbell & Shiller, 1988), and the monthly long-term corporate bond yield (*corp*) (e.g., Chan, Chen, & Hsieh, 1985). In addition, the analysis is based on three macroeconomic variables: the monthly long-term government bond yield (*gov*) (e.g., Chen, Roll, & Ross, 1986), the monthly inflation rate (*infl*) (e.g., Chen et al., 1986; Ferson & Harvey, 1991), and the monthly unemployment rate (*unrate*) (e.g., Boyd, Hu, & Jagannathan, 2005; Rapach, Wohar, & Rangvid, 2005).¹⁶

2.2.3 Model Selection Approaches

Since univariate models are typically unstable over time, it might be fruitful to combine information from different sources. To do so, we extend our analysis using methods related to the statistical learning literature and introduce two approaches that deal with parameter shrinkage and variable selection. The question we want to answer is: Is it possible to utilize the information in variables to improve the predictability that goes beyond that of the univariate regressions?

Adaptive Elastic Net (AEN) Following Rapach et al. (2013), we use the adaptive elastic net estimation technique which, similar to ordinary least squares (OLS), minimizes the sum of squared residuals, but subject to two penalty terms. We use the multiple predictive regression model:

$$ER_{t+k} = \alpha_k + \beta'_k X_t + \epsilon_{t+k}, \quad (2.2)$$

¹⁵All variables are expressed in percent. Thus, they are independent of the currency. To compute the inflation rate, we use the consumer price index (CPI), denominated in domestic currency.

¹⁶Table A.1 of the Appendix to this chapter presents the tickers for each of the time series.

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where ER_{t+k} is the market excess return from month t to $t+k$ and $\beta'_k = (\beta_{k,1}, \dots, \beta_{k,M})$, where $m = 1, \dots, M$, is the vector of slope parameters. X_t is the vector of M forecasting variables observed at the end of month t , and ϵ_{t+k} represents the regression error term over k month(s). The adaptive elastic net procedure aims to address the problem that highly-parametrized forecast combinations of multiple predictors are typically in-sample overfitted and perform very poorly out-of-sample. The penalty terms in the optimization aim to provide regularization that ensures a sparse model.¹⁷ The adaptive elastic net entails minimizing the following objective function:

$$\min_{\beta_k} \left[\sum_{t=0}^{T-1} (ER_{t+k} - \alpha_k - \beta'_k X_t)^2 + \lambda_1 \sum_{m=1}^M \omega_m |\beta_{k,m}| + \lambda_2 \sum_{m=1}^M \beta_{k,m}^2 \right], \quad (2.3)$$

where λ_1 and λ_2 are the parameters of the penalty terms of Tibshirani (1996) least absolute shrinkage and selection operator (lasso) and of the ridge regression, respectively. We follow Zou (2006) and adjust the elastic net approach of Zou & Hastie (2005) by the weighting term $\omega_m = |\hat{\beta}_{k,m}|^{-\gamma}$ for $\gamma > 0$, where $\hat{\beta}_{k,m}$ is the OLS estimate of $\beta_{k,m}$ from Equation (2.2). To find the minimum, for given parameters we solve Equation (2.3) using the algorithm provided by Friedman, Hastie, & Tibshirani (2010), selecting the optimal parameter combination by five-fold cross-validation.¹⁸

Mean Forecast Combination (MFC) Rapach, Strauss, & Zhou (2010) find that using forecast combinations yield substantial improvements in the out-of-sample predictability (relative to single variable predictions) for the U.S. The authors argue that different variables capture complementary

¹⁷We also try a simple multiple predictive regression without the penalty terms of Equation (2.3). This approach clearly falls short of the adaptive elastic net in terms of out-of-sample performance.

¹⁸Following Zou (2006), we use the values of 0, 0.5, 1, and 2 as possible γ s and 100 equally-spaced different values for λ_1 and λ_2 , with the maximum being the value from which on all β_k -parameters will be set to zero.

information about the state of the economy. Forecast combinations provide more stable estimates than simple multiple regressions and, thereby, reduce the forecast volatility. To compute the combined out-of-sample forecast, we first run a kitchen sink regression and select all variables that yield a significant slope coefficient at at least the 10 % significance level. Finally, equipped with these B variables, where $b = 1, \dots, B$, we compute the combined out-of-sample forecast ($\widehat{ER}_{t+k}^{c, oos}$) as:

$$\widehat{ER}_{t+k}^{c, oos} = \frac{1}{B} \sum_{b=1}^B \widehat{ER}_{t+k}^{b, oos}, \quad (2.4)$$

where $\widehat{ER}_{t+k}^{b, oos}$ is the univariate out-of-sample forecast of predictor b .¹⁹ If no variable yields a significant slope estimate, we set the combined forecast $\widehat{ER}_{t+k}^{c, oos}$ equal to the historical mean estimate.

2.3 International Return Predictability

2.3.1 Summary Statistics

Before discussing our main findings, it is instructive to look at the summary statistics reported in Table 2.1. The time series are denominated in the countries' respective domestic currencies. All countries are grouped according to their geographic regions, i.e., Africa, America, Asia Pacific, Europe, and the Middle East.

We observe that America exhibits the highest (annualized) average market excess return of 11.79 %.²⁰ For the U.S., we find an average

¹⁹Rapach et al. (2010) suggest the median and the truncated mean as two further combination approaches. They obtain a superior performance of the mean forecast combination approach. Following them, we concentrate on that approach.

²⁰In some countries, the (nominal) market excess returns are unusually high. This is caused by high inflation rates. We account for this by subtracting the risk-free rate from the corresponding market return. However, due to unexpected inflation, the market excess returns nevertheless display high values, induced by uncommon average (annual) inflation rates of, e.g., 65.16 %, 34.48 %, 34.38 %, 26.60 %, 19.47 %, 14.91 %, and 12.69 % in Argentina, Romania, Peru, Chile, Israel, Venezuela, and Ukraine.

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(annualized) market excess return (standard deviation) of 6.15 % (16.49 %). These figures are similar to those reported, e.g., by Goyal & Welch (2008).

By comparison, (annualized) average market excess returns of more than 5 % and 3 %, respectively, indicate that market risk premia in countries in Asia Pacific, Africa, and the Middle East are somewhat lower. Europe displays the lowest (annualized) average market excess return, with 2.56 %. Germany and the U.K. exhibit (annualized) average excess returns (standard deviations) of 4.04 % (33.92 %) and 4.52 % (13.75 %), respectively.²¹

What drives these high average market excess returns? Jorion & Goetzmann (1999) show that the average U.S. real return is high compared to that of other countries. Furthermore, the literature broadly discusses whether the U.S. equity premium is overestimated.²² However, we find substantial average equity excess returns across all regions.

Brailsford, Handley, & Maheswaran (2008) document that the historical

²¹For almost all countries the average market excess returns are positive. There are, however, some exceptions. These include Bahrain, Brazil, Bulgaria, Croatia, Ecuador, Ghana, Hungary, Iceland, Kenya, Lebanon, Namibia, Philippines, Russian Federation, Slovakia Republic, and Turkey. For these countries the sample periods are relatively short. Thus, the negative average market excess return might be affected by strongly negative excess returns during the recent crises. In Brazil, there is a strong increase in the price level around January 1993, driven by extraordinary inflation expectations. This temporary increase induces a sharp drop in returns, which yields a negative average market excess return.

²²Claus & Thomas (2001) provide evidence by using analysts' earnings forecasts and show that in the U.S. and in Canada, France, Germany, Japan, and the U.K., the equity premium estimates amount to 3% p.a. at the maximum. Using dividend and earnings growth rates, Fama & French (2002) document a large discrepancy between the expected U.S. equity premium and the realized average market excess return for the period 1951–2000. Using both the dividend and earnings growth model, the approaches suggest equity premia of 2.55 % and 4.32 %, respectively, rather than 7.43 % p.a. Donaldson, Kamstra, & Kramer (2010) show similar findings and provide evidence for a U.S. equity premium of around 3.5 % p.a. Van Ewijk, De Groot, & Santing (2012) argue that inconsistencies in how to compute the equity premium might lead to differences in the estimates of up to 3.5 percentage points. Avdis & Wachter (2017) confirm the overestimation of historical averages of the U.S. equity premium. While using maximum likelihood estimation and taking dividend and price information into account, they provide evidence for a strong reduction from 6.4% to 5.1% p.a. They find similar results for the equity premia in Asia and the European Union, however, although to a smaller extent.

estimates of the equity premium in Australia are upward biased due to poor data quality. Analyzing the time period 1958–2005, the authors provide evidence for a reduced equity premium of more than 6% p.a. The lack of data quality might be responsible for the large differences in the average market excess returns we observe in our sample among countries within the same geographical region. Among others, we may refer to the African countries Botswana (10.06 %) and Morocco (9.59 %), in comparison to South Africa (2.86 %).

Shackman (2006) and Erbas & Mirakhor (2010) show that there are significant differences in the equity premia between countries. They document that equity premia are higher in emerging markets than in developed economies. Van Ewijk et al. (2012) confirm these results. Emerging countries seem to exhibit larger equity premia than the U.S. The highest premia are observable in the Asian Tiger countries with 15.21 %, whereas Italy, among the G7 countries, has the lowest, 1.17 %. Equity premia in Australia and Japan, and in Western Europe appear to be similar to that in the U.S. In addition, the authors argue that larger volatility in GDP (higher nominal interest rates) is (are) associated with larger (lower) equity premia.²³

Our results confirm these patterns. In particular, the Asian Tiger countries Korea and Hong Kong seem to have large average (annualized) market excess returns of 15.21 % and 9.20 %, respectively, whereas Singapore and Taiwan exhibit excess returns of more than 5 %. Considering the European countries, we find similar patterns, for example, when

²³Based on a steady-state model, Campbell (2008) shows that the (geometric) average equity premia for the world, the U.S., and Canada of 3.9 %, 4.1 %, and 3.6 % are lower than the realized market excess returns of 4.7 %, 5.5 %, and 4.5 % for the sample period 1900–2005, as documented in Dimson, Marsh, & Staunton (2008). Dimson, Marsh, & Staunton (2008, 2011) also show a reduction of the equity premium estimate in the U.S. and the U.K. The overestimation of sample averages in the existing literature arises from econometric concerns and distorted dividend expectations. The authors conclude that investors expect a global equity premium of 4.5 % to 5 % p.a.

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comparing Estonia (13.09 %), Latvia (6.03 %), and Lithuania (3.14 %). In contrast, we notice that most Western European countries exhibit average (annualized) market excess returns ranging from 0.5 % to 6 %, whereas in Australia (Japan), with 7.81 % (5.04 %), we detect an average market excess return somewhat higher (lower) than in the U.S.

2.3.2 In-Sample Analysis

We start our main analysis by studying the in-sample predictability of market excess returns. We estimate the following (univariate) regression model of the k -month(s) ahead excess return including a constant and the predictor variable:

$$ER_{t+k} = \alpha_k + \beta_k X_t + \epsilon_{t+k}, \quad (2.5)$$

where all variables are as previously defined. For our analysis, we focus on the 12-month predictability of excess returns (Goyal & Welch, 2008).

To draw inferences about the predictability of the market risk premium, we test the null hypothesis that the future excess return cannot be predicted using the variable X_t . In the case of no predictability, we expect that $\beta_k = 0$. In this case, we would conclude that the best predictor of the future market excess return is a constant, i.e., the recursive mean. On the other hand, if the slope loading is statistically significant, there is evidence of predictability. To quantify the degree of significant predictability across countries, we report average R^2 s in our main tables. We base our statistical inference on a bootstrapped distribution, as suggested by Rapach & Wohar (2006). Following this approach, we avoid a small-sample bias (Stambaugh, 1999) and account for serial correlation in the error terms (Richardson & Stock,

1989).²⁴

Table 2.2 visualizes and Table A.2 of the Appendix to this chapter provides detailed regression results for each country. In discussing our results, however, we focus on the more dense exposition of Table 2.3, where we aggregate the regression results over the geographical regions. We investigate each potential predictor separately.²⁵

We observe a substantial predictive power for all variables. In Africa, *dy* and *pe* have the highest predictive power, indicated by average R^2 s (fractions of significant R^2 s) of 8.41 % (62.50 %) and 14.43 % (88.89 %), respectively. *gov* and *infl* also display predictive ability, demonstrated by average R^2 s (fractions) of 3.91 % (66.67 %) and 1.15 % (33.33 %), respectively. For *corp* and *unrate*, we do not have sufficient data for African countries. Overall, the price-earnings ratio appears to be the best in-sample predictor of African market excess returns.

In America, all variables evince a high degree of predictability. In particular *dy*, *pe*, and *unrate* appear to be very good in-sample predictors with average R^2 s of 8.56 %, 9.31 %, and 9.76 %, which are significant for 81.82 %, 72.73 %, and 62.50 % of the cases, respectively. All other predictors also possess (if there is sufficient data to run our tests) noteworthy predictive ability. *gov* yields an average R^2 of 2.47 % (significant for 3 out of 5 countries). *infl* has a high predictive power which, however, seems to be driven mostly by high-inflation countries in Latin America. For example,

²⁴First, we set up the following null hypothesis: $ER_t = a_0 + \epsilon_{1,t}$ and $X_t = b_0 + b_1 X_{t-1} + \epsilon_{2,t}$, where a_0 , b_0 , and b_1 are the regression coefficients and $\epsilon_{1,t}$ and $\epsilon_{2,t}$ are the error terms, respectively. We then estimate the process under the null hypothesis of no predictability via OLS. Second, we form a series of error terms and set up our pseudo sample. For the pseudo sample, we calculate both the in- and out-of-sample statistics. Finally, we repeat this procedure 1,000 times.

²⁵We impose two conditions to be able to make reliable inferences from our results. First, at least 10 years of observations must be available to include a variable for the in-sample analysis. Second, there must be at least 30 out-of-sample observations to consider the out-of-sample performance of a variable. Note that tables reporting the aggregated results are based on equally weighted portfolios. However, due to the conditions imposed, the number of countries per portfolio might differ slightly.

2.3. INTERNATIONAL RETURN PREDICTABILITY

Table 2.2: Graphical Representation of Return Predictability – Country View

This table presents a visualization of the significance of in-sample and out-of-sample R^2 s for different predictor variables and forecast combinations. We sample the data at the monthly frequency, and we predict the future 12-month excess return. \square , \blacksquare , \blacksquare indicate significance of the respective statistics at the 10 %, 5 %, and 1 % level, respectively. A white cell denotes no significant predictive power, whereas “-” indicates insufficient data availability. “dy” denotes the dividend yield, “pe” the price-earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007).

Region	Country	In-Sample R^2						Out-of-Sample R^2 (R^2_{oos})							
		dy	pe	corp	gov	infl	unrate	dy	pe	corp	gov	infl	unrate	AEN	MFC
Africa	Botswana	■	■	-	■	-	-	■	-	-	-	-	-	-	-
	Ghana	■	■	-	-	-	-	-	■	-	-	-	-	-	-
	Kenya	■	-	-	-	-	-	-	■	-	-	■	-	■	■
	Mauritius	■	■	-	■	-	-	-	■	-	-	■	-	-	-
	Morocco	■	■	-	■	-	-	-	-	-	-	-	-	-	-
	Namibia	-	■	-	-	■	-	-	-	-	-	■	-	-	-
	Nigeria	■	■	-	-	■	-	■	■	-	-	-	-	-	-
	South Africa	■	■	-	-	■	-	■	■	-	-	■	-	-	-
Tunisia	■	■	-	■	-	-	-	-	-	-	-	-	-	-	
America	Argentina	-	-	-	-	■	-	-	-	-	-	■	-	-	-
	Brazil	■	■	-	-	■	-	-	-	-	■	■	■	■	■
	Canada	■	■	-	■	-	-	-	-	-	-	■	■	■	■
	Chile	■	■	-	-	■	-	-	-	-	-	■	■	■	■
	Colombia	■	■	-	-	-	■	-	-	-	-	-	-	-	-
	Ecuador	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	Jamaica	■	■	-	-	■	-	■	■	-	■	■	■	■	■
	Mexico	■	■	-	■	-	-	■	■	-	■	■	■	■	■
	Peru	■	■	-	-	■	-	■	■	-	■	■	■	■	■
	Trinidad and Tobago	-	-	-	-	■	-	-	-	-	■	■	■	■	■
	United States	■	■	-	■	-	-	■	■	-	■	■	■	■	■
Venezuela	■	■	-	-	■	-	-	-	-	-	■	■	■	■	
Asia Pacific	Australia	■	■	-	■	-	■	■	■	-	-	-	■	■	■
	Bangladesh	■	■	-	-	-	-	-	-	-	-	-	-	-	-
	China	■	■	-	-	-	-	■	■	-	■	-	-	-	-
	Hong Kong	■	■	-	■	-	■	■	■	-	-	■	■	■	■
	India	■	■	-	■	■	-	■	■	-	■	■	■	■	■
	Indonesia	■	■	-	-	-	-	■	■	-	-	-	■	■	■
	Japan	■	■	-	■	■	-	■	■	-	■	■	■	■	■
	Korea	■	■	-	-	■	-	■	■	-	■	■	■	■	■
	Malaysia	■	■	-	-	■	-	■	■	-	■	■	■	■	■
	New Zealand	■	■	-	■	-	-	■	■	-	-	-	■	■	■
	Pakistan	■	■	-	■	■	-	■	■	-	■	■	■	■	■
	Philippines	■	■	-	■	■	-	■	■	-	■	■	■	■	■
	Singapore	■	■	-	-	-	-	■	■	-	-	-	■	■	■
	Sri Lanka	■	■	-	■	■	-	■	■	-	■	■	■	■	■
	Taiwan	■	■	-	■	■	-	■	■	-	■	■	■	■	■
	Thailand	■	■	-	■	■	-	■	■	-	■	■	■	■	■
	Vietnam	-	-	-	-	■	-	-	-	-	-	-	-	-	-

Table 2.2: Graphical Representation of Return Predictability –
Country View (continued)

Region	Country	In-Sample R ²						Out-of-Sample R ² (R ² _{oos})							
		dy	pe	corp	gov	infl	unrate	dy	pe	corp	gov	infl	unrate	AEN	MFC
Europe	Austria	■		■	■	■								■	■
	Belgium		■		■	■	■							■	■
	Bulgaria	—	■		■	■	■				■	■			
	Croatia														
	Czech Republic	■	■			■	■				■	■			■
	Denmark		■						■						■
	Estonia		■			■					■	■		■	■
	Finland	■	■				■		■		■	■		■	■
	France	■			■					■	■	■		■	■
	Germany	■	■	■	■	■	■		■						■
	Greece	■			■						■				
	Hungary	■										■			
	Iceland	—	—		■	■	■				■	■	■		
	Ireland		■		■	■	■		■						
	Italy	■	■		■		■					■	■	■	■
	Latvia	■													
	Lithuania				■		■								
	Luxembourg	■			■										
	Malta	—	—		■		■								
	Netherlands	■	■	■	■	■	■		■	■	■	■	■	■	■
	Norway	■		■					■	■			■	■	■
	Poland	■	■		■	■	■				■	■		■	■
	Portugal	■	■		■	■	■				■	■		■	■
	Romania	■			■	■	■		■			■			
	Russian Federation	■			■	■	■		■		■	■			■
	Slovakia Republic											■			
	Slovenia	■			■		■				■				
	Spain	■	■							■	■	■		■	■
	Sweden	■			■	■	■		■	■	■	■	■	■	■
	Switzerland	■	■		■	■	■					■	■	■	■
Ukraine	—	■													
United Kingdom	■	■	■	■	■	■		■					■	■	
Middle East	Bahrain		■					■							
	Cyprus	—			■	■				■	■				
	Egypt		■						■						
	Israel	■	■			■	■				■	■	■	■	
	Jordan	■	■								■				
	Kuwait	—									■		■		
	Lebanon		■							■			■	■	
	Oman	—				■									
	Qatar	—													
	Saudi Arabia	—	■			■	■				■		■	■	
	Turkey	■	■			■	■		■					■	■

2.3. INTERNATIONAL RETURN PREDICTABILITY

Table 2.3: Return Predictability and Regions – Aggregated View

This table summarizes the in-sample and out-of-sample return predictability for different regions. We sample the data at the monthly frequency and predict the future 12-month excess return. “Mean” indicates the average R^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R^2 s, respectively. “Mean | Significant” is the mean of the R^2 s given they are significant at at least the 10% significance level. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively. R^2 and R_{OOS}^2 are the in-sample and out-of-sample R^2 , respectively. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007).

		dy				pe				corp				gov			
Region	Statistic	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
		Africa	R^2 R_{OOS}^2	8.41 2.40	8 3	62.50 66.67	13.01 7.75	14.43 0.10	9 7	88.89 42.86	16.20 20.33	0.21 -4.18	1 1	0.00 0.00		3.91 -29.70	6 4
America	R^2 R_{OOS}^2	8.56 -7.67	11 9	81.82 44.44	10.38 12.68	9.31 -3.84	11 11	72.73 18.18	12.74 22.60	2.86 -0.81	2 2	100.00 50.00	2.86 1.44	2.47 6.08	5 5	60.00 20.00	3.97 54.63
Asia Pacific	R^2 R_{OOS}^2	12.28 14.54	16 15	75.00 66.67	16.33 24.34	11.47 2.11	16 16	81.25 50.00	14.08 13.53	1.19 2.28	4 4	50.00 25.00	2.02 27.80	2.73 -10.21	13 13	69.23 53.85	3.78 5.08
Europe	R^2 R_{OOS}^2	4.36 -2.53	26 22	76.92 36.36	5.64 9.04	3.39 -12.74	28 23	53.57 17.39	6.00 1.42	1.32 0.41	10 10	50.00 50.00	2.54 9.20	5.49 -31.22	30 29	80.00 17.24	6.81 9.11
Middle East	R^2 R_{OOS}^2	12.01 10.03	5 4	60.00 100.00	19.07 10.03	9.09 -50.32	7 6	85.71 16.67	10.45 24.68					1.13 7.36	3 2	33.33 100.00	2.53 7.36

		infl				unrate				AEN				MFC			
Region	Statistic	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
		Africa	R^2 R_{OOS}^2	1.15 -1.26	9 9	33.33 33.33	2.91 1.14					-6.39	9	11.11	1.45	-2.91	9
America	R^2 R_{OOS}^2	4.80 -11.53	11 11	72.73 54.55	6.57 2.40	9.76 11.01	8 7	62.50 71.43	15.43 18.73	-13.46	11	54.55	4.40	-9.84	11	54.55	4.04
Asia Pacific	R^2 R_{OOS}^2	1.99 -6.75	15 15	60.00 46.67	3.19 2.94	10.47 5.75	8 8	100.00 62.50	10.47 13.17	0.10	17	52.94	16.82	4.56	17	64.71	15.29
Europe	R^2 R_{OOS}^2	1.47 -8.02	32 32	34.38 40.63	3.96 3.96	5.78 -1.23	30 30	70.00 56.67	8.16 12.77	-2.12	32	43.75	8.28	2.89	32	50.00	9.74
Middle East	R^2 R_{OOS}^2	4.47 0.68	10 9	40.00 44.44	10.81 9.96	16.77 -36.83	3 2	100.00 50.00	16.77 1.42	-2.26	10	40.00	9.46	2.77	10	40.00	12.35

the predictive power in Argentina ($R^2 = 23.93\%$), Brazil ($R^2 = 2.63\%$), Chile ($R^2 = 3.11\%$), Peru ($R^2 = 14.69\%$), and Venezuela ($R^2 = 3.37\%$) is very high, whereas, e.g., in the U.S. and Canada, there is a smaller degree of predictability. Thus, the predictive ability of *infl* may be hard to exploit in practice.

In Asia Pacific and Europe, we detect a similar pattern to that in America. All variables seem to have substantial predictive ability. *dy*, *pe*, *gov*, and *unrate* in particular display a very good performance, indicated by both substantial shares of countries for which we find significant predictability and high average in-sample R^2 s. For the Middle East, we detect a similar pattern.

Overall, we detect substantial in-sample predictability for, in principle, all of our predictive variables. Thus, subject to a verification out-of-sample, it seems that aggregate market excess returns are strongly predictable across the globe.

2.3.3 Out-of-Sample Analysis

We continue the analysis by examining the return predictability out-of-sample. Following Rapach & Wohar (2006), we use an initial training window of 10 years to estimate the forecasting model presented in Equation (2.5) in order to obtain the first parameter estimates.²⁶ Equipped with these and using the most recent observation of the forecasting variable, we generate the first excess return forecast. Afterwards, we re-estimate the forecasting model by rolling the training window forward by one month. Thus, with the new parameter estimates, we again forecast the market excess return over the next 12 months. We base our out-of-sample analysis

²⁶Using an initial training window of 20 years, as suggested by Goyal & Welch (2008), we obtain similar results. However, some countries drop off due to their short time series. Therefore, for our main analysis, we use an initial training window of 10 years.

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on a 10-year rolling window to capture the potential time-varying effects in the coefficients of the predictive regression.²⁷

Following Campbell & Thompson (2008), we use the out-of-sample R^2 (R_{oos}^2) to assess the out-of-sample performance of different models, i.e.:

$$R_{oos}^2 = 1 - \frac{MSE_u}{MSE_r}, \quad (2.6)$$

where MSE_u and MSE_r are the mean squared errors of the unrestricted and restricted models, respectively. The unrestricted model is based on Equation (2.5) or one of our model selection approaches. In the case of the restricted model, we impose the null hypothesis that excess returns are unpredictable, i.e., $\beta_k = 0$. Thus, based on the R_{oos}^2 we can answer the question: What predictive power in excess of the historical mean can one achieve by using the variable X_t ? A variable has noteworthy predictive power if it exhibits a positive and significant R_{oos}^2 , indicating an overall outperformance over the historical mean.

To assess whether the predictability is significantly higher than that of the historical mean, we compute the $MSE - F$ statistic suggested by McCracken (2007):

$$MSE - F = (N - k + 1) \times \left(\frac{MSE_r - MSE_u}{MSE_u} \right), \quad (2.7)$$

where N denotes the number of out-of-sample forecasts. All other variables are as previously defined. The null hypothesis is that the restricted model performs at most as well as the unrestricted model, i.e., $MSE_r \leq MSE_u$. The alternative is that the unrestricted model provides smaller forecast errors than the restricted model.

While out-of-sample predictability is “the ultimate test of any predictive model” (Campbell, 2008), out-of-sample tests are somewhat less powerful

²⁷Due to the overlapping observations, we obtain serial correlation in the error terms. We account for this by using the bootstrap algorithm of Rapach & Wohar (2006).

than in-sample tests of return predictability (Inoue & Kilian, 2005; Cochrane, 2008). For out-of-sample tests, the sample employed for estimating parameters is only a subset of that used for in-sample estimates. A larger sample naturally improves the accuracy of the estimates and enhances the power of statistical tests. Thus, it is likely that we detect a somewhat lower degree of out-of-sample predictability.

Similar to the in-sample analysis, Table 2.2 visualizes and Table A.2 of the Appendix to this chapter provides detailed regression results, while we focus the discussion on the aggregated out-of-sample regression results in Table 2.3.²⁸

We also observe a substantial predictive power for all variables. In African countries, we find noteworthy predictive power for dy and pe , demonstrated by average R^2 s (fractions) of 2.40 % (66.67 %) and 0.10 % (42.86 %), respectively. $infl$ has some, whereas gov seems to have no predictive ability at all. For most countries in these regions, we do not have sufficient data to compute R^2_{oos} s for $corp$ and $unrate$. Overall, market excess returns are predictable for most African countries.

Compared to the in-sample study, we detect a reduced though still substantial predictability for all predictors in America, Asia Pacific, Europe, and the Middle East. For example, dy achieves significant R^2_{oos} s for 44.44 %, 66.67 %, and 36.36 % of the countries of the three regions, respectively. Similar, though typically somewhat weaker predictive power materializes for $unrate$, $infl$, pe , $corp$, and gov (broadly ordered by the strength of the predictability).

²⁸Studying the results carefully, the reader might wonder why the results for the predictability of dy and $corp$ in the U.S. differ from those in Goyal & Welch (2008). For one reason, in their tables, Goyal & Welch (2008) present results for an expanding instead of a rolling window, as in our specification. Second, we use a 10-year instead of a 20-year rolling window that they employ for their graphs. It thus seems that the optimal predictive relation changes frequently and one can enhance the out-of-sample predictability by accounting for this.

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The last two columns in Table 2.3 show the results of the adaptive elastic net as well as of the mean forecast combination approach.²⁹ We observe that both approaches yield good out-of-sample predictions. For Africa, there is generally not much data available. Thus, it is not surprising that the model selection approaches do not work that well there, with only one country for which we can detect a significant R_{oos}^2 . For the remaining regions, however, we find high shares of significant R_{oos}^2 s, even though the sample for the two model selection approaches spans more countries than are typically available for a single predictor variable. For *MFC*, the share of significant R_{oos}^2 is at least 40.00 % for America, Asia Pacific, Europe, and the Middle East. The overall performance of *AEN* is somewhat weaker than that of *MFC*. In total, also considering the substantially broader sample considered for *MFC*, we regard the mean forecast combination approach as the best for out-of-sample predictions.

2.3.4 Economic Utility Gains

While the previous analysis is statistical in nature, for investors it is very important whether and how predictability can be translated into economic gains by portfolio allocation strategies. However, the relation between out-of-sample R^2 and economic utility gains from such a portfolio allocation strategy has been found to be complex (Rapach & Zhou, 2013). Therefore, in this section, we also study whether it is possible to obtain economic utility gains.

We assume that an investor either has mean–variance preferences or that mean–variance preferences provide a reasonable second-order Taylor approximation to the investor’s true utility function (Fleming, Kirby, &

²⁹For the adaptive elastic net and the mean forecast combination approach, we use the MSPE-adjusted test statistic of Clark & West (2007). A parametric bootstrap is only possible for univariate or multiple predictive regressions, using homogenous time series for the predictors.

Ostdiek, 2001). The investor decides to allocate a fraction ω_t of her wealth to the risky market portfolio and the remainder, i.e. $1 - \omega_t$, to the risk-free asset. Her objective function is:

$$\max_{\omega_t} E_t \left(r_{p,t+k} - \frac{\gamma}{2} \sigma_{p,t+k}^2 \right), \quad (2.8)$$

where $E_t(\cdot)$ is the expectation operator, $\sigma_{p,t+k}^2$ the conditional variance of the portfolio from t to $t+k$, and γ is the coefficient of relative risk-aversion. $r_{p,t+k}$ is the simple return of the investor's portfolio between t and $t+k$. Since our previous analysis is based on log rather than simple returns, we use a second-order Taylor expansion to transform the returns.³⁰ Thus, we can express the objective function as follows:

$$\max_{\omega_t} E_t \left(R_{p,t+k} - \frac{\gamma - 1}{2} \sigma_{p,t+k}^2 \right), \quad (2.9)$$

where $R_{p,t+k}$ is the log-return on the portfolio. For the conditional return variances, we use an estimate based on a five-year rolling window.

Optimizing Equation (2.9), one can obtain the optimal weight invested in the risky asset as (Jordan et al., 2014):

$$\omega_t = \frac{E_t(ER_{t+k} + \frac{1}{2}\sigma_{t+k}^2)}{\gamma E_t(\sigma_{t+k}^2)} = \frac{E_t(ER_{t+k})}{\gamma E_t(\sigma_{t+k}^2)} + \frac{1}{2\gamma}. \quad (2.10)$$

Thus, the optimal weight positively depends on the expected future excess return, while it is reduced for higher realized variance and levels of relative risk-aversion.

For each month in our out-of-sample analysis, we compute the weight ω_t and also the realized return over the next k months of the portfolio. To avoid short-selling and excessive leverage, we follow Campbell & Thompson (2008) and impose the restriction that ω_t has to be between 0 and 1.5. The

³⁰The second-order Taylor expansion leads to the following relationship: $R_t \approx r_t - \frac{1}{2}\sigma_t^2$, where R_t , r_t , and σ_t^2 are the log-return, simple return, and variance at time t , respectively. In doing so, we express the simple return as a function of log-return and variance.

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certainty equivalent return (CER) is:

$$CER = \bar{r}_p - \frac{\gamma}{2}\sigma_p^2, \quad (2.11)$$

where \bar{r}_p is the average simple return on the portfolio, and σ_p^2 is the variance of the portfolio returns. The utility gain (ΔCER) of using a certain predictor is the difference between the CER of a strategy using that predictor and the CER when using the historical mean benchmark return.

Table 2.4 reports the results for $\gamma = 3$ (Friend & Blume, 1975). For each region and predictive variable, we observe that the out-of-sample return predictability also translates to substantial economic gains. While the average utility gains are negative for some predictor–region combinations, across all regions and predictors there is a substantial share of countries, for which we can detect positive utility gains. Among the individual predictors, especially *dy* and *unrate* appear to yield high utility gains. In particular the combination approaches *AEN* and *MFC* yield high utility gains.

Tables A.3 and A.4 of the Appendix to this chapter repeat the analysis for $\gamma = 6$ and $\gamma = 9$, respectively. For these higher levels of risk-aversion, we find somewhat weaker aggregate results, but it is still possible to obtain substantial utility gains for all regions and predictors. Finally, Table A.5 of the Appendix to this chapter reports the utility gains for $\gamma = 3$, when taking transaction costs into account. We follow Balduzzi & Lynch (1999) and assume transaction costs of 50 basis points per transaction proportional to the asset’s traded size $|\omega_{t+k} - \omega_t|$, where ω_t is the portfolio weight before re-balancing at $t + k$. Note that transaction costs arise for both strategies: that based on a predictor variable and that based on the historical mean. Hence, it is not surprising that we observe very similar results after transaction costs. Our findings are largely unaffected by these.

Table 2.4: Economic Utility Gains ($\gamma = 3$) – Aggregated View

This table reports the utility gains ($\Delta CERs$) with $\gamma = 3$ in percent relative to a benchmark strategy based on the historical mean. We sample the data at the monthly frequency, and we predict the future 12-month excess return. “Mean” indicates the average ΔCER . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of $\Delta CERs$ greater than zero, respectively. “Mean | > 0 ” is the mean ΔCER given it is greater than zero. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively.

Region	dy				pe				corp				gov			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	2.02	3	66.67	3.61	-0.32	7	57.14	1.16	0.43	1	100.00	0.43	-0.46	4	75.00	1.11
America	-0.46	9	33.33	1.21	-0.29	11	63.64	0.61	0.56	2	100.00	0.56	-0.34	5	60.00	0.31
Asia Pacific	1.16	15	53.33	2.91	0.66	16	68.75	1.39	0.40	4	25.00	3.69	0.14	13	53.85	1.00
Europe	-0.75	22	40.91	0.70	-0.55	22	36.36	0.67	0.59	10	70.00	1.66	-0.40	29	44.83	0.77
Middle East	0.37	4	50.00	2.39	-0.51	6	16.67	5.57					0.42	2	100.00	0.42

Region	infl				unrate				AEN				MFC			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	-0.02	9	55.56	0.25					0.48	9	66.67	1.09	0.55	9	66.67	1.11
America	-3.07	11	45.45	0.18	1.56	7	71.43	2.86	-2.66	11	36.36	1.67	-2.79	11	36.36	0.92
Asia Pacific	-0.11	15	46.67	0.33	1.22	8	75.00	1.70	0.65	17	64.71	1.94	1.10	17	70.59	1.73
Europe	-0.46	32	31.25	0.70	0.26	30	76.67	1.34	0.38	32	71.88	1.51	0.29	32	71.88	1.22
Middle East	-1.00	9	44.44	0.71	0.45	2	50.00	1.44	-0.97	10	50.00	0.42	-0.86	10	40.00	0.57

2.4 What Drives Market Return Predictability?

A longstanding question related to return predictability is whether there is predictability due to rationally time-varying expected returns (e.g., Fama & French, 1989) or due to market inefficiency, caused by financial frictions or possibly even by irrational deviations of prices from their

2.4. WHAT DRIVES MARKET RETURN PREDICTABILITY?

fundamental values (e.g., Shiller, Fischer, & Friedman, 1984; Summers, 1986), or due to a combination of these. Making use of our large cross-section of countries, in this section, we provide evidence on this issue. To set the stage, we first develop five hypotheses which we test in the following.

Time-Varying Expected Returns Fama & French (1989) find that expected returns vary considerably across the business cycle. The authors show that expected returns behave counter-cyclically, implying higher expected returns when economic conditions are weak, and vice versa. Thus, any predictability that is due to time-varying aggregate risk or risk preferences is entirely consistent with market efficiency. One could argue that if time-varying expected returns are an important driver of predictability, the predictability should be stronger for countries for which the business cycles vary more strongly, i.e., those with higher GDP volatility. Furthermore, Diebold & Yilmaz (2008) document a robust cross-sectional link between GDP volatility and stock market volatility. This leads us to the following hypothesis:

Hypothesis 1. *Countries with higher GDP volatility exhibit better out-of-sample predictability.*

A further measure of frequently changing business conditions is the share of recessions during our sample period. In recessions, investors exhibit a higher risk-aversion and therefore require a higher risk premium, which implies a better return predictability in these states (Cochrane, 1999, 2007). Rapach et al. (2010), Henkel et al. (2011), Dangel & Halling (2012), and Garcia (2013) analyze the U.S. and the G7 countries and document a stronger return predictability in recessions. Cujean & Hasler (2017) provide a theoretical model with disagreement to explain these results. More concretely, Henkel et al. (2011) show that, for the U.S., there seems to be

a positive relation between the proportion of recession months and return predictability. This leads us to our second hypothesis:

Hypothesis 2. *Countries with more frequent bad states exhibit better out-of-sample predictability.*

This hypothesis might be somewhat controversial. The findings of the previous literature indicate that predictability is stronger in recessions. However, we set up unconditional predictive regressions. The optimal predictive technology might face severe model uncertainty and parameter instability across different stages of the business cycle, and hence might change strongly from “good” to “bad” states (Dangl & Halling, 2012). It is thus possible that we find a worse overall predictability in countries with frequent bad states.³¹

Market Inefficiency Rösch, Subrahmanyam, & van Dijk (2017) argue that financial frictions, such as limited capital or transaction costs, severely reduce market efficiency. This reduced market efficiency may cause slow information diffusion and delayed price reactions to new information, and may cause predictability of returns in the time series. Thus, if market inefficiency is the main driver of return predictability, we expect returns in countries with small and restricted capital markets to be better predictable. This leads us to the following two hypotheses:

Hypothesis 3. *Countries with higher market capitalizations exhibit worse out-of-sample predictability.*

Hypothesis 4. *Countries with higher market openness exhibit worse out-of-sample predictability.*

³¹Furthermore, Henkel et al. (2011) find that for France, Germany, and Italy (out of their sample of the G7 countries), the difference is not statistically significant towards the 5 % significance level. It is thus possible that the relation between predictability and bad states holds only for very large countries.

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Finally, Jordan et al. (2014) suggest using GDP per capita as a proxy for market development, which leads us to:

Hypothesis 5. *Countries with higher GDP per capita exhibit worse out-of-sample predictability.*

We sort the countries into five portfolios, according to their GDP volatility, frequency of bad states, market capitalization, market openness, and GDP per capita. Portfolio 1 (5) contains the countries with the lowest (highest) values for the respective characteristic. We base our analysis on out-of-sample predictability of the mean forecast combination approach, which yields both high predictability and good data availability across the regions. To synchronize the evidence on predictability with the availability of data on the sorting variables, for this analysis, we limit our sample period to that for which the sorting variables are available. Table 2.5 reports the results.

GDP Volatility We first explore the effect of GDP volatility on return predictability. GDP volatility is computed as the volatility of the annual GDP growth rates. We find that the evidence is not entirely clear-cut. While in all portfolios there is a share of more than 30 % of the countries with significant R_{oos}^2 s, we observe the highest average R_{oos}^2 s for portfolios 1, 2, and 5. Thus, on the one hand, consistent with Hypothesis 1, returns in countries with high GDP volatility are very well predictable. However, returns are also very well predictable in those countries that exhibit only low GDP volatility. Thus, overall we cannot confirm Hypothesis 1.

A possible explanation for this result is that GDP volatility is not a perfect measure of variation in business cycles. Indeed, we find that countries that exhibit lower GDP volatility are typically associated with higher GDP

**Table 2.5: Return Predictability and Sorting Characteristics –
Aggregated View**

This table reports portfolio sorts of countries according to different characteristics, indicated in the panel headings. We present average out-of-sample results based on the mean forecast combination approach. We sample the data at the monthly frequency, and we predict the future 12-month excess return. We sort the countries according to the respective sorting characteristic into five portfolios. Portfolio 1 (5) contains the countries with the lowest (highest) value of the sorting characteristic. “Mean” indicates the average R_{oos}^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R_{oos}^2 s, respectively. “Mean | Significant” is the mean of the R_{oos}^2 s given they are significant at at least the 10% significance level. Statistical inference is based on the MSPE-adjusted test statistic of Clark & West (2007).

Portfolio	GDP Volatility				Bad States			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Portfolio 1	5.08	15	40.00	13.12	11.86	16	62.50	18.48
Portfolio 2	4.00	16	62.50	10.59	3.58	16	56.25	9.42
Portfolio 3	-8.25	16	43.75	13.17	-7.82	15	40.00	8.82
Portfolio 4	-1.03	16	31.25	7.49	0.61	16	43.75	8.90
Portfolio 5	5.24	15	60.00	20.37	-4.76	16	43.75	5.56

Portfolio	Market Capitalization				Market Openness				GDP per Capita			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Portfolio 1	0.30	11	27.27	3.01	-6.31	15	26.67	15.37	-2.32	15	40.00	15.63
Portfolio 2	-7.58	11	36.36	16.01	5.77	15	46.67	12.22	-12.82	16	37.50	5.18
Portfolio 3	8.54	11	81.82	12.45	-4.90	16	31.25	17.75	4.95	16	50.00	14.87
Portfolio 4	10.81	11	81.82	12.31	3.31	16	62.50	11.29	4.46	16	43.75	16.27
Portfolio 5	12.81	11	81.82	14.07	8.05	15	46.67	17.26	10.65	15	66.67	13.99

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per capita.³² Thus, perhaps GDP volatility is not a perfect proxy for the degree of time-variation in expected returns.

Bad States To proxy for the share of bad states, we use the relative frequency of negative return observations in our sample (Lakonishok, Shleifer, & Vishny, 1994).³³ We sort the countries according to that ratio: the higher the ratio, the more bad states occurred in the respective country.

The analysis reveals a clear pattern between the frequency of bad states and return predictability. The average R_{oos}^2 s as well as the share of significantly positive R_{oos}^2 s are highest for portfolios 1 and 2. Thus, the aggregate excess returns appear to be much better predictable in countries that exhibit a small number of bad states. Hence, the data delivers only very little support for Hypothesis 2. It is likely, though, that the optimal predictive technology differs for bad and good states. In this case, returns in countries with fewer bad states might be better predictable simply because the data generating process – influenced by issues like policy shocks, technological advances, institutional changes, or learning of investors (Timmermann, 2008) – changes less frequently.

Market Capitalization Next, we scrutinize whether the size of an economy, proxied by aggregate market capitalization, systematically affects the predictability of market excess returns. In doing so, we sort the countries according to their stock market capitalizations, adjusted by the GDP implicit price deflator.

³²Due to limited space, we do not present the tables that display the portfolio compositions per characteristic.

³³Directly measuring the frequency of recessions would be preferable. However, we can only obtain data about recessions for the OECD countries and a reduced time series from the OECD. Therefore, we follow Lakonishok et al. (1994) and proxy recessions by the frequency of negative market returns.

We find that the three portfolios of countries with the highest market capitalizations are clearly best predictable. The average R_{oos}^2 s (fractions of significant R_{oos}^2 s) for portfolios 3 to 5 amount to 8.54 % (81.82 %), 10.81 % (81.82 %), and 12.81 % (81.82 %), while the numbers are considerably lower for portfolios 1 and 2. Thus, these results are at odds with Hypothesis 3.

Market Openness We also examine the relationship between market openness and return predictability. We find that aggregate excess returns of countries in portfolios 2, 4, and 5 are best predictable. Thus, the data also does not support Hypothesis 4: it is clearly visible that predictability in the most closed economies is not superior.

GDP per Capita Finally, we sort the countries according to their average GDP per capita. We find that aggregate excess returns in countries with higher GDP per capita are, in general, more predictable than those in countries with lower GDP per capita. The highest average R_{oos}^2 of 10.65 % results for portfolio 5. This portfolio also has the highest share of significant R_{oos}^2 s (66.67 %). Thus, we also find no empirical support for Hypothesis 5.

One might argue that by using the mean forecast combination approach for all, we do not uncover the full scale of predictability in some countries. Therefore, we repeat the previous analysis using the ex-post best predictive technology for each country (measured by the level of R_{oos}^2). While it would not have been possible to implement such a strategy in real-time, this approach comes closer to analyzing the maximum predictability that is possible to achieve in each country.

We present these results in Table A.6 of the Appendix to this chapter. For GDP volatility, we uncover a weakly increasing relation of average R_{oos}^2 s. Thus, with the ex-post best predictors, Hypothesis 1 gains a little more support, but still clearly not enough to accept it. For the frequency of bad

2.5. FURTHER ANALYSES

states, the results are also largely similar as before. The portfolio of countries with the highest percentage share of bad states is least predictable. For the three remaining sorting characteristics, we detect similar patterns as before. In general, market excess returns in better developed countries appear to be somewhat better predictable, also when using the ex-post best predictive technology.

Overall, our findings suggest that it is more difficult to predict market returns in low-developed and less open economies. Thus, it seems very unlikely that aggregate return predictability is caused by market inefficiency. On the contrary, our results rather indicate that predictability is positively related to these rough measures of market efficiency. The main intuition for why returns in efficient markets are predictable is time-variation in expected returns due to variation in business cycles. However, our results also cannot confirm that excess returns in countries with more business cycle variations are better predictable. One potential reason for this is, though, that we do not have the perfect proxies for business cycle variations.

2.5 Further Analyses

In this section, we perform further analyses. First, to check the robustness of our results, we perform a subsample analysis and investigate the post-1990 time period. Second, we employ economically motivated sign restrictions. Third, we examine the effect of U.S. predictors on the predictability of international market risk premia. Finally, we analyze the market return predictability from the perspective of a U.S. investor, i.e., when denominating returns in USD.

2.5.1 Post-1990 Time Period

To examine the robustness of our results, we analyze the time period after 1990. Studying a reduced period of time substantially reduces the heterogeneity in our dataset in terms of data quality and lengths of the time series. Thus, with this analysis, we primarily test the robustness of our main results with respect to imbalances in the dataset. We consider 1990 as a reasonable breakpoint since it broadly coincides with structural changes that occurred in many countries around this time, e.g., due to the decay of the Soviet Union. In the post-1990 period, many countries are characterized by a stronger market as opposed to a planned economy and deregulation strengthened capital markets. Consequently, there might be a structural break around that data that implies changes in the predictability of aggregate excess returns. Timmermann & Granger (2004) and Chordia, Roll, & Subrahmanyam (2008) argue that markets behave efficiently at the present time. On the other hand, Pesaran & Timmermann (2002) and Lettau & Van Nieuwerburgh (2008) argue that predictability has disappeared since the 1990s due to parameter instability and further structural breaks. Thus, it is also possible that we cannot observe any return predictability for this most recent subperiod.

Table 2.6 visualizes the detailed results, whereas Table 2.7 reports the aggregated regression results for in- and out-of-sample return predictability. The post-1990 time period reveals, compared to the initial analysis based on the maximal possible sample periods (see Table 2.3), similar patterns for all regions, both in- and out-of-sample. In some instances, aggregate market excess returns seem to be even better predictable when only considering the post-1990 period. Table 2.8 reports the economic utility gains for $\gamma = 3$ and Table A.7 of the Appendix to this chapter summarizes the results, when accounting for transaction costs. Again, the results are very similar to those

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for our entire sample period.

Overall, the results for the reduced time period are qualitatively similar as for our main study period. We find a substantial predictability of aggregate market returns in all regions, as well as substantial utility gains for many predictor–country combinations, also for the substantially shorter post-1990 period. The observation of strong return predictability in the more recent period, which is typically characterized as more efficient, further strengthens the view that it is not market inefficiency that drives the return predictability.

However, the heterogeneity in time series is less of a concern for establishing predictability than for the cross-country analysis. Therefore, we also repeat this analysis for the post-1990 sample period. Table 2.9 summarizes these results. These are overall very similar to those for the entire sample period. There seems to be a negative relation of return predictability with the frequency of bad states. Furthermore, predictability is positively related to proxies for market efficiency and market openness.

2.5.2 Restricted Predictability

Following Campbell & Thompson (2008), we impose two economically motivated restrictions to improve the out-of-sample predictability of market returns. First, we set the out-of-sample slope estimate equal to zero whenever it has a different sign to that of the in-sample estimate.³⁴ Second, we set the out-of-sample forecast equal to zero whenever it is negative (Campbell & Thompson, 2008).

Table 2.10 presents the aggregated out-of-sample regression results. Imposing both restrictions generally slightly enhances the aggregate return predictability. For most regions and predictors, the average R_{oos}^2 is somewhat

³⁴It is worthwhile to mention that this restriction cannot be implemented in real-time. Thus, the analysis suffers from a look-ahead bias.

**Table 2.6: Graphical Representation of Return Predictability –
Country View (Post-1990)**

This table presents a visualization of the significance of in-sample and out-of-sample R^2 s for different predictor variables and forecast combinations. We sample the data at the monthly frequency, and we predict the future 12-month excess return. \square , \blacksquare , \blacksquare indicate significance of the respective statistics at the 10 %, 5 %, and 1 % level, respectively. A white cell denotes no significant predictive power, whereas “–” indicates insufficient data availability. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007). The sample period spans from January 1990 to December 2015.

Region	Country	In-Sample R^2						Out-of-Sample R^2 (R^2_{OOS})							
		dy	pe	corp	gov	infl	unrate	dy	pe	corp	gov	infl	unrate	AEN	MFC
Africa	Botswana	\blacksquare	\blacksquare	–	\square	–	–	\blacksquare	–	–	–	–	–	–	–
	Ghana	\square	\blacksquare	–	–	–	–	–	\blacksquare	–	–	–	–	–	–
	Kenya	–	–	–	–	\blacksquare	–	–	–	–	–	–	–	–	–
	Mauritius	\square	\blacksquare	–	\blacksquare	–	–	–	\blacksquare	–	\blacksquare	–	–	–	–
	Morocco	\blacksquare	–	–	\blacksquare	–	–	–	–	–	–	–	–	–	–
	Namibia	–	\blacksquare	–	–	\square	–	–	–	–	\square	–	–	–	–
	Nigeria	\blacksquare	\blacksquare	–	–	\blacksquare	–	–	\blacksquare	–	–	–	–	–	–
	South Africa	\square	\blacksquare	\blacksquare	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	\blacksquare	\blacksquare	–	–	\blacksquare
	Tunisia	\square	\blacksquare	–	\square	–	–	–	–	–	–	–	–	–	–
America	Argentina	–	\square	–	–	\blacksquare	–	\blacksquare	\blacksquare	–	–	\blacksquare	–	\square	
	Brazil	\blacksquare	\blacksquare	–	–	\blacksquare	–	\blacksquare	–	–	\blacksquare	\blacksquare	\square	\square	
	Canada	\blacksquare	–	\square	–	–	–	\blacksquare	–	–	–	\blacksquare	\blacksquare	\blacksquare	
	Chile	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	\blacksquare	–	–	–	\blacksquare	\blacksquare	\blacksquare	
	Colombia	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	\blacksquare	–	–	–	\blacksquare	\blacksquare	\blacksquare	
	Ecuador	–	–	–	–	–	–	–	–	–	–	–	–	–	
	Jamaica	\blacksquare	\blacksquare	–	–	\blacksquare	–	–	\blacksquare	–	–	–	–	–	
	Mexico	\blacksquare	\blacksquare	–	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	\blacksquare	–	\square	\square	
	Peru	\blacksquare	\square	–	–	\blacksquare	\blacksquare	–	–	–	–	\blacksquare	\blacksquare	\square	
	Trinidad and Tobago	\blacksquare	–	–	–	–	–	–	–	–	–	–	–	–	
	United States	\blacksquare	\blacksquare	–	–	\square	\blacksquare	\blacksquare	\square	\blacksquare	\blacksquare	\blacksquare	\blacksquare	\square	
	Venezuela	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	\blacksquare	\blacksquare	\square	
Asia Pacific	Australia	\blacksquare	\blacksquare	\square	\square	–	\square	\blacksquare	\blacksquare	–	–	–	\square	\square	
	Bangladesh	\blacksquare	\blacksquare	–	–	–	–	–	–	–	–	–	–	–	
	China	\square	\blacksquare	–	–	–	–	–	\blacksquare	–	–	–	–	–	
	Hong Kong	\blacksquare	\blacksquare	–	\square	\blacksquare	–	–	–	–	\square	\blacksquare	\blacksquare	\blacksquare	
	India	\blacksquare	\blacksquare	–	\blacksquare	–	–	–	\blacksquare	\square	–	–	\square	\square	
	Indonesia	\blacksquare	\blacksquare	–	–	–	–	–	\blacksquare	–	–	–	–	–	
	Japan	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	–	–	\blacksquare	–	–	–	–	
	Korea	\blacksquare	\blacksquare	\blacksquare	–	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	–	\square	\square	
	Malaysia	\blacksquare	\blacksquare	–	–	\square	–	–	–	\square	–	–	\square	\square	
	New Zealand	\blacksquare	\blacksquare	–	\blacksquare	–	–	–	–	\blacksquare	–	–	–	\square	
	Pakistan	\blacksquare	\blacksquare	–	\square	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	–	–	–	
	Philippines	\blacksquare	\blacksquare	–	\blacksquare	\blacksquare	–	–	–	\blacksquare	\blacksquare	–	\square	\square	
	Singapore	\blacksquare	\blacksquare	–	–	\blacksquare	–	–	–	\blacksquare	\square	–	–	\square	
	Sri Lanka	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	–	–	\blacksquare	\square	–	–	–	
	Taiwan	\blacksquare	\blacksquare	\blacksquare	\blacksquare	\blacksquare	\blacksquare	–	–	\blacksquare	\square	\blacksquare	\square	\square	
	Thailand	\blacksquare	\blacksquare	–	–	\blacksquare	\blacksquare	–	–	\blacksquare	\square	\blacksquare	\square	\square	
Vietnam	–	–	–	–	\blacksquare	–	–	–	–	–	–	–	–		

2.5. FURTHER ANALYSES

Table 2.6: Graphical Representation of Return Predictability – Country View (Post-1990) (continued)

Region	Country	In-Sample R ²						Out-of-Sample R ² (R ² _{oos})							
		dy	pe	corp	gov	infl	unrate	dy	pe	corp	gov	infl	unrate	AEN	MFC
Europe	Austria	■	■	■	■	■	■						■		
	Belgium		■	■	■	■	■					■	■		■
	Bulgaria	-	■		■	■	■	-	-	-		■	■		■
	Croatia				-	-	-								
	Czech Republic	■	■		■	■	■					■	■		■
	Denmark	■	■		■	■	■	■				■	■	■	■
	Estonia	-						-	-	-		■	■	■	■
	Finland		■		■	■	■					■	■		■
	France	■	■		■	■	■	■				■	■	■	■
	Germany		■	■	■	■	■							■	■
	Greece	■			■	■	■		■				■		
	Hungary	■			■	■	■					■	■		
	Iceland	-	-		■	■	■	-	-	-		■	■	■	
	Ireland		■		■	■	■		■			■	■		
	Italy	■		■	■	■	■					■	■	■	
	Latvia	■					■								
	Lithuania				■	■	■								
	Luxembourg	-	-					-	-	-					
	Malta	-	-		■	■	■	-	-	-					
	Netherlands						■		■				■	■	■
	Norway	■	■	■	■	■	■	■		■			■	■	■
	Poland	■	■		■	■	■						■	■	■
	Portugal	■	■		■	■	■								■
	Romania	■			■	■	■	■				■	■		■
	Russian Federation	■			■	■	■	■			■	■	■		■
	Slovakia Republic	■			■	■	■					■	■		
Slovenia	■			■	■	■				■	■				
Spain						■									
Sweden	■	■	■	■	■	■						■	■	■	
Switzerland		■				■						■	■	■	
Ukraine	-	■													
United Kingdom	■	■				■	■	■			■	■	■		
Middle East	Bahrain		■				■								
	Cyprus	-			■	■				■	■	■			
	Egypt		■					■							
	Israel	■	■			■	■				■				
	Jordan	■	■				■								
	Kuwait					■					■			■	
	Lebanon		■							■	■		■	■	
	Oman				■										
	Qatar														
	Saudi Arabia	■	■			■					■		■	■	
	Turkey	■	■			■	■				■			■	

CHAPTER 2. PREDICTING THE EQUITY PREMIUM: COMPREHENSIVE EVIDENCE FROM A LARGE SAMPLE

Table 2.7: Return Predictability – Aggregated View (Post-1990)

This table summarizes the in-sample and out-of-sample return predictability for different regions. We sample the data at the monthly frequency, and we predict the future 12-month excess return. “Mean” indicates the average R^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R^2 s, respectively. “Mean | Significant” is the mean of the R^2 s given they are significant at at least the 10% significance level. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and mean forecast combination approach, respectively. R^2 and R^2_{oos} are the in-sample and out-of-sample R^2 , respectively. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007). The sample period spans from January 1990 to December 2015.

		dy				pe				corp				gov			
Region	Statistic	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
		Africa	R^2	7.59	8	62.50	11.68	13.74	9	88.89	15.43	12.05	1	100.00	12.05	4.05	6
	R^2_{oos}	-2.29	3	66.67	2.08	1.01	7	57.14	16.09	13.53	1	100.00	13.53	-21.04	4	25.00	6.76
America	R^2	9.00	11	72.73	12.15	8.56	11	72.73	11.76	1.90	2	50.00	2.89	2.53	4	25.00	9.28
	R^2_{oos}	-1.31	9	55.56	9.03	2.77	11	45.45	12.24	-3.25	2	50.00	0.63	9.63	4	50.00	30.37
Asia	R^2	14.69	16	75.00	19.48	10.47	16	87.50	11.95	3.96	4	100.00	3.96	4.34	13	69.23	6.08
Pacific	R^2_{oos}	15.74	15	66.67	27.65	1.15	16	50.00	10.72	3.82	4	50.00	17.21	-3.28	13	61.54	11.57
Europe	R^2	5.51	25	60.00	8.95	3.66	28	50.00	6.87	4.30	8	75.00	5.68	6.09	30	73.33	8.21
	R^2_{oos}	-1.21	21	28.57	13.16	-12.90	23	17.39	3.42	-10.90	8	12.50	2.81	-37.81	29	10.34	13.89
Middle East	R^2	5.93	5	60.00	8.93	9.07	7	85.71	10.43					1.13	3	33.33	2.53
	R^2_{oos}	12.26	4	100.00	12.26	-74.99	6	16.67	24.68					7.36	2	100.00	7.36

		infl				unrate				AEN				MFC			
Region	Statistic	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
		Africa	R^2	2.30	9	44.44	4.86										
	R^2_{oos}	-0.76	9	22.22	5.08					-4.60	9	0.00		-2.53	9	11.11	12.35
America	R^2	5.33	11	63.64	8.08	10.21	8	75.00	13.51	0.88	11	54.55	18.42	8.92	11	45.45	16.83
	R^2_{oos}	-5.06	11	45.45	3.98	15.55	7	85.71	19.85								
Asia	R^2	1.46	15	40.00	3.28	10.73	8	100.00	10.73	6.29	17	58.82	22.33	11.25	17	52.94	23.61
Pacific	R^2_{oos}	-7.08	15	60.00	2.26	1.53	8	50.00	11.56								
Europe	R^2	1.81	32	40.63	4.11	11.17	30	83.33	13.34	-3.12	32	34.38	28.95	2.90	32	34.38	16.46
	R^2_{oos}	-0.54	32	18.75	8.24	1.17	30	63.33	16.24								
Middle East	R^2	1.28	10	40.00	2.59	16.77	3	100.00	16.77	-7.29	10	30.00	2.23	-0.65	10	30.00	2.80
	R^2_{oos}	-2.19	9	55.56	2.68	-36.83	2	50.00	1.42								

2.5. FURTHER ANALYSES

Table 2.8: Economic Utility Gains ($\gamma = 3$) – Aggregated View (Post-1990)

This table reports the utility gains ($\Delta CERs$) with $\gamma = 3$ in percent relative to a benchmark strategy based on the historical mean. We sample the data at the monthly frequency, and we predict the future 12-month excess return. “Mean” indicates the average ΔCER . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of $\Delta CERs$ greater than zero, respectively. “Mean | > 0 ” is the mean ΔCER given it is greater than zero. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively. The sample period spans from January 1990 to December 2015.

Region	dy				pe				corp				gov			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	0.36	3	66.67	2.49	-0.09	7	57.14	1.49	3.32	1	100.00	3.32	0.09	5	60.00	1.66
America	-0.06	9	44.44	0.81	0.42	11	81.82	1.11	0.43	2	50.00	1.78	-0.03	4	75.00	0.69
Asia Pacific	0.98	15	60.00	2.61	0.10	16	43.75	1.44	0.74	4	50.00	2.26	0.61	13	61.54	1.59
Europe	-0.93	21	28.57	1.22	-0.89	22	22.73	1.13	-0.34	8	62.50	0.98	-0.94	29	31.03	1.23
Middle East	0.31	4	50.00	2.43	-0.53	6	16.67	5.57					0.42	2	100.00	0.42

Region	infl				unrate				AEN				MFC			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	0.09	9	44.44	0.72					0.55	9	66.67	1.26	0.64	9	66.67	1.27
America	0.03	11	63.64	0.32	1.76	7	71.43	3.12	1.80	11	81.82	2.69	1.03	11	81.82	1.43
Asia Pacific	0.21	15	66.67	0.64	0.95	8	62.50	1.93	1.20	17	70.59	2.64	1.63	17	76.47	2.38
Europe	-0.62	32	21.88	0.96	1.02	30	73.33	2.51	1.75	32	68.75	3.67	0.71	32	62.50	2.22
Middle East	-0.49	9	55.56	0.77	-1.17	3	33.33	1.44	-0.94	11	54.55	0.48	-0.41	10	60.00	0.48

**Table 2.9: Return Predictability and Sorting Characteristics –
Aggregated View (Post-1990)**

This table reports portfolio sorts of countries according to different characteristics, indicated in the panel headings. We present average out-of-sample results based on the mean forecast combination approach. We sample the data at the monthly frequency, and we predict the future 12-month excess return. We sort the countries according to the respective sorting characteristic into five portfolios. Portfolio 1 (5) contains the countries with the lowest (highest) value of the sorting characteristic. “Mean” indicates the average R_{oos}^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R_{oos}^2 s, respectively. “Mean | Significant” is the mean of the R_{oos}^2 s given they are significant at at least the 10% significance level. Statistical inference is based on the MSPE-adjusted test statistic of Clark & West (2007). The sample period spans from January 1990 to December 2015.

Portfolio	GDP Volatility				Bad States			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Portfolio 1	9.32	15	46.67	14.06	18.07	16	68.75	19.72
Portfolio 2	8.50	16	50.00	16.49	2.15	16	25.00	22.28
Portfolio 3	-4.17	16	31.25	19.02	6.76	15	46.67	15.01
Portfolio 4	4.74	16	25.00	11.30	0.75	16	31.25	15.98
Portfolio 5	3.65	15	40.00	22.66	-5.25	16	25.00	7.24

Portfolio	Market Capitalization				Market Openness				GDP per Capita			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Portfolio 1	-0.70	11	9.09	1.27	-3.53	15	26.67	18.48	0.81	15	13.33	35.75
Portfolio 2	3.97	11	45.45	10.82	10.45	15	40.00	16.01	-1.52	16	37.50	10.57
Portfolio 3	13.73	11	72.73	13.76	-4.43	16	12.50	15.98	4.60	16	43.75	16.00
Portfolio 4	16.15	11	81.82	17.98	7.28	16	56.25	13.87	8.57	16	37.50	21.20
Portfolio 5	11.75	11	36.36	25.80	13.71	15	60.00	19.99	9.40	15	60.00	14.73

2.5. FURTHER ANALYSES

Table 2.10: Restricted Return Predictability – Aggregated View

This table reports the average results of out-of-sample predictions using economically motivated restrictions. We sample the data at the monthly frequency, and we predict the future 12-month excess return. Following Campbell & Thompson (2008), we impose two restrictions: (i) we set the out-of-sample slope estimate equal to zero whenever it is different to that of the in-sample estimate, (ii) we set the out-of-sample forecast equal to zero whenever it is negative. “Mean” indicates the average R_{oos}^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R_{oos}^2 s, respectively. “Mean | Significant” is the mean of the R_{oos}^2 s given they are significant at at least the 10% significance level. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. Statistical inference is based on the MSPE-adjusted test statistic of Clark & West (2007).

Region	dy				pe				corp			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Africa	4.46	3	66.67	9.27	-7.15	7	42.86	2.09	2.27	1	100.00	2.27
America	-7.55	9	55.56	10.02	-4.84	11	36.36	7.11	2.62	2	100.00	2.62
Asia Pacific	14.59	15	73.33	20.40	7.85	16	81.25	9.91	0.93	4	25.00	7.93
Europe	0.31	22	50.00	8.57	-1.62	23	47.83	3.57	2.87	10	70.00	8.37
Middle East	6.64	4	75.00	8.57	-3.57	6	16.67	23.24				

Region	gov				infl				unrate			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Africa	-20.67	4	25.00	5.36	-0.28	9	33.33	2.33				
America	7.75	5	20.00	54.13	-9.08	11	81.82	4.20	10.98	7	85.71	13.38
Asia Pacific	-5.96	13	69.23	5.83	-3.60	15	73.33	3.09	6.15	8	62.50	11.71
Europe	-7.07	29	48.28	7.44	-7.11	32	50.00	4.72	-0.65	30	66.67	7.34
Middle East	9.55	2	100.00	9.55	0.41	9	44.44	10.33	-4.10	2	0.00	

higher with the restriction than without and the shares of significant R_{oos}^2 s increase. However, there are also cases where both decrease.

2.5.3 Return Predictability based on U.S. Predictors

Rapach et al. (2013) demonstrate that lagged U.S. returns are a superior predictor of the returns of industrialized non-U.S. countries. These findings suggest that investors may primarily rely on information on macroeconomic fundamentals from the U.S. instead of that of a local country. We thus ask the question: Do U.S. predictors have superior predictive power for non-U.S. market excess returns compared to domestic variables?

Table 2.11 presents the aggregated regression results. Overall, using U.S. predictors enables us to analyze more countries per region in predicting market returns due to the better data availability and longer time series of U.S. variables. Thus, the comparison with the return predictability based on domestic variables is not entirely straightforward. However, we are able to analyze and compare the overall predictive performance.

In general, the out-of-sample predictability is slightly reduced when using U.S. predictors. Only for America, i.e., the region geographically closest to and maybe economically most strongly dependent on the U.S., is there typically a consistently better predictability when using U.S. variables over using local predictors. For all other regions, the average R_{oos}^2 s are sometimes somewhat higher, but typically there is a smaller share of significant R_{oos}^2 s. To some extent, however, the U.S. *gov* variable seems to be a stronger predictor of future returns than most local long-term government bond rates, likely reflecting the leading role of the United States Dollar as global reserve currency.

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Table 2.11: Return Predictability and Regions based on U.S. Predictors – Aggregated View

This table summarizes the in-sample and out-of-sample return predictability for different regions using U.S. predictor variables. We sample the data at the monthly frequency, and we predict the future 12-month excess return. “Mean” indicates the average R^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R^2 s, respectively. “Mean | Significant” is the mean of the R^2 s given they are significant at at least the 10% significance level. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and mean forecast combination approach, respectively. R^2 and R^2_{oos} are the in-sample and out-of-sample R^2 , respectively. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007).

Region	Statistic	dy				pe				corp				gov			
		Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Africa	R^2	5.88	9	77.78	7.48	2.89	9	77.78	3.60	4.64	9	66.67	6.85	5.48	9	55.56	9.61
	R^2_{oos}	-4.14	9	33.33	4.29	-7.03	9	22.22	7.03	2.00	9	44.44	10.33	-2.09	9	33.33	3.73
America	R^2	4.09	11	72.73	5.59	0.82	11	36.36	1.88	5.65	11	72.73	7.71	5.29	11	72.73	7.26
	R^2_{oos}	7.40	11	81.82	9.35	2.57	11	54.55	6.70	12.11	11	81.82	15.51	9.94	11	72.73	16.05
Asia Pacific	R^2	2.15	17	88.24	2.43	1.44	17	64.71	2.16	1.38	17	41.18	3.03	1.60	17	41.18	3.42
	R^2_{oos}	1.20	17	52.94	4.82	-2.29	17	41.18	4.43	-5.80	17	52.94	7.80	-4.98	17	47.06	7.71
Europe	R^2	1.70	32	56.25	2.93	1.25	32	46.88	2.51	1.95	32	53.13	3.54	2.41	32	50.00	4.57
	R^2_{oos}	-5.40	32	15.63	6.24	-1.82	32	46.88	4.42	-3.47	32	31.25	8.84	-6.40	32	21.88	7.40
Middle East	R^2	5.08	11	72.73	6.92	1.00	11	54.55	1.71	3.85	11	36.36	10.29	4.14	11	45.45	8.67
	R^2_{oos}	-10.22	11	36.36	11.41	-7.50	11	18.18	13.04	-2.26	11	63.64	9.86	-2.91	11	54.55	14.48

Region	Statistic	infl				unrate				AEN				MFC			
		Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Africa	R^2	0.53	9	22.22	1.47	2.85	9	77.78	3.49								
	R^2_{oos}	-1.19	9	0.00		-1.00	9	33.33	5.52	-8.40	9	44.44	18.05	11.08	9	33.33	15.73
America	R^2	0.42	11	45.45	0.64	3.81	11	100.00	3.81								
	R^2_{oos}	1.17	11	45.45	4.24	0.60	11	54.55	7.11	15.02	11	81.82	18.87	14.47	11	81.82	15.13
Asia Pacific	R^2	1.01	17	41.18	1.99	2.21	17	70.59	3.09								
	R^2_{oos}	-0.17	17	52.94	2.50	-1.80	17	41.18	3.29	-9.99	17	58.82	12.45	6.16	17	41.18	12.86
Europe	R^2	0.67	32	43.75	1.14	2.43	32	71.88	3.27								
	R^2_{oos}	0.83	32	62.50	1.88	-6.96	32	40.63	2.63	-11.36	32	43.75	7.67	5.07	32	43.75	9.06
Middle East	R^2	0.79	11	18.18	3.14	2.20	11	36.36	5.09								
	R^2_{oos}	-1.28	11	27.27	1.48	-19.47	11	18.18	5.85	-24.57	11	9.09	37.37	4.94	11	18.18	27.19

2.5.4 Return Predictability from the Perspective of a (Non-Hedged) U.S. Investor

In this section, we analyze the market return predictability from the perspective of a U.S. investor. As discussed earlier, domestic excess returns can be regarded as currency-hedged excess returns for a U.S. investor. Thus, in this section, by analyzing all time series denominated in USD, we essentially assume that investors do not hedge their currency risk. Thus, we can partially answer the question: Does the exchange rate systematically affect return predictability?

Table 2.12 shows the aggregated regression results. Overall, we find similar results as in the domestic analysis, both in- and out-of-sample. However, since one has to ideally predict both the foreign market return *and* changes in the exchange rate, there are small differences, especially for countries with a high exchange rate volatility. Generally, we observe a slight decrease, in the average R_{oos}^2 s and the share of significant R_{oos}^2 s. It thus seems it is advisable to separate the prediction of market returns and exchange rate. Worthwhile to mention is the overall weaker performance of *infl*, indicating a weaker influence of high-inflation countries on return predictability in USD.

Table A.8 of the Appendix to this chapter provides the results for the restricted return predictability. We find similar results compared to the analysis on the basis of domestic currencies. In general, we observe a slight worsening using market returns denominated in USD.

For robustness, Tables A.9 and A.10 of the Appendix to this chapter show the aggregated results for the post-1990 time period, and the return predictability from the perspective of a U.S. investor. In all cases, we find similar results compared to our previous analyses.

2.5. FURTHER ANALYSES

Table 2.12: Return Predictability and Regions – Aggregated View (in USD)

This table summarizes the in-sample and out-of-sample return predictability for different regions. We sample the data at the monthly frequency, and we predict the future 12-month excess return. The time series of the market indices are denominated in USD. “Mean” indicates the average R^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R^2 s, respectively. “Mean | Significant” is the mean of the R^2 s given they are significant at at least the 10% significance level. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively. R^2 and R^2_{OOS} are the in-sample and out-of-sample R^2 , respectively. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007).

		dy				pe				corp				gov			
Region	Statistic	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
		Africa	R^2	5.06	8	75.00	6.55	12.85	9	77.78	16.42	0.31	1	0.00		4.44	6
	R^2_{OOS}	9.74	3	100.00	9.74	4.79	7	42.86	22.74	-6.23	1	0.00		-0.04	4	50.00	1.97
America	R^2	6.14	11	72.73	8.29	9.26	11	63.64	14.30	2.47	2	100.00	2.47	2.72	6	66.67	3.83
	R^2_{OOS}	0.48	9	55.56	10.37	2.18	11	27.27	24.28	0.04	2	50.00	1.52	2.78	6	16.67	48.79
Asia	R^2	9.15	16	87.50	10.42	9.89	16	75.00	13.12	0.91	4	50.00	1.76	2.90	13	61.54	4.55
Pacific	R^2_{OOS}	13.85	15	73.33	20.45	3.77	16	56.25	13.03	1.30	4	25.00	19.87	-6.64	13	53.85	7.50
Europe	R^2	3.24	26	61.54	5.08	3.48	28	50.00	6.52	1.05	10	50.00	1.78	4.27	30	63.33	6.66
	R^2_{OOS}	-5.42	22	27.27	10.84	-13.18	23	0.00		0.24	10	50.00	9.73	-12.59	29	17.24	14.85
Middle East	R^2	9.60	5	40.00	23.09	8.68	7	71.43	11.95					1.71	3	66.67	2.53
	R^2_{OOS}	3.90	4	75.00	9.66	-38.71	6	16.67	17.02					5.31	2	100.00	5.31

		infl				unrate				AEN				MFC			
Region	Statistic	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
		Africa	R^2	0.33	9	11.11	0.22										
	R^2_{OOS}	-1.56	9	22.22	1.71					1.63	9	22.22	1.92	3.92	9	22.22	8.81
America	R^2	0.41	11	36.36	0.98	10.93	8	75.00	14.53								
	R^2_{OOS}	-5.34	11	0.00		15.22	7	71.43	23.92	-4.35	12	41.67	2.73	-2.58	12	50.00	2.57
Asia	R^2	0.59	15	33.33	1.53	8.77	8	87.50	10.01								
Pacific	R^2_{OOS}	-12.11	15	13.33	1.87	2.80	8	50.00	12.87	-4.38	17	52.94	13.00	0.35	17	76.47	11.88
Europe	R^2	0.66	32	25.00	1.98	6.46	30	83.33	7.72								
	R^2_{OOS}	-4.30	32	6.25	1.19	-2.89	30	43.33	15.99	-5.73	32	28.13	4.08	0.42	32	43.75	6.63
Middle East	R^2	0.76	10	20.00	2.15	14.98	3	100.00	14.98								
	R^2_{OOS}	-1.11	9	11.11	6.23	-16.65	2	0.00		-5.01	10	20.00	3.83	-3.13	10	20.00	2.10

2.6 Conclusion

We comprehensively analyze equity premium predictability using a long sample period and a broad cross-section of countries. Overall, we detect substantial predictability of 12-month aggregate excess returns around the globe. We detect a comparably higher degree of predictability for American, Asian Pacific, and European countries, whereas countries in Africa and the Middle East exhibit less predictability.

Analyzing the determinants of return predictability, we find that it is unlikely that predictability is driven by market inefficiency. There is only little predictability for market excess returns in countries with low stock market capitalization, little market openness, and small GDP per capita. On the other hand, returns in countries with high manifestations of these characteristics are, in general, better predictable. Finally, we find that high GDP volatility and frequent bad states hinder return predictability.

A Appendix

In this section, we provide additional material for Chapter 2: “Predicting the Equity Premium: Comprehensive Evidence from a Large Sample”.

CHAPTER 2. PREDICTING THE EQUITY PREMIUM: COMPREHENSIVE EVIDENCE FROM A LARGE SAMPLE

Table A.1: Tickers of the Time Series

This table reports the tickers of the time series. “GFD” and “WB” denote the Global Financial Database and the World Bank, respectively. Time series marked by a “*” are retrieved from Datastream. Time series marked by a “**” are obtained from the extended dataset of Goyal & Welch (2008). “DC” denotes “Domestic Currency”.

Country	Stock Market Index (USD) [GFD]	Stock Market Index (DC) [GFD]	3-Month T-Bill Rate (DC) [GFD]	Dividend Yield [GFD]	Price-Earnings Ratio [GFD]	Long-Term Gov. Bond Yield [GFD]	Long-Term Corp. Bond Yield [GFD]	Inflation Rate [GFD]	Unemployment Rate [GFD]	Ann. GDP Growth Rate (DC) [WB]	GDP per Capita (USD) [WB]	Stock Market Capitalization (USD) [GFD]
Argentina	_JBGD	_JBGD	ITARG3D	SYARGYM	-	-	IGARG10D	CPARGM	-	ARG	ARG	SCARGM
Australia	_AORDAD	_AORDAD	ITAUS3D	SYAUSYM	-	INAISW	IGAUS10D	-	UNAUSM	AUS	AUS	SCAUSM
Austria	_WBKID	_WBKID	ITAUT3M	SYAUTYM	SYAUTPM	INAUTD	IGAUTI0D	CPAUTM	UNAUTM	AUT	AUT	SCAUTM
Bahrain	_BAXD	_BAXD	ITBHR3M	SYBHRYM	SYBHRPM	-	-	CPBHRM	-	BHR	BHR	-
Bangladesh	BDDSGEND,	BDDSGEND,	ITBGD3M	SYBGDYM	SYBGDFM	-	IGBGD10M	CPBGDM	-	BGD	BGD	SCBGDM
	BDINDEXW	BDINDEXW										
Belgium	_BSP1D	_BSP1D	ITBEL3D	SYBELYM	SYBELPM	INBE1W	IGBEL10D	CPBELM	UNBELM	BEL	BEL	SCBELM
Bosswana	_DCIBTD	_DCIBTD	ITBWA3M	SYBWAYM	SYBWAYPM	-	IGBWA10D	CPBWAM	-	BWA	BWA	-
Brazil	_IBX50D,	_IBX50D,	ITBRA3D	SYBRAYM	SYBRAPM	-	IGBRA10D	CPBRAM	UNBRAM	BRA	BRA	SCBRAM
	BRBYD	BRBYD										
Bulgaria	_SOFTXD,	_SOFTXD,	ITBGR3M	SYBGRYM	SYBGRPM	-	IGBGR10D	CPBGRM	UNBGRM	BGR	BGR	SCBGRM
	BGFBSM	BGFBSM										
Canada	_TRGSPTSE,	_TRGSPTSE,	ITCAN3D	SYCANVTM	SYCANPTM	INCANL1W	IGCAN10D	CPCANM	UNCANM	CAN	CAN	SCCANM
	CAINDEXM	CAINDEXM										
Chile	_TRCHLSTM,	_TRCHLSTM,	ITCHL3D	SYCHLYM	SYCHLPM	-	IGCHL10D	CPCHLM	UNCHLM	CHL	CHL	SCCHLM
	CLIGPARM	CLIGPARM										
China	_TRCHNSTM	_TRCHNSTM	ITCHN3W	SYCHNYM	SYCOLPM	-	IGCHN10D	CPCHNM	-	CHN	CHN	SCCHNM
Colombia	_IGBCD	_IGBCD	ITCOL3W	SYCOLYM	SYCOLPM	-	IGCOL10D	CPCOLM	UNCOLM	COL	COL	SCCOLM
Croatia	_CRBEXD	_CRBEXD	ITHRV3M	SYHRVYM	SYHRVPM	-	IGHRV10D	CPHRVM	UNHRVM	HRV	HRV	-
Cyprus	_CYP1D,	_CYP1D,	ITCYP3M	-	-	-	IGCYP10D	CPCYPM	UNCYPM	CYP	CYP	SCCYPM
	CYMAIND	CYMAIND										
Czech Republic	_PXD	_PXD	ITCZE3D	SYCZEM	SYCZEPM	-	IGCZE10D	CPCZEM	UNCZEM	CZE	CZE	-
	_OMXCPID	_OMXCPID										SCDNKM
Denmark	BYG_ECUBVGH*	-	ITDNK3D	SYDNKYM	SYDNKPM	INDNKEW	IGDNK10D	CPDNKM	UNDNKM	DNK	DNK	-
Ecuador	_EFGID	-		SYECUYM	SYECUPM	-	_RBQD	CPECUM	EDCUNPP	EGY	EGY	-
Egypt	_OMXTGID	_EFGID	ITEGY3D	SYEGYM	SYEGYPM	-	IGEST10M	CPEGYM	UNESTM	EST	EST	-
Estonia	_OMXHPID	_OMXHPID	EIBOR3M	SYESTYM	SYESTPM	-	IGFIN10D	CPFINM	UNFINM	FIN	FIN	SCFINM
Finland	_CACTD	_CACTD	ITFRA3D	SYFRAYM	SYFRAPM	INFR1W	IGFRA10D	CPFRAAM	UNFRAAM	FRA	FRA	SCFRAAM
France	_CDAXD	_CDAXD	ITDEU3D	SYDEUYM	SYDEUPM	INDEUD	IGDEU10D	CPDEUM	UNDEUM	DEU	DEU	SCDEUM
Germany	_GHAGHD	_GHAGHD	ITGHA3M	SYGHAYM	SYGHAPM	-	IGGRC10D	CPGRGM	UNGRGM	GHA	GHA	SCGHAM
Ghana	_ATGD	_ATGD	ITGRC3D	SYGRGYM	SYGRGPM	-	IGHRG10D	CPHRGM	UNHRGM	HRG	HRG	SCHRGM
Greece	_HSD	_HSD	ITHUN3D	SYHUNYM	SYHUNPM	-	IGHUN10D	CPHUNM	UNHUNM	HUN	HUN	-
Hong Kong	_BUXD	_BUXD	ITIND3D	SYINDYM	SYINDPM	-	IGIND10D	CPINDM	UNINDM	IND	IND	SCINDM
Hungary	_OMXHPID	_OMXHPID	ITIND6D	SYINDYM	SYINDPM	-	IGIDN10D	CPIDNM	-	IND	IND	SCIDNM
Iceland	_BSESND	_BSESND	ITIRL3M	SYIRLYM	SYIRLPM	-	IGIRL10D	CPIRLM	UNIRLM	IRL	IRL	SCIRLM
Indonesia	_JKSED	_JKSED	ITISR3D	SYISRYM	SYISRPM	-	IGISR10D	CPISRM	UNISRM	ISR	ISR	SCISRM
Ireland	_ITLIVAD	_ITLIVAD	ITITA3D	SYITAYM	SYITAPM	INTAM	IGITA10D	CPITAM	UNITAM	ITA	ITA	SCITAM
Israel	_BGHD	_BGHD	ITJAM3M	SYJAMYM	SYJAMPM	-	IGJAM10D	CPJAMM	-	JAM	JAM	SCJAMM
Italy	_JMJASEXD	_JMJASEXD	ITJPN3D	SYJPNYM	SYJPNPM	INJPNW	IGJPN10D	CPJPNM	UNJPNM	JPN	JPN	SCJPNM
Jamaica	_TOPXD	_TOPXD										
Japan	_AMMAND	_AMMAND	IBJOR3M	SYJORYM	SYJORPM	-	IGJOR3M	CPJORM	-	JOR	JOR	-
Jordan												

Table A.1: Tickers of the Time Series (continued)

Country	Stock Market Index (USD) [GFD]	Stock Market Index (DC) [GFD]	3-Month T-Bill Rate (DC) [GFD]	Dividend Yield [GFD]	Price-Earnings Ratio [GFD]	Long-Term Gov. Bond Yield [GFD]	Long-Term Corp. Bond Yield [GFD]	Inflation Rate [GFD]	Unemployment Rate [GFD]	Ann. GDP Growth Rate (DC) [WB]	GDP per Capita (USD) [WB]	Stock Market Capitalization (USD) [GFD]
Kenya	_NSE20D	_ITKEN3D	ITKEN3D	SYKENYM	SYKENPM	-	IGKEN10D	CPKENM	-	KEN	KEN	SCKENM
Korea	TRKORSTM	TRKORSTM	ITKOR12D	SYKORYM	SYKORPM	-	IGKOR10D	CPKORM	-	KOR	KOR	SCKORM
Kuwait	_KAWSED,	_KAWSED,	ITKWT3M	SYKWTYM	SYKWTPM	-	-	CPKWTM	-	KWT	KWT	-
Latvia	_OMXRGD	_ITLVA3D	ITLVA3D	SYLVAYM	SYLVAPM	-	IGLVA10D	CPLVAAM	UNLVA	LVA	LVA	-
Lebanon	_BLSD	_ITLBN3M	ITLBN3M	SYLBNYM	SYLBNPM	-	IGLBN10D	CPLBNM	-	LBN	LBN	SCLBNM
Lithuania	_OMXVGD	_ITLIT3D	ITLIT3D	SYLITYM	SYLITPM	-	IGLIT10D	CPLITUM	UNLITUM	LITU	LITU	-
Luxembourg	_LUCXD	_ICLUXTM	ICLUXTM	SYLUXYM	-	-	IGLUX10D	CPLUXM	UNLUXM	LUX	LUX	SCLUXM
Malaysia	TRMYSSTM	TRMYSSTM	ITMYS3D	SYMYSYM	SYMYSPM	-	IGMYS10D	CPMYSM	UNMYSM	MYS	MYS	SCMYSM
Malta	MLTSED	_ITMLT3M	ITMLT3M	-	-	-	IGMLT10D	CPMLTUM	UNMLTUM	MLT	MLT	SCMLTUM
Mauritius	_MDEXD	_ITMUS3W	ITMUS3W	SYMUSYM	SYMUSPM	-	IGMUS3M	CPMUSM	UNMUSM	MUS	MUS	SCMUSM
Mexico	_IRTD,	MXINDEXM	ITMEX3D	SYMEXYM	SYMEXPM	-	IGMEX10D	CPMEXM	UNMEXM	MEX	MEX	SCMEXM
Morocco	_CFG25D	_ITMAR3M	ITMAR3M	SYMARMYM	SYMARPM	-	IGMAR3M	CPMARM	-	MAR	MAR	-
Namibia	_OVRNMD	_ITNAM3M	ITNAM3M	SYNAMYM	SYNAMPM	-	IGNAM10M	CPNAMM	-	NAM	NAM	-
Netherlands	_AAXD	_ITNLD3D	ITNLD3D	SYNLDYAM	SYNLDPM	INNLDDEW	IGNLD10D	CPNLDM	UNNLDM	NLD	NLD	SCNLDM
New Zealand	_NZCID	_ITNZL3D	ITNZL3D	SYNZLYM	SYNZLPM	-	IGNZL10D	-	-	NZL	NZL	SCNZLM
Nigeria	_NGSEIND	_ITNGA3M	ITNGA3M	SYNGAYM	SYNGAPM	-	-	CPNGAM	UNNGAM	NGA	NGA	-
Norway	_OBXPD	_ITNOR3D	ITNOR3D	SYNORYM	SYNORPM	INNOR3D	IGNOR10D	CPNORM	UNNORM	NOR	NOR	SCNORM
Oman	_MSID	_ITBOM3M	ITBOM3M	SYOMINYM	SYOMINPM	-	-	CPOMINM	-	OMN	OMN	SCOMINM
Pakistan	_KSED	_ITPAK3D	ITPAK3D	SYPAKYM	SYPAKPM	-	IGPAK10D	CPPAKM	UNPAKM	PAK	PAK	SCPAKM
Peru	SPBLPGPT	SPBLPGPT	PEBOR3M	SYPERYM	SYPERPM	-	IGPER9D	CPPERM	UNPERM	PER	PER	SCPERM
Philippines	_PSID	_ITPHL3D	ITPHL3D	SYPHYM	SYPERPM	-	IGPHL10D	CPPHLM	UNPHLM	PHL	PHL	SCPHLM
Poland	_WIGD,	PLGENNM	ITPOL3D	SYPOLYM	SYPOLPM	-	IGPOL10D	CPPOLM	UNPOLM	POL	POL	SCPOLM
Portugal	_PSI20D	_ITPRT3M	ITPRT3M	SYPRTYM	SYPRTPM	-	IGPRT10D	CPPRTM	UNPRTM	PRT	PRT	SCPRTM
Qatar	_QSID	_ITQAT3M	ITQAT3M	SYQTRYM	SYQTRPM	-	-	CPQATM	-	QAT	QAT	-
Romania	_BETCD,	_ITROU3M	ITROU3M	SYROUYM	-	-	IGROU10D	CPROUM	UNROUM	ROU	ROU	-
Russian Federation	ROBUCHM	ROBUCHM	ITRUS3D	SYRUSYM	SYRUSPM	INRUSXD	IGRUS10D	CPRUSM	UNRUSM	RUS	RUS	SCRUSM
Saudi Arabia	_IRISD	_ITSAU3D	ITSAU3D	SYSAUYM	SYSAUPM	-	IGSAU10M	CPSAUM	-	SAU	SAU	SCSAUM
Singapore	_TASID	_ITSGP3D	ITSGP3D	SYSGPYM	SYSGPPM	-	IGSGP10D	CPSPGM	-	SGP	SGP	SCSGPM
Slovenia	_FTFSTAD	_ITSVK3M	ITSVK3M	SYSVKYM	SYSVKPM	-	IGSVK10D	CPSVKM	UNSVKM	SVK	SVK	-
Slovakia Republic	_SAXD	_ITSVN3M	ITSVN3M	SYSVNYM	SYSVNPM	-	IGSVN10D	CPSVNM	UNSVNM	SVN	SVN	-
Slovenia	_SBITOPD	_ITZAF3D	ITZAF3D	ZAVALIM	SYZAFPM	INZAFD	IGZAF10D	CPZAFM	-	ZAF	ZAF	SCZAFM
South Africa	_JALSHD	_ITESP3D	ITESP3D	SYESPYM	SYESPPM	-	IGESP10D	CPESPAM	UNESPAM	ESP	ESP	SCESPAM
Spain	_SMSID	_ITLKA3D	ITLKA3D	SYLKAYM	SYLKAPM	-	IGLKA3D	CPLKAM	UNLKAM	LKA	LKA	SCLKAM
Sh Lanka	_CSED,	LKINDEXM	-	-	-	-	-	-	-	-	-	-
Sweden	_OMXS8GI	_ITSWE3D	ITSWE3D	SYSWEYM	SYSWEPM	INSWEW	IGSWE10D	CPSWEM	UNSWEM	SWE	SWE	SCSWEW
Switzerland	_SPIDX	_ITCHE3D	ITCHE3D	SYCHEYM	SYCHEPM	_ZD3A7YD	IGCHE10D	CPCHEM	UNSCHEM	CHE	CHE	SCCHEM
Taiwan	_TWIID	_ITWAI3D	ITWAI3D	SYWAIYM	SYWAINPM	INTWNSM	IGTWAI10D	CPTWMM	UNTWMM	-	-	SCTWMM
Thailand	TRTHASTM	TRTHASTM	ITTHA3D	SYTHAYM	SYTHAPM	-	IGTHAI10D	CPTHAM	UNTHAM	THA	THA	SCTHAM
Trinidad and Tobago	TTALLD	TTALLD	ITTO3M	SYTOYM	SYTOPM	-	-	CPTTOM	-	TTO	TTO	SCTTOM
Tunisia	_TUNINDD	_ITUN3M	ITUN3M	SYTUNYM	SYTUNPM	-	IGTUN10M	CPTUNM	UNTUNM	TUN	TUN	-
Turkey	TRRIBLED	TRRIBLED	ITTUR3D	SYTURYM	SYTURPM	-	IGTUR10D	CPTURM	UNTURM	TUR	TUR	SCTURM
Ukraine	_PFTSID	_ITUKR3D	ITUKR3D	-	SYUKRPM	-	-	CPUKRM	UNUKRM	UKR	UKR	SCGUKRM
United Kingdom	_TFTASD	tbl**	ITGBR3D	DPTASD	PFTASD	INGBRW	IGGBR10D	CPGBRCM	UNGBRCM	GBR	GBR	SCGGBRM
United States	_SPXTRD	_ITVND3D	tbl**	SYUSAYM	SYUSAPM	INUSADJD	IGUSAI10D	CPUSAM	UNUSACUM	USA	USA	USNYCAPM
Venezuela	_IBCD	ITVEN3D	ITVEN3D	SYVENYM	SYVENPM	-	IGVEN5M	CPVENM	UNVENM	VEN	VEN	-
Vietnam	_VNID	_ITVNM3M	ITVNM3M	SYVNMYM	SYVNMPM	-	IGVNM10D	CPVNM	UNVNM	VNM	VNM	-

Table A.2: Return Predictability and Regions – Country View

This table reports the in-sample and out-of-sample return predictability for the countries in our sample. We sample the data at the monthly frequency, and we predict the future 12-month excess return. We report the t -statistics (t -stat) in parentheses. ΔCER denotes the economic utility gain (with $\gamma = 3$) in percentage points relative to a benchmark strategy based on the historical mean. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively. R^2 and R^2_{oos} are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. For better orientation, we print all significant (at at least 10 %) observations in **bold**. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007).

Country			dy	pe	corp	gov	infl	unrate	AEN	MFC	
Africa	Botswana	R^2	22.83***	20.23***		2.04*	0.24				
		R^2_{oos}	7.84***	-21.41			-1.45		-13.73	-7.27	
		t -stat	(9.50)	(-6.23)		(1.69)	(-0.85)				
		ΔCER	2.99	1.45			0.14		1.35	1.55	
	Ghana	R^2	0.00	13.24***			0.70				
		R^2_{oos}		24.85***			-1.18		4.96	0.86	
		t -stat	(-0.07)	(-4.83)			(-1.25)				
		ΔCER		0.08			-0.47		-0.43	-0.52	
	Kenya	R^2	0.35	29.93***			0.28				
		R^2_{oos}		-26.40			1.32***		1.45**	1.06*	
		t -stat	(0.71)	(8.08)			(1.31)				
		ΔCER		-5.69			-0.92		-0.90	-0.96	
	Mauritius	R^2	1.92*	20.30***		5.41***	0.00				
		R^2_{oos}		33.62***			-1.80		21.67	8.69	
		t -stat	(1.67)	(-6.24)		(2.88)	(0.01)				
		ΔCER		1.95			0.23		0.65	0.57	
	Morocco	R^2	9.28***	0.25		13.66***	0.28				
		R^2_{oos}		-9.48			-65.08		-13.76	-1.06	
		t -stat	(3.81)	(0.69)			(6.55)	(0.94)			
		ΔCER		-0.62			-5.18	-0.02	-0.91	-0.17	
	Namibia	R^2		8.03***		0.25	2.32***				
		R^2_{oos}					-4.63		-2.37	-4.37	
		t -stat		(-3.20)		(0.77)	1.76**	(-2.49)			
		ΔCER				1.24	0.60		0.96	0.82	
	Nigeria	R^2	25.89***	18.67***			5.81***				
		R^2_{oos}	7.65***	2.53**			-0.44		4.89	9.87	
		t -stat	(9.34)	(-7.53)			(4.46)				
		ΔCER	4.23	1.16			0.07		1.65	1.36	
	South Africa	R^2	4.54***	5.11***	0.21	0.21	0.61***				
		R^2_{oos}	-8.30	-2.99	-4.18	-2.11	0.35***		-5.16	1.36	
		t -stat	(5.09)	(-5.95)	(-1.26)	(-1.61)	(-2.64)				
		ΔCER	-1.17	-0.55	0.43	0.28	0.23		0.52	0.29	
	Tunisia	R^2	2.50*	14.12***		1.88**	0.07				
		R^2_{oos}					-47.00		-55.40	-35.29	
		t -stat	(-1.82)	(4.61)		(1.97)	(0.35)				
		ΔCER				1.80	-0.03		1.41	2.06	
America	Argentina	R^2	0.31	0.43			23.93***				
		R^2_{oos}	-12.57	-19.30			4.02***		-0.99	-2.24	
		t -stat	(1.00)	(-1.29)			(13.44)				
		ΔCER	-0.59	0.19			-18.01		-17.25	-17.97	

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**Table A.2: Return Predictability and Regions – Country View
(continued)**

Country		dy	pe	corp	gov	infl	unrate	AEN	MFC
Brazil	R^2	2.45**	14.11***			2.63***	0.69		
	R^2_{oos}	-29.23	-30.74			4.31***	9.42***	4.17*	3.87*
	$t - stat$	(2.84)	(-7.27)			(4.40)	(-1.44)		
	ΔCER	-0.82	-0.48			-2.34	1.84	-2.27	-2.23
Canada	R^2	4.55***	0.00	5.48***	2.11***	0.10	0.00		
	R^2_{oos}	-0.95	-6.77	-3.06	-9.13	-1.10	-5.87	1.42***	1.66*
	$t - stat$	(6.80)	(-0.02)	(-6.36)	(-5.08)	(-1.10)	(-0.08)		
	ΔCER	0.70	0.25	0.62	-0.30	0.09	0.56	2.21	1.14
Chile	R^2	34.38***	44.55***			3.11***	9.68***		
	R^2_{oos}	28.28***	23.80***			1.65***	5.17***	5.87***	4.09**
	$t - stat$	(13.96)	(-15.83)			(4.56)	(5.99)		
	ΔCER	2.64	2.53			0.15	4.21	1.98	1.22
Colombia	R^2	5.23***	5.26***			0.02	32.54***		
	R^2_{oos}	-31.64	-15.18			-15.62		-29.96	-7.21
	$t - stat$	(4.22)	(-4.23)			(0.40)	(7.95)		
	ΔCER	-3.43	-1.93			-0.29		-0.45	-0.41
Ecuador	R^2								
	R^2_{oos}								
	$t - stat$								
	ΔCER								
Jamaica	R^2	11.15***	19.87***		0.44	3.15***			
	R^2_{oos}		21.40***		-6.28	2.20***		-1.06	3.28**
	$t - stat$	(4.10)	(-6.16)		(1.24)	(4.21)			
	ΔCER		-3.82		-2.33	-0.92		-1.29	-0.58
Mexico	R^2	22.29***	12.06***		9.28***	0.16	0.22		
	R^2_{oos}	12.78***	-0.85		54.63***	0.34**	-10.73	5.53*	1.75
	$t - stat$	(9.61)	(-6.65)		(4.05)	(-1.13)	(-0.84)		
	ΔCER	-0.25	0.04		0.06	-0.21	-0.68	-0.23	-0.40
Peru	R^2	4.08***	1.65**			14.69***	17.88***		
	R^2_{oos}	8.28***	-0.01			-122.88	64.30***	-117.86	-122.19
	$t - stat$	(3.27)	(-2.10)			(13.00)	(5.94)		
	ΔCER	0.27	0.78			-12.95	6.27	-12.36	-12.60
Trinidad and Tobago	R^2	0.40	0.01			1.24**			
	R^2_{oos}		0.54			1.88***		3.92**	4.48**
	$t - stat$	(0.75)	(0.13)			(2.12)			
	ΔCER		0.28			0.02		0.43	0.50
United States	R^2	2.38***	1.02***	0.23*	0.51***	0.41***	3.50***		
	R^2_{oos}	1.37***	-1.90	1.44***	-5.42	-1.65	6.05***	5.72***	6.88***
	$t - stat$	(6.49)	(-4.23)	(-1.67)	(-2.99)	(-2.62)	(5.40)		
	ΔCER	-0.32	0.20	0.50	0.36	0.32	1.43	2.06	0.82
Venezuela	R^2	6.94***	3.42***		0.01	3.37***	13.56***		
	R^2_{oos}	-45.37	-13.23		-3.42	-0.02	8.72***	-20.82	-2.65
	$t - stat$	(4.89)	(-3.67)		(0.20)	(5.63)	(-5.47)		
	ΔCER	-2.32	-1.20		0.51	0.33	-2.69	-2.06	-0.19
Asia Pacific	R^2	5.15***	0.32	0.57	3.11***		2.26***		
	R^2_{oos}	6.02***	-8.34	27.80***	-6.80		-5.18	21.25***	23.71***
	$t - stat$	(9.27)	(-1.33)	(-1.39)	(-7.13)		(4.53)		
	ΔCER	0.96	0.60	3.69	1.77		1.15	2.64	2.59
Bangladesh	R^2	13.82***	23.63***			0.01			
	R^2_{oos}		-8.45			-1.37		-4.52	-4.06
	$t - stat$	(4.75)	(-8.02)			(-0.19)			
	ΔCER		1.36			-0.44		-0.13	-0.02
China	R^2	0.26	1.72*			0.65			
	R^2_{oos}	-2.93	4.67***			2.43**		-15.50	3.94
	$t - stat$	(0.78)	(-2.04)			(-1.25)			
	ΔCER	-0.15	-0.81			0.34		-7.18	-0.04
Hong Kong	R^2	30.46***	30.70***		2.88**	0.35	13.49***		
	R^2_{oos}	34.80***	6.14***		-2.05	-0.69	9.42***	21.91***	19.22***
	$t - stat$	(14.84)	(-14.93)		(-2.54)	(-1.46)	(5.75)		
	ΔCER	4.19	1.96		-0.44	0.37	1.63	3.06	2.87

CHAPTER 2. PREDICTING THE EQUITY PREMIUM: COMPREHENSIVE
EVIDENCE FROM A LARGE SAMPLE

Table A.2: Return Predictability and Regions – Country View
(continued)

Country		dy	pe	corp	gov	infl	unrate	AEN	MFC
India	R^2	25.54***	12.26***		0.85***	0.25*			
	R^2_{oos}	39.02***	26.31***		0.80***	-0.78		12.65**	8.91*
	$t - stat$	(10.51)	(-6.71)		(3.04)	(1.65)			
	ΔCER	4.36	2.58		-0.08	0.04		0.56	0.13
Indonesia	R^2	23.10***	20.56***			0.04			
	R^2_{oos}	40.94***	5.99***			-2.46		17.54*	19.07*
	$t - stat$	(9.30)	(-8.78)			(-0.38)			
	ΔCER	7.38	0.68			-0.01		3.23	3.02
Japan	R^2	7.29***	5.81***	1.47***	0.01	4.63***	0.45*		
	R^2_{oos}	11.25***	-1.52	-5.00	-29.45	2.81***	1.87***	-14.20	2.57***
	$t - stat$	(8.91)	(-6.60)	(3.71)	(0.26)	(7.28)	(-2.02)		
	ΔCER	-0.71	0.67	-0.53	0.11	-0.52	0.59	1.23	0.95
Korea	R^2	17.04***	20.13***	2.56***	1.25	0.00	28.67***		
	R^2_{oos}	7.61***	12.84***	-7.07	-115.42	0.85***	22.17***	30.30	25.78
	$t - stat$	(11.30)	(-11.09)	(3.68)	(1.47)	(-0.12)	(15.36)		
	ΔCER	0.72	2.24	-0.97	-1.64	-0.19	0.67	2.36	2.08
Malaysia	R^2	17.80***	9.27***		0.10	2.49***			
	R^2_{oos}	17.03***	-7.30		0.63***	-0.62		11.14***	14.65**
	$t - stat$	(10.44)	(-7.17)		(-0.71)	(-3.59)			
	ΔCER	0.07	0.30		0.39	0.04		1.58	1.66
New Zealand	R^2	0.00	0.07		1.56***				
	R^2_{oos}	-8.68	-39.20		0.73***			-20.08	0.37
	$t - stat$	(0.02)	(-0.48)		(-3.99)				
	ΔCER	-0.76	-0.60		-0.26			-0.38	-0.17
Pakistan	R^2	30.14***	30.60***		1.61***	1.14***	32.34***		
	R^2_{oos}	46.68***	33.80***		-2.55	4.13***	13.25***	35.23*	29.83*
	$t - stat$	(11.79)	(-11.92)		(3.25)	(-2.74)	(10.37)		
	ΔCER	4.41	3.89		0.77	0.72	4.89	2.47	2.45
Philippines	R^2	0.19	1.41**		13.05***	7.71***			
	R^2_{oos}	19.94***	10.23***		-12.05	7.82***		13.36***	14.17***
	$t - stat$	(-0.88)	(-2.38)		(-5.68)	(-7.87)			
	ΔCER	-0.50	-0.71		-2.66	-1.15		-0.65	-0.78
Singapore	R^2	18.17***	12.34***		0.04	3.07***			
	R^2_{oos}	20.07***	-0.03		16.99***	-0.06		14.14**	12.84***
	$t - stat$	(10.57)	(-8.42)		(0.29)	(-4.33)			
	ΔCER	1.17	0.02		1.22	0.59		2.52	2.34
Sri Lanka	R^2	0.03	3.37***		0.65*	0.05	1.94**		
	R^2_{oos}	-3.41	-3.81		0.23**	-0.86	-13.58	-8.59	-1.73
	$t - stat$	(0.26)	(-3.02)		(1.71)	(-0.51)	(-2.17)		
	ΔCER	-1.34	0.96		0.21	-0.10	-0.22	-0.91	0.14
Taiwan	R^2	6.31***	11.28***	0.15	6.30***	2.41***	0.79*		
	R^2_{oos}	-0.92	8.31***	-6.60	1.69**	0.77***	-1.12	4.13***	8.65***
	$t - stat$	(4.66)	(-6.40)	(-0.72)	(-4.00)	(-3.76)	(1.88)		
	ΔCER	-1.75	-2.09	-0.62	-0.05	-0.42	1.28	0.40	0.73
Thailand	R^2	1.19*	0.08		4.02***	2.58***	3.82***		
	R^2_{oos}	-9.31	-5.94		14.50***	1.77***	19.14***	-2.00	14.60**
	$t - stat$	(1.97)	(-0.60)		(-4.19)	(-3.54)	(2.57)		
	ΔCER	-0.69	-0.50		2.54	0.24	-0.21	1.32	1.76
Vietnam	R^2					4.39***			
	R^2_{oos}					-114.99		-114.95	-114.99
	$t - stat$					(-2.76)			
	ΔCER					-1.10		-1.10	-1.10
Europe Austria	R^2	0.82**	0.16	3.83***	8.41***	10.27***	0.26		
	R^2_{oos}	-6.04	-25.26	-1.45	-1.28	-6.60	-0.18	2.59***	3.63**
	$t - stat$	(-2.42)	(0.79)	(-4.89)	(-9.75)	(10.81)	(1.51)		
	ΔCER	-0.33	1.57	0.06	-0.40	-0.71	0.37	0.63	0.23
Belgium	R^2	0.01	0.80**	0.15	0.68***	0.43**	2.44***		
	R^2_{oos}	-8.00	-0.36	-1.53	-2.55	-33.09	9.67***	3.29***	3.93
	$t - stat$	(0.29)	(-2.10)	(0.88)	(-3.00)	(-3.00)	(5.15)		
	ΔCER	-1.41	-0.97	-0.05	0.10	-0.42	0.62	1.08	0.28

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**Table A.2: Return Predictability and Regions – Country View
(continued)**

Country		dy	pe	corp	gov	infl	unrate	AEN	MFC
Bulgaria	R^2		27.18***		10.46***	5.73***	26.57***		
	R_{oos}^2				-4.55	4.27***	4.70***	-7.94	-1.85
	$t - stat$		(-6.64)		(-5.40)	(-3.92)	(8.03)		
	ΔCER				-4.48	-0.70	0.27	-4.17	-3.97
Croatia	R^2	0.04	0.66			1.01			
	R_{oos}^2					-0.38		0.35	0.14
	$t - stat$	(0.23)	(-0.92)			(-1.47)			
	ΔCER					1.55		1.72	1.68
Czech Republic	R^2	12.92***	4.90***		1.03	6.89***	18.23***		
	R_{oos}^2	-4.55	-17.91		-13.39	3.38***	28.59***	19.77	14.23*
	$t - stat$	(5.94)	(-3.50)		(-1.35)	(-4.33)	(7.51)		
	ΔCER	-0.07	-2.36		-0.31	1.03	3.29	2.53	2.56
Denmark	R^2	0.10	2.06***	0.14	0.68***	0.08	0.75**		
	R_{oos}^2	1.65***	-3.23	-17.44	-0.14	-0.03	-0.35	8.86***	7.20*
	$t - stat$	(0.74)	(-3.38)	(0.54)	(-3.16)	(-0.68)	(2.74)		
	ΔCER	0.67	-1.51	-3.67	0.00	-0.31	0.35	0.83	0.19
Estonia	R^2				11.15***	0.03	13.39***		
	R_{oos}^2				-8.45	23.16***	22.02***	33.33*	20.60**
	$t - stat$				(-4.51)	(-0.28)	(5.75)		
	ΔCER				-2.69	2.18	3.28	2.89	2.54
Finland	R^2	0.55*	2.06**		0.05	0.14	4.01***		
	R_{oos}^2	1.07***	-8.43		1.94***	3.19***	11.21***	8.60	11.78*
	$t - stat$	(1.87)	(2.60)		(0.73)	(-1.26)	(5.25)		
	ΔCER	0.86	-1.36		-0.25	0.09	2.07	0.76	1.22
France	R^2	0.82***	0.33	0.07	0.29*	0.03	0.20		
	R_{oos}^2	-1.99	-8.72	32.09***	0.34***	0.20***	7.49***	5.01***	11.44***
	$t - stat$	(3.31)	(1.31)	(0.34)	(-1.98)	(0.57)	(-1.22)		
	ΔCER	0.13	-0.50	5.58	0.49	-0.41	1.08	1.65	1.02
Germany	R^2	0.73***	0.89**	1.89***	0.55***	0.72**	1.13***		
	R_{oos}^2	1.81***	-12.04	1.21***	-6.30	-214.23	-6.22	-7.69	0.38*
	$t - stat$	(-3.50)	(-2.22)	(-3.65)	(-3.05)	(3.54)	(3.43)		
	ΔCER	-0.48	-0.54	0.87	-0.43	-1.64	0.94	0.44	-0.16
Greece	R^2	3.56***	0.33		1.31**	0.35*	0.22		
	R_{oos}^2	-8.15	-1.77		-22.66	0.09**	-16.70	-20.06	1.41
	$t - stat$	(4.09)	(-1.23)		(2.19)	(-1.60)	(0.63)		
	ΔCER	-1.34	-2.01		-4.49	-1.00	-6.68	-0.72	-0.77
Hungary	R^2	5.10***	0.63		1.95**	0.02	0.43		
	R_{oos}^2	-0.98	-5.27		-24.89	-8.56	3.00***	-18.37	1.87
	$t - stat$	(3.66)	(1.29)		(1.94)	(0.25)	(-0.99)		
	ΔCER	-2.84	-0.04		0.61	-0.92	0.46	0.59	0.24
Iceland	R^2				40.87***	12.80***	11.75***		
	R_{oos}^2					11.65***	1.09**	11.40*	25.82
	$t - stat$				(-9.41)	(-6.20)	(5.90)		
	ΔCER					-3.29	-5.63	-5.03	-2.59
Ireland	R^2	0.04	1.41**		0.36*	3.08***	5.91***		
	R_{oos}^2	-1.30	4.34***		-5.37	0.01	-2.87	-6.64	-4.21
	$t - stat$	(0.33)	(2.05)		(-1.86)	(-2.61)	(4.90)		
	ΔCER	1.01	-0.82		1.43	-3.16	0.47	2.13	2.05
Italy	R^2	0.36**	1.16**	0.15	1.26***	0.06	7.70***		
	R_{oos}^2	-1.45	-2.20	-9.83	-4.98	-5.31	8.82***	0.68***	4.27*
	$t - stat$	(-1.98)	(-2.18)	(-1.00)	(-4.06)	(0.81)	(7.84)		
	ΔCER	-2.83	-0.74	-2.00	-0.92	-0.57	0.08	0.28	0.13
Latvia	R^2	11.73***	1.24		0.07	0.00	3.15***		
	R_{oos}^2				-44.49	-7.80	-3.64	-32.29	2.99
	$t - stat$	(3.94)	(1.27)		(-0.36)	(0.03)	(2.68)		
	ΔCER				-0.30	-0.07	1.58	-0.25	1.07
Lithuania	R^2		0.02		1.88**	0.66	4.58***		
	R_{oos}^2				-24.43	-16.69	-3.13	-30.88	-22.24
	$t - stat$		(-0.15)		(-2.02)	(-1.23)	(3.29)		
	ΔCER				-4.66	-3.44	-0.10	-4.11	-4.12

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Table A.2: Return Predictability and Regions – Country View
(continued)

Country		dy	pe	corp	gov	infl	unrate	AEN	MFC
Luxembourg	R^2	2.30*			2.00***	0.07	0.01		
	R_{oos}^2	-53.52			-7.24	-1.11	-17.11	-16.53	-7.71
	$t - stat$	(1.90)			(3.32)	(-0.72)	(0.21)		
	ΔCER	-6.42			1.03	-0.23	0.10	1.31	1.39
Malta	R^2				16.19***	0.07	3.28***		
	R_{oos}^2				-15.57	-0.69	-45.53	-39.59	-35.03
	$t - stat$				(-5.86)	(-0.40)	(-2.77)		
	ΔCER				-0.36	-0.16	-1.97	-2.37	-2.00
Netherlands	R^2	0.46	0.06	5.86***	1.24***	0.08	3.57***		
	R_{oos}^2	-4.77	0.00**	7.30***	-9.00	0.51***	17.04***	16.31***	8.75***
	$t - stat$	(1.58)	(0.55)	(-3.33)	(-3.74)	(0.93)	(6.43)		
	ΔCER	0.32	0.42	4.36	-0.32	-0.38	2.03	2.00	0.89
Norway	R^2	9.04***	0.11	0.62*	0.03	0.18	0.60***		
	R_{oos}^2	7.65***	-1.39	1.86***	-1.41	-0.64	6.05***	2.37***	7.94**
	$t - stat$	(7.35)	(0.77)	(1.81)	(-0.64)	(-1.43)	(2.69)		
	ΔCER	1.12	0.81	0.27	0.16	0.08	0.40	0.76	0.59
Poland	R^2	10.70***	13.13***		12.67***	0.01	2.34***		
	R_{oos}^2	-15.63	-58.01		-16.91	0.97***	8.07***	-5.50	-1.25
	$t - stat$	(5.49)	(-6.43)		(-5.20)	(0.17)	(2.60)		
	ΔCER	-3.53	0.14		-0.17	-0.53	1.50	0.90	0.36
Portugal	R^2	1.30**	3.59***		5.18***	1.06***	3.12***		
	R_{oos}^2	-2.14	-3.86		3.09***	1.28***	-10.12	2.35**	12.17***
	$t - stat$	(2.06)	(-3.47)		(7.10)	(3.15)	(3.51)		
	ΔCER	-1.53	-3.32		0.04	-0.36	-1.69	0.99	1.22
Romania	R^2	11.85***			5.40***	0.29	18.35***		
	R_{oos}^2	41.00***			-654.70	0.12*	-129.59	-11.37	-8.08
	$t - stat$	(5.04)			(2.93)	(-0.97)	(6.65)		
	ΔCER	0.69			-0.07	-1.14	-0.24	-1.07	-0.90
Russian Federation	R^2	4.49***	0.01		9.36***	1.48*	0.42		
	R_{oos}^2	2.23**	-5.01		14.97***	-1.96	3.73***	-3.54	11.72*
	$t - stat$	(3.17)	(-0.17)		(4.71)	(1.89)	(1.00)		
	ΔCER	-0.95	-1.11		2.87	0.26	2.09	1.49	2.19
Slovakia Republic	R^2	0.03	0.60		27.42***	0.19	35.40***		
	R_{oos}^2		-11.60		-60.72	-0.45	64.35***	-3.85	-3.97
	$t - stat$	(0.21)	(0.96)		(-9.52)	(-0.69)	(10.52)		
	ΔCER		-1.44		-1.83	0.81	4.04	1.66	1.86
Slovenia	R^2	21.64***	0.63		2.43**	0.10	3.44***		
	R_{oos}^2		-0.11		25.18***	-1.41	-18.40	-3.07	-7.45
	$t - stat$	(6.24)	(-0.99)		(1.94)	(0.51)	(2.84)		
	ΔCER		-0.70		0.28	-0.86	-6.70	-3.40	-2.64
Spain	R^2	0.47*	1.44**		0.18	0.05	0.16		
	R_{oos}^2	-12.80	0.56**		-1.32	2.30***	8.37***	2.06**	6.32***
	$t - stat$	(1.94)	(-2.48)		(-1.43)	(0.70)	(1.00)		
	ΔCER	-1.07	0.21		1.15	0.72	2.26	2.05	1.36
Sweden	R^2	1.16***	0.26	0.01	0.00	0.06	0.06		
	R_{oos}^2	1.22***	-2.80	3.52***	-7.18	0.34***	4.80***	2.75***	14.06***
	$t - stat$	(3.99)	(-1.19)	(-0.27)	(-0.01)	(-0.82)	(0.85)		
	ΔCER	0.92	1.10	0.14	0.12	0.17	1.50	2.77	2.37
Switzerland	R^2	1.01**	1.18**		1.53***	0.83***	1.74***		
	R_{oos}^2	-6.55	-1.22		-8.55	-0.39	8.04***	3.10***	8.66**
	$t - stat$	(2.45)	(2.55)		(-4.30)	(-3.09)	(4.21)		
	ΔCER	-0.01	0.21		0.69	0.13	1.39	2.41	1.43
Ukraine	R^2		2.57*			0.05			
	R_{oos}^2					-6.82		-6.75	-7.78
	$t - stat$		(-1.76)			(-0.30)			
	ΔCER					-1.36		-1.34	-1.63
United Kingdom	R^2	12.20***	9.26***	0.48***	0.20*	0.28*	0.13		
	R_{oos}^2	15.66***	0.78***	-11.65	-4.71	-1.93	-0.23	22.46***	12.70***
	$t - stat$	(12.31)	(-8.03)	(2.87)	(1.85)	(-1.85)	(1.42)		
	ΔCER	0.60	0.92	0.36	0.97	-0.06	0.67	2.91	1.20

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**Table A.2: Return Predictability and Regions – Country View
(continued)**

Country			dy	pe	corp	gov	infl	unrate	AEN	MFC
Middle East	Bahrain	R^2	1.35	12.08***			0.02			
		R^2_{oos}	14.42***	-41.20			-8.23		-11.32	-4.78
		$t - stat$	(1.56)	(5.11)			(0.27)			
		ΔCER	0.07	-0.06			-1.64		-1.20	-0.86
Cyprus		R^2				2.53**	0.01	11.45***		
		R^2_{oos}				11.47***	-0.86	1.42**	4.27	1.54
		$t - stat$				(-2.30)	(0.15)	(4.80)		
		ΔCER				0.51	-0.34	1.44	0.01	-0.04
Egypt		R^2	1.48	13.23***			0.51			
		R^2_{oos}		24.68***			-17.88		-17.15	-18.12
		$t - stat$	(1.40)	(-5.21)			(-1.16)			
		ΔCER		5.57			-2.87		-2.68	-2.69
Israel		R^2	14.62***	0.92			36.47***	4.99***		
		R^2_{oos}	9.09***	-1.51			31.97***		32.49***	31.68***
		$t - stat$	(6.54)	(1.31)			(21.28)	(2.77)		
		ΔCER	-0.32	-0.07			-3.84		-3.89	-4.02
Jordan		R^2	5.85***	2.96***		0.04	0.07			
		R^2_{oos}	10.17***	-9.25			0.05*		-1.45	8.48
		$t - stat$	(3.93)	(-2.76)		(-0.22)	(-0.57)			
		ΔCER	4.71	-2.63			0.30		-0.74	0.84
Kuwait		R^2					0.00			
		R^2_{oos}					0.58**		0.59*	0.19
		$t - stat$					(0.11)			
		ΔCER					0.05		0.05	-0.23
Lebanon		R^2		20.22***		0.83				
		R^2_{oos}				3.24**			3.08**	1.27**
		$t - stat$		(-5.45)		(1.35)				
		ΔCER				0.33			0.32	0.10
Oman		R^2					1.33*			
		R^2_{oos}					-6.24		-6.14	-9.00
		$t - stat$					(-1.73)			
		ΔCER					1.07		1.09	0.65
Qatar		R^2					0.82			
		R^2_{oos}								
		$t - stat$					(-1.09)			
		ΔCER								
Saudi Arabia		R^2		12.67***			3.84***			
		R^2_{oos}		-36.16			7.25***		1.58*	4.84*
		$t - stat$		(-5.41)			(-3.24)			
		ΔCER		-2.58			1.44		0.64	0.71
Turkey		R^2	36.72***	1.56**			1.60**	33.86***		
		R^2_{oos}	6.44***	-238.48			-0.56	-75.09	-28.50	11.62**
		$t - stat$	(14.15)	(-2.34)			(-2.37)	(9.55)		
		ΔCER	-2.97	-3.29			-3.14	-0.54	-3.28	-3.05

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Table A.3: Economic Utility Gains ($\gamma = 6$) – Aggregated View

This table reports the utility gains ($\Delta CERs$) with $\gamma = 6$ in percent relative to a benchmark strategy based on the historical mean. We sample the data at the monthly frequency, and we predict the future 12-month excess return. “Mean” indicates the average ΔCER . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of $\Delta CERs$ greater than zero, respectively. “Mean | > 0 ” is the mean ΔCER given it is greater than zero. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively.

Region	dy				pe				corp				gov			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	1.02	3	66.67	1.91	-0.17	7	57.14	0.69	-0.41	1	0.00		-0.96	4	25.00	0.56
America	-0.50	9	22.22	1.22	-0.23	11	36.36	0.49	0.08	2	100.00	0.08	-1.14	5	40.00	0.20
Asia Pacific	-0.07	15	33.33	1.79	-0.08	16	43.75	0.83	0.05	4	25.00	2.66	-0.23	13	30.77	0.94
Europe	-0.74	22	22.73	0.30	-0.36	22	31.82	0.37	-0.19	10	30.00	1.62	-0.58	29	24.14	0.63
Middle East	-0.01	4	50.00	1.18	-1.32	6	16.67	2.91					0.25	2	100.00	0.25

Region	infl				unrate				AEN				MFC			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	-0.14	9	44.44	0.12					-0.19	9	44.44	0.52	0.04	9	44.44	0.58
America	-2.83	11	36.36	0.07	0.58	7	57.14	1.72	-2.96	11	36.36	0.83	-2.87	11	36.36	0.52
Asia Pacific	-0.15	15	53.33	0.14	0.31	8	62.50	1.02	-0.69	17	41.18	0.78	0.22	17	52.94	0.90
Europe	-0.53	32	25.00	0.40	-0.31	30	50.00	0.73	-0.58	32	46.88	0.72	-0.23	32	50.00	0.77
Middle East	-2.19	9	44.44	0.36	0.69	2	50.00	1.65	-2.40	10	40.00	0.25	-1.99	10	30.00	0.23

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Table A.4: Economic Utility Gains ($\gamma = 9$) – Aggregated View

This table reports the utility gains ($\Delta CERs$) with $\gamma = 9$ in percent relative to a benchmark strategy based on the historical mean. We sample the data at the monthly frequency, and we predict the future 12-month excess return. “Mean” indicates the average ΔCER . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of $\Delta CERs$ greater than zero, respectively. “Mean | > 0 ” is the mean ΔCER given it is greater than zero. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively.

Region	dy				pe				corp				gov			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	0.70	3	66.67	1.31	-0.10	7	57.14	0.52	-0.36	1	0.00		-1.00	4	25.00	0.36
America	-0.41	9	22.22	0.82	-0.17	11	36.36	0.34	-0.01	2	50.00	0.03	-0.97	5	40.00	0.15
Asia Pacific	-0.32	15	33.33	1.16	-0.32	16	43.75	0.56	-0.19	4	25.00	1.80	-0.27	13	30.77	0.71
Europe	-0.61	22	22.73	0.13	-0.28	22	31.82	0.18	-0.31	10	30.00	1.00	-0.54	29	24.14	0.40
Middle East	-0.04	4	50.00	0.79	-1.16	6	16.67	1.97					-0.05	2	50.00	0.11

Region	infl				unrate				AEN				MFC			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	-0.13	9	44.44	0.08					-0.33	9	44.44	0.35	-0.07	9	44.44	0.40
America	-2.54	11	27.27	0.05	0.28	7	57.14	1.06	-2.77	11	27.27	0.42	-2.59	11	36.36	0.33
Asia Pacific	-0.14	15	46.67	0.11	0.00	8	62.50	0.61	-0.78	17	35.29	0.62	0.00	17	52.94	0.61
Europe	-0.41	32	21.88	0.30	-0.32	30	46.67	0.49	-0.67	32	31.25	0.48	-0.29	32	46.88	0.50
Middle East	-1.64	9	44.44	0.24	-0.26	2	0.00		-1.99	10	40.00	0.17	-1.55	10	30.00	0.15

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**Table A.5: Economic Utility Gains ($\gamma = 3$) and Transaction Costs
– Aggregated View**

This table reports the utility gains ($\Delta CERs$) with $\gamma = 3$ in percent relative to a benchmark strategy based on the historical mean. We assume transaction costs of 50bp per transaction. We sample the data at the monthly frequency, and we predict the future 12-month excess return. “Mean” indicates the average ΔCER . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of $\Delta CERs$ greater than zero, respectively. “Mean | > 0” is the mean ΔCER given it is greater than zero. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively.

Region	dy				pe				corp				gov			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	1.97	3	66.67	3.57	-0.39	7	57.14	1.08	0.36	1	100.00	0.36	-0.53	4	75.00	1.04
America	-0.52	9	33.33	1.16	-0.33	11	54.55	0.65	0.50	2	100.00	0.50	-0.38	5	60.00	0.29
Asia Pacific	1.09	15	46.67	3.24	0.60	16	62.50	1.46	0.35	4	25.00	3.64	0.09	13	53.85	0.96
Europe	-0.81	22	40.91	0.63	-0.58	22	36.36	0.64	0.54	10	60.00	1.88	-0.50	29	41.38	0.77
Middle East	0.32	4	50.00	2.37	-0.54	6	16.67	5.51					0.40	2	100.00	0.40

Region	infl				unrate				AEN				MFC			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	-0.04	9	55.56	0.23					0.57	9	66.67	1.07	0.52	9	66.67	1.07
America	-3.09	11	45.45	0.17	1.53	7	71.43	2.82	0.13	11	63.64	1.35	-2.83	11	36.36	0.87
Asia Pacific	-0.12	15	46.67	0.31	1.19	8	75.00	1.67	1.62	17	82.35	2.09	1.04	17	70.59	1.67
Europe	-0.52	32	31.25	0.68	0.20	30	76.67	1.30	0.91	32	75.00	1.92	0.19	32	68.75	1.17
Middle East	-1.02	9	44.44	0.68	0.47	2	50.00	1.47	-0.19	10	50.00	0.79	-0.89	10	40.00	0.54

Table A.6: Return Predictability and Sorting Characteristics – Aggregated View with Ex-Post R_{oos}^2 s

This table reports portfolio sorts of countries according to different characteristics, indicated in the panel headings. We present out-of-sample results based on the predictor that exhibits the highest R_{oos}^2 ex-post. We sample the data at the monthly frequency, and we predict the future 12-month excess return. We sort the countries according to the respective sorting characteristic into five portfolios. Portfolio 1 (5) contains the countries with the lowest (highest) value of the sorting characteristic. “Mean” indicates the average R_{oos}^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R_{oos}^2 s, respectively. “Mean | Significant” is the mean of the R_{oos}^2 s given they are significant at at least the 10% significance level. Statistical inference is based on the MSPE-adjusted test statistic of Clark & West (2007).

Portfolio	GDP Volatility				Bad States			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Portfolio 1	2.53	15	33.33	12.75	15.35	16	50.00	21.59
Portfolio 2	10.34	16	37.50	15.46	14.72	16	50.00	24.45
Portfolio 3	19.10	16	43.75	20.21	12.67	15	40.00	21.04
Portfolio 4	15.80	16	50.00	22.25	9.09	16	43.75	12.88
Portfolio 5	10.73	15	33.33	24.33	4.80	16	25.00	8.48

Portfolio	Market Capitalization				Market Openness				GDP per Capita			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Portfolio 1	10.09	11	27.27	5.59	-0.36	15	26.67	24.22	7.40	15	46.67	27.39
Portfolio 2	9.74	11	54.55	21.48	15.48	15	40.00	13.92	16.81	16	50.00	20.85
Portfolio 3	14.64	11	63.64	18.71	18.54	16	43.75	26.41	13.41	16	31.25	13.07
Portfolio 4	16.07	11	63.64	11.69	13.94	16	50.00	17.96	12.77	16	31.25	25.75
Portfolio 5	13.72	11	45.45	18.77	11.58	15	26.67	27.29	8.26	15	40.00	7.50

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**Table A.7: Economic Utility Gains ($\gamma = 3$) and Transaction Costs
– Aggregated View (Post-1990)**

This table reports the utility gains ($\Delta CERs$) with $\gamma = 3$ in percent relative to a benchmark strategy based on the historical mean. We assume transaction costs of 50bp per transaction. We sample the data at the monthly frequency, and we predict the future 12-month excess return. “Mean” indicates the average ΔCER . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of $\Delta CERs$ greater than zero, respectively. “Mean | > 0 ” is the mean ΔCER given it is greater than zero. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and the mean forecast combination approach, respectively. The sample period spans from January 1990 to December 2015.

Region	dy				pe				corp				gov			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	0.27	3	66.67	2.46	-0.16	7	57.14	1.41	3.19	1	100.00	3.19	0.03	5	60.00	1.59
America	-0.14	9	33.33	0.98	0.37	11	72.73	1.19	0.36	2	50.00	1.71	-0.07	4	75.00	0.69
Asia Pacific	0.91	15	53.33	2.85	0.04	16	43.75	1.39	0.70	4	50.00	2.21	0.55	13	53.85	1.76
Europe	-0.99	21	28.57	1.14	-0.92	22	22.73	1.10	-0.40	8	50.00	1.17	-0.99	29	27.59	1.32
Middle East	0.25	4	50.00	2.39	-0.56	6	16.67	5.51					0.40	2	100.00	0.40

Region	infl				unrate				AEN				MFC			
	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0	Mean	Nobs	Percentage	Mean > 0
Africa	0.07	9	44.44	0.68					0.60	9	66.67	1.18	0.61	9	66.67	1.22
America	0.01	11	54.55	0.36	1.74	7	71.43	3.09	3.16	11	90.91	3.62	0.98	11	81.82	1.39
Asia Pacific	0.20	15	66.67	0.63	0.92	8	62.50	1.89	2.28	17	76.47	3.14	1.57	17	76.47	2.32
Europe	-0.64	32	21.88	0.94	0.96	30	66.67	2.72	2.28	32	75.00	3.83	0.66	32	62.50	2.17
Middle East	-0.52	9	55.56	0.74	-1.15	3	33.33	1.47	0.09	10	70.00	0.92	-0.45	10	60.00	0.44

**Table A.8: Restricted Return Predictability – Aggregated View
(in USD)**

This table reports the average results of out-of-sample predictions using economically motivated restrictions. We sample the data at the monthly frequency, and we predict the future 12-month excess return. The time series of the market indices are denominated in USD. Following Campbell & Thompson (2008), we impose two restrictions: (i) we set the out-of-sample slope estimate equal to zero whenever it is different to that of the in-sample estimate, (ii) we set the out-of-sample forecast equal to zero whenever it is negative. “Mean” indicates the average R_{oos}^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R_{oos}^2 s, respectively. “Mean | Significant” is the mean of the R_{oos}^2 s given they are significant at at least the 10% significance level. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. Statistical inference is based on the MSPE-adjusted test statistic of Clark & West (2007).

Region	dy				pe				corp			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Africa	9.47	3	100.00	9.47	-3.13	7	28.57	5.00	3.38	1	100.00	3.38
America	2.56	9	66.67	10.83	4.42	11	45.45	12.92	2.87	2	100.00	2.87
Asia Pacific	14.78	15	80.00	18.67	8.75	16	81.25	11.40	1.34	4	50.00	2.98
Europe	-3.82	22	27.27	8.55	-5.10	23	8.70	1.22	1.22	10	40.00	12.76
Middle East	4.32	4	75.00	7.14	-3.27	6	50.00	9.12				

Region	gov				infl				unrate			
	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Africa	0.05	4	50.00	2.49	-0.92	9	33.33	2.22	13.83	7	85.71	16.85
America	4.47	6	33.33	23.15	-4.53	11	54.55	1.58	5.48	8	62.50	11.12
Asia Pacific	-5.58	13	46.15	9.80	-4.58	15	40.00	3.95	-0.45	30	46.67	13.23
Europe	-6.90	29	31.03	4.46	-1.99	32	40.63	3.88	-13.60	2	0.00	
Middle East	9.27	2	100.00	9.27	0.35	9	55.56	3.03				

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**Table A.9: Return Predictability – Aggregated View (Post-1990)
(in USD)**

This table summarizes the in-sample and out-of-sample return predictability for different regions. We sample the data at the monthly frequency, and we predict the future 12-month excess return. The time series of the market indices are denominated in USD. “Mean” indicates the average R^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R^2 s, respectively. “Mean | Significant” is the mean of the R^2 s given they are significant at at least the 10% significance level. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and mean forecast combination approach, respectively. R^2 and R^2_{oos} are the in-sample and out-of-sample R^2 , respectively. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007). The sample period spans from January 1990 to December 2015.

Region	Statistic	dy				pe				corp				gov			
		Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Africa	R^2	6.32	8	62.50	9.67	14.12	9	77.78	18.00	7.84	1	100.00	7.84	4.97	6	83.33	5.94
	R^2_{oos}	27.19	3	100.00	27.19	7.62	7	42.86	29.41	10.78	1	100.00	10.78	3.22	4	75.00	4.19
America	R^2	7.27	11	72.73	9.85	9.10	11	63.64	14.03	2.32	2	50.00	3.73	1.91	5	20.00	8.14
	R^2_{oos}	-0.82	9	55.56	8.31	4.52	11	45.45	15.20	-1.95	2	50.00	0.63	5.96	5	40.00	27.45
Asia Pacific	R^2	14.21	16	87.50	16.21	10.02	16	81.25	12.23	2.47	4	100.00	2.47	3.93	13	61.54	6.12
	R^2_{oos}	15.55	15	66.67	28.16	2.07	16	43.75	13.22	3.76	4	25.00	23.67	-2.19	13	69.23	10.02
Europe	R^2	5.15	25	64.00	7.80	3.62	28	50.00	6.76	3.46	8	62.50	5.49	4.80	30	66.67	7.04
	R^2_{oos}	-4.22	21	33.33	9.16	-12.24	23	4.35	0.96	-7.15	8	37.50	3.01	-18.19	29	10.34	17.19
Middle East	R^2	5.41	5	80.00	6.74	8.91	7	85.71	10.39					1.71	3	66.67	2.53
	R^2_{oos}	7.69	4	100.00	7.69	-49.82	6	16.67	17.02					5.31	2	100.00	5.31

Region	Statistic	infl				unrate				AEN				MFC			
		Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
Africa	R^2	0.35	9	0.00						6.64	9	33.33	15.50	7.40	9	33.33	17.47
	R^2_{oos}	-1.54	9	22.22	1.72												
America	R^2	0.59	11	27.27	1.63	11.57	8	87.50	13.22	5.92	12	58.33	17.02	5.26	12	33.33	20.11
	R^2_{oos}	-5.66	11	9.09	1.19	19.87	7	85.71	24.36								
Asia Pacific	R^2	0.69	15	20.00	2.48	9.47	8	87.50	10.82	4.51	17	41.18	29.90	8.87	17	47.06	21.91
	R^2_{oos}	-9.91	15	26.67	1.76	2.36	8	50.00	11.72								
Europe	R^2	1.04	32	43.75	1.83	9.68	30	80.00	12.03	-6.17	32	34.38	19.57	-0.48	32	31.25	13.84
	R^2_{oos}	-3.59	32	9.38	1.23	-3.18	30	36.67	18.98								
Middle East	R^2	0.90	10	20.00	2.20	14.98	3	100.00	14.98								
	R^2_{oos}	-1.01	9	22.22	3.27	-16.65	2	0.00		-5.87	10	20.00	3.87	-3.87	10	20.00	2.10

A. APPENDIX

Table A.10: Return Predictability and Regions based on U.S. Predictors – Aggregated View (in USD)

This table summarizes the in-sample and out-of-sample return predictability for different regions using U.S. predictor variables. We sample the data at the monthly frequency, and we predict the future 12-month excess return. The time series of the market indices are denominated in USD. “Mean” indicates the average R^2 . “Nobs” and “Percentage” denote the number of countries and the percentage fraction of significant R^2 s, respectively. “Mean | Significant” is the mean of the R^2 s given they are significant at at least the 10% significance level. “dy” denotes the dividend yield, “pe” the price–earnings ratio, “gov” the long-term government bond yield, “corp” the long-term corporate bond yield, “infl” the inflation rate, and “unrate” the unemployment rate. “AEN” and “MFC” denote the adaptive elastic net and mean forecast combination approach, respectively. R^2 and R^2_{oos} are the in-sample and out-of-sample R^2 , respectively. For simple regression models, statistical inference is based on a bootstrapped distribution, while for AEN and MFC we use the MSPE-adjusted test statistic of Clark & West (2007).

		dy				pe				corp				gov			
Region	Statistic	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
		Africa	R^2	3.52	9	77.78	4.44	3.61	9	66.67	5.22	3.48	9	55.56	6.13	2.09	9
	R^2_{oos}	-7.89	9	0.00		-1.74	9	44.44	3.56	8.13	9	88.89	9.39	2.15	9	55.56	8.84
America	R^2	0.98	12	66.67	1.42	1.24	12	50.00	2.34	1.59	12	66.67	2.33	1.46	12	75.00	1.84
	R^2_{oos}	-2.08	12	58.33	3.60	-5.09	12	25.00	2.23	-0.42	12	83.33	7.94	3.80	12	75.00	8.09
Asia	R^2	0.93	17	47.06	1.89	2.52	17	70.59	3.49	1.22	17	52.94	2.07	1.89	17	70.59	2.58
Pacific	R^2_{oos}	1.12	17	52.94	5.85	-2.80	17	29.41	4.78	-2.28	17	58.82	6.89	-1.10	17	52.94	8.01
Europe	R^2	1.40	32	53.13	2.36	1.52	32	56.25	2.58	1.05	32	40.63	2.34	1.04	32	37.50	2.54
	R^2_{oos}	-7.58	32	18.75	3.52	-0.97	32	43.75	5.50	-8.14	32	40.63	3.93	-7.20	32	15.63	7.32
Middle	R^2	4.21	11	90.91	4.61	0.93	11	36.36	1.86	1.36	11	54.55	2.29	1.23	11	45.45	2.33
East	R^2_{oos}	-16.23	11	9.09	0.29	-10.17	11	18.18	3.94	-6.87	11	45.45	5.00	-10.38	11	27.27	7.60

		infl				unrate				AEN				MFC			
Region	Statistic	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant	Mean	Nobs	Percentage	Mean Significant
		Africa	R^2	0.99	9	55.56	1.55	2.20	9	55.56	3.64	2.73	9	44.44	24.76	6.79	9
	R^2_{oos}	-0.43	9	44.44	0.91	-3.66	9	33.33	2.23								
America	R^2	0.74	12	50.00	1.30	1.76	12	91.67	1.92					7.80	12	50.00	9.22
	R^2_{oos}	-1.45	12	25.00	0.32	-1.76	12	33.33	4.81	-27.14	12	66.67	11.98				
Asia	R^2	1.43	17	82.35	1.61	2.42	17	70.59	3.26					7.21	17	47.06	11.46
Pacific	R^2_{oos}	-0.78	17	41.18	3.25	-1.74	17	47.06	3.49	-7.78	17	70.59	12.28				
Europe	R^2	1.14	32	62.50	1.63	1.88	32	68.75	2.62					4.71	32	46.88	8.75
	R^2_{oos}	1.94	32	68.75	3.19	-9.94	32	21.88	1.71	-11.88	32	40.63	8.59				
Middle	R^2	0.23	11	0.00		1.02	11	54.55	1.48					2.14	11	9.09	15.74
East	R^2_{oos}	-1.68	11	18.18	1.13	-23.14	11	0.00		-31.16	11	0.00					

Chapter 3

Predicting the Equity Market with Option-Implied Variables*

3.1 Introduction

A growing literature, e.g., Jiang & Tian (2005), Bollerslev et al. (2009), and Driessen et al. (2013), documents the predictive power of option-implied variables for equity excess returns and realized variance. The growing number of option-implied predictors raises several questions: Which variables really forecast market excess returns? Do the variables that predict market excess returns also forecast realized variance? Does predictability lead to economic gains? These are some of the questions we want to study.

The main contribution of this chapter is to provide a comprehensive analysis of the forecasting ability of variables separately proposed in recent literature on option-implied predictors. We perform our analysis following the methodological background of Goyal & Welch (2008). Importantly, we

*This chapter is based on the Paper “Predicting the Equity Market with Option-Implied Variables” authored by Fabian Hollstein, Marcel Prokopczuk, Björn Tharann, and Chardin Wese Simen, forthcoming in the *European Journal of Finance*, 2018.

do not only analyze return predictability, but consider the predictability of variance at the same time. This is important from a portfolio choice perspective, since both quantities are needed for a portfolio decision. As such, we do not only consider statistical predictability, but also analyze the economic significance of return and variance predictability. We find that several variables, including the correlation risk premium (*CRP*) and the variance risk premium (*VRP*), predict the monthly excess return of the S&P 500. This is the case both in- and out-of-sample. We also show that both the *CRP* and the *VRP* predict not only the market excess return but also its realized variance. We note that most of the variables we study have strong predictive power for realized variance but not for market excess return.

When studying the economic effects of the documented predictability in the context of portfolio choice, we find that relative to the agent who assumes that the mean and variance of the market return are unpredictable, a mean–variance agent with a risk-aversion coefficient of 3 who uses the information content of *CRP* would realize utility gains of 5.03 % p.a. Relatedly, we find that a return timing strategy based on the *VRP* leads to lower utility gains than those afforded by the strategy based on the recursive mean. This indicates that the statistical predictability of excess returns and realized variance, respectively, by the *VRP* does not always translate to economic gains. We conjecture that this result is due to the fact that individual variables lead to a large dispersion in the forecast estimation. Forecast combinations instead appear to generate stable forecasts for both excess returns and realized variance, and add economic value. Further, we link this result also to the sign-switching behavior of the *VRP* around economically important periods.

A variable is considered to have predictive power if it passes two tests. First, it has to generate statistically significant forecasts. In this case the

3.1. INTRODUCTION

variable contains key information about the variation in the market risk premium and the realized variance, respectively. Bollerslev et al. (2009) and Drechsler & Yaron (2011) argue that time-varying economic uncertainty is captured by the variance risk premium, and thus, affects the variation in the market risk premium. Driessen et al. (2009, 2013) state that the time-varying correlation risk is linked to economic uncertainty, and thus, also relates to the market price of return risk. Second, the variable needs to add economic value. Since the predictability, measured by the R^2 , is, in general, small in magnitude, and thus the question arises whether it is economically meaningful. Does an investor obtain an increase in utility by taking the variable into account? This aspect is often ignored in the existing literature. Our results show that *CRP* emerges as the only predictor that passes both tests.

We analyze the predictability of different specifications of the *VRP* as robustness. We follow Andersen & Bondarenko (2013), Andersen, Bondarenko, & Gonzalez-Perez (2015), and Feunou, Jahan-Parvar, & Okou (2017) and decompose the total variance risk premium into the downside and upside components. The results show that the upside and downside variance risk premia also pass both tests by providing evidence for significantly predicting excess returns and realized variance in-sample, and in adding economic value based on a timing strategy.

Our work relates to the literature on the predictability of the market excess return and/or its associated realized variance using option-implied quantities. Bollerslev et al. (2009) document the predictive power of the variance risk premium for S&P 500 excess returns, and Bollerslev et al. (2014) document similar results for a broad range of international equity indices. Pyun (2018) provides evidence of a weak out-of-sample performance of the variance risk premium for S&P 500 excess returns. Driessen et al. (2009, 2013) show that the correlation risk premium predicts S&P 500

excess returns, whereas Cosemans (2011) points out that the correlation risk premium and the systematic part of individual variance risk premia are the drivers of the predictive power of the variance risk premium for market excess returns. Zhou (2013) documents the predictive power of the S&P 500 implied correlation index for S&P 500 index returns. Xing, Zhang, & Zhao (2010) find that the option-implied smirk contains information about the cross-section of equity returns. Cremers & Weinbaum (2010) document that deviations from the put-call parity, measured as the difference in implied volatility between pairs of call and put options of U.S. stocks, contain information about the cross-section of stock returns and have predictive power for these. Rehman & Vilkov (2012) and Stilger et al. (2017) show that implied skewness of individual U.S. stocks has predictive power for future returns. Jiang & Tian (2005) and Kourtis et al. (2016) establish the forecasting power of the S&P 500 option-implied variance for realized variance. The above mentioned studies use different sample periods and statistical techniques to document their results, thus, making the interpretation and comparison of the findings somewhat difficult. We use a common sample period and recent developments in the literature on predictability to thoroughly analyze all these variables.

Our study also relates to the literature on the economic value of predictability. Typically, the literature analyzes the implications of return predictability for a return timing strategy (e.g., Campbell & Thompson, 2008; Çakmaklı & van Dijk, 2016). Similarly, studies on realized variance predictability only explore the implications for a volatility/variance timing strategy (Fleming et al., 2001). Unlike these studies, we jointly study the impact of return and variance timing. This is important because in a mean–variance framework, the optimal portfolio weight invested in the risky asset depends on both the expected return and the expected realized variance. If a forecasting variable predicts both the market excess return

3.2. DATA AND METHODOLOGY

and the realized variance, it might be potentially important to account for these two effects when computing the optimal weight.

The remainder of this chapter proceeds as follows. Section 3.2 introduces the data and explains the construction of the main variables. Section 3.3 presents the main empirical results. Section 3.4 discusses some further results. Section 3.5 provides additional results. Finally, Section 3.6 concludes.

3.2 Data and Methodology

3.2.1 Data

We obtain our data from three distinct sources. First, we retrieve the monthly time series of the S&P 500 total return index as well as the corresponding dividend payments from the Center for Research in Security Prices (CRSP) database. Second, we obtain S&P 500 index option data from OptionMetrics. The OptionMetrics dataset contains information about option contracts available in the market as well as standardized options, both of which are useful for our analysis (see Section 3.2.2). Third, we use intraday data on the S&P 500 index sampled at the 5-minute frequency from Thomson Reuters Tick History (TRTH). In sampling the intraday data, we focus on the normal trading hours, i.e. from 09:30 AM to 04:00 PM (EDT). Our sample period extends from January 1996 to December 2014. It is worth pointing out that although the CRSP database covers a period starting before 1996, this is not the case for the OptionMetrics and TRTH. Starting our sample in January 1996 allows us to guarantee the availability of data from all three databases.

3.2.2 Variables

Armed with the dataset introduced above, we are now able to construct our main variables.

Market Excess Return We compute the excess return on the S&P 500 index by subtracting the riskless rate for the corresponding period from the total return on the equity index:

$$ER_{t+1} = 12 \times \log \left(\frac{P_{t+1}}{P_t} \right) - rf_t, \quad (3.1)$$

where ER_{t+1} is the (annualized) monthly excess return on the S&P 500 index at the end of month $t + 1$. P_{t+1} and P_t denote the total return price index at the end of months $t + 1$ and t , respectively. rf_t refers to the (annualized) riskless rate observed at the end of month t .¹ Following Goyal & Welch (2008), we use the 1-month T-bill rate to proxy for the riskless rate.

Realized Variance In order to estimate the realized variance of the stock market, we exploit developments in the literature on high-frequency financial econometrics. Andersen, Bollerslev, Diebold, & Labys (2003) show that by sampling data at the intraday level, one can improve the accurate measurement of realized variance. Building on this insight, we use intraday prices sampled at the 5-minute frequency to compute the realized variance of the asset:

$$RV_{t+1} = \frac{360}{N} \times \left[\sum_{i=1}^N \left(\sum_{j=1}^{m-1} \log \left(\frac{S_{t+\frac{i}{N},j+1}}{S_{t+\frac{i}{N},j}} \right)^2 \right) + \log \left(\frac{S_{t+\frac{i}{N},1}}{S_{t+\frac{i-1}{N},m}} \right)^2 \right], \quad (3.2)$$

where RV_{t+1} is the realized variance at the end of month $t+1$. The first term to the right of the equality sign simply annualizes the variance estimate,

¹Throughout this chapter, we use the convention that the riskless rate is given the subscript for the time when it is observed. Thus, the riskless rate is observed at time t even though it is realized at time $t + 1$.

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where N is the number of days between the end of month t and that of month $t+1$. Each day contains m intraday observations. $S_{t+\frac{i}{N},j+1}$ and $S_{t+\frac{i}{N},j}$ are the spot prices observed on day $t+\frac{i}{N}$ at times $j+1$ and j , respectively. The last term to the right of the equality sign simply reflects the effect of overnight returns. In particular, it captures the impact of the return from the end of the previous day to the opening of the following day.

Option-Implied Moments Recent studies document the information content of option-implied moments, e.g., Jiang & Tian (2005), Prokopczuk & Wese Simen (2014), and Kourtis et al. (2016), for realized variance. We exploit the theoretical results of Bakshi, Kapadia, & Madan (2003) to construct the risk-neutral variance (VAR^{BKM}), skewness ($SKEW^{BKM}$), and excess kurtosis ($EXKURT^{BKM}$):

$$VAR^{BKM} = \frac{e^{r\tau}V - \mu^2}{\tau}, \quad (3.3)$$

$$SKEW^{BKM} = \frac{e^{r\tau}W - 3\mu e^{r\tau}V + 2\mu^3}{[e^{r\tau}V - \mu^2]^{3/2}}, \quad (3.4)$$

$$EXKURT^{BKM} = \frac{e^{r\tau}X - 4\mu e^{r\tau}W + 6e^{r\tau}\mu^2V - 3\mu^4}{[e^{r\tau}V - \mu^2]^2} - 3, \quad (3.5)$$

where r denotes the continuously compounded (annualized) interest rate for the period from t to $t + \tau$. We use the Ivy curve from OptionMetrics to proxy for the interest rate. Essentially, this curve is based on London Interbank Offered Rate (LIBOR) and Eurodollar futures.² τ indicates the time to expiration of each option, expressed as a fraction of a year. Note that all variables are contemporaneously observed. In the expressions above

²We use this interest rate curve to be consistent with the empirical literature on option prices (e.g., Bali & Hovakimian, 2009; McGee & McGroarty, 2017). Obviously, one may wonder if our main results hold if we substitute the OptionMetrics curve with the term-structure of Treasury rates. The effect on our main findings is negligible. The intuition behind this result is that most of our analysis focuses on options of short time to maturity. Because the interest rate is always multiplied by the time to maturity, we find that the interest rate proxy has very little impact on our results.

V , W , X , and μ are defined as follows:

$$\begin{aligned} V &= \int_{K=0}^S \frac{2(1 + \log[\frac{S}{K}])}{K^2} P(K) dK \\ &+ \int_{K=S}^{\infty} \frac{2(1 - \log[\frac{K}{S}])}{K^2} C(K) dK, \end{aligned} \quad (3.6)$$

$$\begin{aligned} W &= \int_{K=S}^{\infty} \frac{6 \log[\frac{K}{S}] - 3(\log[\frac{K}{S}])^2}{K^2} C(K) dK \\ &- \int_{K=0}^S \frac{6 \log[\frac{S}{K}] + 3(\log[\frac{S}{K}])^2}{K^2} P(K) dK, \end{aligned} \quad (3.7)$$

$$\begin{aligned} X &= \int_{K=S}^{\infty} \frac{12(\log[\frac{K}{S}])^2 + 4(\log[\frac{K}{S}])^3}{K^2} C(K) dK \\ &+ \int_{K=0}^S \frac{12(\log[\frac{S}{K}])^2 + 4(\log[\frac{S}{K}])^3}{K^2} P(K) dK, \end{aligned} \quad (3.8)$$

$$\mu = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V - \frac{e^{r\tau}}{6} W - \frac{e^{r\tau}}{24} X, \quad (3.9)$$

where K and S are the strike and spot prices, respectively. $C(K)$ and $P(K)$ denote the call and put prices of strike K , respectively. All other variables are as previously defined.

At the end of each calendar month, we use the OptionMetrics database to extract the standardized options data of 1-month maturity, the contemporaneous spot price, and the interest rate of corresponding maturity. We retain only out-of-the-money option prices. It is worth pointing out that the integrals in the formulas above implicitly assume the existence of a wide range of strike prices. Alas, this is not perfectly true in the market. Thus, we follow Chang, Christoffersen, Jacobs, & Vainberg (2012) by computing a fine grid of 1,000 equidistant interpolated moneyness levels, i.e. K/S , ranging from 0.3 % to 300 %. For each moneyness level on that grid, we interpolate the implied volatility using a spline interpolation method. For moneyness levels outside of the moneyness range observed in the market, we simply use a nearest neighborhood algorithm to extrapolate the implied

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volatilities (Jiang & Tian, 2005). In practice, this means that if a moneyness level is lower (higher) than the lowest (highest) moneyness level available in the market, we simply use the implied volatility corresponding to the lowest (highest) level of moneyness available in the market. Next, we plug the implied volatilities into the Black & Scholes (1973) option pricing model to obtain the corresponding out-of-the-money option prices. Finally, we follow Bali, Hu, & Murray (2017b) by using a trapezoidal rule to approximate the integrals that appear in the formulas above and obtain the risk-neutral moments of 1-month maturity.

Variance Risk Premium The variance risk premium is defined as the difference between the risk-neutral and physical expectations of variance:

$$VRP_t = E_t^{\mathbb{Q}}(\sigma_{t+1}^2) - E_t^{\mathbb{P}}(\sigma_{t+1}^2), \quad (3.10)$$

where $E_t(\cdot)$ is the expectation operator conditional on the information available at time t . The superscripts \mathbb{Q} and \mathbb{P} indicate that the expectation is computed under the risk-neutral and physical measures, respectively. In order to proxy for the risk-neutral expectation of variance, we use VAR^{BKM} . This choice is motivated by Du & Kapadia (2012) who show that the risk-neutral variance of Bakshi et al. (2003) is robust to jumps.

While the expression above clearly defines the variance risk premium, it is of very little practical use. The reason for this is that it involves the physical expectation of future variance, which is not directly observable. Therefore, we follow the lead of Bollerslev et al. (2009) and Driessen et al. (2013) in positing a simple random walk model for the future variance under the physical measure. That is, we assume that the expectation of the future variance under the physical measure equals its most recent realization. Thus, we can compute the VRP as follows:

$$VRP_t = VAR_t^{BKM} - RV_t. \quad (3.11)$$

Note that all variables are annualized and observed at the end of each calendar month.

Correlation Risk Premium Driessen et al. (2013) establish the predictive power of the correlation risk premium for future aggregate stock returns. The authors observe that the equity index is a portfolio of individual equities (Driessen et al., 2009). An upshot of this is that the variance of the market index return is equal to the weighted average variance of individual stocks and covariance terms. Assuming further that the pairwise correlation between different stocks is the same for all stocks, they are able to derive the following formula:

$$IC_t = \frac{E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\Psi,s}^2 ds] - \sum_{\psi=1}^{\Theta} \omega_{\psi}^2 E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds]}{\sum_{\psi=1}^{\Theta} \sum_{\chi \neq \psi} \omega_{\psi} \omega_{\chi} E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds] E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\chi,s}^2 ds]}, \quad (3.12)$$

where IC_t is the implied correlation at time t . Θ denotes the number of stocks in the stock market. $E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\Psi,s}^2 ds]$ and $E_t^{\mathbb{Q}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds]$ are the risk-neutral expected variance of the index (Ψ) and of the individual stock (ψ), respectively. As before, we proxy these expectations with the risk-neutral variance of Bakshi et al. (2003). w_{ψ} and w_{χ} are the weights of stocks ψ and χ in the market index Ψ , respectively.

The intuition developed above also holds under the physical measure, thus yielding the following formula for the realized correlation at time t :

$$RC_t = \frac{E_t^{\mathbb{P}}[\int_t^{t+\tau} \sigma_{\Psi,s}^2 ds] - \sum_{\psi=1}^{\Theta} \omega_{\psi}^2 E_t^{\mathbb{P}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds]}{\sum_{\psi=1}^{\Theta} \sum_{\chi \neq \psi} \omega_{\psi} \omega_{\chi} E_t^{\mathbb{P}}[\int_t^{t+\tau} \sigma_{\psi,s}^2 ds] E_t^{\mathbb{P}}[\int_t^{t+\tau} \sigma_{\chi,s}^2 ds]}, \quad (3.13)$$

where RC_t is the realized correlation at time t . All other variables are as previously defined. As before, we use the historical variance computed over the most recent period to proxy for the physical expectation of the future variance.

The CRP at time t is then defined as the difference between the risk-neutral and physical expectations of future correlation, yielding the

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following result:

$$CRP_t = IC_t - RC_t, \quad (3.14)$$

To obtain this variable, we use standardized options (of time to maturity of one month) on the S&P 500 index as well as options data on all constituents of the index. All options are observed at the end of each calendar month.

Implied Volatility Smirk Measure Xing et al. (2010) document the predictive power of the implied volatility smirk.³ Our construction of this variable broadly mirrors theirs. At the end of each calendar month, we retain all S&P 500 index options with positive open interest and a time to maturity between 10 and 60 days. We discard all option prices with a midquote price below \$0.125. We also purge all options with implied volatility outside of the interval [3%; 200%]. We define the out-of-the-money put options as the put options with a moneyness level between 0.8 and 0.95. Note that by moneyness level, we understand the ratio of the strike price over the stock price, i.e. K/S . Relatedly, we define at-the-money call options as call options with a moneyness level between 0.95 and 1.05. The smirk measure is simply computed as follows:

$$SMIRK_t = VOL_t^{OTMP} - VOL_t^{ATMC}, \quad (3.15)$$

where $SMIRK_t$ is the smirk measure at time t . VOL_t^{OTMP} denotes the implied volatility of out-of-the-money puts. To be more precise, this is the volume-weighted average of the implied volatilities of all out-of-the-money put options. VOL_t^{ATMC} refers to the volume-weighted average of all implied volatilities of at-the-money calls at time t .

³Xing et al. (2010) analyze the predictive ability of the implied volatility smirk in the cross-section of stock returns. Motivated by the intertemporal capital asset pricing model (ICAPM) of Merton (1973), if SMIRK is priced in the cross-section, it also has to predict the investment opportunity set in the time series (Maio & Santa-Clara, 2012).

3.3 Main Results

Before discussing our main findings, it is instructive to look at the summary statistics reported in Table 3.1. We can observe a positive market risk premium of around 6 % p.a. The risk premium exhibits a standard deviation of around 16 % p.a. We also notice that the sample moments of the VRP and the CRP are consistent with those reported in previous works (Driessen et al., 2009, 2013). In particular, we can see that although positive on average, the VRP is negatively skewed and prone to extreme movements as indicated by its high kurtosis, suggesting a sign-switching behavior. This observation could carry important implications for the predictive ability of this variable. We shall return to this point later.

The table also reports the AR(1) coefficient of each variable. We notice that the autoregressive coefficient of these variables is typically lower than that of the valuation ratios such as the (log) dividend to price ratio routinely analyzed in empirical works, e.g., Goyal & Welch (2003). This suggests that our analysis does not suffer from the statistical issues that affect these earlier works. We can also see that the AR(1) coefficient of the realized variance is much higher than that of the market risk premium, likely indicating that there might be a stronger evidence of predictability in the realized variance series than in the market excess returns.

Table 3.2 presents the sample correlation coefficients among all the predictive variables. While most variables are only weakly correlated, there is a high correlation between $SKEW^{BKM}$ and $EXKURT^{BKM}$ (-0.92). This suggests that these variables contain very similar information.

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Table 3.1: Summary Statistics

This table summarizes key statistics about several variables. CRP denotes the correlation risk premium. IC is the implied correlation. RC is the realized correlation. ER is the market excess return. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). RV is the realized variance. $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). SMIRK is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. VRP^{HAR} denotes the variance risk premium based on the HAR–RV model. VRP^{DOWN} is the downside variance risk premium. VRP^{UP} is the upside variance risk premium. $VRP^{DOWN,HAR}$ is the downside variance risk premium based on the HAR–RV model. Finally, $VRP^{UP,HAR}$ is the upside variance risk premium based on the HAR–RV model. “Mean”, “Std Dev”, “Skew”, and “Kurt” denote the mean, standard deviation, skewness, and kurtosis, respectively. The last two columns show the AR(1) coefficient and the number of observations, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

	Mean	Std Dev	Skew	Kurt	AR(1)	Nobs
<i>CRP</i>	0.0941	0.1019	0.1409	3.2970	0.2496	228
<i>IC</i>	0.4166	0.1403	0.5092	3.1725	0.7621	228
<i>RC</i>	0.3225	0.1398	0.8731	3.5571	0.5854	228
<i>ER</i>	0.0591	0.1555	-0.8294	4.4268	0.0900	228
<i>EXKURT^{BKM}</i>	0.7571	0.2840	0.4887	3.0378	0.7522	228
<i>RV</i>	0.0317	0.0519	7.3129	75.2277	0.6333	228
<i>SKEW^{BKM}</i>	-0.8698	0.1978	0.2588	3.0325	0.6611	228
<i>SMIRK</i>	0.1326	0.2522	0.1584	3.4828	0.3299	228
<i>VAR^{BKM}</i>	0.0474	0.0427	3.3066	18.0518	0.7880	228
<i>VRP</i>	0.0157	0.0284	-5.0586	61.7528	0.1340	228
<i>VRP^{HAR}</i>	0.0459	0.0414	3.2330	17.3103	0.7887	228
<i>VRP^{DOWN}</i>	-0.0136	0.0249	-7.5246	79.4665	0.5899	228
<i>VRP^{UP}</i>	-0.0143	0.0244	-7.5439	78.4141	0.6219	228
<i>VRP^{DOWN,HAR}</i>	0.0016	0.0015	2.7589	13.2030	0.7708	228
<i>VRP^{UP,HAR}</i>	0.0007	0.0007	1.7649	7.6611	0.5894	228

Table 3.2: Correlation Matrix

This table reports the correlations among all predictive variables. CRP denotes the correlation risk premium. IC is the implied correlation. RC is the realized correlation. ER is the market excess return. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). RV is the realized variance. $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. VRP^{HAR} denotes the variance risk premium based on the HAR-RV model. VRP^{DOWN} is the downside variance risk premium. VRP^{UP} is the upside variance risk premium. $VRP^{DOWN,HAR}$ is the downside variance risk premium based on the HAR-RV model. Finally, $VRP^{UP,HAR}$ is the upside variance risk premium based on the HAR-RV model. All data are sampled at the monthly frequency and relate to the S&P 500 index.

	CRP	IC	RC	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
CRP	0.37												
IC	-0.36	0.74											
RC	0.20	0.06	-0.09										
$EXKURT^{BKM}$	-0.22	-0.24	-0.08	-0.92									
$SKEW^{BKM}$	-0.06	0.31	0.35	-0.02	-0.10								
$SMIRK$	-0.04	0.54	0.57	-0.38	0.17	0.35							
VAR^{BKM}	0.40	0.24	-0.05	-0.03	0.02	-0.14	-0.02						
VRP	-0.04	0.54	0.57	-0.38	0.17	0.35	1.00	-0.01					
VRP^{HAR}	0.26	-0.30	-0.49	0.29	-0.12	-0.36	-0.82	0.59	-0.81				
VRP^{DOWN}	0.27	-0.29	-0.48	0.28	-0.13	-0.36	-0.81	0.60	-0.80	0.98			
VRP^{UP}	0.06	0.62	0.58	-0.31	0.09	0.33	0.97	0.17	0.97	-0.68	-0.67		
$VRP^{DOWN,HAR}$	0.18	0.44	0.31	-0.46	0.32	0.13	0.71	0.60	0.72	-0.24	-0.21	0.79	
$VRP^{UP,HAR}$													

3.3.1 Return Predictability

In-Sample Analysis We start by assessing the in-sample predictability of the equity risk premium. To do so, we estimate the standard regression model of the month-ahead excess return on a constant and the predictive variable(s):

$$ER_{t+1} = \beta_0 + \beta_1 X_t + \epsilon_{t+1}, \quad (3.16)$$

where ER_{t+1} is the excess return on the market realized at the end of month $t + 1$. β_0 and β_1 are the intercept and slope parameters, respectively. X_t represents the forecasting variable(s) observed at the end of month t . Finally, ϵ_{t+1} is the regression error term at $t + 1$.

Table 3.3 summarizes the results for each predictive variable. The regression model enables us to ascertain whether the equity risk premium is time-varying or constant. Under the null hypothesis that the future excess return cannot be predicted using X_t , we would expect that $\beta_1 = 0$. As a result, the expected market excess return would simply be constant. One implication of this is that the best estimate of the future excess return is simply its recursive mean. If there is evidence of predictability, we would expect to see that the slope loading is statistically significant. To avoid a small-sample bias (Stambaugh, 1999) and serial correlation in the error terms (Richardson & Stock, 1989), we base all our statistical inferences on the bootstrapped distribution obtained by implementing the framework of Rapach & Wohar (2006).⁴

We can see that the *CRP*, *SMIRK*, and *VRP* are statistically significant in the univariate regressions. This is illustrated by their

⁴We estimate our process under the null hypothesis of no predictability via OLS, i.e. $ER_t = a_0 + \epsilon_{1,t}$ and $X_t = b_0 + b_1 X_{t-1} + \epsilon_{2,t}$, where a_0 , b_0 , and b_1 are the regression coefficients and $\epsilon_{1,t}$ and $\epsilon_{2,t}$ are the error terms, respectively. We then form a series of error terms and set up our pseudo sample. For the pseudo sample, we compute the in-sample and out-of-sample statistics. Finally, we repeat this procedure 1,000 times. In the case of multiple regressions, we adjust the procedure by taking the multiple variables into account and, in-sample, by using the F -statistic rather than the individual t -statistic.

Table 3.3: Return Predictability

This table reports the regression results of monthly excess returns on a constant, which we denote by β_0 , and the lagged predictive variable(s). We report the t -statistics in parentheses. Statistical inferences are based on a bootstrapped distribution. The historical mean serves as naive benchmark. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). SMIRK is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R^2 and R_{oos}^2 are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

β_0	-0.032 (-0.67)	-0.035 (-0.34)	-0.136 (-0.84)	0.096** (2.40)	0.056 (1.05)	-0.023 (-0.59)	-0.193 (-1.49)	-0.284* (-1.65)	-0.310 (-1.56)
CRP	0.957*** (2.76)						0.341 (0.90)	0.321 (0.84)	0.325 (0.85)
$EXKURT^{BKM}$		0.123 (0.96)					0.175 (1.26)		-0.100 (-0.26)
$SKEW^{BKM}$			-0.224 (-1.22)					-0.272 (-1.46)	-0.398 (-0.77)
SMIRK				-0.290** (-2.06)			-0.279* (-1.88)	-0.293** (-1.96)	-0.296* (-1.97)
VAR^{BKM}					0.028 (0.03)		1.147 (1.22)	0.945 (1.07)	0.799 (0.77)
VRP						5.176*** (4.26)	4.438*** (3.31)	4.422*** (3.31)	4.392*** (3.27)
R^2	3.28***	0.41	0.66	1.84**	0.00	7.47***	7.91***	8.13***	7.74***
R_{oos}^2	2.81***	-1.22	-0.53	0.07	-5.41	5.50***	-2.86**	-2.67**	-4.04

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t -statistics of 2.76, -2.06 , and 4.26. The positive and significant slope estimate related to the VRP confirms and updates, using a more recent sample period, the result of Bollerslev et al. (2009). It is also consistent with the authors' intuition that the VRP encodes information about time-variations in economic uncertainty. Note also that, if as argued by Driessen et al. (2013), CRP accounts for most of the VRP , then one would expect that CRP predicts future excess returns with a positive sign as we find in the data, since it has been documented that the VRP predicts the market excess return (Bollerslev et al., 2009).

The result that CRP predicts future returns is consistent with that in Driessen et al. (2009, 2013). There is a strong relationship between correlations and returns. It seems that correlations between stocks are time-varying and that correlations increase when returns are low.^{5,6} Moreover, the authors document a strong predictive power of IC for future returns, supported by a correlation of 0.24 between IC and VRP , shown in Table 3.2.⁷ Pollet & Wilson (2010) provide evidence for predictive power of (average) realized correlations for stock returns at a quarterly horizon.

The finding that $SMIRK$ predicts future returns with a negative sign extends the results of Xing et al. (2010) to the time series of the market

⁵They show that an increase in market correlations has two main effects. First, diversification possibilities are lowered, thus, investors face limitations in their portfolio formations and suffering from a welfare reduction. Second, there is a rise in market volatility. One implication is that index options become relatively expensive compared to individual options. They represent a hedge against changes in market correlations, thus, also against losses due to diversification limitations.

⁶The use of CRP (and of IC and RC) can be theoretically motivated by the ICAPM of Merton (1973). It directly affects future investment opportunities, i.e. investors' future diversification benefits as well as the market variance. Moreover, Driessen et al. (2013) argue that CRP appears to drive dividend growth volatility, and also the volatility of dividend growth volatility, consistent with the argumentation of Bollerslev et al. (2009) for VRP . One implication is that CRP matters for both return as well as variance predictability.

⁷Driessen et al. (2009, 2013) document that IC strictly exceeds RC , indicating the existence of a large CRP . Our data support these findings. We observe a mean IC (RC) of 41.66 % (32.25 %), generating a mean CRP of 9.41 %.

excess return. The intuition behind this result is simple. An increase in *SMIRK* implies a stronger demand for out-of-the-money put options. This increased demand signals that investors are actively purchasing insurance against expected declines in the stock index. The negative slope estimate of *SMIRK* is consistent with this intuition.

It is also worth comparing the predictive power of individual variables. A cursory look at the in-sample R^2 reveals that *VRP* has the highest predictive power for future excess returns ($R^2 = 7.47\%$). The second most powerful predictor is the *CRP*, with an R^2 of 3.28%. While the slope estimate on the *VRP* is similar to that documented by Bollerslev et al. (2009), it is worth noticing that the predictive power, we document at the monthly horizon, is much higher, indicating that, if anything, the predictive ability of the *VRP* is much larger in the more recent sample period.

It is worthwhile to analyze the performance of individual variables over time. Figure 3.1 plots the in-sample cumulative differences in squared forecast errors (CDSFE).⁸ We observe a similar (in-sample) performance in the case of *CRP* and *VRP*, indicated by a sharp increase during the global financial crisis in 2008/2009, and a steady rise during the post crisis period. The findings suggest the outperformance of the unrestricted model to the restricted model, particularly in times of distress. It seems that investors can exploit the information content of both variables in times of high risk-aversion.

In the case of $EXKURT^{BKM}$ and $SKEW^{BKM}$, we find an increase of the performance during the global financial crisis, however, afterwards there is a steady decline, suggesting the superior performance of the restricted model. Both variables appear to have substantial predictive

⁸Please note that whenever there is a rise of the in-sample (or out-of-sample) performance, the unrestricted model outperforms the restricted model, and vice versa. In this case, a variable provides a better forecast than the benchmark model.

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power, particularly in crises.

SMIRK shows the strongest increase in the CDSFE plot during the global financial crisis, indicating that investors look for a hedge against a further market downturn, by buying put options. Finally, in the case of VAR^{BKM} , we see no strong fluctuations in its CDSFE, suggesting a similar performance of both the unrestricted and restricted model. Generally, we also find a strong increase in the performance after the dot-com bubble in 2001. This is true for all variables, except *SMIRK*.

To analyze the joint predictive ability of different variables, we perform three multiple regressions. Due to the high correlation between $SKEW^{BKM}$ and $EXKURT^{BKM}$, we run the regressions also once without the first and once without the second variable.⁹ In all cases we find that only *SMIRK* and *VRP* retain their statistical significance.¹⁰ Overall, the adjusted R^2 increases to 7.91 %, 8.13 %, and 7.74 % in the first, second and third case, respectively.

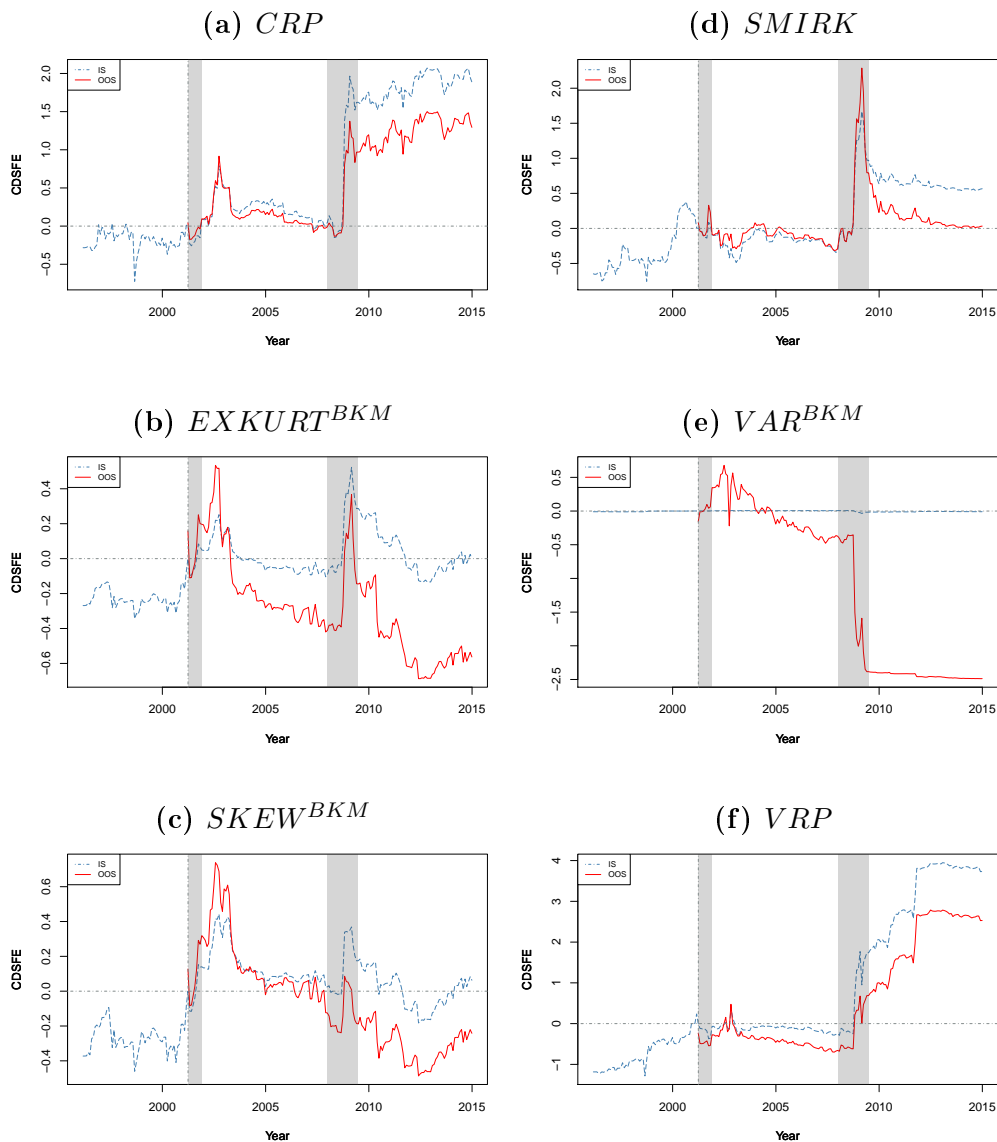
Out-of-Sample Results We now turn our focus to the out-of-sample evidence of return predictability. We use an initial training window of 5 years to first estimate the forecasting model presented in Equation (3.16). Equipped with the parameter estimates and the most recent observation of the forecasting variable in the training window, we are able to generate the first excess return forecast. The following month, we expand the training window by one observation month and re-estimate the forecasting model. With the new parameter estimates, we forecast the market excess return for the next month. We proceed analogously for all months, except the last month of

⁹We present the results of the multiple regressions only for return predictability. In the case of realized variance predictability, we skip these regressions due to multicollinearity.

¹⁰*CRP* does not retain their statistical significance in the multiple regressions. It seems that other variables, mainly *VRP*, capture the information content. In-sample multiple regressions have no explanatory power for out-of-sample predictability. For further details, we also refer to the forthcoming out-of-sample analysis.

Figure 3.1: Return Predictability

This figure plots the in- and out-of-sample performances of individual variables. We regress monthly excess returns on a constant and the lagged predictive variable. On the ordinate, there are the cumulative differences in squared forecast errors (CDSFE). The in-sample performance is the difference between the cumulative squared demeaned excess return and the cumulative squared regression residual, and the out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error from the unrestricted model. The grey bars indicate the U.S. recessions, published by the NBER. All data are sampled at the monthly frequency and relate to the S&P 500 index.



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our sample period.

In order to assess the out-of-sample performance of different models, we follow Campbell & Thompson (2008) and define the out-of-sample R^2 (R_{oos}^2) as follows:

$$R_{oos}^2 = 1 - \frac{MSE_u}{MSE_r}, \quad (3.17)$$

where MSE_u and MSE_r are the mean squared errors of the unrestricted and restricted models, respectively. The unrestricted model is based on Equation (3.16). The restricted model imposes the null hypothesis that returns are unpredictable, i.e. $\beta_1 = 0$. Thus the R_{oos}^2 sheds light on the question: How large an improvement in forecast accuracy can one achieve by accounting for the predictive power of variable X_t ? The higher the R_{oos}^2 the better. A variable has notable predictive power if it exhibits a positive and significant R_{oos}^2 , indicating an overall outperformance of the predictive variable.

In order to gauge whether the potential improvement is statistically significant, we compute the $MSE - F$ statistic of McCracken (2007):

$$MSE - F = H \times \left(\frac{MSE_r - MSE_u}{MSE_u} \right), \quad (3.18)$$

where H denotes the number of out-of-sample forecasts. All other variables are as previously defined. Briefly, the null hypothesis is that the restricted model performs at most as well as the unrestricted model, i.e. $MSE_r \leq MSE_u$. The alternative is that the unrestricted model provides smaller forecast errors than the restricted model. As can be seen from the last set of results in Table 3.3, *CRP* and *VRP* yield statistically significant improvements in the out-of-sample performance relative to the simple recursive mean. This result is noteworthy given that Goyal & Welch (2003) argue that the recursive mean is a tough benchmark to beat. Overall, these results suggest that *CRP* and *VRP* contain important information about next-month's market excess returns both in- and out-of-sample. In contrast, the multiple regressions do not improve the predictive power out-of-sample.

In Figure 3.1, we observe a similar development of the out-of-sample performances as in-sample. Except for VAR^{BKM} , showing a sharp drop during the global financial crisis, indicating a superior performance of the restricted model. It seems that investors have to rely on the historical mean rather than on VAR^{BKM} in times of distress.

3.3.2 Variance Predictability

We now turn our attention to the predictability of the realized variance. In particular, we ask the question: Can any of the forecasting variables be used to predict next-month's realized variance?

In-Sample Using all the sample information, we estimate the following regression model:

$$RV_{t+1} = \gamma_0 + \gamma_1 X_t + \gamma_2 RV_t + \epsilon_{t+1}, \quad (3.19)$$

where γ_0 , γ_1 , and γ_2 are the intercept and slope parameters, respectively. All other variables are as previously defined. We include the lag of realized variance, because realized variance is a strongly persistent process, indicated by its AR(1) coefficient of 0.63, shown in Table 3.1.¹¹ To account for the persistence, we use a fitted AR(1) process as naive benchmark rather than the historical mean variance.¹²

Table 3.4 summarizes the results of the in-sample analysis. We notice that all variables have predictive power for future realized variance, as evidenced by their statistically significant R^2 s.¹³ The R^2 s range from

¹¹Since realized variance is strongly persistent, future realized variance is primarily predictable by its current value. Ignoring the lag of realized variance allows the other lagged variables to partially capture this persistence. In particular VAR^{BKM} and RV are highly correlated. We refer to this point later in Table 3.4.

¹²In Section 3.5.3, we use the historical mean variance as naive benchmark and show the results.

¹³Although CRP has a t -statistic of -1.59 , this variable generates a statistically significant improvement in the in-sample R^2 of 40.80 %. We also refer to Section 3.5.3.

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Table 3.4: Variance Predictability

*This table reports the regression results of monthly realized variance on a constant, which we denote by γ_0 , the lagged predictive variable, and the lagged realized variance RV. We report the t-statistics in parentheses. Statistical inferences are based on a bootstrapped distribution. A fitted AR(1) model serves as naive benchmark. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). SMIRK is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R^2 and R_{oos}^2 are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.*

γ_0	0.016*** (3.80)	0.031*** (3.57)	0.035*** (2.78)	0.010*** (2.98)	0.002 (0.49)	0.002 (0.49)
RV	0.612*** (11.51)	0.596*** (11.14)	0.621*** (12.01)	0.585*** (10.67)	0.374*** (4.06)	0.750*** (12.26)
CRP	-0.043 (-1.59)					
$EXKURT^{BKM}$		-0.024** (-2.37)				
$SKEW^{BKM}$			0.026* (1.91)			
SMIRK				0.027** (2.40)		
VAR^{BKM}					0.376*** (3.37)	
VRP						0.376*** (3.37)
R^2	40.80**	41.60**	41.09**	41.64**	43.03**	43.03**
R_{oos}^2	3.18***	3.34***	2.40***	3.89***	3.78***	3.78***

40.80 % to 43.03 %. These results are interesting for several reasons. First, they indicate that the predictability of realized variance is much stronger than that of excess returns. Second, they reveal that CRP , $SMIRK$, and VRP are able to predict (in-sample) not only next-month's market excess return (see Table 3.3) but also realized variance. Third, the risk-neutral variables of Bakshi et al. (2003) that do not predict future excess returns matter for realized variance forecasting. For instance, $EXKURT^{BKM}$ predicts next-month's realized variance with a predictive power equal to 41.60 %. An implication of this result is that when assessing the information content of a predictive variable, it is advisable to investigate whether it predicts not only excess returns but also realized variance. We observe that VAR^{BKM} and VRP have similar t -statistics and R^2 s, which is not surprising due to the construction of VRP and the used regression model in Equation (3.19).

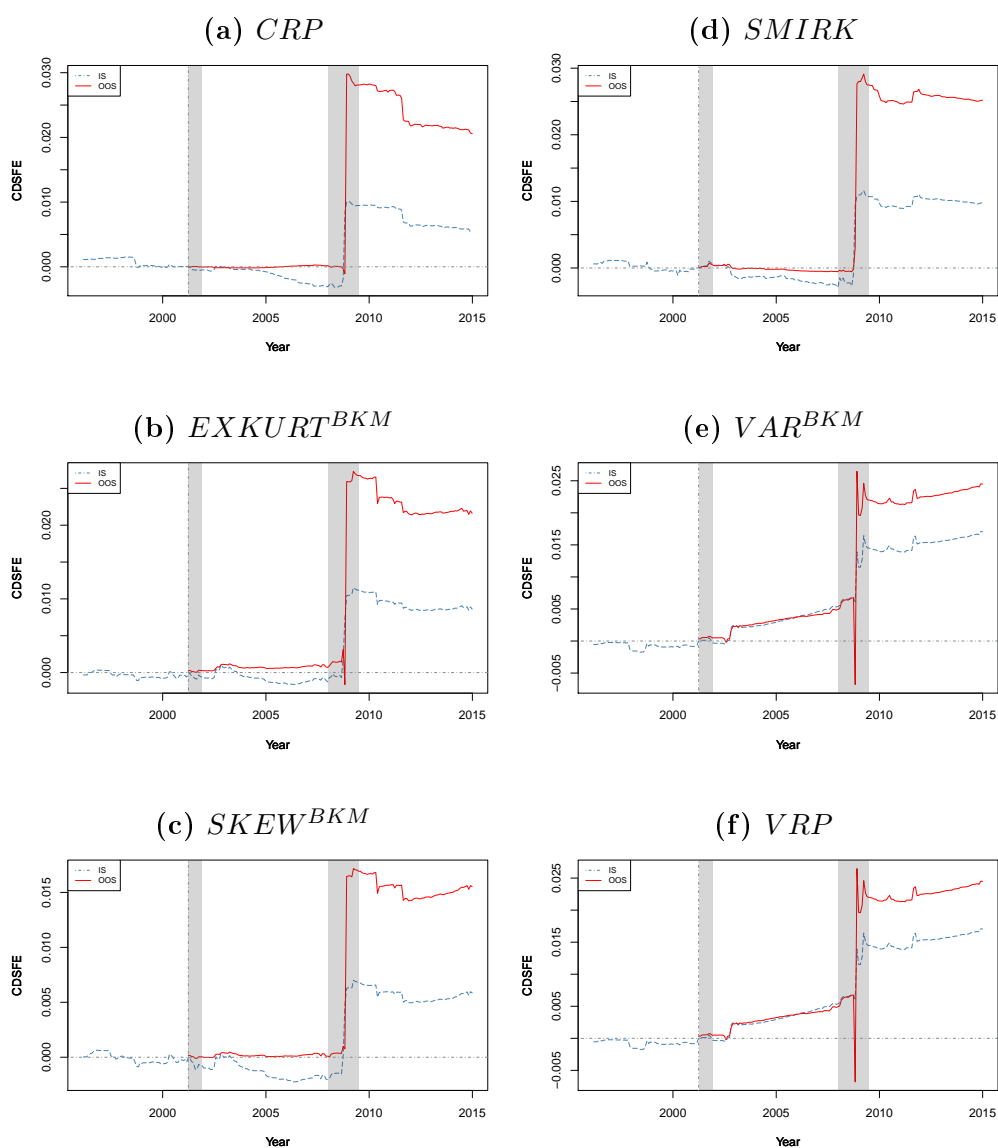
Figure 3.2 shows the CDSFE for all individual variables predicting the next month's realized variance. There is a similar pattern for the variables. We observe a strong increase in their performance during the global financial crisis in 2008/2009, indicating the outperformance of the unrestricted model to the restricted model. It seems that investors can exploit the information content of the variables, particularly in times of high variance.

Out-of-Sample We conduct our analysis out-of-sample in a similar way as before. Specifically, we use the first 5 years of observations to initially estimate the model parameters (see Equation (3.19)). Having done this, we then make a forecast for the following month. We expand the training window by one observation month and repeat all steps. This procedure mirrors that used for the return predictability analysis with the only difference that we assume a fitted AR(1) process as naive benchmark and that we forecast realized variance rather than the market excess return. The

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Figure 3.2: Variance Predictability

This figure plots the in- and out-of-sample performances of individual variables. We regress monthly realized variance on a constant, the lagged predictive variable, and the lagged realized variance. On the ordinate, there are the cumulative differences in squared forecast errors (CDSFE). The in-sample performance is the difference between the cumulative squared demeaned excess return and the cumulative squared regression residual, and the out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error from the unrestricted model. The grey bars indicate the U.S. recessions, published by the NBER. All data are sampled at the monthly frequency and relate to the S&P 500 index.



last row of Table 3.4 shows the R_{oos}^2 s. All variables that predict realized variance in-sample are also predictors out-of-sample. The R_{oos}^2 s range from 2.40 % for $SKEW^{BKM}$ to 3.89 % for $SMIRK$.¹⁴ In Figure 3.2, we observe a similar pattern as in-sample. In particular in times of distress, investors should rely on the information content of the predictive variables rather than on the forecast of a fitted AR(1) model.

3.3.3 Portfolio Choice Implications

We now study the portfolio choice implications of the predictability results reported earlier. To do this, we consider an investor with mean-variance preferences. The agent allocates a fraction ω_t of her wealth to the risky portfolio and the remainder, i.e. $1 - \omega_t$, to the risk-free asset. The agent's objective function is:

$$\max_{\omega_t} E_t^{\mathbb{P}} \left(r_{p,t+1} - \frac{\gamma}{2} \sigma_{p,t+1}^2 \right), \quad (3.20)$$

where $E_t^{\mathbb{P}}(\cdot)$ is the physical expectation operator. $\sigma_{p,t+1}^2$ is the conditional variance of the portfolio from t to $t + 1$. γ is the coefficient of relative risk-aversion. $r_{p,t+1}$ is the next-period's (simple) return on the investor's portfolio. This return is the weighted average of the (simple) return on the risky stock and on the risk-free asset. Because our earlier analysis focuses on log-returns rather than simple returns, we use a second-order Taylor expansion to express the simple return as a function of the log-return and realized variance.¹⁵ Thus, we can express the objective function as follows:

$$\max_{\omega_t} E_t \left(R_{p,t+1} - \frac{\gamma - 1}{2} \sigma_{p,t+1}^2 \right), \quad (3.21)$$

¹⁴When using the recursive mean as benchmark model, we obtain R_{oos}^2 s of -5.31 % for CRP , -5.13 % for $EXKURT^{BKM}$, -6.16 % for $SKEW^{BKM}$, -4.54 % for $SMIRK$, -4.65 % for VAR^{BKM} , and -4.65 % for VRP . The results support the use of a fitted AR(1) process (rather than the historical mean variance) as natural benchmark model.

¹⁵More precisely, the approximation yields the following relationship: $R_t \approx r_t - \frac{1}{2}RV_t$, where R_t , r_t , and RV_t are the log-return, simple return, and realized variance at time t , respectively.

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where $R_{p,t+1}$ is the log-return on the portfolio and all other variables are as previously defined.

Using the first-order condition, it is straightforward to derive the optimal weight invested in the risky asset (Jordan et al., 2014):

$$\omega_t = \frac{E_t(ER_{t+1} + \frac{1}{2}RV_{t+1})}{\gamma E_t(RV_{t+1})} = \frac{E_t(ER_{t+1})}{\gamma E_t(RV_{t+1})} + \frac{1}{2\gamma}. \quad (3.22)$$

The expression above shows that the optimal allocation to the risky asset depends on the expected excess return, the risk-aversion parameter, and the expected realized variance. One implication of this expression is that, holding everything else constant, the allocation to the risky stock rises with expected returns. In other words, if realized variance is unpredictable and a forecasting variable X_t positively (negatively) predicts excess returns, then the agent would invest more (less) in the risky stock as X_t increases. In contrast, if a variable X_t positively predicts future variance (and not returns), then the share of wealth invested in the risky stock decreases with the variable X_t .

Note that the preceding discussion focuses only on the predictability of either returns or variance and does not explore the case where both moments are predictable by the same variable. The share of the position in the stock will be determined by two (potentially offsetting) forces, one that increases with the expected excess return and the other that decreases with the expected realized variance.

In light of the preceding discussion, we find it interesting to distinguish between three cases. The first one deals with the case where only excess returns might be predictable. The second case allows for the predictability of realized variance alone. The third case deals with the possibility that both excess returns and realized variance are predictable by the same variable X_t .¹⁶

¹⁶To be consistent with Section 3.3.2, we predict realized variance by the variable X_t and the lag of realized variance.

For a given case (ξ) and each calendar month of our out-of-sample window, we compute the weight ω_t and also the realized return of the portfolio. We impose the restriction that whenever the forecast of the market excess return or of the realized variance (or of both) in Equation (3.22) equals zero, we set the portfolio weight equal to $1/(2\gamma)$. Further, following Campbell & Thompson (2008) and Jordan, Vivian, & Wohar (2017), we impose the restriction that ω_t is bounded from below by 0 and from above by 1.5. Economically, the lower bound implies that the agent does not short-sell the risky asset. The upper bound prevents the agent from taking on excessive leverage. At the end of the sample period, we compute the certainty equivalent return as follows:

$$CER^{(\xi)} = \bar{r}_p - \frac{\gamma}{2}\sigma_p^2, \quad (3.23)$$

where $CER^{(\xi)}$ is the certainty equivalent return associated with strategy ξ . This number is expressed in percent per annum. \bar{r}_p is the average (annualized) return on the portfolio. σ_p^2 is the variance of the portfolio returns.

Our approach consists in computing the utility gain ($\Delta CER^{(\xi)}$), the difference between $CER^{(\xi)}$ and the certainty equivalent return of the naive strategy that assumes that the first two moments are unpredictable, and thus relies on simple historical averages. We do this for each of the three scenarios in turn.

We also compute the Sharpe Ratio (SR) of each strategy ξ :

$$SR^{(\xi)} = \frac{\bar{R}_p - rf}{\sigma_p}, \quad (3.24)$$

where \bar{R}_p is the average log-return on the portfolio. Similar to the certainty equivalent return analysis, we compute the improvement in SR by taking the difference between $SR^{(\xi)}$ and the SR linked to the naive strategy that assumes that the market excess return and realized variance are

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unpredictable. We use an approach suggested by Jobson & Korkie (1981) and after taking the correction done by Memmel (2003) into account, we test whether the improvement is statistically significant.

Table 3.5 reports our results for different values of risk-aversion. We can see that statistical evidence of excess return predictability does not necessarily imply important economic gains. For instance, while the *VRP* predicts both excess returns and realized variance, a timing strategy relying on this variable would have underperformed the naive strategy. One possible explanation for this result is the following. Shortly before the crisis period, the variance risk premium is high (since the historical variance is low). Because *VRP* predicts future returns with a positive sign, this result implies that an agent should hold more (rather than less) stocks. As a result of this increased position, the strategy incurs more severe losses as the economy slides into recession. Similarly, as the economy recovers, the variance risk premium is low, implying that the agent should hold a small position in the stock. Because of this, the agent misses out on the rally in the market. Further, it seems that, though *VRP* predicts both returns and variance individually with a positive sign, the joint predictability is associated with large variance, thus, generating negative certainty equivalent returns.¹⁷

In contrast, one can see that relative to an agent with risk-aversion $\gamma = 3$ who assumes that the market excess return and the realized variance are unpredictable, the agent who exploits the information content of *CRP* would improve her utility by 5.03 % p.a. The finding is consistent with Driessen et al. (2009, 2013), who document that index options represent a hedge against changes in market correlations, and also against losses due to diversification limitations.

Table B.1 of the Appendix to this chapter shows the portfolio choice implications taking turnover and transaction costs into account. Following

¹⁷We refer to Section 3.4.2 for further details.

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Table 3.5: Economic Value

*This table reports utility gains and Sharpe Ratios for each of the three scenarios. Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] and the lagged realized variance predict the realized variance. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row], and in the latter case, by both the forecasting variable [name in row] and the lagged realized variance. The historical mean return, and a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a naive strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.*

Panel A: $\gamma = 3$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	5.46	-0.01	5.03	0.46**	0.13	0.39*
<i>EXKURT^{BKM}</i>	5.39	2.83	6.39	0.51***	0.29*	0.50**
<i>SKEW^{BKM}</i>	1.86	2.32	3.84	0.16	0.24*	0.30*
<i>SMIRK</i>	2.96	2.33	3.21	0.30	0.25**	0.27
<i>VAR^{BKM}</i>	-7.28	6.39	-4.24	-0.42***	0.38***	-0.19
<i>VRP</i>	-6.10	7.80	-2.60	-0.41*	0.51***	-0.09

Panel B: $\gamma = 6$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	3.05	-4.27	2.29	0.45**	-0.04	0.40*
<i>EXKURT^{BKM}</i>	3.92	2.42	4.90	0.63***	0.38**	0.62***
<i>SKEW^{BKM}</i>	1.20	1.17	2.48	0.22	0.25**	0.41**
<i>SMIRK</i>	2.07	0.80	2.26	0.38*	0.22*	0.36
<i>VAR^{BKM}</i>	-10.70	5.53	-5.54	-0.60***	0.49***	-0.24
<i>VRP</i>	-8.49	5.46	-8.16	-0.60***	0.59***	-0.36

Panel C: $\gamma = 9$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	1.71	-5.26	0.96	0.40*	-0.07	0.42*
<i>EXKURT^{BKM}</i>	2.82	2.11	3.34	0.67***	0.40***	0.63**
<i>SKEW^{BKM}</i>	0.58	0.87	0.74	0.20	0.24**	0.39*
<i>SMIRK</i>	1.40	0.50	1.69	0.38*	0.18*	0.40*
<i>VAR^{BKM}</i>	-10.28	3.76	-4.09	-0.63***	0.49***	-0.25
<i>VRP</i>	-8.15	3.72	-7.67	-0.63***	0.63***	-0.42*

Panel D: $\gamma = 12$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	1.25	-5.88	-0.14	0.40*	-0.10	0.41
<i>EXKURT^{BKM}</i>	2.11	1.75	2.29	0.67***	0.40***	0.64**
<i>SKEW^{BKM}</i>	0.44	0.50	-0.14	0.20	0.21**	0.38
<i>SMIRK</i>	1.05	0.36	1.21	0.38*	0.17*	0.40*
<i>VAR^{BKM}</i>	-8.37	2.80	-3.12	-0.63***	0.49***	-0.25
<i>VRP</i>	-6.18	2.30	-6.73	-0.63***	0.60***	-0.44*

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DeMiguel, Garlappi, & Uppal (2009), we define the turnover for strategy ξ as the average sum of the absolute values of the trades, i.e.:

$$Turnover = \frac{1}{T-H} \sum_{t=1}^{T-H} \left(|\omega_{t+1}^{(\xi)} - \omega_t^{(\xi)}| \right), \quad (3.25)$$

where $T-H$ is the training window over which the moments are estimated and $\omega_{t+1}^{(\xi)}$ is the portfolio weight before rebalancing at $t+1$. All other variables are as previously defined. For the benchmark strategy, we observe an absolute value of the turnover ($Turnover_{abs}$) of 0.0448 which can be interpreted as the average percentage of wealth traded in each out-of-sample period. For our three strategies, we report the turnover ($Turnover_{rel}^{(\xi)}$) relative to the benchmark case. We notice that all strategies exhibit higher turnovers than the benchmark, indicated by values larger than one.

We follow Balduzzi & Lynch (1999) and include transaction costs of 50 basis points per transaction proportional to the asset's traded size $|\omega_{t+1}^{(\xi)} - \omega_t^{(\xi)}|$. Table B.1 reports the corresponding utility gains and Sharpe Ratios. We observe that transaction costs have a systematic impact on the results, however, the results are qualitatively similar. An agent who relies on *CRP* would still improve her utility by 1.38 % p.a., indicating the robustness of that trading strategy.

3.4 Further Analyses

3.4.1 Sign Restriction

Campbell & Thompson (2008) propose to impose two economically motivated restrictions when studying the question of predictability. The authors suggest to set the slope estimate in the out-of-sample analysis equal to zero whenever its sign differs from that of the in-sample analysis. They also suggest to set the out-of-sample forecast equal to zero whenever

its negative. Before discussing our findings, it is worth emphasizing that the first constraint is not implementable in real-time. This is because the implementation would require the agent to know about the sign of the in-sample slope parameter, i.e., to have information about future data, thus, introducing a look-ahead bias.

The first set of results in Table 3.6 reports the findings when imposing the first restriction. Panel A shows, when doing so, that the main results remain: the *CRP* and *VRP* are the two best option-implied predictors for the market excess return. It is worth noticing that imposing the restriction has very little effect on the R_{os}^2 related to the forecasting variables (see Table 3.3 for comparison). This suggests that the sign of the relationship between the forecasting variables *CRP* and *VRP* and future excess returns is relatively stable out-of-sample.

We also impose the restriction on the slope of the realized variance forecasting regression. In other words, we set the slope estimate equal to zero, if the sign of the recursively estimated parameter is different from that obtained in-sample.¹⁸ Overall, we can see from Panel B of Table 3.6 that this restriction has very little impact on our main results.

The second set of results in Table 3.6 reports the findings when imposing the second restriction. Finally, the last entries of each panel show the results when we jointly impose the restrictions (on the sign of the slope and the sign of the return/variance forecast). Summarized, in both cases

¹⁸To be consistent with Section 3.3.2, we impose the restriction for both the variable X_t and the lag of realized variance.

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Table 3.6: Out-of-Sample Analysis: Restriction

This table reports the results of the out-of-sample analysis after imposing economically motivated restrictions. We report the MSE-F statistics in parenthesis. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). SMIRK is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. The historical mean return, and a fitted AR(1) model for realized variance serve as naive benchmarks. "(I)" denotes the imposition of the first restriction, where we set the slope estimate in the out-of-sample analysis equal to zero, whenever its sign differs from that of the in-sample analysis. "(II)" denotes the imposition of the second restriction, where we set the forecast equal to zero, whenever it is negative. "(I+II)" denotes the joint imposition of both restrictions. R_{oos}^2 is the out-of-sample R^2 . *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: Return Predictability

		CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	SMIRK	VAR^{BKM}	VRP
(I)	R_{oos}^2	2.81*** (4.83)	-1.22 (-2.02)	-0.53 (-0.87)	0.07 (0.12)	-3.84 (-6.18)	5.50*** (9.73)
(II)	R_{oos}^2	2.69** (4.61)	0.37 (0.62)	0.56 (0.95)	0.93 (1.57)	-3.39 (-5.48)	4.43*** (7.74)
(I+II)	R_{oos}^2	2.69** (4.61)	0.37 (0.62)	0.56 (0.95)	0.93 (1.57)	-2.95 (-4.79)	4.43*** (7.74)

Panel B: Variance Predictability

		CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	SMIRK	VAR^{BKM}	VRP
(I)	R_{oos}^2	3.28*** (5.67)	3.34*** (5.77)	2.40** (4.10)	3.89*** (6.76)	3.78*** (6.57)	3.78*** (6.57)
(II)	R_{oos}^2	3.18** (5.48)	3.44*** (5.95)	2.40** (4.10)	3.89*** (6.76)	3.78*** (6.57)	3.78** (6.57)
(I+II)	R_{oos}^2	3.28** (5.67)	3.44** (5.95)	2.40** (4.10)	3.89*** (6.76)	3.78** (6.57)	3.78** (6.57)

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Table 3.7: Economic Value: Restriction I

*This table reports utility gains and Sharpe Ratios for each of the three scenarios, after imposing the first economically motivated restriction following Campbell & Thompson (2008). Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] predicts the variance of market returns. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row]. The historical mean return, and a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.*

Panel A: $\gamma = 3$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	5.46	6.12	6.87	0.46**	0.54***	0.60***
<i>EXKURT^{BKM}</i>	5.39	6.35	8.01	0.51***	0.61***	0.76***
<i>SKEW^{BKM}</i>	1.86	6.26	6.88	0.16	0.57***	0.63***
<i>SMIRK</i>	2.96	5.00	4.88	0.30	0.55***	0.52***
<i>VAR^{BKM}</i>	-8.81	6.96	-1.53	-0.48***	0.52***	-0.10
<i>VRP</i>	-6.10	6.96	-4.33	-0.41*	0.55***	-0.35*
Panel B: $\gamma = 6$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	3.05	3.91	5.11	0.45**	0.44***	0.69***
<i>EXKURT^{BKM}</i>	3.92	4.58	6.46	0.63***	0.59***	0.90***
<i>SKEW^{BKM}</i>	1.20	4.11	5.60	0.22	0.53***	0.80***
<i>SMIRK</i>	2.07	2.91	3.14	0.38*	0.51***	0.57**
<i>VAR^{BKM}</i>	-11.50	4.88	-0.85	-0.63***	0.66***	-0.08
<i>VRP</i>	-8.49	4.88	-2.80	-0.60***	0.68***	-0.37*
Panel C: $\gamma = 9$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	1.71	2.61	3.33	0.40*	0.35***	0.64**
<i>EXKURT^{BKM}</i>	2.82	3.11	5.17	0.67***	0.52***	0.94***
<i>SKEW^{BKM}</i>	0.58	2.84	4.03	0.20	0.47***	0.80***
<i>SMIRK</i>	1.40	1.96	2.17	0.38*	0.49***	0.58***
<i>VAR^{BKM}</i>	-10.81	3.26	-0.58	-0.66***	0.66***	-0.08
<i>VRP</i>	-8.15	3.26	-1.88	-0.63***	0.68***	-0.37*
Panel D: $\gamma = 12$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	1.25	1.96	2.62	0.40*	0.30***	0.66**
<i>EXKURT^{BKM}</i>	2.11	2.35	4.05	0.67***	0.47***	0.93***
<i>SKEW^{BKM}</i>	0.44	2.17	3.14	0.20	0.44***	0.80***
<i>SMIRK</i>	1.05	1.47	1.63	0.38*	0.49***	0.58***
<i>VAR^{BKM}</i>	-8.77	2.44	-0.44	-0.66***	0.66***	-0.08
<i>VRP</i>	-6.18	2.44	-1.42	-0.63***	0.68***	-0.37*

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Table 3.8: Economic Value: Restriction II

This table reports utility gains and Sharpe Ratios for each of the three scenarios, after imposing the second economically motivated restriction following Campbell & Thompson (2008). Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] predicts the variance of market returns. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row]. The historical mean return, and a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	5.46	6.22	6.88	0.46**	0.55***	0.61***
EXKURT ^{BKM}	5.39	6.35	8.01	0.51***	0.61***	0.76***
SKEW ^{BKM}	1.86	6.26	6.88	0.16	0.57***	0.63***
SMIRK	2.96	5.00	4.88	0.30	0.55***	0.52***
VAR ^{BKM}	-7.28	6.96	-1.48	-0.42***	0.53***	-0.10
VRP	-6.10	6.96	-4.33	-0.41*	0.55***	-0.35*
Panel B: $\gamma = 6$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	3.05	3.81	5.02	0.45**	0.43***	0.69***
EXKURT ^{BKM}	3.92	4.58	6.46	0.63***	0.59***	0.90***
SKEW ^{BKM}	1.20	4.11	5.60	0.22	0.53***	0.80***
SMIRK	2.07	2.91	3.14	0.38*	0.51***	0.57**
VAR ^{BKM}	-10.70	4.88	-0.82	-0.60***	0.67***	-0.07
VRP	-8.49	4.88	-2.80	-0.60***	0.68***	-0.37*
Panel C: $\gamma = 9$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.71	2.54	3.23	0.40*	0.34***	0.63**
EXKURT ^{BKM}	2.82	3.11	5.17	0.67***	0.52***	0.94***
SKEW ^{BKM}	0.58	2.84	4.03	0.20	0.47***	0.80***
SMIRK	1.40	1.96	2.17	0.38*	0.49***	0.58***
VAR ^{BKM}	-10.28	3.26	-0.57	-0.63***	0.67***	-0.07
VRP	-8.15	3.26	-1.88	-0.63***	0.68***	-0.37*
Panel D: $\gamma = 12$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.25	1.91	2.55	0.40*	0.29***	0.65**
EXKURT ^{BKM}	2.11	2.35	4.05	0.67***	0.47***	0.93***
SKEW ^{BKM}	0.44	2.17	3.14	0.20	0.44***	0.80***
SMIRK	1.05	1.47	1.63	0.38*	0.49***	0.58***
VAR ^{BKM}	-8.37	2.44	-0.43	-0.63***	0.67***	-0.07
VRP	-6.18	2.44	-1.42	-0.63***	0.68***	-0.37*

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Table 3.9: Economic Value: Restrictions I and II

*This table reports utility gains and Sharpe Ratios for each of the three scenarios, after imposing both economically motivated restrictions following Campbell & Thompson (2008). Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] predicts the variance of market returns. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row]. The historical mean return, and a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.*

Panel A: $\gamma = 3$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	5.46	6.12	6.87	0.46**	0.54***	0.60***
<i>EXKURT^{BKM}</i>	5.39	6.35	8.01	0.51***	0.61***	0.76***
<i>SKEW^{BKM}</i>	1.86	6.26	6.88	0.16	0.57***	0.63***
<i>SMIRK</i>	2.96	5.00	4.88	0.30	0.55***	0.52***
<i>VAR^{BKM}</i>	-8.81	6.96	-1.53	-0.48***	0.52***	-0.10
<i>VRP</i>	-6.10	6.96	-4.33	-0.41*	0.55***	-0.35*
Panel B: $\gamma = 6$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	3.05	3.91	5.11	0.45**	0.44***	0.69***
<i>EXKURT^{BKM}</i>	3.92	4.58	6.46	0.63***	0.59***	0.90***
<i>SKEW^{BKM}</i>	1.20	4.11	5.60	0.22	0.53***	0.80***
<i>SMIRK</i>	2.07	2.91	3.14	0.38*	0.51***	0.57**
<i>VAR^{BKM}</i>	-11.50	4.88	-0.85	-0.63***	0.66***	-0.08
<i>VRP</i>	-8.49	4.88	-2.80	-0.60***	0.68***	-0.37*
Panel C: $\gamma = 9$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	1.71	2.61	3.33	0.40*	0.35***	0.64**
<i>EXKURT^{BKM}</i>	2.82	3.11	5.17	0.67***	0.52***	0.94***
<i>SKEW^{BKM}</i>	0.58	2.84	4.03	0.20	0.47***	0.80***
<i>SMIRK</i>	1.40	1.96	2.17	0.38*	0.49***	0.58***
<i>VAR^{BKM}</i>	-10.81	3.26	-0.58	-0.66***	0.66***	-0.08
<i>VRP</i>	-8.15	3.26	-1.88	-0.63***	0.68***	-0.37*
Panel D: $\gamma = 12$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
<i>CRP</i>	1.25	1.96	2.62	0.40*	0.30***	0.66**
<i>EXKURT^{BKM}</i>	2.11	2.35	4.05	0.67***	0.47***	0.93***
<i>SKEW^{BKM}</i>	0.44	2.17	3.14	0.20	0.44***	0.80***
<i>SMIRK</i>	1.05	1.47	1.63	0.38*	0.49***	0.58***
<i>VAR^{BKM}</i>	-8.77	2.44	-0.44	-0.66***	0.66***	-0.08
<i>VRP</i>	-6.18	2.44	-1.42	-0.63***	0.68***	-0.37*

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our main results remain unchanged.¹⁹ We also repeat our economic value analysis using these economically motivated constraints. Tables 3.7 to 3.9 document that imposing the restriction(s) does (do) not affect our main conclusions on the economic value of the predictive power of both *CRP* and *VRP*.

3.4.2 Forecast Combination

Rapach et al. (2010) suggest the use of forecast combinations. The pooled forecast is the weighted average of all G individual forecasts, where $g = 1, \dots, G$, i.e., $\widehat{ER}_{t+1}^{pool} = \sum_{g=1}^G x_{g,t} \widehat{ER}_{g,t+1}$ and $\widehat{RV}_{t+1}^{pool} = \sum_{g=1}^G x_{g,t} \widehat{RV}_{g,t+1}$, based on Equation (3.16) and (3.19), respectively. $x_{g,t}$ is the weight of the individual forecast in the pooled one.

Following the literature, we use three approaches. Table 3.10 shows the out-of-sample R^2 s of (i) the mean forecast combination, where the weight is simply $1/G$ for $g = 1, \dots, G$, (ii) the median forecast combination, where the pooled forecast is just the median of all individual forecasts, and (iii) the trimmed mean forecast combination, where $x_{g,t} = 0$ in the case of the individual forecasts with the smallest and largest value, respectively, and $x_{g,t} = 1/(G - 2)$ for the remaining forecasts.

The mean forecast combination exhibits superior performance in the case of return predictability ($R_{oos}^2 = 3.11\%$), whereas the median forecast combination in the case of variance predictability ($R_{oos}^2 = 4.83\%$). The

¹⁹Table B.2 of the Appendix to this chapter reports the frequency of how often the restrictions are binding. Panel A shows the results for return predictability. We observe that the first restriction is not binding. This is true for all variables, except VAR^{BKM} , indicated by a frequency of 35. The second restriction is binding more frequently, indicated by frequencies from 29 for $SKEW^{BKM}$ to 77 for *VRP*. It seems that the forecast restriction matters more for excess return predictability. Panel B of Table B.2 shows the frequencies in the case of variance predictability. We find that the first (second) restriction is binding only for *CRP* ($EXKURT^{BKM}$) with a frequency of 75 (3). Lagged realized variance appears to be not affected by the (first) restriction(s) at all, indicating the persistence of that variable. The findings reveal that the imposition of economically motivated restrictions matters more for return rather than variance predictability.

Table 3.10: Out-of-Sample Analysis: Forecast Combinations

This table reports the results of the out-of-sample analysis after the use of forecast combinations. The mean forecast combination [MeanFC], the median forecast combination [MedianFC], and the trimmed mean forecast combination [TrMeanFC] are used as alternative specifications. We report the MSE-F statistics in parenthesis. The historical mean return, and a fitted AR(1) model for realized variance serve as naive benchmarks. Six forecasting variables are used. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). SMIRK is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R_{oos}^2 is the out-of-sample R^2 . *, **, and *** indicate statistical significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: Return Predictability			
	MeanFC	MedianFC	TrMeanFC
R_{oos}^2	3.11*** (5.37)	1.72*** (2.91)	2.36*** (4.03)

Panel B: Variance Predictability			
	MeanFC	MedianFC	TrMeanFC
R_{oos}^2	4.16*** (7.24)	4.83*** (8.48)	4.54*** (7.94)

findings are interesting for several reasons. First, they support the results of Rapach & Zhou (2013) who argue that forecast combinations yield more stable forecasts and increase the forecasting performance. Second, the findings show a substantial increase in the magnitude of the R_{oos}^2 s. In the case of return predictability, the mean forecast combination generates an

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R_{oos}^2 which is substantially larger than for all individual variables, except for VRP . The median forecast combination outperforms all individual variables, predicting realized variance. Third, the findings support our previous conclusion. It seems that individual predictive variables generate notable variance when predicting excess returns and realized variance, respectively.

Table 3.11 reports the economic value for different values of risk-aversion. Compared with our previous findings, all forecast combinations, in particular the median forecast combination, generate substantial certainty equivalent returns. For $\gamma = 3$, an annualized utility gain of 6.73% (relative to the naive strategy) may be achieved, when both return and variance are predicted by the combined forecast. It seems that forecast combinations rather than individual variables, generate more stable forecasts, thus, leading to significant positive utility gains.

3.4.3 Predictability of the Sharpe Ratio

After predicting excess returns and realized variance in isolation, we want to answer the question: What predictive power do the variables have, when predicting excess returns and realized variance jointly? In doing so, we estimate the following regression model:

$$\frac{ER_{t+1}}{\sqrt{RV_{t+1}}} = \varphi_0 + \varphi_1 X_t + \epsilon_{t+1}, \quad (3.26)$$

where $\frac{ER_{t+1}}{\sqrt{RV_{t+1}}}$ is the Sharpe Ratio, and φ_0 and φ_1 are the intercept and slope parameters, respectively. All other variables are as previously defined.

Table 3.12 documents the results for each predictive variable. The regression model (3.26) enables us to assess whether each variable has predictive power, when predicting excess returns and realized variance jointly. We find that CRP , $SKEW^{BKM}$, and VRP have predictive power

Table 3.11: Economic Value: Forecast Combinations

*This table reports utility gains and Sharpe Ratios for each of the three scenarios based on forecast combinations. Scenario 1 assumes that realized variance is unpredictable and that the forecast combination only predicts excess returns. Scenario 2 assumes that excess returns are unpredictable but that the forecast combination predicts the variance of market returns. Scenario 3 implicitly assumes that excess returns and variance can be predicted by the forecast combination. The historical mean return, and a fitted AR(1) model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.*

Panel A: Mean Forecast Combination

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	1.08	6.41	5.35	0.09	0.61***	0.50***
$\gamma = 6$	0.96	4.09	3.78	0.14	0.66***	0.63***
$\gamma = 9$	0.65	2.75	2.69	0.14	0.64***	0.66***
$\gamma = 12$	0.49	2.06	2.05	0.14	0.64***	0.66***

Panel B: Median Forecast Combination

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	2.85	6.52	6.73	0.28*	0.67***	0.67***
$\gamma = 6$	1.21	4.22	4.55	0.19	0.74***	0.80***
$\gamma = 9$	0.82	2.82	3.12	0.19	0.73***	0.81***
$\gamma = 12$	0.62	2.12	2.34	0.19	0.73***	0.81***

Panel C: Trimmed Mean Forecast Combination

	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
$\gamma = 3$	1.59	6.51	5.73	0.14	0.63***	0.55***
$\gamma = 6$	0.96	4.11	3.98	0.15	0.69***	0.68***
$\gamma = 9$	0.65	2.75	2.77	0.15	0.68***	0.70***
$\gamma = 12$	0.49	2.06	2.08	0.15	0.68***	0.70***

Table 3.12: Predictability of the Sharpe Ratio

This table reports the regression results of monthly Sharpe Ratios on a constant, which we denote by φ_0 , and the lagged predictive variable(s). We report the t -statistics in parentheses. Statistical inferences are based on a bootstrapped distribution. A fitted AR(1) model serves as naive benchmark. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). SMIRK is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R^2 and R^2_{oos} are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

φ_0	0.445 (1.53)	0.076 (0.12)	-0.776 (-0.80)	1.092*** (4.50)	1.005*** (3.12)	0.669*** (2.74)	-0.444 (-0.55)	-1.174 (-1.10)	-1.552 (-1.27)
CRP	5.084** (2.43)						3.120 (1.33)	2.910 (1.24)	2.969 (1.26)
$EXKURT^{BKM}$		1.125 (1.46)					1.155 (1.34)		-1.469 (-0.62)
$SKEW^{BKM}$			-1.958* (-1.79)					-1.948 (-1.69)	-3.786 (-1.19)
SMIRK				-1.262 (-1.48)			-1.262 (-1.38)	-1.373 (-1.49)	-1.423 (-1.54)
VAR^{BKM}					-1.710 (-0.34)		4.272 (0.73)	3.104 (0.57)	0.963 (0.15)
VRP						16.265** (2.17)	10.744 (1.30)	10.751 (1.30)	10.302 (1.24)
R^2	2.56**	0.94	1.40*	0.97	0.05	2.04**	2.57*	3.03**	2.76*
R^2_{oos}	2.99**	-0.50	0.96	0.24	-0.45	1.54*	-2.80*	-1.30**	-3.15*

for the future Sharpe Ratio, indicated by their statistically significant t -statistics of 2.43, -1.79 , and 2.17. A look at the in-sample R^2 s reveals that CRP and VRP have the highest (in-sample) predictive power of 2.56 % and 2.04 %, respectively.²⁰

The further analysis shows that CRP and VRP also contain important information about the future Sharpe Ratio out-of-sample, indicated by R^2_{oos} s of 2.99 % and 1.54 %. The findings suggest that CRP and VRP are able to predict excess returns and realized variance not only in isolation but also jointly.

3.5 Additional Analysis

To use more information in estimating the realized variance, we follow Corsi (2009) and Sévi (2014) and use the heterogenous autoregressive (HAR) model. The $HAR-RV$ model provides a conditional estimate for realized variance that accounts for different trading horizons. Further, in the previous analysis, we examine the total variance risk premium. However, Andersen & Bondarenko (2013), Andersen et al. (2015), and Feunou et al. (2017) show how to decompose the variance risk premium into downside and upside components. In the following section, we analyze the predictability of both components separately.

We follow Andersen & Bondarenko (2013) and Andersen et al. (2015) and use the downside and upside model-free implied variance. Following the arguments of Feunou et al. (2017), investors dislike increases in the volatility of the underlying, which is associated with an increase in the probability of severe losses. Investors hedge against these downward movements, thus, we expect that the downside variance risk premium is the main driver of

²⁰The multiple predictive regressions show no significant variables, indicating that multiple regressions are able to predict excess returns and realized variance in isolation rather than jointly.

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the variance risk premium. Further, to get a better estimate for the physical expectation of variance, we analogously use the downside and upside realized variance.

3.5.1 Variables

Variance Risk Premium based on HAR–RV Model We define the variance risk premium based on the *HAR–RV* model (VRP^{HAR}) as the difference between the risk-neutral variance (VAR^{BKM}) and the *RV*, estimated on the basis of the *HAR* model (RV^{HAR}):

$$VRP_t^{HAR} = VAR_t^{BKM} - RV_t^{HAR}, \quad (3.27)$$

where VAR_t^{BKM} is as previously defined. Analogously to Section 3.2.2 and using Equation (3.2), we follow Christoffersen (2012) and define

$$RV_{D,t+\frac{i}{N}} \equiv RV_{t+\frac{i}{N}}, \quad (3.28)$$

$$\begin{aligned} RV_{W,t+\frac{i}{N}} &\equiv RV_{(t+\frac{i}{N})-4,t+\frac{i}{N}} \\ &= \left[RV_{(t+\frac{i}{N})-4} + RV_{(t+\frac{i}{N})-3} + RV_{(t+\frac{i}{N})-2} + RV_{(t+\frac{i}{N})-1} + RV_{t+\frac{i}{N}} \right] / 5, \end{aligned} \quad (3.29)$$

$$\begin{aligned} RV_{M,t+\frac{i}{N}} &\equiv RV_{(t+\frac{i}{N})-20,t+\frac{i}{N}} \\ &= \left[RV_{(t+\frac{i}{N})-20} + RV_{(t+\frac{i}{N})-19} + \dots + RV_{t+\frac{i}{N}} \right] / 21 \end{aligned} \quad (3.30)$$

as the daily, weakly, and monthly realized variance on day $t + \frac{i}{N}$, respectively.²¹ Further, $RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20}$ is the realized variance over the next 21 days, i.e.:

$$RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20} = \left[RV_{(t+\frac{i}{N})+1} + RV_{(t+\frac{i}{N})+2} + \dots + RV_{(t+\frac{i}{N})+20} \right] / 21. \quad (3.31)$$

²¹Since we now work with daily rather than intraday data, we follow the common approach and define one month as 21 trading days.

Finally, to compute RV_t^{HAR} , we run the following regression:

$$\begin{aligned} RV_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20} &= \phi_0 + \phi_D RV_{D,t+\frac{i}{N}} + \phi_W RV_{W,t+\frac{i}{N}} \\ &+ \phi_M RV_{M,t+\frac{i}{N}} + \epsilon_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20}, \end{aligned} \quad (3.32)$$

where ϕ_0 , ϕ_D , ϕ_W , and ϕ_M are the regression coefficients, and $\epsilon_{(t+\frac{i}{N})+1,(t+\frac{i}{N})+20}$ is the error term over the next 21 days. The fitted values are the forecasted RV and represent RV_t^{HAR} .

Downside and Upside Variance Risk Premium We define the downside and upside variance risk premium (VRP^{DOWN} and VRP^{UP}) as the difference between the downside and upside model-free implied variance ($(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$) and the downside and upside realized variance (RV^{DOWN} and RV^{UP}), respectively:

$$VRP_t^{DOWN} = (\sigma_t^{\mathbb{Q}^-})^2 - RV_t^{DOWN}, \quad (3.33)$$

$$VRP_t^{UP} = (\sigma_t^{\mathbb{Q}^+})^2 - RV_t^{UP}. \quad (3.34)$$

To obtain $(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$, we follow Andersen & Bondarenko (2013) and Andersen et al. (2015) and use their corridor implied volatility method to decompose the model-free implied variance into different parts, and define the model-free implied variance $(\sigma_t^{\mathbb{Q}})^2$ as:

$$(\sigma_t^{\mathbb{Q}})^2 = 2 \int_0^\infty \frac{M(K)}{K^2} dK = (\sigma_t^{\mathbb{Q}^-})^2 + (\sigma_t^{\mathbb{Q}^+})^2, \quad (3.35)$$

where $M(K) = \min(P(K), C(K))$ is the minimum price of the put and call with maturity of 1 month and strike K . Consistently, we also compute the grid of 1,000 equidistant interpolated moneyness levels of out-of-the money option prices, as described above. Finally, to compute $(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$, we assume the threshold Se^θ with $\theta = 0$:

$$(\sigma_t^{\mathbb{Q}^-})^2 = 2 \int_0^{Se^\theta} \frac{M(K)}{K^2} dK, \quad (3.36)$$

$$(\sigma_t^{\mathbb{Q}^+})^2 = 2 \int_{Se^\theta}^\infty \frac{M(K)}{K^2} dK. \quad (3.37)$$

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We then use the trapezoidal rule to approximate the integrals, as outlined above.

Following Barndorff-Nielsen, Kinnebrock, & Shephard (2010), we decompose the realized variance into the upside and downside realized variance for a given threshold κ . Imposing $\kappa = 0$, we compute RV_t^{DOWN} (RV_t^{UP}) on the basis of Equation (3.2), however, using only log-returns that are at most (least) equal to κ .

Downside and Upside Variance Risk Premium based on HAR–RV Model We define the downside and upside variance risk premium based on the *HAR–RV* model ($VRP^{DOWN,HAR}$ and $VRP^{UP,HAR}$) as the difference between the downside and upside model-free implied variance ($(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$) and the downside and upside realized variance, estimated on the basis of the *HAR* model ($RV^{DOWN,HAR}$ and $RV^{UP,HAR}$), respectively:

$$VRP_t^{DOWN,HAR} = (\sigma_t^{\mathbb{Q}^-})^2 - RV_t^{DOWN,HAR}, \quad (3.38)$$

$$VRP_t^{UP,HAR} = (\sigma_t^{\mathbb{Q}^+})^2 - RV_t^{UP,HAR}, \quad (3.39)$$

where $(\sigma_t^{\mathbb{Q}^-})^2$ and $(\sigma_t^{\mathbb{Q}^+})^2$ are as previously defined. To compute $RV_t^{DOWN,HAR}$ ($RV_t^{UP,HAR}$), we follow the steps described above, however, using RV^{DOWN} (RV^{UP}) instead of RV .

3.5.2 Results

Table B.3 of the Appendix to this chapter reports the regression results for the different specifications predicting the next month’s excess return and realized variance, respectively. In Panel A, we observe that all specifications exhibit an inferior performance in predicting excess returns compared to the *VRP* as proposed by Bollerslev et al. (2009). However, we notice that VRP^{UP} , VRP^{DOWN} , and $VRP^{UP,HAR}$ have still (in-sample)

significant predictive power, indicated by t -statistics between 2.47 and 2.17, and in-sample R^2 s from 2.65 % to 2.05 %.

In Panel B of Table B.3, we find that all specifications have a similar (insignificant) in-sample predictive power for RV as VRP . We observe noteworthy significant out-of-sample predictability for VRP^{HAR} ($R_{oos}^2 = 3.40$ %), VRP^{DOWN} ($R_{oos}^2 = 4.34$ %), and $VRP^{UP,HAR}$ ($R_{oos}^2 = 4.63$ %).

We now turn our attention to the portfolio choice implications. Table B.4 of the Appendix to this chapter reports the results of the economic value. For an agent with risk-aversion of $\gamma = 3$, we observe that VRP^{UP} (VRP^{DOWN}) provides substantial improvements in the utility gain of 6.74 % p.a. (6.31 % p.a.) and in the Sharpe Ratio of 0.71 (0.59).

Overall, the results confirm our previous findings in providing evidence for a stronger variance than return predictability. We also observe that VRP^{DOWN} , VRP^{UP} , and $VRP^{UP,HAR}$ predict in-sample both returns and realized variance. In addition, we notice that VRP^{HAR} , VRP^{DOWN} , and $VRP^{UP,HAR}$ strongly predict realized variance out-of-sample. Finally, the results reveal that VRP^{UP} and VRP^{DOWN} provide evidence for generating statistically significant economic value.

3.5.3 Alternative Approach of Variance Predictability

In our main analysis, we included lagged realized variance as an additional predictor, when predicting realized variance as it is well known that variance is a persistent process. To see whether our results are driven by this choice, we repeat the analysis without including lagged realized variance. We now estimate the following regression model for realized variance:

$$RV_{t+1} = \gamma_0 + \gamma_1 X_t + \epsilon_{t+1}, \quad (3.40)$$

3.5. ADDITIONAL ANALYSIS

where all variables are as previously defined. Under the null hypothesis of no predictability, the variable X_t has no predictive power for future realized variance. In this case, we expect that $\gamma_1 = 0$, and that the best estimate for future realized variance would be its mean. Accordingly, the historical mean variance serves as benchmark model. Using this specification, we are able to analyze the individual predictive power of variables subject to the standard approach in extant literature. Tables B.5 and B.6 of the Appendix to this chapter summarize the results of the predictability and economic value analysis.

In Table B.5, we find that all variables have in-sample predictive power for future realized variance. CRP turns out to have significant predictive ability, indicated by a t -statistic of -3.72 . We notice that the in-sample R^2 s are smaller compared with our previous results. They range from 3.19 % for $SKEW^{BKM}$ to 38.83 % for VAR^{BKM} .

In the out-of-sample analysis, we observe that the variables that predict realized variance in-sample are also predictors out-of-sample. This is true for all variables with the exception of VRP , which does not yield an improvement relative to the recursive mean. We justify this pattern by the sign-switching behavior of VRP . The R^2_{oos} s range from 1.88 % for CRP to 34.65 % for VAR^{BKM} . It seems that, using the standard methodology, the predictive power of some variables increases, compared to our previous results.

In the economic value analysis, shown in Table B.6, we find similar results as before. It seems that statistical evidence of predictability does not necessarily imply important economic gains. One can see that relative to an agent with risk-aversion $\gamma = 3$ who assumes that the market excess return and the realized variance are unpredictable, the agent who exploits the information content of CRP would improve her utility by 4.63 % p.a. Overall, the results confirm our previous findings.

3.6 Conclusion

This chapter comprehensively studies the predictive power of option-implied variables for future excess returns and realized variance. A variable is considered to have predictive power if it exhibits statistically significant forecasting power and also adds economic value. We find that the correlation risk premium and the variance risk premium emerge as statistically significant predictors of both the market excess return and the realized variance. This is true both in- and out-of-sample.

We then investigate the economic value of the documented predictability. Our results highlight an important contrast between the two variables. Relative to a naive strategy that assumes that excess returns and realized variance are unpredictable, the agent who relies on the correlation risk premium as a timing signal realizes utility gains of 5.03 % p.a. In contrast, the timing strategy that uses the variance risk premium as timing signal yields lower certainty equivalent returns than a naive strategy that assumes constant excess returns and realized variance. Thus, our analysis shows that statistical evidence of predictability does not necessarily translate to economic value. Moreover, we find that forecast combinations generate stable forecasts for both excess returns and realized variance, and that they add substantial economic value.

We further decompose the total variance risk premium into the downside and upside components, and analyze the predictability of different versions of the variance risk premium. We show that the upside and downside variance risk premia have noteworthy (in-sample) predictive power for excess returns and realized variance. Further, a timing strategy provides substantial utility gains.

B Appendix

In this section, we provide additional material for Chapter 3: “Predicting the Equity Market with Option-Implied Variables”.

CHAPTER 3. PREDICTING THE EQUITY MARKET WITH
OPTION-IMPLIED VARIABLES

Table B.1: Economic Value with Turnover and Transaction Costs

*This table reports the turnover, the utility gains, and the Sharpe Ratios for each of the three scenarios. Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in column] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in column] and the lagged realized variance predict the realized variance. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in column], and in the latter case, by the forecasting variable [name in column] and the lagged realized variance. The historical mean return, and a fitted AR(1) model for realized variance serve as naive benchmarks. $Turnover_{abs}$ is the monthly absolute value of the turnover for the naive strategy. $Turnover_{rel}^{(i)}$ represents the monthly relative turnover of strategy i related to the benchmark. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.*

Panel A: $\gamma = 3$

	<i>CRP</i>	<i>EXKURT^{BKM}</i>	<i>SKEW^{BKM}</i>	<i>SMIRK</i>	<i>VAR^{BKM}</i>	<i>VRP</i>
<i>Turnover_{abs}</i>	0.0448	0.0448	0.0448	0.0448	0.0448	0.0448
<i>Turnover_{rel}⁽¹⁾</i>	12.1906	5.4513	5.5545	8.9341	2.2193	9.6821
<i>Turnover_{rel}⁽²⁾</i>	4.8831	5.5580	2.9157	2.7424	2.7127	3.9283
<i>Turnover_{rel}⁽³⁾</i>	14.6331	8.2202	6.6146	10.9321	3.4473	11.5826
$\Delta CER^{(1)}$	2.48	4.19	0.64	0.85	-7.62	-8.46
$\Delta CER^{(2)}$	-1.03	1.60	1.81	1.87	5.94	7.04
$\Delta CER^{(3)}$	1.38	4.46	2.33	0.55	-4.91	-5.47
$\Delta SR^{(1)}$	0.21	0.39**	0.06	0.05	-0.43***	-0.57***
$\Delta SR^{(2)}$	0.06	0.20	0.21	0.21**	0.36***	0.47***
$\Delta SR^{(3)}$	0.13	0.36*	0.20	0.06	-0.22	-0.25

Panel B: $\gamma = 6$

	<i>CRP</i>	<i>EXKURT^{BKM}</i>	<i>SKEW^{BKM}</i>	<i>SMIRK</i>	<i>VAR^{BKM}</i>	<i>VRP</i>
<i>Turnover_{abs}</i>	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247
<i>Turnover_{rel}⁽¹⁾</i>	15.9051	7.0084	7.0350	9.3238	4.2300	12.5610
<i>Turnover_{rel}⁽²⁾</i>	10.6311	10.8603	6.8986	4.7041	5.8114	9.8254
<i>Turnover_{rel}⁽³⁾</i>	25.8225	16.2198	13.7024	18.2632	5.2006	18.7912
$\Delta CER^{(1)}$	0.88	3.03	0.30	0.85	-11.25	-10.32
$\Delta CER^{(2)}$	-5.70	0.95	0.29	0.26	4.83	4.18
$\Delta CER^{(3)}$	-1.36	2.62	0.64	-0.28	-6.18	-10.91
$\Delta SR^{(1)}$	0.18	0.49***	0.10	0.10	-0.61***	-0.73***
$\Delta SR^{(2)}$	-0.14	0.25	0.20*	0.16	0.44***	0.49***
$\Delta SR^{(3)}$	0.12	0.41*	0.27	0.06	-0.28	-0.54**

B. APPENDIX

Table B.1: Economic Value with Turnover and Transaction Costs (continued)

Panel C: $\gamma = 9$

	<i>CRP</i>	<i>EXKURT^{BKM}</i>	<i>SKEW^{BKM}</i>	<i>SMIRK</i>	<i>VAR^{BKM}</i>	<i>VRP</i>
<i>Turnover_{abs}</i>	0.0151	0.0151	0.0151	0.0151	0.0151	0.0151
<i>Turnover_{rel}⁽¹⁾</i>	18.4886	8.8266	9.2375	10.2124	5.7328	15.0938
<i>Turnover_{rel}⁽²⁾</i>	15.6516	16.8364	10.1848	5.1486	6.6592	17.8674
<i>Turnover_{rel}⁽³⁾</i>	36.6566	26.1824	20.6825	24.7431	5.7841	22.0822
$\Delta CER^{(1)}$	0.15	2.11	-0.18	0.57	-10.81	-9.58
$\Delta CER^{(2)}$	-6.59	0.70	0.03	0.13	3.25	2.20
$\Delta CER^{(3)}$	-2.17	1.01	-1.03	-0.41	-4.53	-9.70
$\Delta SR^{(1)}$	0.13	0.50***	0.07	0.10	-0.65***	-0.74***
$\Delta SR^{(2)}$	-0.18	0.25*	0.18*	0.14	0.44***	0.49***
$\Delta SR^{(3)}$	0.14	0.39	0.22	0.10	-0.29	-0.59***

Panel D: $\gamma = 12$

	<i>CRP</i>	<i>EXKURT^{BKM}</i>	<i>SKEW^{BKM}</i>	<i>SMIRK</i>	<i>VAR^{BKM}</i>	<i>VRP</i>
<i>Turnover_{abs}</i>	0.0108	0.0108	0.0108	0.0108	0.0108	0.0108
<i>Turnover_{rel}⁽¹⁾</i>	19.5157	9.1852	10.0488	10.6805	6.4946	15.8094
<i>Turnover_{rel}⁽²⁾</i>	18.2998	21.0369	12.2949	5.3345	6.8723	24.3221
<i>Turnover_{rel}⁽³⁾</i>	45.3856	34.0648	25.9198	27.6275	6.0582	23.5223
$\Delta CER^{(1)}$	0.07	1.58	-0.17	0.43	-8.86	-7.25
$\Delta CER^{(2)}$	-7.04	0.49	-0.24	0.08	2.43	0.77
$\Delta CER^{(3)}$	-2.90	0.09	-1.78	-0.48	-3.45	-8.30
$\Delta SR^{(1)}$	0.12	0.50***	0.07	0.10	-0.65***	-0.75***
$\Delta SR^{(2)}$	-0.21	0.25*	0.14	0.13	0.44***	0.43**
$\Delta SR^{(3)}$	0.11	0.38	0.21	0.09	-0.29	-0.59***

Table B.2: Out-of-Sample Analysis: Restriction – Frequencies

This table reports the frequency of how often the economically motivated restrictions imposed are binding in the out-of-sample analysis, shown in Table 3.6. Panel A shows the frequency for each individual variable, predicting the next month's excess return. Panel B shows the frequency for each individual variable as well as lagged realized variance, predicting the next month's realized variance. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. The historical mean return, and a fitted $AR(1)$ model for realized variance serve as naive benchmarks. "(I)" denotes the imposition of the first restriction, where we set the slope estimate in the out-of-sample analysis equal to zero, whenever its sign differs from that of the in-sample analysis. "(II)" denotes the imposition of the second restriction, where we set the forecast equal to zero, whenever it is negative. "(I+II)" denotes the joint imposition of both restrictions. "(I+II) (I)" ("(I+II) (II)") refers to the frequency of the first (second) restriction in the case of the joint imposition of both restrictions. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: Return Predictability

		CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
(I)		0	0	0	0	35	0
(II)		53	32	29	62	56	77
(I+II)	(I)	0	0	0	0	35	0
(I+II)	(II)	53	32	29	62	50	77

Panel B: Variance Predictability

		CRP	$EXKURT^{BKM}$	$SKEW^{BKM}$	$SMIRK$	VAR^{BKM}	VRP
(I)		75	0	0	0	0	0
(II)		0	3	0	0	0	0
(I+II)	(I)	75	0	0	0	0	0
(I+II)	(II)	0	3	0	0	0	0
Lagged Realized Variance							
(I)		0	0	0	0	0	0
(II)		-	-	-	-	-	-
(I+II)	(I)	0	0	0	0	0	0
(I+II)	(II)	-	-	-	-	-	-

Table B.3: Return and Variance Predictability of VRP Specifications

Panel A of this table reports the regression results of monthly excess returns on a constant, which we denote by β_0 , and the lagged predictive variable. Panel B reports the regression results of monthly realized variance on a constant, which we denote by γ_0 , the lagged predictive variable, and the lagged realized variance. Statistical inferences are based on a bootstrapped distribution. The historical mean return, and a fitted $AR(1)$ model for realized variance serve as naive benchmarks. VRP^{HAR} denotes the variance risk premium based on the HAR-RV model. VRP^{DOWN} is the downside variance risk premium. VRP^{UP} is the upside variance risk premium. $VRP^{DOWN,HAR}$ is the downside variance risk premium based on the HAR-RV model. Finally, $VRP^{UP,HAR}$ is the upside variance risk premium based on the HAR-RV model. R^2 and R_{oos}^2 are the in-sample and out-of-sample R^2 , respectively. We report the t -statistics in parentheses. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: Return Predictability

	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
R^2	0.00	2.23**	2.65**	0.38	2.05**
R_{oos}^2	-5.37	-1.13	-2.38	-4.10	-1.25
$t - stat$	(0.10)	(2.26)	(2.47)	(0.93)	(2.17)

Panel B: Variance Predictability

	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
R^2	42.95	41.03	40.34	41.19	43.94
R_{oos}^2	3.40***	4.34***	-3.46	-4.05	4.63***
$t - stat$	(3.32)	(1.85)	(0.89)	(2.01)	(3.90)

Table B.4: Economic Value of VRP Specifications

*This table reports utility gains and Sharpe Ratios for each of the three scenarios. Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in column] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in column] and the lagged realized variance predict the realized variance. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in column], and in the latter case, by the forecasting variable [name in column] and the lagged realized variance. The historical mean return, and a fitted $AR(1)$ model for realized variance serve as naive benchmarks. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.*

Panel A: $\gamma = 3$

	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
$\Delta CER^{(1)}$	-7.41	0.24	2.25	-9.33	-9.25
$\Delta CER^{(2)}$	6.29	7.40	6.73	5.17	5.11
$\Delta CER^{(3)}$	-4.36	6.31	6.74	-4.99	-8.24
$\Delta SR^{(1)}$	-0.43***	0.04	0.19**	-0.55***	-0.58***
$\Delta SR^{(2)}$	0.38***	0.69***	0.71***	0.37***	0.40***
$\Delta SR^{(3)}$	-0.20	0.59***	0.71***	-0.29*	-0.51**

Panel B: $\gamma = 6$

	VRP^{HAR}	VRP^{DOWN}	VRP^{UP}	$VRP^{DOWN,HAR}$	$VRP^{UP,HAR}$
$\Delta CER^{(1)}$	-10.71	-1.91	0.96	-11.09	-10.73
$\Delta CER^{(2)}$	5.47	5.94	5.12	3.70	4.81
$\Delta CER^{(3)}$	-6.36	4.47	6.13	-6.32	-8.17
$\Delta SR^{(1)}$	-0.60***	-0.12	0.17*	-0.64***	-0.69***
$\Delta SR^{(2)}$	0.46***	0.74***	0.60***	0.40***	0.62***
$\Delta SR^{(3)}$	-0.27	0.61**	0.79***	-0.37**	-0.59***

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Table B.4: Economic Value of *VRP* Specifications (continued)

Panel C: $\gamma = 9$

	<i>VRP^{HAR}</i>	<i>VRP^{DOWN}</i>	<i>VRP^{UP}</i>	<i>VRP^{DOWN,HAR}</i>	<i>VRP^{UP,HAR}</i>
$\Delta CER^{(1)}$	-10.65	-2.43	0.63	-10.89	-9.83
$\Delta CER^{(2)}$	3.72	4.24	3.21	2.49	4.36
$\Delta CER^{(3)}$	-4.72	3.39	4.63	-5.68	-6.97
$\Delta SR^{(1)}$	-0.62***	-0.21	0.17*	-0.65***	-0.73***
$\Delta SR^{(2)}$	0.47***	0.67***	0.45**	0.36***	0.76***
$\Delta SR^{(3)}$	-0.29	0.64**	0.80***	-0.40**	-0.60***

Panel D: $\gamma = 12$

	<i>VRP^{HAR}</i>	<i>VRP^{DOWN}</i>	<i>VRP^{UP}</i>	<i>VRP^{DOWN,HAR}</i>	<i>VRP^{UP,HAR}</i>
$\Delta CER^{(1)}$	-8.65	-2.20	0.47	-10.35	-7.82
$\Delta CER^{(2)}$	2.78	3.15	2.25	1.85	3.43
$\Delta CER^{(3)}$	-3.60	2.53	3.25	-4.61	-5.49
$\Delta SR^{(1)}$	-0.63***	-0.23*	0.17*	-0.62***	-0.72***
$\Delta SR^{(2)}$	0.47***	0.61***	0.43*	0.34***	0.80***
$\Delta SR^{(3)}$	-0.29	0.65**	0.76**	-0.40**	-0.59***

Table B.5: Variance Predictability: Alternative Approach

This table reports the regression results of monthly realized variance on a constant, which we denote by γ_0 , and the lagged predictive variable(s). We report the t -statistics in parentheses. Statistical inferences are based on a bootstrapped distribution. The historical mean serves as naive benchmark. CRP denotes the correlation risk premium. $EXKURT^{BKM}$ is the risk-neutral kurtosis of Bakshi et al. (2003). $SKEW^{BKM}$ is the risk-neutral skewness of Bakshi et al. (2003). $SMIRK$ is the option smirk. VAR^{BKM} is the risk-neutral variance of Bakshi et al. (2003). Finally, VRP is the variance risk premium computed as the difference between the risk-neutral variance of Bakshi et al. (2003) and the most recent observation of the realized variance. R^2 and R_{OOS}^2 are the in-sample and out-of-sample R^2 , respectively. *, **, and *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. The sample period extends from January 1996 to December 2014. All data are sampled at the monthly frequency and relate to the S&P 500 index.

γ_0	0.043*** (9.49)	0.074*** (7.84)	0.073*** (4.71)	0.022*** (6.09)	-0.004 (-1.00)	0.038*** (9.88)	0.017* (1.82)	0.023* (1.79)	0.023 (1.54)
CRP	-0.123*** (-3.72)						-0.072** (-2.56)	-0.071** (-2.53)	-0.071** (-2.52)
$EXKURT^{BKM}$		-0.057*** (-4.78)					-0.013 (-1.26)		-0.001 (-0.03)
$SKEW^{BKM}$			0.047*** (2.72)					0.019 (1.34)	0.018 (0.46)
$SMIRK$				0.071*** (5.53)			0.026** (2.38)	0.027** (2.43)	0.027** (2.42)
VAR^{BKM}					0.756*** (11.95)		0.658*** (9.44)	0.675*** (10.33)	0.673*** (8.70)
VRP						-0.399*** (-3.36)	-0.245** (-2.47)	-0.243** (-2.45)	-0.243** (-2.44)
R^2	5.80***	9.24***	3.19***	11.97***	38.83***	4.79***	45.47***	45.53***	45.28***
R_{OOS}^2	1.88***	8.04***	2.65***	8.61***	34.65***	-2.92	12.21***	12.20***	9.48***

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Table B.6: Economic Value: Alternative Approach

This table reports utility gains and Sharpe Ratios for each of the three scenarios. Scenario 1 assumes that the realized variance is unpredictable and that the forecasting variable [name in row] only predicts the excess returns. Scenario 2 assumes that the excess returns are unpredictable but that the variable [name in row] predicts the realized variance. Scenario 3 implicitly assumes that the excess returns and the realized variance can be predicted by the forecasting variable [name in row]. The historical mean serves as naive benchmark for both return and variance predictability. $\Delta CER^{(1)}$, $\Delta CER^{(2)}$, and $\Delta CER^{(3)}$ are the annualized utility gains relative to a naive strategy that assumes unpredictable excess returns and realized variance, achieved by following strategy 1, 2, and 3, respectively. Similarly, $\Delta SR^{(1)}$, $\Delta SR^{(2)}$, and $\Delta SR^{(3)}$ are the annualized improvements in Sharpe Ratios achieved by following strategy 1, 2, and 3, respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency and relate to the S&P 500 index.

Panel A: $\gamma = 3$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	5.46	1.63	4.63	0.46**	0.11	0.40*
EXKURT ^{BKM}	5.39	3.69	6.24	0.51***	0.34***	0.58***
SKEW ^{BKM}	1.86	1.78	3.28	0.16	0.13**	0.29
SMIRK	2.96	1.47	2.91	0.30	0.14	0.30
VAR ^{BKM}	-7.28	7.19	-1.65	-0.42***	0.50***	-0.09
VRP	-6.10	-1.57	-5.43	-0.41*	-0.13	-0.41*
Panel B: $\gamma = 6$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	3.05	1.50	2.86	0.45**	0.14*	0.43*
EXKURT ^{BKM}	3.92	3.05	4.83	0.63***	0.40***	0.70***
SKEW ^{BKM}	1.20	1.30	2.36	0.22	0.14**	0.37**
SMIRK	2.07	1.10	2.13	0.38*	0.14	0.37*
VAR ^{BKM}	-10.70	5.67	-0.45	-0.60***	0.71***	0.02
VRP	-8.49	-0.98	-6.14	-0.60***	-0.12	-0.53**
Panel C: $\gamma = 9$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.71	1.04	1.56	0.40*	0.12*	0.38
EXKURT ^{BKM}	2.82	2.27	3.74	0.67***	0.40***	0.74***
SKEW ^{BKM}	0.58	0.88	1.76	0.20	0.13**	0.41**
SMIRK	1.40	0.75	1.47	0.38*	0.14	0.38*
VAR ^{BKM}	-10.28	3.94	-0.18	-0.63***	0.73***	0.05
VRP	-8.15	-0.65	-6.22	-0.63***	-0.10	-0.58**
Panel D: $\gamma = 12$						
	$\Delta CER^{(1)}$	$\Delta CER^{(2)}$	$\Delta CER^{(3)}$	$\Delta SR^{(1)}$	$\Delta SR^{(2)}$	$\Delta SR^{(3)}$
CRP	1.25	0.78	0.87	0.40*	0.10*	0.36
EXKURT ^{BKM}	2.11	1.80	2.93	0.67***	0.40***	0.74***
SKEW ^{BKM}	0.44	0.66	1.35	0.20	0.13**	0.42**
SMIRK	1.05	0.57	1.10	0.38*	0.14	0.38*
VAR ^{BKM}	-8.37	2.95	-0.15	-0.63***	0.73***	0.05
VRP	-6.18	-0.49	-5.82	-0.63***	-0.10	-0.59**

Chapter 4

Predictability in Commodity Markets: Evidence from more than a Century*

4.1 Introduction

A growing literature has analyzed the predictability of commodity spot returns and/or volatilities, mostly using variables that are known to predict equity returns (e.g., Gorton & Rouwenhorst, 2006; Gargano & Timmermann, 2014). The growing number of predictive variables raises several questions: Which variables known to predict stock returns can also predict commodity returns? Do the variables that predict commodity returns also forecast commodity return volatilities? Does predictability vary over the business cycle? Had the introduction of derivatives trading influence

*This chapter is based on the Working Paper “Predictability in Commodity Markets: Evidence from more than a Century” authored by Marcel Prokopczuk, Björn Tharann, and Chardin Wese Simen, 2018.

on the degree of predictability? These are some of the questions we want to answer.

The interest in commodity markets has grown rapidly over recent decades. Although commodities have been traded on exchanges for more than 100 years in the U.S., commodities as an asset class are still relatively unexplored. Due to the poor performance of stocks and bonds, investors have turned to commodities as a new investment class (e.g., Bessembinder & Chan, 1992; Gorton & Rouwenhorst, 2006; Kogan et al., 2009). Erb & Harvey (2006) show that commodities and equities have similar average returns. Due to the low correlation with stocks and bonds, commodities are useful to achieve a high degree of portfolio diversification and serve as a good hedge against inflation (e.g., Sadorsky, 2002; Gorton & Rouwenhorst, 2006; Lien & Yang, 2008; Symeonidis et al., 2012).

Commodities also attract attention by being predictable, with financial and macroeconomic variables that are known to possess predictive power for stocks and bonds (e.g., Bessembinder & Chan, 1992; Bailey & Chan, 1993; Chen et al., 2010; Pierdzioch et al., 2016). Capital constraints and limitations for hedging also affect commodity prices and thus the predictability of commodity returns (De Roon, Nijman, & Veld, 2000; Hong & Yogo, 2012; Acharya, Lochstoer, & Ramadorai, 2013). Last but not least, being able to predict the prices (or returns) of commodities is naturally very important for the real industry. In many sectors, commodities are one of the most important inputs to production. It is thus of great interest to be able to accurately model the expected return on commodity prices.

The main goal of this chapter is to provide the most comprehensive evidence on the predictive power of macroeconomic variables for commodity excess returns and volatilities to date. In doing so, we make three contributions to the literature.

First, in contrast to the existing literature, we analyze a very long

4.1. INTRODUCTION

sample period of more than 140 years and use a comprehensive set of commodity markets and predictive variables. Indeed, our sample spans the period from January 1871 to December 2015 and covers 30 commodities and 16 predictive variables. A variable is considered to have predictive power if it exhibits significant predictive ability out-of-sample.

Second, we do not only analyze the predictability of excess returns, which is the focus of most existing studies, but also the predictability of volatilities. In doing so, we use the same time periods and techniques as for the returns to ensure a comparable analysis.

Third, in contrast to previous studies, our data allow us to get new insights from analyzing a long sample period as well as the strength of the predictability around economically important events such as the introduction of derivatives trading. Our long sample also enables us to analyze the predictability of both excess returns and volatilities for different states of the economy. Following Cujean & Hasler (2017), we examine expansions and recessions separately.

We find that there is evidence for short- and long-term predictability for both commodity excess returns and volatilities. We observe, however, more predictability at longer horizons. These improvements are more pronounced for the predictability of excess returns rather than that of volatilities.

In more detail, we find that the growth of industrial production, the market risk premium, and the default return spread are the most reliable predictive variables in the short-term. At long horizons, we find that interest rate-related variables – specifically, the 3-month Treasury bill rate, the default yield spread, the long-term U.S. government bond yield, and the term spread – are the most reliable predictive variables.

Analyzing the short-term volatility predictability, we detect that the dividend–price ratio, the dividend yield, the inflation rate, and the long-term government bond yield are the most important predictive variables. For

longer horizons, the earnings–price ratio, the default yield spread, and the term spread contribute to the predictability.

The structural break analysis shows that the introduction of derivatives trading has a substantial effect on the degree of return and volatility predictability. It also provides evidence that volatility has been systematically affected by the introduction of derivatives trading and the beginning of the global financial crisis.

Our study directly relates to the literature on commodity return predictability. Bessembinder & Chan (1992), Bailey & Chan (1993), and Bjornson & Carter (1997) use the dividend yield, the default return spread, Treasury bill rates, and long-term government bond yields to forecast commodity futures returns. De Roon et al. (2000) focus on the forecasting power of hedging pressure. Hong & Yogo (2012) and Acharya et al. (2013) extend that work using open interest and limits to arbitrage proxies, respectively. Etula (2013) shows that lagged effective risk-aversion and the market excess return predict energy returns. We extend these studies by analyzing a broad set of commodities and we examine numerous predictive variables together that have been studied in isolation in the existing literature.

Chen et al. (2010) demonstrate the predictive power of commodity currency exchange rates for country-specific commodity spot indices. Gargano & Timmermann (2014) use commodity spot indices to examine the predictive ability of several variables over a somewhat longer sample period than typically analyzed in the existing literature. Analyzing different states of the economy, they find stronger evidence for predictability during recessions. We focus on individual commodities rather than an aggregated index and are thus able to analyze commodity-specific and sector-specific effects.

Our study also relates to the interplay between macroeconomic

4.2. DATA AND METHODOLOGY

aggregates and commodity volatilities. Veronesi (1999) documents the link between investors' uncertainty about fundamental variables and volatility clustering. Bansal & Yaron (2004) show that there is a strong relationship between fundamentals and time-varying stock market volatility. Mele (2007) points out the effect of stages of the economy on stock market return volatility. Paye (2012) demonstrates that macroeconomic variables have predictive power for stock market volatility, particularly around the beginning of recessions. Pierdzioch et al. (2016) use macroeconomic and financial variables to predict the volatility of gold-price fluctuations, while Prokopczuk, Symeonidis, & Wese Simen (2016) analyze the drivers of commodity variance. We contribute to this literature by analyzing not only return predictability but also volatility predictability. In addition, we extend these studies by analyzing the linkage between return and volatility predictability and business cycle stages.

The remainder of this chapter proceeds as follows. Section 4.2 introduces the data and describes the variables. Section 4.3 presents the main empirical results. Section 4.4 discusses the time-variation analysis. Section 4.5 provides the business cycle analysis. Section 4.6 discusses further results. Finally, Section 4.7 concludes.

4.2 Data and Methodology

This section introduces the data used for the empirical analysis. It then explains the main variables in detail.

4.2.1 Data

We obtain our data from three distinct sources. First, we retrieve the monthly time series of spot prices for 30 different commodities from the

Global Financial Database (GFD). Our sample period extends from January 1871 to December 2015, covering almost 150 years. We focus on commodities traded in the U.S. and that are denominated in United States Dollar (USD). Table 4.1 lists all the commodity markets we analyze. We focus on spot prices rather than on futures prices since we can obtain a much longer history for the former. Using futures prices has the advantage that one can analyze the profitability of a trading strategy from the perspective of a financial investor. Although interesting, this is not our goal. Our objective is to analyze the spot market to identify potential economic linkages between macroeconomic variables and commodity excess returns and volatilities.¹ Second, we consider most of the predictive variables employed by Goyal & Welch (2008), which they use to predict the equity premium.² Third, like Gargano & Timmermann (2014), we also consider industrial production, money supply, and the unemployment rate from the Federal Reserve Bank of St. Louis (FRED).

4.2.2 Variables

Commodity Excess Return Since some commodity markets are known to exhibit seasonal patterns, we deseasonalize the commodity returns by running the following regression on the full sample period:

$$R_{t+1} = \sum_{j=1}^{12} \delta_j D_{j,t+1} + \epsilon_{t+1}, \quad (4.1)$$

where $R_{t+1} = \left(\frac{P_{t+1} - P_t}{P_t} \right)$ is the simple return on the commodity at the end of month $t + 1$. P_{t+1} and P_t denote the price at the end of months $t + 1$ and t , respectively. $D_{j,t+1}$ are monthly dummy variables to account for different

¹Knowledge about the future price development of physical commodities is important for producers and consumers, e.g., for planning purposes of future purchases and sales.

²The extended data set is available at <http://www.hec.unil.ch/agoyal/>.

Table 4.1: Summary Statistics Commodity Returns

This table summarizes (non-annualized) key statistics for commodity returns. "Mean", "Std Dev", "Skew", and "Kurt" denote the mean, standard deviation, skewness, and kurtosis, respectively. The next three columns show the first-order autoregressive coefficient and the p-value of the Jarque-Bera and Augmented Dicky Fuller test, respectively. "First Obs." and "Nobs" denote the first observation of the time series and the number of observations. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Sector	Commodity	Mean	Std Dev	Skew	Kurt	AR(1)	JB p-value	ADF p-value	First Obs.	Nobs
Agriculturals	Butter	0.0047	0.0769	0.3462	10.8597	0.0825	<0.01	<0.01	01.1890	1512
	Cocoa	0.0042	0.0779	1.3929	13.3732	0.0578	<0.01	<0.01	01.1871	1740
	Coffee Arabica	0.0043	0.0712	1.4251	10.2132	0.2879	<0.01	<0.01	02.1960	671
	Corn Oil	0.0048	0.0850	0.9109	9.6072	0.2050	<0.01	<0.01	08.1924	1097
	Cotton	0.0028	0.0617	0.3051	14.8481	0.1524	<0.01	<0.01	01.1871	1740
	Live Cattle	0.0034	0.0525	1.0037	13.7484	0.1948	<0.01	<0.01	01.1871	1740
	Lean Hog	0.0056	0.0927	1.8014	14.5589	-0.0043	<0.01	<0.01	01.1871	1740
	Milk	0.0036	0.0528	0.7454	9.6180	0.2198	<0.01	<0.01	02.1890	1511
	Oranges	0.0283	0.2245	5.1073	79.8298	0.0111	<0.01	<0.01	02.1914	1223
	Soybean Oil	0.0046	0.0842	1.0609	8.8736	0.0763	<0.01	<0.01	02.1911	1259
	Soybeans	0.0044	0.0775	0.9309	10.9084	0.0881	<0.01	<0.01	12.1913	1225
	Soybean Meal	0.0064	0.1006	1.5570	17.1419	-0.1225	<0.01	<0.01	11.1929	1034
	Sugar	0.0040	0.0915	1.9721	14.9091	0.1623	<0.01	<0.01	01.1871	1740
	Wheat	0.0043	0.0828	0.5997	8.5674	-0.0476	<0.01	<0.01	01.1871	1740
Wool	0.0024	0.0512	0.7640	16.7863	0.3243	<0.01	<0.01	01.1890	1512	
Yellow Corn	0.0049	0.0851	0.7701	9.8353	-0.0406	<0.01	<0.01	01.1871	1740	
Energies	Coal	0.0028	0.0507	2.1719	34.2273	0.1318	<0.01	<0.01	01.1932	1008
	Heating Oil	0.0080	0.0923	0.8861	11.1544	0.0248	<0.01	<0.01	02.1967	587
	Natural Gas	0.0172	0.1641	1.7593	14.5080	-0.1702	<0.01	<0.01	01.1976	452
	Unleaded Regular Gas	0.0084	0.1118	1.6087	13.6043	-0.0541	<0.01	<0.01	11.1973	506
	WTI Oil	0.0047	0.0832	1.6486	14.9942	0.1757	<0.01	<0.01	01.1871	1740
Metals	Aluminium	0.0020	0.0470	1.2388	19.5472	0.0234	<0.01	<0.01	01.1910	1272
	Gold	0.0028	0.0345	1.8444	19.8144	0.0862	<0.01	<0.01	01.1871	1740
	High Grade Copper	0.0034	0.0691	2.0898	32.4764	0.0033	<0.01	<0.01	01.1871	1740
	Nickel	0.0064	0.1125	3.3572	30.8451	0.2174	<0.01	<0.01	01.1980	432
	Palladium	0.0097	0.1007	1.1296	10.8833	-0.0661	<0.01	<0.01	01.1968	576
	Platinum	0.0046	0.0633	1.7233	18.3757	0.1257	<0.01	<0.01	02.1910	1271
	Silver	0.0031	0.0601	1.0823	20.7601	0.0752	<0.01	<0.01	01.1871	1740
	Tin	0.0033	0.0570	0.7731	12.4076	0.2142	<0.01	<0.01	01.1871	1740
	Zinc	0.0031	0.0614	1.3287	15.4648	0.1567	<0.01	<0.01	01.1871	1740

monthly mean returns, and δ_j and ϵ_{t+1} are the coefficients associated with the dummy variables $D_{j,t+1}$, and the error term, respectively.

We then compute the excess return on a commodity as the difference between the monthly simple return on the commodity and the monthly riskless rate from the corresponding period:

$$ER_{t+1} = R_{t+1}^d - Rf_t, \quad (4.2)$$

where ER_{t+1} is the monthly excess return on the specific commodity at the end of month $t + 1$. R_{t+1}^d denotes the deseasonalized monthly commodity return. Rf_t refers to the riskless rate observed at the end of month t .³ Following Goyal & Welch (2008), we use the 1-month Treasury bill rate to proxy for the riskless rate.⁴

Commodity Volatility To compute a measure of dispersion on the basis of monthly excess return data, we follow Schwert (1989).⁵ First, we estimate a 12th-order autoregression for the commodity excess returns, i.e.:

$$ER_t = \sum_{i=1}^{12} \eta_i ER_{t-i} + \epsilon_t, \quad (4.3)$$

where ER_t is the monthly deseasonalized commodity excess return, η_i are the regression coefficients, and $\hat{\epsilon}_t$ are the realized error terms. Second, we use the absolute value of the realized error terms $|\hat{\epsilon}_t|$ to estimate a 12th-order autoregression, i.e.:

$$|\hat{\epsilon}_t| = \sum_{i=1}^{12} \rho_i |\hat{\epsilon}_{t-i}| + u_t, \quad (4.4)$$

³Throughout this chapter, we use the convention that the riskless rate is given the subscript for the time when it is observed. Thus, the riskless rate is observed at time t even though it is realized at time $t + 1$.

⁴We obtain similar results when using commodity excess returns for deseasonalization rather than commodity returns in Equation (4.1). The riskless rate does not exhibit a seasonal component and thus does not influence the results.

⁵In the case of daily excess returns, we would compute the monthly variance as the sum of the squared daily excess returns. Due to our long sample period there are no daily excess returns available. Thus, we compute the monthly volatility on the basis of monthly excess returns, following the procedure suggested by Schwert (1989).

4.2. DATA AND METHODOLOGY

where ρ_i are the regression coefficients and u_t the realized error terms. The absolute value of the fitted values represents the conditional monthly standard deviation, which we denote by σ_t , and serves as measure of dispersion.

Predictive Variables To analyze whether macroeconomic variables carry information about future commodity excess returns and volatilities, we follow the literature on stock return predictability and use 16 predictive variables that are usually considered to have predictive power for stock returns. The variables are related to the equity market, to the fixed income market, and to the overall economy.

In particular, we consider the dividend–payout ratio (de) computed as the difference between the log of monthly dividends and the log of monthly earnings. The dividends (earnings) are computed as the trailing sum of dividends (earnings) paid on the S&P 500 index over the past year. Further, we use the dividend–price ratio (dp) as the difference between the log of monthly dividends and the log of monthly prices on the S&P 500 stock index, the dividend yield (dy) as the difference between the log of monthly dividends and the log of lagged monthly prices, the earnings–price ratio (ep) as the difference between the log of monthly earnings and the log of monthly prices, the market risk premium (erp) as the difference between the change in the monthly log prices of the S&P 500 total return index and the monthly continuously compounded 1-month Treasury bill rate, and the monthly stock variance ($svar$) computed as the sum of squared daily returns on the S&P 500.

As interest rate-related variables, we use the default return spread (dfr) computed as the difference between monthly long-term U.S. corporate bond returns on AAA- and BAA-rated bonds and monthly long-term U.S. government bond returns, the default yield spread (dfy) as the

difference between monthly U.S. BAA- and AAA-rated corporate bond yields, the monthly long-term U.S. government bond returns (ltr), the monthly long-term U.S. government bond yields (lty), the monthly 3-month Treasury bill rate (tbl), and the term spread (tms) as the difference between the monthly long-term yield on U.S. government bonds and the monthly 3-month Treasury bill rate.

As variables that are related to the overall economy, we use the growth of industrial production ($\Delta indpro$) computed as the change in the logarithm of the monthly industrial production, the growth of the money stock M1 ($\Delta M1$) as the change in the logarithm of the monthly money stock, the monthly inflation rate ($infl$) calculated as the simple return on the U.S. consumer price index (CPI), and the monthly unemployment rate ($unrate$).⁶

4.3 Empirical Analysis

4.3.1 Summary Statistics

Before turning to our main analysis, it is instructive to look at the summary statistics and correlation matrices of our variables. We classify the commodities into three groups: agricultural, energy, and metal commodities.

Table 4.1 reports some (non-annualized) summary statistics of the deseasonalized returns. We observe that the average monthly returns are between 0.24 % for wool and 2.83 % for oranges, 0.28 % for coal and 1.72 %

⁶The monthly data of the dividends on the S&P 500 index, earnings on the S&P 500, prices on the S&P 500, U.S. BAA- and AAA-rated corporate bond returns, U.S. BAA- and AAA-rated corporate bond yields, long-term U.S. government bond returns, long-term U.S. government bond yields, 1-month Treasury bill rate, and 3-month Treasury bill rate are obtained from the extended data set provided by Goyal & Welch (2008). The monthly data for industrial production, money supply M1, and unemployment rate with tickers "INDPRO", "M1", and "UNRATE" are obtained from FRED. The monthly U.S. consumer price index (ticker: "CPUSAM") and the monthly prices of the S&P 500 total return index (ticker: "_SPXTRD") are retrieved from the GFD.

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for natural gas, and 0.20 % for aluminium and 0.97 % for palladium in the agricultural, energy, and metal sector, respectively. These numbers are in line with former studies of, e.g., Gorton, Hayashi, & Rouwenhorst (2012), although they analyze futures returns.⁷ Table 4.2 presents some (non-annualized) summary statistics of the volatilities. They range from 2.97 % for milk to 13.60 % for oranges in the agricultural sector, 2.64 % for coal to 10.12 % for natural gas in the energy sector, and 1.67 % for gold to 7.34 % for nickel in the metal sector. The high first-order autoregressive coefficients are noteworthy, indicating a higher persistence and thus a potentially better predictability on the basis of their own current values, compared to commodity returns.

Table C.1 of the Appendix to this chapter reports some (non-annualized) summary statistics for the predictor variables. In particular, the classical predictors de , dp , dy , and ep are characterized by high monthly standard deviations between 31.58 % and 43.11 %, respectively. Most predictors also exhibit high first-order autoregressive coefficients, indicating that they might be predictable themselves.

Tables C.2 to C.4 of the Appendix to this chapter report the correlation matrices of the commodity returns and volatilities, and the predictive variables. In Table C.2, we see that in the agricultural sector, the related commodities soybeans, soybean oil, and soybean meal exhibit high correlations between 0.43 and 0.82, indicating a similar information content. Further, we notice that wheat, yellow corn, and soybean commodities show notable correlations between 0.35 and 0.60, which might be due to the fact that they serve as substitutes. Within the energy sector, we observe co-movements across heating oil, unleaded regular gas, and WTI oil,

⁷The high average monthly return of oranges is explained through sharp changes in the monthly price level over time.

Table 4.2: Summary Statistics Commodity Volatilities

This table summarizes (non-annualized) key statistics for commodity volatilities. "Mean", "Std Dev", "Skew", and "Kurt" denote the mean, standard deviation, skewness, and kurtosis, respectively. The next three columns show the first-order autoregressive coefficient and the p-value of the Jarque-Bera and Augmented Dicky Fuller test, respectively. "First Obs." and "Nobs" denote the first observation of the time series and the number of observations. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Sector	Commodity	Mean	Std Dev	Skew	Kurt	AR (1)	JB p-value	ADF p-value	First Obs.	Nobs
Agriculturals	Butter	0.0476	0.0257	1.5002	6.8745	0.8131	<0.01	<0.01	01.1892	1488
	Cocoa	0.0472	0.0238	0.8376	3.8873	0.6544	<0.01	<0.01	01.1873	1716
	Coffee Arabica	0.0481	0.0168	1.1906	6.8446	0.6684	<0.01	<0.01	02.1962	647
	Corn Oil	0.0563	0.0255	1.6649	8.3588	0.6606	<0.01	<0.01	08.1926	1073
	Cotton	0.0394	0.0176	2.2277	14.5611	0.6599	<0.01	<0.01	01.1873	1716
	Live Cattle	0.0348	0.0104	1.6270	9.5387	0.4651	<0.01	<0.01	01.1873	1716
	Lean Hog	0.0637	0.0143	1.8366	10.2461	0.5721	<0.01	<0.01	01.1873	1716
	Milk	0.0297	0.0179	1.5367	6.7992	0.7723	<0.01	<0.01	02.1892	1487
	Oranges	0.1360	0.0610	3.7660	38.1728	0.6972	<0.01	<0.01	02.1916	1199
	Soybean Oil	0.0571	0.0273	1.3680	5.9171	0.7275	<0.01	<0.01	02.1913	1235
	Soybeans	0.0518	0.0233	2.0257	10.7609	0.6684	<0.01	<0.01	12.1915	1201
	Soybean Meal	0.0687	0.0274	1.3406	6.5212	0.6474	<0.01	<0.01	11.1931	1010
	Sugar	0.0563	0.0293	1.1128	3.8258	0.9089	<0.01	<0.01	01.1873	1716
	Wheat	0.0567	0.0205	0.8654	4.6742	0.7625	<0.01	<0.01	01.1873	1716
Wool	0.0284	0.0160	2.3342	13.2643	0.5975	<0.01	<0.01	01.1892	1488	
Yellow Corn	0.0594	0.0207	1.1023	5.3220	0.5444	<0.01	<0.01	01.1873	1716	
Energies	Coal	0.0264	0.0194	2.8941	18.2071	0.4091	<0.01	<0.01	01.1934	984
	Heating Oil	0.0631	0.0284	1.1639	5.9624	0.6948	<0.01	<0.01	02.1969	563
	Natural Gas	0.1012	0.0633	1.4952	5.8421	0.7659	<0.01	<0.01	01.1978	428
	Unleaded Regular Gas	0.0752	0.0282	1.0959	5.4098	0.3854	<0.01	<0.01	11.1975	482
	WTI Oil	0.0461	0.0319	1.4269	5.4384	0.8702	<0.01	<0.01	01.1873	1716
Metals	Aluminium	0.0239	0.0218	1.8390	7.7716	0.8491	<0.01	<0.01	01.1912	1248
	Gold	0.0167	0.0189	1.7882	6.4849	0.8922	<0.01	<0.01	01.1873	1716
	High Grade Copper	0.0374	0.0207	2.2678	11.8227	0.7846	<0.01	<0.01	01.1873	1716
	Nickel	0.0734	0.0336	3.2820	25.4281	0.3805	<0.01	<0.01	01.1982	408
	Palladium	0.0640	0.0160	0.8444	4.1945	0.3538	<0.01	<0.01	01.1970	552
	Platinum	0.0354	0.0203	1.7032	7.4293	0.7473	<0.01	<0.01	02.1912	1247
	Silver	0.0339	0.0258	2.1273	10.6922	0.8046	<0.01	<0.01	01.1873	1716
	Tin	0.0363	0.0129	1.0356	4.5111	0.7611	<0.01	<0.01	01.1873	1716
Zinc	0.0358	0.0202	2.2554	13.7324	0.7831	<0.01	<0.01	01.1873	1716	

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indicated by high correlations between 0.63 and 0.74.⁸ In the metal sector all commodities exhibit moderate correlations. However, there is a high degree of correlation between silver and gold (0.74), which is also consistent with former studies.

In Table C.3 of the Appendix to this chapter, we observe similar patterns for volatilities within the sectors. There are additional notable correlations between tin and zinc volatility of 0.46, nickel and high grade copper of 0.47, and soybean oil and corn oil of 0.48. In Table C.4 of the Appendix to this chapter, we see high correlations between the interest rate-related variables, namely, *ltr* and *dfr* of -0.46 , *lty* and *dfy* of 0.51 , and *tbl* and *lty* of 0.89 ; also between *unrate* and *tms* of 0.56 , and *unrate* and *dfy* of 0.64 . We also observe similar information content between the related variables *ep* and *dp*, and *dy*, respectively, indicated by a correlation of 0.78 . Finally, *dp* and *dy* exhibit a correlation of 0.99 .

4.3.2 Return Predictability

In-Sample Analysis To assess the in-sample predictability for commodity excess returns, we follow the methodology of Rapach & Wohar (2006). We estimate the following regression model of the k -month(s) ahead excess return on a constant and the predictive variable:

$$ER_{t,t+k} = \alpha_k + \beta_k X_t + \epsilon_{t,t+k}, \quad (4.5)$$

where $ER_{t,t+k}$ is the commodity excess return from month t to $t + k$, α_k and β_k are the intercept and slope parameters of the respective forecast horizon, respectively, and $\epsilon_{t,t+k}$ represents the regression error term over the k month(s). X_t is the predictive variable observed at the end of month t .

⁸Which is not surprising, because heating oil is derived from crude oil.

Table 4.3 summarizes the results for each predictive variable, predicting the next month's and the next year's excess return. Panel (A) reports the results for the short-term predictability, whereas Panel (B) focuses on the long-term predictability. Tables 4.4 and 4.5 provide more detailed regression results. Based on the regression model, we examine whether the expected commodity excess return is time-varying or constant. Under the null hypothesis that the future commodity excess return cannot be predicted using X_t , we would expect that the slope would not be significantly different from zero, i.e., $\beta_k = 0$. Thus, the expected commodity excess return would simply be constant, and we would conclude that the best estimate of the future expected excess return is simply its recursive mean. Under the alternative hypothesis, we would expect to see that the slope loading is statistically significant, indicating evidence of predictability. We use the bootstrapped distribution proposed by Rapach & Wohar (2006) to obtain reliable statistical inferences. Thus, we avoid a small-sample bias (Stambaugh, 1999) and serial correlation in the error terms (Richardson & Stock, 1989).⁹

Analyzing the short-term predictability, Panel (A) of Table 4.3 reports the percentage of commodities for which the variable under consideration has predictive power. We find that $\Delta indpro$ and dfr are the most frequent statistically significant variables in the univariate regressions in-sample. This is also supported by their t -statistics shown in Table 4.4. Other frequently significant predictors are erp , $infl$, ltr , tbl , and tms , confirming the previous results of, e.g., Bessembinder & Chan (1992) and Sadorsky (2002). It is also worth analyzing the predictive power of each individual variable. The in-sample R^2 s, presented in Table 4.4, reveal that $\Delta indpro$ in

⁹Under the null hypothesis of no predictability, we generate a pseudo sample and compute the respective in- and out-of-sample statistics. For details, we refer to Rapach & Wohar (2006). For the multiple variable regression case, we adjust the procedure accordingly.

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Table 4.3: Summary Return and Volatility Predictability

This table reports a summary of the regression results of monthly excess returns on a constant and the lagged predictive variable (Panel (A) and (B)), and the regression results of monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable (Panel (C) and (D)). In Panel (A) and (B), we report the percentage of significant in-sample and out-of-sample R^2 s across the variables of predicting the next month's and next year's excess return. In Panel (C) and (D), we report the percentage of significant in-sample F -statistics of the difference between the adjusted R^2 s of the unrestricted and restricted model, and out-of-sample R^2 s across the variables of predicting the next month's and next year's volatility. "de" denotes the dividend–payout ratio, " $\Delta indpro$ " the growth of industrial production, and " $\Delta M1$ " the growth of money supply $M1$. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. All data are sampled at the monthly frequency.

Panel (A): Return Predictability (1 Month)				Panel (B): Return Predictability (12 Months)			
In-Sample		Out-of-Sample		In-Sample		Out-of-Sample	
$\Delta indpro$	63.33	$\Delta indpro$	23.33	<i>tbl</i>	90.00	<i>tbl</i>	70.00
<i>dfr</i>	46.67	<i>erp</i>	20.00	<i>lty</i>	86.67	<i>dfy</i>	56.67
<i>erp</i>	43.33	<i>dfr</i>	16.67	<i>ep</i>	83.33	<i>lty</i>	53.33
<i>infl</i>	43.33	$\Delta M1$	10.00	<i>tms</i>	80.00	<i>tms</i>	43.33
<i>ltr</i>	30.00	<i>infl</i>	10.00	$\Delta indpro$	60.00	<i>de</i>	33.33
<i>tbl</i>	30.00	<i>ltr</i>	6.67	<i>dy</i>	56.67	<i>dy</i>	33.33
<i>tms</i>	30.00	<i>tms</i>	3.33	<i>svar</i>	56.67	<i>dp</i>	26.67
$\Delta M1$	26.67	<i>de</i>	0.00	<i>unrate</i>	56.67	<i>infl</i>	26.67
<i>svar</i>	20.00	<i>dfy</i>	0.00	<i>dfy</i>	53.33	$\Delta M1$	23.33
<i>lty</i>	16.67	<i>dp</i>	0.00	<i>dp</i>	50.00	<i>ep</i>	23.33
<i>dp</i>	13.33	<i>dy</i>	0.00	<i>infl</i>	46.67	<i>unrate</i>	23.33
<i>ep</i>	10.00	<i>ep</i>	0.00	<i>de</i>	40.00	<i>erp</i>	20.00
<i>dfy</i>	6.67	<i>lty</i>	0.00	<i>erp</i>	40.00	$\Delta indpro$	16.67
<i>dy</i>	6.67	<i>svar</i>	0.00	<i>dfr</i>	33.33	<i>dfr</i>	3.33
<i>de</i>	3.33	<i>tbl</i>	0.00	$\Delta M1$	26.67	<i>svar</i>	3.33
<i>unrate</i>	0.00	<i>unrate</i>	0.00	<i>ltr</i>	16.67	<i>ltr</i>	0.00

Panel (C): Volatility Predictability (1 Month)				Panel (D): Volatility Predictability (12 Months)			
In-Sample		Out-of-Sample		In-Sample		Out-of-Sample	
<i>dp</i>	60.00	<i>dp</i>	40.00	$\Delta indpro$	46.67	<i>ep</i>	23.33
<i>dy</i>	56.67	<i>dy</i>	40.00	<i>dfy</i>	43.33	<i>dfy</i>	20.00
<i>svar</i>	56.67	<i>infl</i>	36.67	<i>unrate</i>	36.67	<i>tms</i>	20.00
<i>dfy</i>	50.00	<i>lty</i>	36.67	<i>de</i>	33.33	<i>dy</i>	13.33
<i>unrate</i>	50.00	<i>dfy</i>	30.00	<i>dp</i>	33.33	<i>unrate</i>	13.33
<i>ep</i>	46.67	<i>ep</i>	30.00	<i>dy</i>	33.33	$\Delta indpro$	10.00
<i>lty</i>	43.33	<i>unrate</i>	30.00	<i>ep</i>	33.33	<i>dp</i>	10.00
<i>infl</i>	40.00	<i>de</i>	20.00	<i>svar</i>	33.33	<i>ltr</i>	10.00
<i>de</i>	36.67	$\Delta indpro$	16.67	<i>tms</i>	33.33	<i>tbl</i>	10.00
<i>tbl</i>	36.67	<i>erp</i>	16.67	<i>tbl</i>	3.33	<i>de</i>	6.67
<i>tms</i>	33.33	<i>tbl</i>	13.33	$\Delta M1$	16.67	$\Delta M1$	6.67
<i>erp</i>	23.33	$\Delta M1$	6.67	<i>dfr</i>	13.33	<i>svar</i>	6.67
$\Delta M1$	20.00	<i>dfr</i>	3.33	<i>erp</i>	13.33	<i>erp</i>	3.33
$\Delta indpro$	16.67	<i>ltr</i>	3.33	<i>ltr</i>	13.33	<i>infl</i>	3.33
<i>dfr</i>	10.00	<i>svar</i>	3.33	<i>infl</i>	10.00	<i>dfr</i>	0.00
<i>ltr</i>	10.00	<i>tms</i>	3.33	<i>lty</i>	0.00	<i>lty</i>	0.00

the case of wool has the highest predictive power for future excess returns ($R^2 = 3.04\%$).

The results analyzing the long-term predictability of excess returns are shown in Panel (B) of Table 4.3. We ascertain that *tbl* and *lty* are the most frequent statistically significant variables in the univariate regressions, documented by their large *t*-statistics, shown in Table 4.5, among others, of -11.15 and -8.24 for, e.g., live cattle. The degree of predictability for *ep*, *tms*, and $\Delta indpro$ is also noteworthy. We note that *tbl* has the highest predictive power in the univariate regressions in the case of live cattle ($R^2 = 9.86\%$).

Overall, our findings are consistent with the literature. Fama & French (1989) show that *tms* is related to shorter-term business cycles, whereas *dfy* and *dy* more to long-term cycles. Chen (1991) documents that $\Delta indpro$ and short-term interest yields are positively correlated to expected returns.¹⁰ The relative high correlation between *lty* and *tbl* support the findings and indicate a similar variation. The results also suggest that bond returns, specifically *dfr* and *ltr*, are less suitable for predicting commodity excess returns.

To summarize, in the long-term we find a substantial increase in the frequency of significant predictions by the individual variables. Some variables predict (in-sample) excess returns better in the short-term ($\Delta indpro$), and others better in the long-term (*lty*). Further, there are variables that predict excess returns well in the short- and in the long-term (*tbl*).

Out-of-Sample Results We analyze the out-of-sample results in the spirit of Goyal & Welch (2008). To obtain the first out-of-sample forecast, we

¹⁰In detail, Chen (1991) shows that lagged industrial production, the default yield spread, the term spread, short-term interest yields, and the dividend yield are related to future economic growth. Simultaneously, he shows that the market excess return is positively correlated with future economic conditions.

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estimate the forecasting model presented in Equation (4.5) using an initial estimation window of 10 years. We then generate the first excess return forecast by using the parameter estimates and the most recent observation of the predictive variable in the estimation period. For the following month, we roll the estimation period by one observation month and re-estimate the forecasting model. With the new parameter estimates, we forecast the commodity excess return for the next month. The out-of-sample analysis is based on a rolling window to capture the potential time-varying relationship. To address the average length of a common business cycle, we follow Çakmaklı & van Dijk (2016) and use a 10-year rolling window.¹¹

To be able to compare the out-of-sample performance of different models, we use the out-of-sample R^2 (R_{oos}^2), proposed by Campbell & Thompson (2008), which is given as follows:

$$R_{oos}^2 = 1 - \frac{MSE_u}{MSE_r}, \quad (4.6)$$

where MSE_u and MSE_r are the mean squared errors of the unrestricted and restricted model, respectively. The unrestricted model is presented in Equation (4.5), whereas in the restricted model we assume that $\beta_k = 0$ by imposing the null hypothesis that excess returns are unpredictable. Thus, based on the R_{oos}^2 we answer the question: How large is the additional predictive power using the variable X_t in excess of the predictive power by using the historical mean? An increasing predictive power is associated with a positive R_{oos}^2 . A variable is considered to have predictive power if it exhibits a positive and significant R_{oos}^2 , thus, displaying an overall superior performance of the predictive variable.

To be able to make a statement whether the improvement is statistically

¹¹We analyze the time series for structural breaks and our findings suggest the use of a rolling window.

significant, we compute the $MSE - F$ statistic of McCracken (2007):

$$MSE - F = (N - k + 1) \times \left(\frac{MSE_r - MSE_u}{MSE_u} \right), \quad (4.7)$$

where N denotes the number of out-of-sample forecasts, and k the degree of overlapping observations.¹² All other variables are as previously defined. The null hypothesis is that the restricted model performs at most as well as the unrestricted model, i.e., $MSE_r \leq MSE_u$. Thus, the alternative is that the unrestricted model provides smaller forecast errors than the restricted model.

We first analyze the short-term predictability. The results are summarized in Panel (A) of Table 4.3. We observe that the variables performing best in-sample also perform best out-of-sample. In particular, $\Delta indpro$ is the best performing variable, being significant for 23.33 % of the cases and showing the highest predictive power in the case of natural gas ($R_{oos}^2 = 2.34$ %), documented in Table 4.4.

We now analyze the long-term predictability, given in Panel (B) of Table 4.3. We observe similar patterns as in-sample. Interest rate-related variables, especially tbl , dfy , lty , and tms are the most frequently significant predictive variables with a frequency up to 70 %. dfy exhibits the highest predictive power in the univariate regressions in the case of gold ($R_{oos}^2 = 13.98$ %), shown in Table 4.5.

Overall, similar to the in-sample analysis, in the long-term we find a substantial increase in the frequency of significant predictions by the variables. $\Delta indpro$, dfy , and erp perform best in the short-term, whereas interest rate-related variables, specifically, tbl , dfy , lty , and tms , do best in the long-term. In total, our results are consistent with the literature. We detect a moderate short-term predictability, while the degree of predictability is stronger for longer horizons.

¹²Analogously to Equation (4.5), k equals 1 (12) in the case of predicting the next month's (next year's) excess return.

4.3.3 Volatility Predictability

We now turn our attention to the predictability of commodity volatilities. In particular, we ask the question: Can any of the forecasting variables considered for returns be used to predict the next month's and the next year's volatility, respectively?

In-Sample Analysis Using all the sample information, we estimate the following regression model:

$$\sigma_{t,t+k} = \xi_k + \gamma_k X_t + \delta_k \sigma_t + u_{t,t+k}, \quad (4.8)$$

where $\sigma_{t,t+k}$ is the monthly (average) volatility from month t to $t+k$. ξ_k , γ_k , and δ_k are the intercept and slope parameters, respectively. X_t represents the forecasting variable observed at the end of month t . Finally, $u_{t,t+k}$ is the regression error term over the k month(s). To account for the persistence in volatility, we include the lagged volatility, σ_t , as an additional predictive variable. Accordingly, we use a fitted AR(1) process as naive benchmark to address this property.¹³

Table 4.3 summarizes the results for each predictive variable, predicting the next month's and the next year's volatility. Tables 4.6 and 4.7 provide more detailed regression results. In doing so, we now present the in-sample R^2 improvement (ΔR^2) of the unrestricted model rather than the individual R^2 .¹⁴ We start again by analyzing the short-term predictability, shown in Panel (C) of Table 4.3. The results reveal that all variables have

¹³The strong persistence of commodity volatilities is indicated by their high AR(1) coefficients, shown in Table 4.2, in comparison to commodity returns that show substantial lower AR(1) coefficients (see Table 4.1). Thus, the best predictor for future volatility is mainly its current value. Accordingly, a fitted AR(1) process represents the natural naive benchmark rather than the historical volatility.

¹⁴In more detail, we compute ΔR^2 as the difference between the partial in-sample R^2 s, i.e., as the difference between the adjusted R^2 of the unrestricted and restricted model. Using the corresponding sum of squared residuals, we compute an F -test to determine the significance based on a bootstrapped distribution.

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Table 4.7: Volatility Predictability (12 Months)

*This table reports the regression results of monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable(s). We predict the next year's volatility. Statistical inferences are based on a bootstrapped distribution. "de" denotes the dividend-payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "inflt" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. "MSA" and "MFC" denote the model selection and restricted model, and the combination. ΔR² and R_{nos}² are the in-sample difference between the adjusted R²'s of the unrestricted and restricted model, and the out-of-sample R², respectively. We report the t-statistics of the respective predictive variables in parentheses. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.*

Commodity	Statistic	de	Δindpro	ΔM1	dfr	dfy	dp	dy	ep	erp	inflt	ltr	lty	svar	tbl	tms	unrate	MSA	MFC
Butter	ΔR ²	0.00	0.00***	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
	R _{nos} ² <i>t - stat</i>	-3.53 (-0.26)	-1.31 (-3.00)	-2.79 (0.43)	-0.88 (-0.03)	-3.77 (-0.87)	-1.25 (-1.04)	-4.07 (-0.96)	-2.28 (-0.91)	-0.85 (0.66)	-1.46 (-0.98)	-1.52 (0.82)	-1.52 (0.82)	-0.96 (0.82)	0.00 (0.95)	-7.90 (1.27)	-6.57 (-1.27)	-2.27 (0.97)	-15.96*
Cocoa	ΔR ²	0.00	0.00	0.00	0.00	0.01***	0.01***	0.01***	0.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01*		
	R _{nos} ² <i>t - stat</i>	-2.81 (-2.19)	-1.38 (1.04)	-2.35 (-0.55)	-0.71 (-0.08)	-4.95 (-2.78)	1.79*** (-3.33)	1.80*** (-3.39)	2.09*** (-3.30)	-0.64 (-1.94)	-0.64 (-0.47)	-0.84 (0.11)	-1.80 (-1.05)	-5.37 (0.16)	-15.07 (1.50)	-4.78 (0.75)	-6.10 (-1.36)	-4.74 (-2.24)	-20.37***
Coffee Arabica	ΔR ²	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01*	0.04***	0.51**		-2.034.13
	R _{nos} ² <i>t - stat</i>	-3.42 (0.30)	-1.06 (-0.38)	-1.81 (1.22)	-1.01 (-0.11)	-2.30 (-0.95)	-2.74 (0.76)	-2.74 (0.67)	-6.21 (0.34)	-0.21 (0.34)	-0.77 (-0.68)	-1.08 (-0.38)	-1.40 (-0.44)	-4.35 (-0.27)	-8.20 (-0.68)	-2.23 (-2.08)	2.33*** (3.95)	0.01** (1.29)	-35.07***
Corn	ΔR ²	0.00	0.00	0.00	0.00	0.00	0.00	0.01*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01***	0.00		
	R _{nos} ² <i>t - stat</i>	0.71*** (-1.23)	-0.40 (0.28)	-0.69 (0.18)	-1.38 (0.70)	-0.82 (-0.77)	-1.75 (-2.08)	-1.79 (-2.24)	2.71*** (-3.25)	-1.38 (-1.30)	-1.38 (-1.30)	-1.05 (0.27)	-1.40 (-1.25)	-3.04 (-0.11)	-32.03 (-0.58)	-2.00 (1.08)	0.45*** (2.62)	-1.35 (-1.21)	-15.72***
Cotton	ΔR ²	0.00	0.01***	-0.82	-1.21	-1.35	-1.52	-1.75	-2.70	-0.34	-0.60	-1.34	-3.86	-13.95	-2.68	0.00	0.00	0.00	
	R _{nos} ² <i>t - stat</i>	-1.71 (-1.61)	-0.23 (-3.04)	-0.83 (-1.00)	-0.52 (-0.36)	-1.47 (-0.25)	-1.08 (-0.99)	-1.08 (-1.08)	-0.33 (-1.14)	-0.31 (-1.60)	-0.31 (-1.60)	-0.52 (-2.50)	-0.67 (-0.61)	-4.06 (-0.29)	-13.00 (-0.48)	-3.90 (-0.50)	0.00 (0.63)	0.00 (0.44)	-19.53*
Live Cattle	ΔR ²	0.00	0.01***	-0.33	-1.05	-3.28	-0.90	-0.33	-0.31	-0.59	-0.52	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	R _{nos} ² <i>t - stat</i>	-2.91 (0.49)	-0.83 (-3.02)	-0.32 (1.54)	-1.05 (-0.48)	-3.28 (-2.95)	-0.90 (-1.05)	-0.33 (-1.14)	-0.31 (-1.60)	-0.31 (-1.60)	-0.59 (-2.50)	-0.52 (-2.50)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-37.12**
Lean Hog	ΔR ²	0.00	0.03***	0.00	0.00	0.00	0.00	0.01*	0.02***	0.00	0.00	0.00	0.00	0.01**	0.00	0.00	0.00	0.00	
	R _{nos} ² <i>t - stat</i>	-0.23 (0.94)	-1.31 (-3.78)	-1.42 (-3.78)	-0.79 (-1.15)	-3.28 (-0.33)	-2.20 (-2.15)	-2.65 (-2.27)	-2.65 (-2.27)	0.46*** (-3.30)	0.00* (-0.90)	-0.87 (-1.35)	-1.01 (-0.91)	-4.02 (-0.50)	-2.33 (-2.10)	-2.33 (-0.37)	-3.17 (-0.18)	-3.17 (-0.28)	-18.65**
Milk	ΔR ²	0.00	0.00***	-0.18	-0.83	-0.52	-3.56	-3.85	-2.68	-1.17	-1.86	-1.47	-4.13	-5.60	-4.75	0.00	0.00	0.00	
	R _{nos} ² <i>t - stat</i>	-6.18 (-0.80)	-1.08 (-3.04)	-0.83 (-1.00)	-0.52 (-1.26)	-3.56 (-1.46)	-3.85 (-1.76)	-3.85 (-1.69)	-2.68 (-1.31)	-2.68 (-1.31)	-1.17 (-0.83)	-1.86 (-0.67)	-1.47 (-0.29)	-4.13 (0.46)	-5.60 (0.11)	-4.75 (0.97)	0.00 (-1.23)	0.00 (-1.95)	-21.83**
Oranges	ΔR ²	0.00	0.00	0.00	0.00	0.00	0.01*	0.00	0.00	0.01**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	R _{nos} ² <i>t - stat</i>	-3.98 (-0.99)	-1.75 (-0.87)	-1.20 (-0.44)	-1.42 (-0.44)	-3.52 (-1.36)	-3.15 (-1.83)	-2.62 (-2.11)	-2.62 (-1.83)	-2.24 (-2.28)	-0.38 (-2.11)	-0.94 (-0.54)	-0.58 (-1.87)	-2.95 (-0.99)	-3.03 (-0.50)	-2.97 (-0.04)	0.00 (0.00)	0.00 (0.02)	-25.08**
Soybean Oil	ΔR ²	0.00	0.00	0.00	0.00	0.00*	0.01**	0.01**	0.01***	0.00	0.00	0.00	0.00	0.00	0.00	0.00**	0.02***		
	R _{nos} ² <i>t - stat</i>	-0.94 (-0.23)	-0.93 (0.10)	-1.59 (-0.48)	-1.40 (-0.50)	-4.85 (-1.96)	-1.12*** (-3.14***)	0.90*** (-2.67)	3.14*** (-2.67)	-1.73 (-2.75)	-1.73 (-2.75)	-0.47 (-0.41)	-1.30 (-1.10)	-5.43 (-0.33)	-13.20 (-0.66)	-2.78 (0.66)	-3.18 (-2.17)	-3.82 (-3.70)	-12.67**
Soybeans	ΔR ²	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	R _{nos} ² <i>t - stat</i>	-2.59 (0.17)	-0.66 (-0.22)	-0.35 (-0.87)	-0.58 (-0.63)	-1.73 (-0.81)	-1.14 (-1.84)	-1.14 (-1.88)	-1.14 (-1.88)	0.62*** (-2.14)	-1.04 (-0.34)	-1.94 (-0.41)	-3.42 (-0.65)	-6.17 (-0.69)	-3.45 (-2.12)	-2.42 (-1.31)	-0.83 (-1.38)	-2.12 (-1.66)	-22.22**

predictive power for future volatilities. In particular, dp , dy , and $svar$ provide evidence for predictability in the univariate regressions by their statistically significant t -statistics of 6.24 and 5.09 in the case of live cattle, and 4.29 for the commodity tin, respectively, shown in Table 4.6. Other frequently significant predictive variables are dfy , $unrate$, ep , and lty .

Next, we analyze the long-term predictability of volatilities; here, the results are presented in Panel (D) of Table 4.3. We observe that all variables exhibit predictive power for future volatilities, except lty . Especially, frequent statistically significant variables are $\Delta indpro$ and dfy , indicated by t -statistics of -3.78 for lean hog and -5.17 for unleaded regular gas, respectively, and are associated with ΔR^2s of 0.03 % and 0.15 %, documented in Table 4.7. Other frequently significant variables are $unrate$, de , and dp .

Overall, we find similar patterns for the predictive variables in both the short- and the long-term. However, we do not find an increase in the frequency of significant predictions by the variables in the long-term. These results are interesting for several reasons. First and possibly most surprising, they indicate that there is predictability of volatility beyond its own lag, although volatility is known to be strongly persistent. Second, the findings reveal that many variables that predict commodity returns also predict commodity volatilities. These are, among others, $\Delta indpro$, $svar$, dfy , and tms . These results have an important implication for investigating the predictive power of variables. It is advisable to examine whether variables predict not only excess returns but also volatilities.

Out-of-Sample Results We perform our out-of-sample volatility prediction analysis in a similar way as for returns. In doing so, first, we use the first 10 years of observations to initially estimate the model parameters (see Equation (4.8)). We then predict the next month. We roll the training

4.4. TIME-VARIATION IN PREDICTABILITY

window by one observation month and repeat all steps. Also here, we account for the possibility of structural breaks and use a 10-year rolling window. This procedure is analog to the return predictability analysis, however, we forecast volatility rather than the excess return.

Analyzing the short-term predictability, Panel (C) of Table 4.3 shows that variables performing best in-sample also perform best out-of-sample. Specifically, dp , dy , $infl$, lty , and dfy perform best with a frequency up to 40.00 %. Further, lty has the highest predictive power in the univariate regressions in the case of gold ($R^2_{oos} = 6.16\%$), shown in Table 4.6.

Analyzing the long-term predictability, Panel (D) of Table 4.3 documents similar results as in-sample. In particular ep , dfy , tms , dy , and $unrate$ are the most frequently statistically significant variables predicting future volatilities with a frequency up to 23.33 %. Further, tms has the highest predictive power in the univariate regressions in the case of natural gas ($R^2_{oos} = 5.56\%$), documented in Table 4.7.

Overall, we find a similar fraction of significant predictions by variables in both the short- and long-term. It seems that, despite the high degree of persistence, commodity volatilities are, to some extent, significantly predictable out-of-sample.

4.4 Time-Variation in Predictability

To further analyze the effects of important changes in commodity markets on the predictability of commodity excess returns and volatilities, we examine the variation of predictability around specific events on the basis of a kitchen sink approach.¹⁵ In particular, we ask the question: Does the

¹⁵We run a multiple regression in which we include all predictive variables. dy , ep , and tbl have been excluded due to high correlations and multicollinearity. In the case of volatility predictability, we again include lagged volatility as a further predictive variable, and we present the ΔR^2s .

introduction of derivatives trading systematically affect the predictability of commodity returns and volatilities?

We use data from the Commodity Research Bureau (CRB) to determine the time points of introduction of commodity futures and options, respectively. Moreover, we follow Guidolin & Tam (2013) and additionally use the beginning of the global financial crisis in 2007 as a further break point. Following the definition of U.S. business cycle stages from the National Bureau of Economic Research (NBER), we use December 2007 as starting point for the global financial crisis.

Tables 4.8 to 4.11 report the (in-sample) adjusted R^2s and ΔR^2s , respectively, for different horizons computed on the basis of 10 years of observations before and after the break point. To be able to compare the adjusted R^2s (ΔR^2s), we compute them using 10 years of data (120 observations) before and after the respective event. In the case of the global financial crisis, we use 97 observations due to limited data availability after the event.¹⁶ Panel (A) shows the results with respect to the introduction of derivatives trading, whereas Panel (B) shows them with respect to the beginning of the global financial crisis. Lettau & Van Nieuwerburgh (2008) and Pettenuzzo & Timmermann (2011) analyze the relationship between break points and predictability, and argue that break points are associated with an increase in investment risk due to model instability. Thus, we expect a decrease in the return and volatility predictability after the break points.

4.4.1 Time-Variation in Return Predictability

We start by assessing the time-variation in return predictability. Prior to and after the introduction of futures and options trading, respectively,

¹⁶In the case of futures and options, we impose the restriction that at least 10 years of observations must be available to compute the adjusted R^2s . Missing values in the table are due to a lack of data availability.

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only few commodity excess returns are significantly predictable in the short-term, documented in Panel (A) of Table 4.8. The highest predictability is observable in the case of WTI oil (adjusted $R^2 = 19.20$ %) and high grade copper (adjusted $R^2 = 16.80$ %) prior to the introduction of futures and options, respectively. However, in Panel (B) we observe that, since the global financial crisis, there is a substantial increase in the predictability, in particular in the case of energy commodities. The adjusted R^2 s range from 10.68 % for nickel to 37.10 % for natural gas.

Panel (A) of Table 4.9 reports the results for the long-term and indicates an extensive significant predictability prior to and after the introduction of futures and options trading, respectively. In accordance with our expectation, we find a higher predictability prior to the break points, indicated by adjusted R^2 s ranging from 11.02 % for platinum to 68.36 % for gold, and 7.31 % for platinum to 68.27 % for gold in the case of futures and options, respectively. In the case of the global financial crisis, documented in Panel (B), all commodities show significant predictability before and after the break point. We detect similar patterns as before, displaying a stronger predictability after the break point, indicated by adjusted R^2 s between 28.23 % for butter and 86.49 % for platinum.

Overall, the results provide evidence in favor of our expectation in the case of futures and options trading, respectively. The introduction of derivatives trading seems to be associated with a reduction in commodity return predictability. The global financial crisis represents an exception by showing stronger predictability after December 2007. Specifically here, energy commodities signal a substantial increase in the predictability.

Table 4.8: Time-Variation in Return Predictability (1 Month)

This table summarizes the results about the time-variation in the in-sample return predictability. We predict the next month's excess return. We report the adjusted R^2 's of a kitchen sink approach. We consider three different events. First, the introduction of futures. Second, the introduction of options. Third, the beginning of the global financial crisis in December 2007. "Start" denotes the starting point of trading futures and options, respectively. " R^2 (prior)" and " R^2 (after)" indicate the in-sample R^2 prior to and after the time point of introduction, respectively. We use 120 observations to compute the R^2 's. Here, we impose the restriction that at least 10 years of observations must be available. In the case of the global financial crisis, 97 observations are used. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Panel (A): Introduction of Derivatives Trading:			Panel (B): Financial Crisis		
	Start	R^2 (prior)	R^2 (after)	Start	R^2 (prior)	R^2 (after)
Butter	09.2005	-5.46	12.15**	12.2007	2.32	12.35**
Cocoa	07.1959	4.31	3.34	12.2007	-1.62	5.50
Coffee Arabica	05.2006			12.2007	3.27	-0.95
Corn Oil				12.2007	22.83***	25.60***
Cotton	07.1959	1.79	-5.12	12.2007	8.86*	0.02
Live Cattle	11.1964	3.40	5.77	12.2007	8.46*	7.63
Lean Hog	02.1996	-2.35	-3.50	12.2007	-1.45	-1.87
Milk	01.1996	0.27	5.23	12.2007	5.88	26.64***
Oranges	02.1967	-6.89	-2.81	12.2007	1.19	-2.72
Soybean Oil	07.1959	-1.59	6.70*	12.2007	-4.53	-0.30
Soybeans	07.1959	-4.46	2.37	12.2007	-7.08	-5.25
Soybean Meal	07.1959	-2.09	-3.28	12.2007	-2.63	-10.38
Sugar	01.1961	-6.67	2.12	12.2007	9.48*	-0.45
Wheat	07.1959	-4.14	-4.29	12.2007	3.03	2.18
Wool				12.2007	5.63	12.34*
Yellow Corn	07.1959	-0.93	-3.54	12.2007	6.36	1.25
Coal	07.2001	-1.24	9.61*	12.2007	5.35	17.92**
Heating Oil	11.1978	12.48**	-3.47	12.2007	4.41	19.23***
Natural Gas	04.1990	-1.25	9.39**	12.2007	10.03	37.10***
Unleaded Regular Gas	10.2005	2.83	7.69	12.2007	-1.30	11.87*
WTI Oil	03.1983	19.20***	2.27	12.2007	2.67	24.11***
Aluminium	05.2002	13.73**	10.39*	12.2007	10.61*	12.59*
Gold	12.1974	16.57***	9.90**	12.2007	4.83	16.59***
High Grade Copper	07.1959	-3.28	-3.08	12.2007	-1.62	27.09***
Nickel	03.2015			12.2007	6.81	10.68*
Palladium	01.1977		4.55	12.2007	-4.49	0.38
Platinum	03.1968	5.36	1.01	12.2007	2.23	8.80
Silver	06.1963	1.21	0.94	12.2007	1.23	7.08
Tin				12.2007	5.74	2.07
Zinc				12.2007	0.18	11.08*

Table 4.9: Time-Variation in Return Predictability (12 Months)

This table summarizes the results about the time-variation in the in-sample return predictability. We predict the next year's excess return. We report the adjusted R^2 s of a kitchen sink approach. We consider three different events. First, the introduction of futures. Second, the introduction of options. Third, the beginning of the global financial crisis in December 2007. "Start" denotes the starting point of trading futures and options, respectively. " R^2 (prior)" and " R^2 (after)" indicate the in-sample R^2 prior to and after the time point of introduction, respectively. We use 120 observations to compute the R^2 s. Here, we impose the restriction that at least 10 years of observations must be available. In the case of the global financial crisis, 97 observations are used. *, **, **** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Panel (A): Introduction of Derivatives Trading:				Panel (B):				
	Futures		Options		Financial Crisis				
	Start	R^2 (prior)	R^2 (after)	Start	R^2 (prior)	R^2 (after)	Start	R^2 (prior)	R^2 (after)
Butter	09.2005	23.68***	26.49***	03.1990	41.49***	47.57***	12.2007	22.66***	28.23***
Cocoa	07.1959	48.61***	18.25***				12.2007	38.53***	43.60***
Coffee Arabica	05.2006						12.2007	60.58***	35.83***
Corn Oil							12.2007	27.03***	55.34***
Cotton	07.1959	48.78***	38.79***	01.1990	22.20***	57.74***	12.2007	63.53***	39.04***
Live Cattle	11.1964	34.33***	28.98***	10.1984	45.79***	23.11***	12.2007	47.54***	41.54***
Lean Hog	02.1996	51.12***	21.67***				12.2007	39.71***	41.26***
Milk	01.1996	42.49***	28.19***	01.1996	42.49***	28.19***	12.2007	33.38***	61.44***
Oranges	02.1967	11.25**	6.79*	03.1990	29.55***	8.36*	12.2007	14.49**	40.52***
Soybean Oil	07.1959	35.57***	-0.06	02.1989	55.11***	39.10***	12.2007	60.21***	70.36***
Soybeans	07.1959	21.56***	11.48**	02.1989	54.86***	32.95***	12.2007	58.08***	63.48***
Soybean Meal	07.1959	41.90***	28.93***	02.1989	39.59***	10.50**	12.2007	42.75***	39.24***
Sugar	01.1961	38.82***	65.50***	03.1990	33.34***	44.31***	12.2007	35.54***	69.03***
Wheat	07.1959	44.40***	-4.58	02.1989	47.84***	34.33***	12.2007	32.05***	54.18***
Wool							12.2007	48.07***	32.76***
Yellow Corn	07.1959	49.87***	12.95***	02.1989	43.35***	25.91***	12.2007	51.09***	50.40***
Coal	07.2001	11.53**	8.41*				12.2007	23.17***	65.01***
Heating Oil	11.1978	29.05***	27.55***	02.1989	25.91***	19.33***	12.2007	32.31***	80.70***
Natural Gas	04.1990	47.08***	21.28***	10.1992	41.40***	16.03***	12.2007	20.36**	63.45***
Unleaded Regular Gas	10.2005	25.45***	59.32***	10.2005	25.45***	59.32***	12.2007	27.32***	79.02***
WTI Oil	03.1983	59.24***	38.01***	01.1989	46.23***	27.31***	12.2007	26.27***	80.41***
Aluminium	05.2002	33.47***	17.27***				12.2007	47.20***	62.90***
Gold	12.1974	68.36***	53.26***	09.1988	68.27***	46.94***	12.2007	47.10***	77.58***
High Grade Copper	07.1959	52.41***	57.36***	06.1990	49.13***	46.84***	12.2007	44.74***	83.51***
Nickel	03.2015						12.2007	18.84***	73.08***
Palladium	01.1977		66.09***	01.1968		42.00***	12.2007	26.27***	78.53***
Platinum	03.1968	11.02**	29.45***	10.1990	7.31*	57.70***	12.2007	33.46***	86.49***
Silver	06.1963	57.03***	71.50***	03.1989	31.03***	47.03***	12.2007	43.52***	54.83***
Tin							12.2007	59.50***	59.50***
Zinc							12.2007	28.51***	78.44***

4.4.2 Time-Variation in Volatility Predictability

We now turn our focus to the analysis of the time-variation in volatility predictability. In Table 4.10, we find a similar extent of significant short-term volatility predictability, compared to return predictability, prior to and after the break points. Gold exhibits the highest adjusted ΔR^2 s of 18.17 % prior to the break point in the case of futures, whereas live cattle with 12.29 % prior to the break point in the case of options. We notice that energy commodities show a substantial increase in the predictability since the global financial crisis, indicated by adjusted ΔR^2 s ranging from 14.78 % for unleaded regular gas to 28.32 % for coal. Table 4.11 documents similar results for the volatility predictability in the long-term, which is consistent with our previous findings.

Overall, the results reflect a significant volatility predictability prior to and after the breaks points, in contrast to our expectation. It seems that the introduction of derivatives trading is associated with a general increase in volatility predictability. Further, the entire results confirm our previous findings. There is short-term predictability, while the degree of predictability is similar even for longer horizons. Moreover, when analyzing the predictability of commodities it is advisable not only to examine the return predictability but also the volatility predictability.

4.5 Predictability and Business Cycle Stages

In this section, we analyze the return predictability over business cycle stages. We not only consider the return predictability but also the volatility predictability. Following Cujean & Hasler (2017), we examine expansions and recessions, and additionally we differentiate between early and late expansions and recessions, respectively. To determine expansions

Table 4.10: Time-Variation in Volatility Predictability (1 Month)

This table summarizes the results about the time-variation in the in-sample volatility predictability. We predict the next month's volatility. We report the differences between the adjusted R^2 's of the unrestricted and restricted model based on a kitchen sink approach. We consider three different events. First, the introduction of futures. Second, the introduction of options. Third, the beginning of the global financial crisis in December 2007. "Start" denotes the starting point of trading futures and options, respectively. " ΔR^2 (prior)" and " ΔR^2 (after)" indicate the in-sample R^2 difference prior to and after the time point of introduction, respectively. We use 120 observations to compute the ΔR^2 's. Here, we impose the restriction that at least 10 years of observations must be available. In the case of the global financial crisis, 97 observations are used. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Panel (A): Introduction of Derivatives Trading:				Panel (B): Financial Crisis			
	Start	ΔR^2 (prior)	ΔR^2 (after)		Start	ΔR^2 (prior)	ΔR^2 (after)	
Butter	09.2005	0.45	1.38		12.2007	-1.05	8.44	
Cocoa	07.1959	9.15**	5.06		12.2007	16.20***	17.13***	
Coffee Arabica	05.2006				12.2007	1.75	-0.63	
Corn Oil					12.2007	10.90**	18.10***	
Cotton	07.1959	0.63	5.75*		12.2007	3.07	4.97	
Live Cattle	11.1964	4.07	24.43***		12.2007	22.73***	24.80***	
Lean Hog	02.1996	5.99	-0.89		12.2007	-1.06	2.91	
Milk	01.1996	1.21	4.27		12.2007	-1.43	-0.11	
Oranges	02.1967	5.07	-1.92		12.2007	-3.22	2.73	
Soybean Oil	07.1959	5.79*	-3.87		12.2007	2.13	14.33***	
Soybeans	07.1959	3.87	-4.64		12.2007	6.03	5.29	
Soybean Meal	07.1959	9.81**	-3.30		12.2007	-0.41	0.99	
Sugar	01.1961	2.39	1.67		12.2007	3.15	5.76**	
Wheat	07.1959	6.08*	-0.77		12.2007	-0.17	0.52	
Wool					12.2007	4.72	16.31**	
Yellow Corn	07.1959	4.23	3.55		12.2007	0.45	0.88	
Coal	07.2001	9.87**	20.40***		12.2007	10.47**	28.32***	
Heating Oil	11.1978				12.2007	-1.88	16.14***	
Natural Gas	04.1990	4.75	-0.23		12.2007	8.60	8.56	
Unleaded Regular Gas	10.2005	4.92	10.64**		12.2007	4.01	14.78***	
WTI Oil	03.1983	2.63	2.70*		12.2007	0.03	19.65***	
Aluminium	05.2002	1.61	24.11***		12.2007	12.14**	15.04***	
Gold	12.1974	18.17***	9.36***		12.2007	15.08**	13.67**	
High Grade Copper	07.1959	1.69	3.07		12.2007	2.29	12.54***	
Nickel	03.2015				12.2007	13.14**	8.25	
Palladium	01.1977				12.2007	4.25	15.18**	
Platinum	03.1968	-1.23	0.36		12.2007	-0.07	0.42	
Silver	06.1963	0.29	9.39***		12.2007	0.87	3.93	
Tin					12.2007	-2.07	7.71**	
Zinc					12.2007	11.96***	23.23***	

Table 4.11: Time-Variation in Volatility Predictability (12 Months)

This table summarizes the results about the time-variation in the in-sample volatility predictability. We predict the next year's volatility. We report the differences between the adjusted R^2 's of the unrestricted and restricted model based on a kitchen sink approach. We consider three different events. First, the introduction of futures. Second, the introduction of options. Third, the beginning of the global financial crisis in December 2007. "Start" denotes the starting point of trading futures and options, respectively. " ΔR^2 (prior)" and " ΔR^2 (after)" indicate the in-sample R^2 difference prior to and after the time point of introduction, respectively. We use 120 observations to compute the ΔR^2 's. Here, we impose the restriction that at least 10 years of observations must be available. In the case of the global financial crisis, 97 observations are used. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Panel (A): Introduction of Derivatives Trading:			Panel (B):		
	Futures			Financial Crisis		
	Start	ΔR^2 (prior)	ΔR^2 (after)	Start	ΔR^2 (prior)	ΔR^2 (after)
Butter	09.2005	0.56**	0.75***	12.2007	0.79***	0.26
Cocoa	07.1959	0.19	0.27	12.2007	0.52***	0.86***
Coffee Arabica	05.2006			12.2007	1.27***	0.21
Corn Oil				12.2007	0.74***	0.67***
Cotton	07.1959	0.53***	0.53	12.2007	0.22	0.19
Live Cattle	11.1964	0.52**	0.25***	12.2007	0.70***	0.86**
Lean Hog	02.1996	0.77*	0.47	12.2007	0.75	0.27
Milk	01.1996	0.51***	0.33	12.2007	0.30	0.70
Oranges	02.1967	0.61	0.58***	12.2007	1.99***	-0.97
Soybean Oil	07.1959	0.19	-0.01	12.2007	-0.17	0.32***
Soybeans	07.1959	0.43***	0.45*	12.2007	0.56**	0.29
Soybean Meal	07.1959	0.39	0.22	12.2007	0.44**	0.89***
Sugar	01.1961	1.04***	0.83***	12.2007	0.72**	0.33***
Wheat	07.1959	0.29	0.32	12.2007	0.33***	0.54***
Wool				12.2007	0.19	1.16**
Yellow Corn	07.1959	0.63	1.49***	12.2007	0.74**	0.54
Coal	07.2001	0.42	0.38**	12.2007	-0.01	0.43***
Heating Oil	11.1978			12.2007	1.29**	1.41***
Natural Gas	04.1990	0.35**	0.20	12.2007	0.22	2.07***
Unleaded Regular Gas	10.2005	0.28	1.03***	12.2007	0.38	1.64***
WTI Oil	03.1983	0.79***	0.36**	12.2007	1.00***	1.13***
Aluminium	05.2002	0.63*	0.20	12.2007	0.17	0.80*
Gold	12.1974	0.22***	0.51***	12.2007	0.89**	1.08**
High Grade Copper	07.1959	0.02	0.40*	12.2007	1.15***	1.25***
Nickel	03.2015			12.2007	0.21	0.81**
Palladium	01.1977			12.2007	0.07	0.81**
Platinum	03.1968	0.35*	0.35***	12.2007	1.52***	1.63***
Silver	06.1963	0.55***	0.30***	12.2007	0.76***	0.70**
Tin				12.2007	1.05**	0.84***
Zinc				12.2007	0.39***	0.77***

4.5. PREDICTABILITY AND BUSINESS CYCLE STAGES

and recessions, we follow the classification of the NBER for U.S. business cycle stages. To differentiate between early and late stages, we split up expansions and recessions into two equally large parts.¹⁷

4.5.1 Return Predictability

We start by analyzing the return predictability. Table 4.12 summarizes the (in-sample) results of the long-term predictability for expansions and recessions, respectively. Further, Tables C.5 to C.8 of the Appendix to this chapter report the in-sample and out-of-sample regression results for each business cycle stage, differentiated between early and late expansions and recessions, respectively.¹⁸

We observe that interest rate-related variables, especially *lty* and *tbl*, are the most frequent significant variables predicting excess returns in expansions, confirming our previous results. Here, *lty* shows the highest predictive power in the univariate regressions for unleaded regular gas ($R^2 = 15.88\%$). Further, equity related predictors, i.e., *de*, *dp*, *dy*, and *ep*, display an extensive degree of significant predictions in expansions and recessions. The findings support the fact that, in particular, *tms*, *dfy*, and *dy* are closely related to business cycle stages (e.g., Fama & French, 1989; Chen, 1991; Cochrane, 1999). Moreover, *unrate* exhibits a superior performance in expansions.

Overall, in contrast to the literature, our findings provide evidence in favor of similar return predictability in expansions and recessions. In total, the results are consistent with our previous findings.

¹⁷To obtain meaningful results, we impose the following conditions: We report the out-of-sample results when there are at least 30 out-of-sample observations available. Further, at least 10 years of in-sample observations must be available.

¹⁸We report the out-of-sample results in analogy to our main results, although we know that this is not a "real" out-of-sample analysis, because the business cycle stages have been determined ex post.

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Table 4.12: Return Predictability and Business Cycle Stages (12 Months)

This table reports the in-sample R^2 s of a regression of monthly excess returns on a constant and the lagged predictive variable across business cycle stages. We predict the next year's excess return. "de" denotes the dividend-payout ratio, " $\Delta indpro$ " the growth of industrial production, and " ΔMI " the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "inft" the long-term U.S. government U.S. Treasury bill rate. "ims" is the "ity" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider two business cycle stages. "Exp" denotes expansion, and "Rec" recession. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de		$\Delta indpro$		ΔMI		dfr		dfy		dp		dy		ep	
	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec
Butter	0.01	0.00	1.43*	0.30	0.50*	5.67***	0.05	0.30	0.99***	0.34	0.03	2.08***	0.04	2.91***	0.01	2.19***
Cocoa	0.17	0.23	1.40*	0.32	0.11	0.14	0.00	0.03	0.03	0.49	0.01	0.71*	0.03	0.53	0.20	0.24
Coffee Arabica	0.86***	0.06	8.63***	0.11	0.69*	0.26	0.25	0.28	2.82***	0.34	0.34	0.49	0.16	0.31	0.00	0.29
Corn Oil	2.28***	0.00	0.33	0.05	0.19	0.08	0.01	0.09	1.80***	0.00	0.16	0.00	0.21	0.09	1.14***	0.00
Cotton	2.28***	0.08	1.23***	0.08	2.14***	1.17	0.01	0.09	4.46***	3.98***	1.63***	0.26	1.62***	0.35	0.12	0.66*
Live Cattle	1.18***	0.09	0.90***	0.02	0.29	4.46***	0.29	0.08	3.54***	6.32***	0.19	0.01	0.18	0.04	0.09	0.15
Lean Hog	0.54**	3.22***	0.58**	0.15	0.04	0.38	0.01	0.14	2.47***	0.83	0.00	0.10	0.00	0.11	0.35**	3.87***
Milk	0.04	0.07	0.42*	0.82	0.04	3.10*	0.01	0.09	0.56**	0.74	1.62***	3.52***	1.63***	4.96***	2.51***	4.71***
Oranges	0.23	0.09	1.49*	0.02	0.00	0.16	0.03	0.15	0.45*	3.95***	0.00	0.54	0.00	0.27	0.08	1.07*
Soybean Oil	0.55**	3.89***	0.65**	1.15	0.29	0.21	0.04	0.25	0.87***	4.71***	0.03	1.60**	0.02	2.46***	0.09	0.09
Soybeans	1.03***	0.91	1.45***	1.17*	0.13	0.00	0.04	0.01	2.91***	3.55***	0.00	0.38	0.00	0.76	0.40*	0.02
Soybean Meal	0.56**	0.96	0.28	0.14	0.28	0.52	0.01	0.09	1.37***	3.45***	0.08	0.74	0.06	1.42	0.68**	0.01
Sugar	0.13	0.08	0.00	0.12	0.02	0.04	0.03	0.11	1.00	0.46	0.11	0.49*	0.14	0.50	0.01	1.06**
Wheat	0.25	2.88***	0.49**	1.28*	0.13	0.04	0.15	0.10	0.37*	4.44***	0.05	0.06	0.06	0.13	0.02	1.59***
Wool	0.12	4.57***	0.97***	0.57	0.72**	0.12	0.10	0.19	1.49***	7.35***	0.01	0.20	0.01	0.45	0.02	1.85***
Yellow Corn	0.00	0.09	0.29	0.46	0.32	0.12	0.11	0.25	2.15***	0.59	0.00	0.17	0.00	0.08	0.00	0.03
Coal	3.94***	2.18*	0.06	0.52	0.37	0.44	0.01	0.11	0.04	2.08*	2.96***	2.92**	2.95***	2.70*	0.48**	8.96***
Heating Oil	4.56***	1.99	0.05	0.70	0.16	0.08	0.24	0.02	2.53***	2.59	4.02***	4.89*	4.07***	4.64*	0.94*	5.95**
Natural Gas	0.39	0.31	0.30	0.45	0.90*	8.77***	0.34	1.81	0.67	0.75	5.91***	5.47	6.13***	4.88	5.13***	5.41
Unleaded Regular Gas	1.80***	9.32***	0.15	1.74	0.34	0.05	0.20	0.06	2.20***	2.59	9.32***	0.81	9.42***	0.62	6.10***	2.58
WTI Oil	2.86***	1.42***	0.39*	2.84**	0.00	0.09	0.05	0.54	0.01	0.05	1.52***	0.64*	1.50***	0.69*	0.16	0.04
Aluminium	1.72***	1.59**	0.10	0.10	0.38	0.34	0.28	0.00	0.11	0.11	0.00	1.50**	0.00	1.51**	0.88**	0.06
Gold	1.66***	3.29***	0.00	1.43*	2.09***	0.11	0.08	0.22	0.05	5.35***	0.60***	0.41	0.57**	0.57*	0.00	5.53***
High Grade Copper	0.01	2.50***	0.13	0.02	1.72***	2.64*	0.16	0.21	0.03	2.91***	1.86***	2.49***	1.73***	3.21***	2.67***	0.09
Nickel	1.38**	0.38	0.28	0.53	0.01	0.09	0.61	0.00	0.99*	0.45	0.76	2.81	0.83	2.57	3.20***	2.97
Palladium	0.78*	1.60	0.62	0.97	0.00	0.00	0.00	0.75	7.88***	7.24**	1.16**	13.15***	1.00*	13.58***	0.45	8.40***
Platinum	0.05	3.23***	0.20	2.61**	0.75**	0.47	0.03	0.14	0.00	0.00	0.04	0.79	0.03	0.91	0.14	0.31
Silver	1.02***	0.50	1.00	1.00	0.20	0.36	0.01	0.02	1.07***	2.33**	0.05	0.77**	0.06	0.98**	0.23	0.11
Tin	0.61***	10.09***	0.70**	0.00	0.00	0.42	0.14	0.07	0.15	21.47***	0.22	2.81***	0.19	3.00***	0.00	1.07**
Zinc	0.42**	1.53***	0.56**	0.01	0.05	0.45	0.01	0.06	0.95***	2.06**	0.37**	1.41***	0.37**	1.50***	1.38**	0.03

Table 4.12: Return Predictability and Business Cycle Stages (12 Months) (continued)

Commodity	<i>erp</i>		<i>infl</i>		<i>ltr</i>		<i>lty</i>		<i>star</i>		<i>tbt</i>		<i>tms</i>		<i>unrate</i>	
	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec
<i>Butter</i>	0.18	2.18***	0.01	0.28	0.21	0.07	3.57***	0.02	0.67**	0.30	5.18***	0.07	1.03***	0.20	0.14	2.76*
<i>Cocoa</i>	0.16	0.51*	0.70**	0.06	0.05	0.85	3.21***	0.55	0.29*	1.17**	3.98***	2.88***	0.33	6.36***	0.15	0.55
<i>Coffee Arabica</i>	0.02	1.34	0.10	1.24	0.13	0.45	0.05	3.51*	0.22	7.67***	3.61***	5.39***	8.17***	3.69*	6.38***	0.40
<i>Corn Oil</i>	0.17	1.90**	0.04	0.00	0.00	2.20**	3.10***	0.08	1.19***	0.01	2.93***	0.02	0.01	0.15	0.08	0.34
<i>Cotton</i>	0.06	0.39	0.39**	1.03**	0.00	0.85	2.02***	0.88	0.19	1.15**	4.30***	2.62**	2.38***	5.15***	0.67**	2.48
<i>Live Cattle</i>	0.00	0.46	0.30*	0.09	0.11	0.20	6.41***	2.69***	2.57***	5.14***	10.54***	2.52**	3.06***	0.08	0.13	3.82**
<i>Lean Hog</i>	0.03	0.03	0.08	0.41	0.02	0.00	3.86***	2.40**	0.96***	0.07	4.56***	3.02***	0.25	1.25*	5.20***	1.49
<i>Milk</i>	0.08	3.73***	0.79***	0.13	0.23	0.54	8.04***	0.00	0.96***	2.77***	8.07***	0.28	0.08	2.69**	0.85**	1.47
<i>Oranges</i>	0.01	1.28*	0.13	0.10	0.09	0.07	2.91***	1.08	0.08	1.52*	3.88***	1.18*	0.56**	0.25	0.01	0.64
<i>Soybean Oil</i>	0.03	3.03***	0.00	3.79***	0.01	2.24**	1.67***	0.32	0.21	3.56***	2.49***	1.69**	0.52**	3.73***	0.49*	0.01
<i>Soybeans</i>	0.14	1.92**	0.02	0.58	0.00	1.17	3.47***	0.24	2.36***	2.23**	5.48***	1.30*	1.55***	4.28***	0.21	0.46
<i>Soybean Meal</i>	0.30	3.06**	0.79***	0.00	0.08	0.97	1.76***	0.65	0.22	2.04**	2.95***	1.65*	1.16***	3.79**	0.02	0.08
<i>Sugar</i>	0.20	0.01	0.40**	0.01	0.21	0.03	0.00	0.70	0.02	0.01	0.00	1.12*	0.00	0.89	0.17	1.53
<i>Wheat</i>	0.08	0.51	0.17	0.62*	0.01	0.89	2.36***	1.29*	0.48**	0.30	3.42***	4.50***	0.69**	10.79***	0.40	1.28
<i>Wool</i>	0.00	1.49**	0.11	4.61***	0.08	0.26	0.79**	3.30**	0.34*	3.39***	2.46***	7.07***	2.36***	9.12***	1.22***	0.05
<i>Yellow Corn</i>	0.01	0.57*	0.05	0.02	0.01	1.30*	3.89***	0.01	2.28***	0.01	4.26***	0.33	0.12	2.09**	0.77**	1.26
<i>Cool</i>	0.00	0.18	0.05	7.54***	0.19	0.74	0.91***	0.02	0.28	0.00	0.86**	1.61	0.00	22.26***	0.75**	2.35*
<i>Heating Oil</i>	0.01	0.08	0.07	2.79	0.75*	0.36	8.10***	0.48	0.03	0.08	3.80***	6.21**	0.53	21.68***	4.27***	0.67
<i>Natural Gas</i>	0.21	1.44	0.07	0.05	0.06	1.07	4.25***	15.06***	0.09	0.20	3.15***	15.67***	0.03	6.06*	2.99***	4.64
<i>Unleaded Regular Gas</i>	0.01	0.81	2.75***	0.53	0.78*	1.27	15.88***	0.30	0.14	2.14	9.36***	2.84	0.10	10.06**	9.78***	0.20
<i>WTI Oil</i>	0.00	0.03	0.38*	0.02	0.08	0.17	0.07	0.74	0.16	0.07	0.03	1.21*	0.75**	1.12	1.74***	1.84
<i>Aluminium</i>	0.04	0.01	1.32***	0.13	1.01***	0.09	0.35*	1.55*	0.00	0.02	1.32***	1.05	1.51***	0.09	0.10	0.94
<i>Gold</i>	0.03	0.33	0.56**	0.95**	0.06	0.00	0.06	1.75**	0.01	10.75***	0.05	3.90***	0.00	5.54***	0.00	4.01**
<i>High Grade Copper</i>	0.28*	1.38***	0.10	1.16**	0.19	1.24	3.74***	3.19***	0.72***	0.11	7.23***	5.39***	3.22***	4.62***	0.27	0.05
<i>Nickel</i>	0.13	0.23	0.01	3.73	1.97**	4.99	2.33***	0.03	3.32**	2.82	4.40***	0.16	2.14**	0.58	0.32	0.07
<i>Palladium</i>	0.72*	0.55	0.01	1.09	0.30	0.89	5.60***	15.79***	0.22	6.12**	3.90***	17.32***	0.00	3.98*	1.34**	8.82**
<i>Platinum</i>	0.26	0.21	0.19	1.98**	0.06	0.00	1.29***	1.00	0.00	1.05*	2.50***	2.27**	1.07***	3.22**	0.01	0.96
<i>Silver</i>	0.03	0.54*	0.42**	1.11**	0.01	1.68*	0.50***	0.28	0.00	0.55	0.42*	2.70***	0.01	11.65***	0.40	7.46***
<i>Tin</i>	0.15	0.18	0.22	3.26***	0.20	0.17	3.54***	4.45***	0.34*	9.31***	4.15***	10.33***	0.19	15.11***	0.20	1.75
<i>Zinc</i>	0.01	0.01	0.53**	0.05	0.08	1.16	2.20***	0.35	0.61**	0.24	4.07***	0.51	1.71***	0.31	0.43	0.05

4.5.2 Volatility Predictability

We now turn our attention to the volatility predictability over business cycle stages. Analogously, Table 4.13 summarizes the (in-sample) results for expansions and recessions, respectively. Tables C.9 to C.12 of the Appendix to this chapter report the more detailed in-sample and out-of-sample regression results.

The results reveal a weaker degree of predictability across business cycle stages compared to the return predictability. However, the findings clearly show that $\Delta indpro$, dp , dy , ep , and ltr are the most frequent significant variables predicting commodity volatilities in recessions. In contrast, tms exhibits a superior performance in expansions.

Overall, the results are consistent with our previous findings. First, they verify that there is predictability of volatilities across business cycle stages, despite the high degree of persistence. Second, they provide evidence that most variables predict not only excess returns but also volatilities.

4.6 Further Analyses

4.6.1 Restricted Predictability

Campbell & Thompson (2008) suggest imposing two economically motivated sign restrictions to improve the out-of-sample predictability of the equity premium. Following them, whenever the sign of the slope estimate in the out-of-sample analysis differs from that of the in-sample analysis, we set the estimate equal to zero.¹⁹ Before discussing our findings, it is worthwhile

¹⁹We do not implement the second restriction, because in commodity markets it is not obvious why an investor should exclude negative forecasts of the commodity excess return and commodity volatility, respectively. We analyze individual assets rather than the entire market, thus, it is obvious that commodity excess returns and volatilities do not represent the long-run average of the market.

Table 4.13: Volatility Predictability and Business Cycle Stages (12 Months)

This table reports the in-sample ΔR^2 's of a regression of monthly volatilities on a constant, the lagged volatility, and the logged predictive variable across business cycle stages. We predict the next year's volatility. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "inflt" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "4ms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider two business cycle stages. "Exp" denotes expansion, and "Rec" recession. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de		Δindpro		ΔM1		dfr		dy		dp		dy		ep	
	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec
Butter	0.00	0.01	0.00	-0.07	0.00	0.02	0.00	-0.06	0.00	-0.06	0.00	-0.04	0.00	-0.04	0.00	0.01
Cocoa	0.00	-0.01	0.00	-0.04	0.00	-0.11	0.00	-0.02	0.01	0.03	0.01**	0.01	0.01**	0.01	0.01**	0.01
Coffee Arabica	0.02*	-0.13	0.00	-0.07	0.01*	-0.13	0.00	-0.09	0.00	-0.04	0.00	-0.07	0.00	-0.07	0.00	-0.08
Corn Oil	0.00	-0.05	0.00	0.06	0.00	-0.04	0.00	-0.04	0.00	-0.06	0.01	0.07	0.01	0.10	0.01	0.17*
Cotton	0.00	-0.01	0.00	-0.02	0.00	-0.07	0.00	0.07	0.00	-0.01	0.00	0.01	0.00	0.02	0.00	0.00
Live Cattle	0.00	-0.01	0.01*	0.15**	0.02**	-0.11	0.00	0.09	0.00	-0.04	0.00	-0.01	0.00	-0.01	0.00	0.00
Lean Hog	0.00	-0.02	0.00	-0.02	-0.01	-0.14	0.01	-0.07	-0.01	-0.07	0.01	0.08*	0.01*	0.12**	0.03**	0.15**
Milk	0.00	-0.01	0.00	0.02	0.00	0.26**	0.00	-0.04	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.02
Oranges	0.00	-0.04	0.00	0.05	-0.01	-0.07	0.00	0.10*	0.00	-0.03	0.02*	-0.03	0.01*	-0.04	0.01*	-0.04
Soybean Oil	0.00	-0.03	0.00	-0.02	0.00	-0.07	0.00	-0.03	0.03***	0.08	0.03***	0.19**	0.03***	0.20**	0.03***	0.19**
Soybeans	0.00	-0.06	0.00	-0.06	0.00	-0.11	0.00	-0.03	0.00	-0.03	0.02**	0.17*	0.02**	0.17*	0.04***	0.27**
Soybean Meal	-0.01	-0.10	0.00	-0.11	-0.01	-0.08	0.00	-0.08	-0.01	0.15	0.00	0.25*	0.00	0.21	0.01	0.30*
Sugar	0.00	0.03*	0.00	-0.03	0.00	-0.07	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.01	0.00	-0.01
Wheat	0.00	-0.01	0.00	-0.04	0.01***	-0.08	0.00	-0.04	0.01**	-0.04	0.02**	0.04*	0.02**	0.04*	0.01*	0.03
Wool	0.01*	-0.02	0.00	-0.02	0.00	-0.08	0.00	-0.04	0.00	-0.04	0.01*	0.03	0.01*	0.05	0.00	0.08*
Yellow Corn	0.00	-0.01	0.00	-0.03	0.00	-0.10	0.00	-0.05	-0.01	-0.05	0.01	0.00	0.01	0.02	0.01*	0.06*
Coal	0.00	-0.01	0.00	-0.06	-0.01	-0.06	0.03**	-0.02	0.01**	0.15*	0.01	0.67***	0.02	0.62***	0.01	0.68***
Heating Oil	0.01	0.34	-0.01	-0.23	0.00	-0.10	0.00	-0.22	0.01	0.86*	-0.01	0.06	-0.01	-0.03	-0.01	0.33
Natural Gas	0.04***	-0.16	0.00	-0.19	0.07***	-0.19	0.01	-0.19	0.02**	-0.09	0.02	0.17	0.02	0.22	0.00	0.11
Unleaded Regular Gas	-0.01	0.20	-0.01	-0.17	-0.01	-0.16	-0.01	0.49*	0.06**	0.08	-0.01	0.13	-0.01	0.09	-0.01	0.37
WTI Oil	0.00	-0.01	0.00	-0.05	0.00	0.12	0.00	-0.05	0.00	-0.03	0.01*	0.00	0.01*	0.00	0.00	0.00
Aluminium	0.00	-0.01	0.00	-0.02	0.00**	0.07	0.00	-0.01	0.00	-0.03	0.00	0.06	0.00	0.05	0.01**	0.00
Gold	0.00*	0.00	0.00	0.05	0.00	-0.08	0.01**	-0.04	0.00*	-0.02	0.00	0.06**	0.00	0.05**	0.00	0.03*
High Grade Copper	0.00	0.00	0.00	-0.01	0.00	-0.07	0.00	-0.04	0.02**	-0.01	0.00	0.11***	0.00	0.11**	0.00	0.06*
Nickel	0.02	0.57	-0.02	-0.48	-0.02	-0.44	-0.02	0.50	-0.02	-0.44	0.00	-0.34	0.00	-0.39	0.07*	-0.04
Palladium	0.04*	-0.20	0.02	-0.22	0.04*	-0.21	0.02	0.13	0.01	-0.19	0.02	-0.13	0.01	-0.14	-0.01	-0.18
Platinum	0.00	-0.02	0.00	0.00	0.00	0.00	0.01	-0.02	0.00	-0.02	0.00	0.11*	0.00	0.10*	0.00	0.09*
Silver	0.00	0.05*	0.00	0.01	0.00	-0.12	0.02**	-0.06	0.00	-0.02	0.00	0.16***	0.00	0.15***	0.00	0.03
Tin	0.02**	-0.01	0.01	0.00	-0.01	-0.04	0.00	-0.03	0.01*	-0.02	0.02*	0.05*	0.01*	0.05*	0.00	0.02
Zinc	0.00	-0.03	0.00	0.00	0.00	-0.05	0.00*	-0.08	0.00	-0.07	0.00	0.09*	0.00	0.07*	0.01	0.12**

Table 4.13: Volatility Predictability and Business Cycle Stages (12 Months) (continued)

Commodity	erp		inflation		ltr		lty		star		tbl		tms		unrate	
	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec	Exp	Rec
Butter	0.00*	-0.02	0.00	0.12**	0.00	0.10	0.00	-0.08	0.00	-0.04	0.00	-0.08	0.00	-0.08	0.00	-0.17
Cocoa	0.00	-0.01	0.00	-0.01	0.00	-0.01	0.00	-0.05	0.00	0.01	0.00	-0.05	0.00	-0.06	0.00	0.53**
Coffee Arabica	-0.01	-0.13	0.00	-0.10	0.00	-0.12	-0.01	0.17	0.00	0.66**	0.03**	0.14	0.08***	-0.11	0.01	-0.12
Corn Oil	0.00	-0.01	0.02**	-0.03	0.01	-0.01	0.00	-0.04	-0.01	-0.02	0.01	-0.06	0.03**	-0.01	0.00	0.01
Cotton	0.00	0.06**	0.00	-0.01	0.00	0.13*	0.01	-0.02	0.00	-0.01	0.01	-0.02	0.00	-0.03	0.01*	-0.04
Live Cattle	0.00	-0.01	0.00	0.00	0.00	0.05	0.00	-0.04	0.00	0.02	0.00	-0.05	0.01	-0.01	0.00	0.06
Lean Hog	0.00	0.10**	0.01	0.00	-0.01	0.03	-0.01	-0.05	0.02**	-0.03	-0.01	-0.05	-0.01	-0.08	-0.01	-0.13
Milk	0.00	-0.01	0.00	0.01	0.00	-0.03	0.00	0.00	0.00	-0.01	0.00	0.00	0.01	-0.01	0.00	0.10
Oranges	0.02**	0.02	0.00	-0.01	0.00	0.13*	0.00	0.05	0.00	-0.04	0.00	0.01	0.01*	-0.03	-0.01	-0.07
Soybean Oil	0.00	-0.03	0.00	-0.01	0.00	0.13*	0.00	-0.04	0.00	-0.01	0.00	-0.04	0.03***	-0.04	0.01*	0.16*
Soybeans	0.00	-0.06	0.00	-0.02	0.00	0.08	0.00	-0.07	0.00	-0.06	0.00	-0.06	0.00	0.00	0.00	0.35*
Soybean Meal	0.00	-0.06	0.00	-0.04	0.00	-0.01	0.00	-0.08	-0.01	0.01	0.00	-0.09	0.02*	-0.10	0.00	0.36*
Sugar	0.00	0.00	0.00	0.10***	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00	-0.02	0.00	-0.08
Wheat	0.00	0.00	0.00*	-0.01	0.00	0.07	0.00	-0.04	0.00	-0.03	0.01**	-0.04	0.03***	-0.05	0.02***	-0.03
Wool	0.00	0.00	0.00	-0.02	0.00	-0.03	0.00	-0.03	0.00	-0.02	0.00	-0.04	0.00	-0.03	0.00	-0.06
Yellow Corn	0.00	0.03	0.00	-0.02	0.00	-0.03	-0.01	-0.05	0.00	-0.03	-0.01	-0.05	-0.01	-0.05	0.00	0.05
Coal	0.01	-0.03	0.00	-0.02	0.00	-0.06	0.00	0.00	0.00	-0.05	0.00	0.01	0.02**	-0.04	0.03**	0.20*
Heating Oil	-0.01	0.10	0.02*	1.04**	0.00	-0.16	-0.01	-0.09	-0.01	-0.20	-0.01	0.55	0.01	1.59**	-0.01	0.67*
Natural Gas	0.00	-0.19	0.00	-0.13	0.00	-0.20	0.00	0.55	0.00	-0.20	0.00	0.33	0.02**	-0.15	0.03***	-0.11
Unleaded Regular Gas	-0.01	-0.13	0.03**	0.76**	-0.01	-0.10	-0.01	0.38	-0.01	0.48*	0.03*	0.70**	0.08**	0.60*	-0.01	0.33
WTI Oil	0.00	-0.01	0.00	-0.01	0.00	-0.03	0.01	0.00	0.00	-0.02	0.00	-0.04	0.00	0.02	0.00	0.43**
Aluminium	0.00	-0.02	0.00	0.01	0.00	-0.03	0.00	0.01	0.00**	-0.03	0.00	-0.02	0.01***	0.01	0.01**	0.26**
Gold	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.01	0.00	-0.03	0.00	0.00	0.00	-0.06
High Grade Copper	0.00	-0.01	0.00	0.00	0.00	0.11**	0.00	-0.01	0.00	-0.03	0.00	-0.03	0.01*	-0.03	0.00	-0.07
Nickel	-0.02	0.04	-0.02	0.60	-0.01	1.38**	0.02	-0.26	0.04*	-0.16	0.04	0.27	-0.01	1.42**	-0.02	-0.15
Palladium	0.01	-0.22	0.01	-0.18	0.00	0.05	0.00	-0.21	-0.01	0.15	0.00	-0.19	0.15**	-0.18	0.11***	-0.15
Platinum	0.01*	-0.03	0.03***	0.01	0.00	-0.03	0.00	-0.04	0.01*	-0.01	0.00	-0.02	0.00	0.04	0.00	-0.06
Silver	0.00	-0.02	0.00	0.04*	0.00	-0.04	0.00	0.10	0.00*	-0.01	0.00	0.01	0.01	-0.03	0.00	-0.08
Tin	0.00	0.00	0.01*	-0.02	0.00	-0.01	0.00	-0.01	0.00	-0.02	0.00	-0.02	0.00	-0.03	0.01	-0.06
Zinc	0.00	-0.02	0.00	0.01	0.00	-0.09	0.00	-0.05	0.00	-0.04	0.00	-0.07	0.01*	0.00	0.00	-0.10

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to accentuate that the constraint is not implementable in real-time due to a look-ahead bias. To implement that strategy would require that an investor has information about future risk premia and volatilities, respectively, thus, knowing the in-sample slope estimate.

Panel (A) of Table 4.14 summarizes the results for each variable predicting the next month's and the next year's excess return.²⁰ In the short-term, we observe a slight increase in the frequency of significant predictions across the commodities, especially for $\Delta indpro$, dfr , erp , $svar$, and tbl . In the case of the long-term predictability, there is a substantial increase in the frequency, e.g., in the case of $\Delta indpro$ from 16.67 % to 40.00 %. Further predictors are ltr , dfr , and $svar$. Moreover, the improved performance is also associated with an increase in the predictive power, shown in Table C.13 of the Appendix to this chapter. However, we detect that other variables show an inferior performance by imposing the restriction, indicated by extreme negative R_{oos}^2 s.

Panel (B) of Table 4.14 documents the results for each variable predicting the next month's and the next year's volatility.²¹ We observe similar results as before. $\Delta M1$, erp , $\Delta indpro$, $svar$, ltr , dfr , and tms display an increase in the frequency of significant predictions in the short-term, whereas $\Delta M1$, $\Delta indpro$, ltr , $infl$, and dfr do so in the long-term.

Overall, the results provide evidence in favor for an improvement of the out-of-sample predictability for several variables. In particular, $\Delta indpro$, dfr , and $svar$ benefit from imposing the sign restriction in the case of return predictability, whereas $\Delta M1$, $\Delta indpro$, and ltr do so in the case of volatility predictability. The findings also document a substantial worsening for some variables by imposing the restriction. Thus, we conclude it is necessary to differentiate between variables as to whether the imposition

²⁰Table C.13 of the Appendix to this chapter provides more detailed regression results.

²¹Table C.14 of the Appendix to this chapter provides more detailed regression results.

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of the restriction is worthwhile.

Table 4.14: Summary Restricted Predictability

*This table reports a summary of the out-of-sample results after imposing an economically motivated sign restriction. Panel (A) shows the percentage of significant R_{oos}^2 s across the variables predicting the next month's and the next year's excess return. Panel (B) shows the percentage of significant R_{oos}^2 s across the variables predicting the next month's and the next year's volatility. Following Campbell & Thompson (2008), we impose the restriction that we set the out-of-sample slope estimate equal to zero whenever it is different to that of the in-sample estimate. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. Improvements compared to the unconstrained out-of-sample results (see Table 4.3) are denoted in **bold font**. All data are sampled at the monthly frequency.*

Panel (A): Return Predictability				Panel (B): Volatility Predictability			
1 Month		12 Months		1 Month		12 Months	
Δindpro	26.67	Δindpro	40.00	<i>infl</i>	33.33	ΔM1	23.33
dfr	26.67	<i>tbl</i>	30.00	ΔM1	23.33	Δindpro	20.00
erp	26.67	<i>infl</i>	26.67	erp	23.33	ltr	13.33
<i>ΔM1</i>	10.00	<i>ΔM1</i>	20.00	Δindpro	20.00	<i>dfy</i>	10.00
<i>infl</i>	10.00	<i>erp</i>	16.67	svar	20.00	infl	10.00
svar	10.00	ltr	13.33	<i>dfy</i>	13.33	<i>tms</i>	10.00
<i>ltr</i>	6.67	dfr	10.00	ltr	10.00	<i>svar</i>	6.67
tbl	3.33	<i>dfy</i>	6.67	dfr	6.67	<i>tbl</i>	6.67
<i>tms</i>	3.33	svar	6.67	<i>tbl</i>	6.67	<i>unrate</i>	6.67
<i>de</i>	0.00	<i>tms</i>	6.67	tms	6.67	<i>de</i>	3.33
<i>dfy</i>	0.00	<i>unrate</i>	6.67	<i>ep</i>	3.33	dfr	3.33
<i>dp</i>	0.00	<i>ep</i>	3.33	<i>lty</i>	3.33	<i>ep</i>	3.33
<i>dy</i>	0.00	<i>lty</i>	3.33	<i>unrate</i>	3.33	<i>dp</i>	0.00
<i>ep</i>	0.00	<i>de</i>	0.00	<i>de</i>	0.00	<i>dy</i>	0.00
<i>lty</i>	0.00	<i>dp</i>	0.00	<i>dp</i>	0.00	<i>erp</i>	0.00
<i>unrate</i>	0.00	<i>dy</i>	0.00	<i>dy</i>	0.00	<i>lty</i>	0.00

4.6.2 Time-Variation in Volatility

To further exploit the information content of our long sample, we analyze the volatility variation before and after the introduction of derivatives trading and the beginning of the global financial crisis, respectively.²² In particular, we ask the question: Does the introduction of derivatives trading systematically affect the volatility of commodity returns?

Since the introduction of commodity derivatives trading, these markets have exhibited a steadily increasing trading volume (Gorton & Rouwenhorst, 2006; Gorton et al., 2012). The increase in trading volume reflects the rise in the hedging demand at the futures market.²³ Following Acharya et al. (2013), speculators face restrictions by investing their capital in the futures market. On the other hand, due to these capital constraints the hedging demand of commodity producers cannot be satisfied. Consequently, both the capital constraints and the limitations to hedging affect the spot prices. Thus, we expect an increase in the volatility after these break points. Further, since the global financial crisis represents a shock to the economy, we also expect an increase in the volatility after that break point.

Table 4.15 reports the results for the different events.²⁴ Panel (A) summarizes the results with respect to the introduction of derivatives trading, whereas Panel (B) does so with respect to the beginning of the global financial crisis. Following Snedecor & Cochran (1989), we use an F -test to examine whether there are significant differences in the

²²Note that we focus here on the level of volatility and not on the predictability of volatility, as in Section 4.5.2.

²³In detail, assume that a specific fraction of trading volume reflects the hedging demand of a given number of investors. Accordingly, an increase in trading volume is associated with a rise in the number of investors who look for hedging possibilities. Thus, the hedging demand increases.

²⁴In analogy to Section 4.4, we use 120 observations, and 97 observations in the case of the global financial crisis due to limited data availability. Further, we impose the restriction that in the case of futures and options, respectively, at least 10 years of observations must be available to compute the volatilities.

Table 4.15: Time-Variation in Volatility of Returns

This table summarizes the results about the time-variation in the volatility of commodity returns. We consider three different events. In Panel (A), we consider the introduction of futures and options. In Panel (B), we consider the beginning of the global financial crisis in December 2007. "Start" denotes the starting point of trading futures and options, respectively. "Std Dev (prior)" and "Std Dev (after)" indicate the standard deviation prior to and after the time point of introduction, respectively. " Δ Std Dev" is the difference between the volatility after and before the respective event. We use 120 observations to compute the volatility. Here, we impose the restriction that at least 10 years of observations must be available. In the case of the global financial crisis, 97 observations are used. We use the F -test proposed by Snedecor & Cochran (1989) to determine whether the difference in volatility is statistically significantly different from zero. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Panel (A): Introduction of Derivatives Trading:					Panel (B):						
	Futures		Options			Financial Crisis		Financial Crisis				
	Start	Std Dev (prior)	Std Dev (after)	Δ Std Dev	Start	Std Dev (prior)	Std Dev (after)	Δ Std Dev	Start	Std Dev (prior)	Std Dev (after)	Δ Std Dev
Butter	09.2005	0.1644	0.0780	-0.0864***	03.1990	0.0804	0.0629	-0.0175***	12.2007	0.1211	0.0851	-0.036***
Cocoa	07.1959	0.0784	0.0785	0.0001					12.2007	0.0817	0.0755	-0.0061
Coffee Arabica	05.2006								12.2007	0.0627	0.0652	0.0025
Corn Oil					01.1990	0.0873	0.057	-0.0302***	12.2007	0.0669	0.0705	0.0036
Cotton	07.1959	0.0301	0.0283	-0.0017	10.1984	0.0586	0.0445	-0.0142***	12.2007	0.0585	0.0719	0.0134**
Live Cattle	11.1964	0.0452	0.0472	0.002					12.2007	0.0367	0.0431	0.0065
Lean Hog	02.1996	0.0795	0.1237	0.0442***	01.1996	0.031	0.0559	0.0249***	12.2007	0.0866	0.1028	0.0162*
Milk	01.1996	0.0310	0.0559	0.0249***	03.1990	0.1691	0.2787	0.1095***	12.2007	0.0688	0.0588	-0.01
Oranges	02.1967	0.1962	0.1856	-0.0106	02.1989	0.0908	0.0536	-0.0372***	12.2007	0.5223	0.1744	-0.3479***
Soybean Oil	07.1959	0.0700	0.0546	-0.0154***	02.1989	0.0766	0.0622	-0.0144**	12.2007	0.0857	0.0861	0.0004
Soybeans	07.1959	0.0609	0.0455	-0.0155***	02.1989	0.0689	0.0465	-0.0224***	12.2007	0.0842	0.0838	-0.0004
Soybean Meal	07.1959	0.0895	0.0766	-0.013*	03.1990	0.1622	0.076	-0.0862***	12.2007	0.092	0.1225	0.0305***
Sugar	01.1961	0.0723	0.1384	0.0661***	02.1989	0.0667	0.0713	0.0046	12.2007	0.0854	0.0871	0.0017
Wheat	07.1959	0.0431	0.0416	-0.0014					12.2007	0.0818	0.1259	0.0441***
Wool									12.2007	0.0742	0.0830	0.0087
Yellow Corn	07.1959	0.0427	0.0400	-0.0027	02.1989	0.0761	0.0663	-0.0098	12.2007	0.0846	0.1035	0.0189**
Coal	07.2001	0.0328	0.0823	0.0495***	02.1989	0.0952	0.1173	0.0221**	12.2007	0.0544	0.0813	0.0269***
Heating Oil	11.1978	0.0377	0.0943	0.0566***	10.1992	0.0621	0.1997	0.1377***	12.2007	0.1009	0.0932	-0.0077
Natural Gas	04.1990	0.0497	0.1390	0.0893***	10.2005	0.1509	0.1191	-0.0318**	12.2007	0.2406	0.2105	-0.0301
Unleaded Regular Gas	10.2005	0.1509	0.1191	-0.0318**	01.1989	0.0840	0.0880	0.0039	12.2007	0.1563	0.1115	-0.0413***
WTI Oil	03.1983	0.0641	0.1030	0.0389***					12.2007	0.0886	0.0995	0.0108
Aluminium	05.2002	0.0504	0.0630	0.0126**	09.1988	0.0785	0.0331	-0.0454***	12.2007	0.0489	0.072	0.0231***
Gold	12.1974	0.0581	0.0806	0.0225***	06.1990	0.0839	0.0592	-0.0246***	12.2007	0.0398	0.0573	0.0175***
High Grade Copper	07.1959	0.1048	0.0202	-0.0846***					12.2007	0.0734	0.0815	0.0081
Nickel	03.2015				01.1968				12.2007	0.1106	0.0960	-0.0146
Palladium	01.1977				10.1990	0.0709	0.0461	-0.0249***	12.2007	0.1133	0.0985	-0.0148
Platinum	03.1968	0.0355	0.0378	0.0022	03.1989	0.1281	0.0637	-0.0644***	12.2007	0.0478	0.0771	0.0292***
Silver	06.1963	0.0164	0.0670	0.0506***					12.2007	0.0673	0.1041	0.0368***
Tin									12.2007	0.0636	0.0801	0.0164**
Zinc									12.2007	0.0821	0.0867	0.0046

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volatilities.²⁵

We start by analyzing the effect of derivatives trading on the return volatility, shown in Panel (A) of Table 4.15. With the introduction of futures trading, we observe a general increase in the volatility, in particular in the case of energy commodities. The F -test confirms that there are significant differences in the volatilities. We detect the strongest increase from 4.97 % to 13.90 % for natural gas. Other commodities showing notable rises are lean hog, sugar, and silver. Striking exceptions displaying a sharp drop in the volatility are butter, unleaded regular gas, and high grade copper. In general, the results confirm our expectation of an increasing hedging pressure at the spot market.

With the introduction of commodity options, we find a general increase in the volatility in the case of energy commodities, also confirming our expectation. Specifically, natural gas exhibits a rise from 6.21 % to 19.97 %. Unleaded regular gas represents an exception. As opposed to energy, a general downward trend for metal and agricultural commodities is identifiable, in contrast to our expectation. It seems that the introduction of options is associated with a decrease in the volatility for metals and agriculturals. An exception are oranges, showing an increase from 16.91 % to 27.87 %.

Overall, the results provide evidence in favor of a systematic effect of derivatives trading on commodity volatility, indicated by significant differences in volatilities. In particular, an upward trend in energy commodities is perceivable. Natural gas exhibits the strongest increase, whereas unleaded regular gas always shows a sharp reduction in the volatility. Oranges also display a similar pattern.

Analyzing the time periods around the global financial crisis, documen-

²⁵We examine the null hypothesis that the volatility prior to and the volatility after the break point are equal.

ted in Panel (B) of Table 4.15, there is an ambiguous pattern in volatility. Wheat exhibits the strongest increase from 8.18 % to 12.59 %, and, similarly, in the case of soybean meal, coal, platinum, and silver, whereas oranges show the strongest decrease from 52.23 % to 17.44 %; butter, natural gas, and unleaded regular gas also show a similar pattern. The results only partly confirm our expectation, indicating the presence of further effects.

4.6.3 Model Selection Approach

To gain insights about the predictability of excess returns (volatilities) based on multiple regressions, we perform a model selection approach.²⁶ An investor would use all information available up to the time point t and would select the best performing model to predict the next month's excess return (volatility).²⁷ In doing so, we proceed as follows: For all possible predictor combinations, we compute the MSEs on the basis of the first 10 years of out-of-sample observations.²⁸ Selecting the best performing model, we predict the next month's excess return (volatility). Afterwards, using all information up to the next time point $t + 1$, we compute the MSEs again and predict the next month's excess return (volatility) out-of-sample using the model with the lowest MSE. For all other months, we repeat this procedure analogously. To make inferences about the significance of the R_{oos}^2 s, we use the MSFE-adjusted test statistic of Clark & West (2007), a

²⁶We conducted two further alternative approaches to utilize the information of the given set of variables. Both approaches led to similar results as the model selection approach. First, we used a kitchen sink approach, in which we included all available variables. Second, we followed Rapach et al. (2013) and used an adaptive elastic net estimation procedure that shrinks and select parameters based on two penalty terms (lasso and ridge regressions).

²⁷We start in January 1948 to ensure that all predictive variables are available. Further, *dy*, *ep*, and *tbl* have been excluded due to high correlations and multicollinearity.

²⁸We start by running individual regressions, performing multiple regressions, and we end up with a regression containing all predictors (kitchen sink). Also the historical mean (fitted AR(1) process) serves as potential model. If all models fail, an investor would rely on the historical mean (fitted AR(1) process) as best prediction.

4.6. FURTHER ANALYSES

modified version of the Diebold & Mariano (1995) and West (1996) statistic, for nested models.²⁹

Tables 4.4 to 4.5 and Tables 4.6 to 4.7 show the adjusted R_{oos}^2 s for the (next month's and next year's) return and the (next month's and next year's) volatility predictability, respectively.

In Table 4.4, we observe no joint predictive power in the short-term return predictability, indicated by negative adjusted R_{oos}^2 s. For the long-term return predictability, the results in Table 4.5 indicate that some commodities are predictable, in particular cocoa ($R_{oos}^2 = 10.88\%$), live cattle ($R_{oos}^2 = 0.27\%$), heating oil ($R_{oos}^2 = 0.35\%$), and gold ($R_{oos}^2 = 15.16\%$). Overall, the findings suggest a poor out-of-sample return predictability based on a model selection approach. Only few long-term commodity excess returns are well predictable.³⁰

We now turn our focus on the analysis of the volatility predictability. Tables 4.6 and 4.7 reveal no predictability of commodity volatilities based on a model selection approach. The strong persistence of commodity volatility prevents any predictability of the employed predictive variables, although an optimized approach is used.

4.6.4 Mean Forecast Combination Approach

Another approach to improve the out-of-sample predictability is forecast combinations as suggested, e.g., by Rapach et al. (2010). In doing so, we first run a kitchen sink regression and select all predictive variables that are significant at at least the 10% significance level. Afterwards, we

²⁹Since we use multiple regressions equipped with a different number of variables, the bootstrap algorithm, described in Section 4.3.2, in determining an empirical distribution is not applicable.

³⁰The results are not entirely surprising given the large fluctuations among the predictive variables. Despite the fluctuations, the optimized approach shows that few commodity returns are well predictable, particularly in the long-term, indicating a robust predictability over time.

run univariate regressions to obtain the individual out-of-sample forecasts. Finally, we use the average of all available forecasts to obtain the mean out-of-sample forecast.³¹

Tables 4.4 to 4.5 and Tables 4.6 to 4.7 show the R_{oos}^2 s for the (next month's and next year's) return and the (next month's and next year's) volatility predictability, respectively.

In Table 4.4, we observe that four commodity excess returns are significantly predictable in the short-term, indicated by R_{oos}^2 s between 0.35 % for wool and 1.33 % for gold. In contrast, the results in the long-term analysis reveal that almost all commodity returns are significantly predictable, indicated by R_{oos}^2 s up to 13.49 % for gold. Overall, the findings confirm the stability of the mean forecast combination approach in predicting commodity excess returns, particularly in the long-term. To get an overview about the out-of-sample performance based on the mean forecast combination approach, the plots (a), (b), (c), and (d), (e), (f) in Figure 4.1 show the cumulative differences in squared forecast errors (CDSFE) of coffee arabica, WTI oil, gold, and cocoa, heating oil and gold, for both the short- and long-term.³² In all cases, we observe an increasing out-of-sample performance, indicating a superior performance of the mean forecast combination approach.

Predicting commodity volatilities in the short-term, shown in Table 4.6, we observe that only two commodity volatilities are significantly predictable, indicated by R_{oos}^2 s of 0.33 % for unleaded regular gas, and 4.34 % for nickel. In the long-term analysis (Table 4.7), the results reveal no predictability on

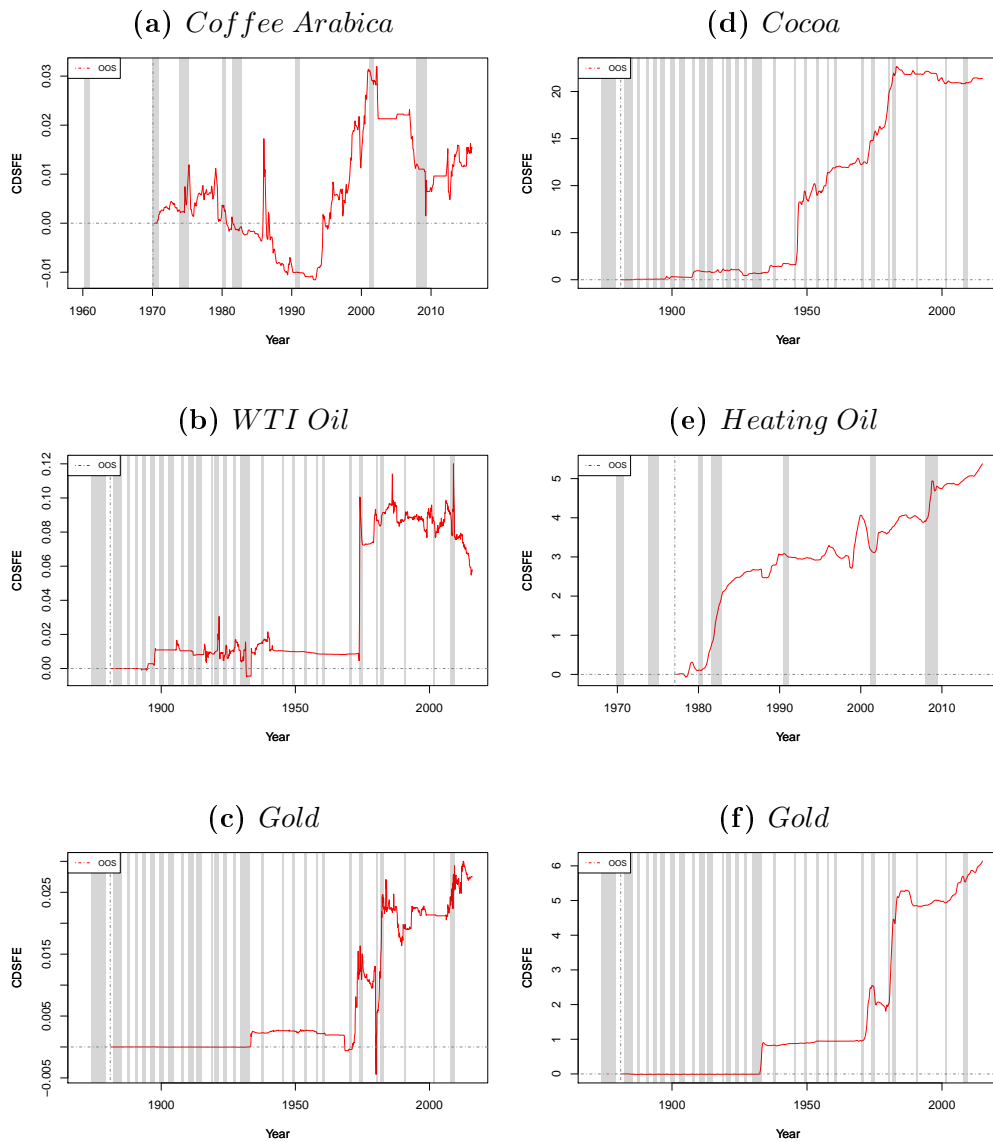
³¹Rapach et al. (2010) argue that forecast combinations reduce the model instability, thus, leading to a superior performance compared to individual forecasts. Further, they show that mean forecast combinations represent robust techniques compared to median and truncated mean forecast combinations.

³²The out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error from the unrestricted model.

4.6. FURTHER ANALYSES

Figure 4.1: Return Predictability (Mean Forecast Combination)

This figure plots the out-of-sample performances based on a mean forecast combination approach. Plots (a)–(c) show the performances of predicting the next month’s excess return. Plots (d)–(f) show the performances of predicting the next year’s excess return. On the ordinate, there are the cumulative differences in squared forecast errors (CDSFE). The out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error from the unrestricted model. The grey bars indicate the U.S. recessions, published by the NBER. All data are sampled at the monthly frequency.



the basis of the mean forecast combination approach. Overall, the strong persistence of commodity volatility prevents any predictability, although a robust approach is used.³³

4.6.5 Sub-Sample Analysis

To further examine the robustness of our results, we analyze the sample period from January 1950 to December 2015. Following Engsted & Pedersen (2010), there might be differences in the predictability during the pre- and post-World War II period, so we are able to avoid incisive events. Table C.15 of the Appendix to this chapter summarizes the return and volatility predictability results for different horizons, and Tables C.16 to C.19 of the Appendix to this chapter provide more detailed information. Overall, the results confirm our main findings.

4.7 Conclusion

This chapter provides comprehensive evidence on the predictive power of a broad set of 16 macroeconomic variables for the returns and volatilities of 30 commodities. Using more than 140 years of data, our long sample enables us to analyze the time-variation in return volatility and in the predictability of commodity return and volatility related to specific break points. A variable is considered to have predictive power if it exhibits significant predictive ability out-of-sample.

³³The large negative R_{oos}^2 s are consistent with our previous findings. Using any predictor in addition to lagged volatility leads to an increase in the deviation between the actual commodity volatility and the predicted one (in comparison to the prediction using lagged volatility only), resulting in a massive underperformance relative to the naive benchmark. This effect is strengthened even in the long-term. Since there is no notable predictability of commodity volatilities, we omit the corresponding CDSFE plots.

4.7. CONCLUSION

We observe short- and long-term predictability in both excess returns and volatilities. Further, there are substantial improvements in the predictive power of variables both in individual predictions and in predictions based on multiple regressions, and in the frequency of significant predictions in the long-term. These effects are more pronounced in return rather than volatility predictability. The break point analysis provides evidence that return volatility, and the return and volatility predictability are systematically affected by the introduction of derivatives trading and the beginning of the global financial crisis.

Finally, our long sample study enables us to analyze the predictability over multiple business cycle stages. Here, we do not only examine expansions and recessions, but also early and late business cycle stages. We find that returns are predictable in both expansions and recessions, whereas volatilities are better predictable in recessions. Several variables exhibit an enhanced predictive performance, when differentiating between business cycle stages.

C Appendix

In this section, we provide additional material for Chapter 4: “Predictability in Commodity Markets: Evidence from more than a Century”.

C. APPENDIX

Table C.1: Summary Statistics Predictive Variables

This table summarizes (non-annualized) key statistics about the predictive variables. “de” denotes the dividend–payout ratio, “ $\Delta indpro$ ” the growth of industrial production, and “ $\Delta M1$ ” the growth of money supply M1. “dfr” is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. “dfy” is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. “dp” is the dividend–price ratio, “dy” the dividend yield, “ep” the earnings–price ratio, “erp” the market risk premium, “infl” the inflation rate, “ltr” the long-term U.S. government bond returns, “lty” the long-term U.S. government bond yields, “svar” the stock variance, and “tbl” the 3-month Treasury bill rate. “tms” is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. “unrate” is the unemployment rate. “Mean”, “Std Dev”, “Skew”, and “Kurt” denote the mean, standard deviation, skewness, and kurtosis, respectively. The next three columns show the first-order autoregressive coefficient and the p-value of the Jarque-Bera and Augmented Dicky Fuller test, respectively. “First Obs.” and “Nobs” denote the first observation of the time series and the number of observations. All data are sampled at the monthly frequency.

Variable	Mean	Std Dev	Skew	Kurt	AR(1)	JB p-value	ADF p-value	First Obs.	Nobs
<i>de</i>	-0.5424	0.3158	0.8124	6.4439	0.9931	<0.01	<0.01	01.1871	1740
<i>$\Delta indpro$</i>	0.0026	0.0193	0.2794	13.9795	0.5076	<0.01	<0.01	02.1919	1163
<i>$\Delta M1$</i>	0.0040	0.0065	1.7852	17.3614	0.2514	<0.01	<0.01	02.1947	827
<i>dfr</i>	0.0003	0.0135	-0.3897	11.0916	-0.1268	<0.01	<0.01	01.1926	1080
<i>dfy</i>	0.0119	0.0071	2.0854	9.7171	0.9767	<0.01	<0.01	01.1919	1164
<i>dp</i>	-3.2088	0.4311	-0.7092	3.3307	0.9941	<0.01	<0.05	01.1871	1740
<i>dy</i>	-3.2054	0.4284	-0.7395	3.3522	0.9940	<0.01	<0.05	02.1871	1739
<i>ep</i>	-2.6663	0.3745	-0.7048	6.4535	0.9884	<0.01	<0.01	01.1871	1740
<i>erp</i>	0.0040	0.0477	-0.4122	11.7655	0.1117	<0.01	<0.01	01.1871	1740
<i>infl</i>	0.0020	0.0072	0.5630	18.4577	0.3031	<0.01	<0.01	01.1875	1691
<i>ltr</i>	0.0048	0.0243	0.6032	7.8052	0.0379	<0.01	<0.01	01.1926	1080
<i>lty</i>	0.0512	0.0269	1.1556	3.8979	0.9966	<0.01	0.87	01.1919	1164
<i>svar</i>	0.0025	0.0049	6.5792	60.9568	0.6201	<0.01	<0.01	02.1885	1571
<i>tbl</i>	0.0349	0.0300	1.0576	4.4489	0.9932	<0.01	0.25	02.1920	1151
<i>tms</i>	0.0163	0.0131	-0.1532	2.9822	0.9625	0.10	<0.01	02.1920	1151
<i>unrate</i>	0.0582	0.0165	0.5723	3.0451	0.9905	<0.01	0.53	01.1948	816

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Table C.2: Correlation Matrix Commodity Returns

This table reports the correlations among all commodity excess returns. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Butter	Cocoa	Coffee Arabica	Corn Oil	Corn	Cotton	Live Cattle	Lean Hog	Milk	Oranges	Soybean Oil	Soybeans	Soybean Meal	Sugar	Wheat	Wool	Yellow Corn	Coal	Heating Oil	Natural Gas	Unleaded Regular Gas	WTI Oil	Aluminum	Gold	High Grade Copper	Nickel	Palladium	Platinum	Silver	Tin	Zinc	
Butter	-0.02																															
Cocoa	0.02	0.11																														
Coffee Arabica	0.12	0.00	0.09																													
Corn Oil	0.05	0.02	-0.02	0.07																												
Corn	-0.02	0.03	-0.01	0.02	0.05																											
Cotton	0.07	0.01	-0.10	0.02	0.01	0.24																										
Live Cattle	0.29	-0.01	-0.05	0.15	0.06	0.00	0.12																									
Lean Hog	0.06	0.02	-0.01	-0.01	0.00	0.01	0.02	0.02																								
Milk	0.03	0.13	0.04	0.29	0.20	0.01	0.12	0.09	-0.08																							
Oranges	-0.02	0.16	0.08	0.19	0.18	0.02	0.03	0.05	-0.10	0.72																						
Soybean Oil	-0.03	0.12	0.09	0.10	0.09	0.02	0.00	0.08	-0.10	0.43	0.82																					
Soybeans	0.06	0.09	0.05	0.05	0.08	-0.06	-0.09	0.07	-0.04	0.13	0.15	0.16																				
Soybean Meal	-0.03	0.14	0.05	0.05	0.08	0.07	0.05	0.03	-0.01	0.37	0.40	0.35	0.11																			
Sugar	0.02	0.09	0.14	0.07	-0.02	-0.02	0.03	0.08	-0.03	0.06	0.05	0.03	-0.01	0.06																		
Wheat	-0.02	0.13	0.01	0.16	0.17	0.00	0.03	0.04	0.00	0.52	0.60	0.53	0.16	0.45	0.02																	
Wool	0.07	0.02	0.10	0.18	0.03	0.07	0.08	0.19	-0.01	0.16	0.14	0.10	0.10	0.10	0.05	0.10	0.05															
Yellow Corn	0.01	0.10	0.03	0.08	-0.04	0.12	0.08	0.01	0.01	0.07	0.05	0.02	-0.03	0.03	0.14	0.01	0.14	0.14														
Coal	-0.02	0.02	-0.03	0.00	0.03	-0.11	0.00	0.01	-0.01	0.04	0.02	-0.02	-0.02	-0.01	0.11	0.03	0.05	0.08	0.19													
Heating Oil	0.03	0.10	0.06	0.11	-0.06	0.07	0.06	0.00	0.01	0.01	0.00	-0.02	-0.02	-0.01	0.14	0.01	0.16	0.63	0.17													
Natural Gas	0.08	0.12	0.02	0.13	-0.09	0.09	0.08	0.05	0.05	0.05	0.06	0.02	-0.06	0.01	0.13	-0.04	0.18	0.74	0.17	0.67												
Unleaded Regular Gas																																
WTI Oil																																
Aluminum	-0.05	0.06	0.13	0.08	0.03	0.11	0.03	0.11	0.03	0.01	0.12	0.10	0.05	0.06	0.04	0.09	0.01	0.17	0.19	-0.01	0.14	0.20										
Gold	-0.02	0.22	0.05	0.01	0.01	0.00	0.03	0.00	-0.02	0.16	0.20	0.14	0.13	0.21	0.07	0.13	0.08	0.12	0.12	0.08	0.18	0.13	0.13									
High Grade Copper	-0.03	0.18	0.12	0.08	0.13	0.05	0.01	0.01	-0.08	0.21	0.20	0.15	0.22	0.18	0.00	0.13	0.20	0.19	0.01	0.16	0.17	0.41	0.31									
Nickel	-0.01	0.05	0.12	0.08	0.07	0.14	0.04	-0.04	-0.07	0.08	0.12	0.10	0.00	0.04	0.13	0.10	0.07	0.16	0.01	0.10	0.11	0.44	0.09	0.32								
Palladium	0.07	0.08	0.13	0.10	0.11	0.04	0.02	0.07	0.01	0.11	0.16	0.14	0.15	0.10	0.02	0.13	0.17	0.10	0.05	0.11	0.13	0.20	0.26	0.23	0.14							
Platinum	0.03	0.17	0.07	0.09	-0.02	0.13	0.07	0.05	0.01	0.12	0.14	0.12	0.03	0.17	0.12	0.10	0.16	0.15	0.11	0.15	0.20	0.30	0.40	0.29	0.22	0.39						
Silver	0.02	0.26	0.06	0.11	0.00	0.03	0.04	0.00	0.03	0.20	0.22	0.16	0.18	0.16	0.11	0.20	0.07	0.13	0.08	0.11	0.17	0.18	0.74	0.34	0.16	0.31	0.40					
Tin	0.06	0.14	0.05	0.18	0.06	0.04	0.09	0.09	-0.06	0.13	0.12	0.05	0.10	0.08	0.01	0.13	0.29	0.23	0.06	0.19	0.23	0.31	0.17	0.35	0.29	0.14	0.19	0.26				
Zinc	-0.03	0.15	0.09	0.08	0.01	0.02	0.08	0.10	-0.12	0.12	0.12	0.08	0.01	0.10	0.12	0.09	0.10	0.09	0.11	0.09	0.13	0.12	0.32	0.16	0.42	0.34	0.18	0.29	0.23	0.35		

Table C.3: Correlation Matrix Commodity Volatilities

This table reports the correlations among all commodity volatilities. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Butter	Cocoa	Coffee Arabica	Corn Oil	Cotton	Live Cattle	Lean Hog	Milk	Oranges	Soybean Oil	Soybeans	Soybean Meal	Sugar	Wheat	Wool	Yellow Corn	Coal	Heating Oil	Natural Gas	Unleaded Regular Gas	WTI Oil	Aluminum	Gold	High Grade Copper	Nickel	Palladium	Platinum	Silver	Tin	Zinc	
Butter	-0.05																														
Cocoa	0.06	-0.12																													
Coffee Arabica	-0.23	0.23	-0.27																												
Corn Oil	-0.09	-0.01	0.07	0.07																											
Cotton	-0.19	0.12	0.14	-0.07	0.03																										
Live Cattle	0.25	-0.01	0.06	-0.05	-0.06	0.00																									
Lean Hog	0.30	0.05	-0.04	-0.18	0.00	-0.18	0.16																								
Milk	0.22	-0.02	0.04	-0.02	0.03	-0.48	-0.06	0.12																							
Oranges	-0.11	0.14	-0.03	0.48	0.15	-0.01	0.14	0.43	0.08																						
Soybean Oil	0.05	0.15	-0.04	0.26	0.06	0.02	0.20	0.31	0.13	0.60																					
Soybeans	-0.01	-0.09	0.04	0.17	0.10	0.07	0.07	0.25	0.11	0.39	0.69																				
Soybean Meal	-0.35	0.11	-0.23	0.36	0.17	0.19	-0.04	-0.19	-0.01	0.35	0.11	0.10																			
Sugar	0.05	0.00	-0.13	0.04	0.09	0.00	0.11	0.44	-0.16	0.24	0.39	0.37	0.06																		
Wheat	0.04	-0.10	-0.07	-0.15	0.05	-0.14	-0.06	0.24	-0.11	-0.11	0.01	0.01	-0.12	0.29																	
Wool	0.05	-0.19	0.10	0.03	0.29	0.12	0.09	0.29	0.17	0.38	0.55	0.64	0.11	0.49	0.08																
Yellow Corn	0.02	0.26	-0.15	0.09	0.01	0.03	0.11	0.29	-0.02	0.20	0.25	0.17	0.04	0.30	0.24	0.16															
Coal	0.13	0.05	0.12	0.06	0.09	-0.07	0.06	-0.03	0.05	0.14	0.03	0.05	0.08	-0.07	-0.04	0.05	0.05														
Heating Oil	0.41	0.06	0.03	-0.02	-0.06	-0.22	0.10	0.27	0.36	0.11	0.17	0.04	-0.18	0.11	0.10	0.10	0.23	0.21													
Natural Gas	0.19	-0.13	0.22	0.02	0.13	-0.20	0.12	0.08	0.06	0.16	0.12	0.17	-0.05	0.08	0.08	0.18	0.11	0.53	0.23												
Unleaded Regular Gas	0.24	-0.02	0.19	-0.04	0.20	-0.02	0.21	0.19	0.09	0.13	0.10	0.13	0.12	0.14	0.08	0.22	0.13	0.60	0.25	0.48											
WTI Oil	-0.09	-0.06	0.03	-0.08	0.02	0.02	0.04	0.01	0.01	0.02	0.10	0.10	0.06	-0.03	0.17	0.15	0.19	0.16	0.08	0.06	0.23										
Aluminum	-0.24	0.30	-0.23	0.30	-0.01	0.04	-0.12	0.09	-0.09	0.17	0.20	0.17	0.30	0.17	-0.01	0.07	0.33	0.03	0.03	-0.04	-0.01	-0.04									
Gold	-0.08	0.14	-0.08	0.07	-0.02	0.13	0.01	0.09	-0.06	0.13	0.19	0.20	0.09	0.04	0.13	0.06	0.36	0.08	0.15	0.00	0.06	0.41	0.31								
High Grade Copper	0.08	-0.07	-0.03	-0.08	-0.04	-0.07	0.03	0.07	-0.04	0.05	0.07	0.10	-0.05	-0.07	0.18	-0.03	0.21	0.12	0.10	0.03	0.10	0.34	0.04	0.47							
Nickel	0.11	0.03	-0.11	0.02	-0.05	-0.14	0.08	0.20	-0.08	0.12	0.06	0.09	0.05	0.26	0.05	0.14	0.21	-0.06	0.10	0.04	0.04	-0.08	0.12	0.05	0.06						
Palladium	-0.04	-0.03	0.09	0.08	0.24	0.11	0.05	0.06	-0.08	0.22	0.17	0.26	0.20	0.12	0.04	0.23	0.10	0.28	0.15	0.22	0.36	0.29	0.14	0.21	0.17	-0.02					
Platinum	-0.12	0.11	-0.26	0.15	0.07	-0.01	0.07	0.22	-0.15	0.14	0.22	0.19	0.12	0.23	0.10	0.16	0.33	-0.13	-0.06	-0.06	-0.14	-0.03	0.60	0.26	0.06	0.15	0.10				
Silver	-0.03	0.15	-0.02	-0.15	0.02	0.03	-0.03	0.40	-0.05	0.02	0.07	0.09	-0.10	0.27	0.22	0.10	0.39	0.06	0.17	0.10	0.16	0.06	0.26	0.20	0.16	0.09	0.15	0.26			
Tin	0.03	-0.04	0.04	-0.21	0.08	0.04	0.16	0.45	0.00	0.07	0.22	0.13	-0.03	0.34	0.33	0.26	0.40	0.03	0.23	0.14	0.18	0.25	0.22	0.28	0.15	-0.01	0.18	0.26	0.46		
Zinc																															

Table C.4: Correlation Matrix Predictive Variables

This table reports the correlations among all predictive variables. "de" denotes the dividend-payout ratio, " $\Delta indpro$ " the growth of industrial production, and " $\Delta M1$ " the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. All data are sampled at the monthly frequency.

Variable	de	$\Delta indpro$	$\Delta M1$	dfr	dfy	dp	dy	ep	erp	infl	ltr	lty	svar	tbl	tms	unrate
de	-0.03															
$\Delta indpro$	0.11	-0.05														
$\Delta M1$	0.12	0.09	-0.01													
dfr	0.22	-0.25	0.27	0.08												
dfy	0.29	-0.02	0.02	0.01	0.12											
dp	0.29	-0.02	0.01	0.03	0.12	0.99										
dy	-0.37	0.00	-0.05	-0.06	-0.03	0.78	0.78									
ep	0.01	0.01	-0.04	0.21	0.00	-0.02	0.08	-0.03								
erp	-0.13	-0.01	-0.03	-0.01	0.08	0.18	0.17	0.26	-0.09							
infl	-0.02	-0.12	0.02	-0.46	0.14	-0.01	-0.01	0.00	0.09	-0.13						
ltr	-0.07	-0.04	0.10	0.00	0.51	0.18	0.17	0.21	-0.08	0.37	0.04					
lty	0.15	-0.10	0.20	-0.14	0.32	-0.08	-0.11	-0.18	-0.33	-0.13	0.14	0.02				
svar	-0.13	-0.05	-0.04	-0.04	0.34	0.28	0.27	0.36	-0.10	0.43	0.04	0.89	-0.05			
tbl	0.16	0.02	0.29	0.08	0.27	-0.26	-0.26	-0.36	0.07	-0.22	0.00	0.03	0.14	-0.42		
tms	0.07	-0.02	0.31	0.07	0.64	0.04	0.05	-0.01	0.08	0.02	0.10	0.40	0.08	0.11	0.56	
unrate																

Table C.5: In-Sample Return Predictability and Business Cycle Stages (1 Month)

This table reports the in-sample R^2 s of a regression of monthly excess returns on a constant and the lagged predictive variable across business cycle stages. We predict the next month's excess return. "de" denotes the dividend-payout ratio, " Δindpro " the growth of industrial production, and " ΔM1 " the growth of money supply. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "itr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "unrate" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider six business cycle stages. "Exp" denotes the expansion, "eExp" the early expansion, "lExp" the late expansion, "Rec" the recession, "eRec" the early recession, "lRec" the late recession. *, **, *** indicate the significance at the 10%, 5%, and 1% significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de						Δindpro						ΔM1					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Butter	0.01	0.00	0.00	0.10	1.23	0.33	0.34**	1.02**	0.02	0.05	0.07	0.01	0.02	0.21	0.00	11.75***	0.02	17.66***
Cocoa	0.07	0.15	0.04	0.04	0.39	0.00	0.52**	0.56	0.30	1.52*	1.87	0.49	0.14	0.88*	0.04	0.37	0.72	0.99
Coffee Arabica	0.00	0.48	0.03	4.69**	0.05	17.16***	0.09	0.15	0.04	3.76*	1.87	1.62	0.08	0.01	0.02	0.13	0.02	1.03
Corn Oil	0.42*	1.17**	0.01	0.01	1.45	0.10	1.22***	1.73**	0.50	0.04	0.21	0.02	0.05	0.07	0.49	0.60	7.94**	1.61
Cotton	0.41**	0.39	0.25	0.05	0.87	0.02	0.29	0.64*	0.03	0.02	1.04	0.24	0.11	0.27	0.43	1.88*	0.02	1.46
Live Cattle	0.10	0.58*	0.06	0.00	0.12	0.02	1.25***	2.37***	0.01	2.01**	0.55	1.70	0.03	0.23	0.00	0.08	6.59**	0.19
Lean Hog	0.03	0.13	0.00	0.20	0.13	0.51	0.22	0.48	0.03	0.04	0.00	0.15	0.02	0.57	0.01	0.11	0.43	0.00
Milk	0.05	0.18	0.01	0.58	0.33	0.18	0.68**	2.69***	0.14	0.83	1.21	0.31	0.02	0.12	0.06	5.91***	1.99	14.50***
Oranges	0.12	0.01	0.41	0.14	0.25	0.08	0.02	0.00	0.00	0.12	0.80	0.03	0.00	0.28	0.02	0.75	1.78	4.42
Soybean Oil	0.52**	1.12**	0.00	0.23	1.74	0.02	2.36***	3.79***	0.43	1.23*	0.55	1.00	0.16	0.22	0.22	0.03	2.79	0.03
Soybeans	0.54***	0.97**	0.22	0.16	2.65*	0.01	1.65***	3.44***	0.09	1.18*	1.14	1.36	0.04	0.08	0.07	0.08	0.21	0.41
Soybean Meal	0.32	0.80	0.06	0.07	1.60	0.42	0.95***	0.92*	1.30**	0.26	0.06	0.73	0.08	0.20	0.10	0.78	0.09	2.55
Sugar	0.00	0.02	0.05	0.00	1.55**	0.95	0.01	0.09	0.02	0.05	0.74	1.21	0.08	0.00	0.53	1.23	0.20	0.70
Wheat	0.01	0.05	0.39	0.11	0.15	0.09	0.27	0.63	0.00	0.39	0.00	1.97	0.15	0.05	0.98*	0.07	1.94	3.18
Wool	0.23	0.86**	0.01	0.01	3.00***	0.79	1.73***	3.07***	0.13	1.95**	0.38	1.62	0.56*	0.00	1.69**	2.42*	3.88	2.14
Yellow Corn	0.01	0.55*	0.26	0.16	0.13	0.29	0.70**	0.97**	0.42	0.59	0.18	0.85	0.00	0.96*	0.88*	0.04	0.83	0.17
Coal	0.46*	0.84*	0.20	1.04	0.64	0.56	0.01	0.01	0.00	0.00	0.26	1.05	0.12	0.36	0.01	0.54	0.69	0.01
Heating Oil	0.65	0.78	0.34	0.39	0.15	5.35	0.12	0.23	0.20	2.95	0.89	4.14	0.19	1.20	0.00	0.17	0.00	1.07
Natural Gas	0.27	0.00	0.56	0.06	0.48	0.13	0.18	0.02	0.29	15.34***	0.92	14.84**	1.95***	2.05*	1.76*	1.26	0.03	8.22
Unleaded Regular Gas	0.59	0.66	0.17	4.21*	0.81	10.33**	0.08	0.05	0.29	0.16	0.00	10.26*	0.14	0.07	0.04	0.37	0.30	5.56
WTI Oil	0.02	0.03	0.44	0.07	0.23	2.33***	0.62**	1.13**	0.08	0.66	2.71*	0.03	0.05	0.00	0.02	0.77	3.66	0.61
Aluminum	0.01	0.40	0.25	0.01	2.84**	1.36	0.01	0.00	0.11	0.79	0.19	0.43	0.00	0.00	0.03	12.25***	0.66	23.24***
Gold	0.01	0.63*	0.71**	0.19	0.57	0.36	0.34**	2.71***	0.16	0.24	0.08	0.01	0.00	0.00	0.84	1.36**	0.21	1.81
High Grade Copper	0.03	0.11	0.02	0.71*	0.33	2.59***	0.34**	0.37	0.43	1.85***	1.21	1.28	0.03	0.09	0.07	4.53**	1.51	1.72
Nickel	0.01	1.82*	0.92	6.78*	6.59	15.55**	0.37	0.70	0.30	0.00	0.36	8.97	0.15	2.51*	0.09	0.04	4.74	0.82
Palladium	0.70*	0.03	1.08	0.32	8.81**	1.27	0.10	0.17	0.19	0.15	3.59	0.05	0.05	0.11	0.11	0.45	0.20	1.86
Platinum	0.06	0.20	0.01	0.45	2.89**	1.47	0.01	0.05	0.12	1.19*	0.94	1.75	0.06	0.29	0.07	0.11	0.78	0.26
Silver	0.15	0.01	0.51*	0.10	0.19	0.13	0.06	0.00	0.17	0.40	0.09	2.48*	0.14	0.01	0.72	0.00	1.00	2.28
Tin	0.01	0.11	0.01	0.07	2.34**	2.47***	0.46**	0.57	0.12	0.86	2.70*	0.13	0.53*	1.05*	0.15	1.64	0.52	2.17
Zinc	0.08	0.14	0.03	2.27***	0.02	5.40***	0.10	0.22	0.02	0.38	0.05	0.65	0.21	0.28	1.33**	3.12*	0.61	2.81

CHAPTER 4. PREDICTABILITY IN COMMODITY MARKETS:
EVIDENCE FROM MORE THAN A CENTURY

Table C.5: In-Sample Return Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	df _r				df _y				df _p					
	Exp	eExp	lExp	Rec	eRec	lRec	Rec	eRec	lExp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	0.15	0.16	0.13	0.01	0.07	0.04	0.08	0.62	0.04	0.02	0.01	0.12	3.18**	0.88
<i>Cocoa</i>	0.20	0.79*	0.03	0.24	0.11	0.25	1.11	0.64	0.80	0.03	0.33	0.11	0.47	0.38
<i>Coffee Arabica</i>	0.65*	0.10	2.14**	2.56	2.16	4.23	0.14	4.23	8.62**	0.05	0.00	0.04	0.65	0.01
<i>Corn Oil</i>	0.05	0.08	0.94*	0.49	0.17	0.23	0.17	0.36	0.18	0.27	0.71	0.13	2.09**	10.12***
<i>Cotton</i>	0.03	0.01	0.15	0.50	0.25	4.57**	1.81***	2.08***	0.63	0.44**	0.72*	0.40	0.06	0.14
<i>Live Cattle</i>	0.27	0.22	0.26	0.47	0.03	0.05	0.27	0.66	1.20	0.09	0.03	0.18	0.01	0.10
<i>Lean Hog</i>	0.00	0.04	0.02	0.69	0.08	0.30	0.20	0.83*	0.01	0.00	0.00	0.02	0.12	0.17
<i>Milk</i>	0.02	0.26	0.04	0.93	2.50*	0.68	1.00	1.12	0.65	0.27*	0.30	0.21	0.03	0.38
<i>Oranges</i>	0.00	0.22	0.32	0.01	0.63	0.66	0.25	0.37	0.18	0.43**	0.11	0.52	0.04	1.05
<i>Soybean Oil</i>	0.02	0.20	0.78*	0.21	0.13	0.19	0.54**	0.82*	0.51	0.43**	0.84**	0.18	2.38**	6.78***
<i>Soybeans</i>	0.04	0.01	0.11	0.08	0.89	0.62	0.59***	1.08**	1.08	0.05	0.01	0.11	2.91**	1.27
<i>Soybean Meal</i>	0.02	0.26	0.03	0.08	3.23*	0.01	0.14	0.32	0.01	0.00	0.00	0.01	0.64	1.09
<i>Sugar</i>	0.01	0.07	0.10	0.32	0.29	0.55	0.03	0.00	0.31	0.00	0.01	0.02	0.52*	1.26*
<i>Wheat</i>	0.00	0.01	0.01	0.00	0.29	0.08	0.08	0.07	0.31	0.00	0.12	0.02	0.01	0.19
<i>Wool</i>	0.53**	1.34**	0.31	8.51***	0.01	16.97***	1.81***	2.23***	0.55	0.33*	0.05	0.76**	2.83***	7.61***
<i>Yellow Corn</i>	0.01	0.02	0.20	0.52	0.02	4.14**	0.34	0.49	0.17	0.02	0.10	0.00	0.25	0.74
<i>Coal</i>	0.34*	2.29***	0.00	0.79	0.19	0.06	0.06	0.73*	0.23	0.00	0.03	0.08	0.19	3.68*
<i>Heating Oil</i>	0.24	1.89**	0.00	14.42***	9.89**	8.05*	0.12	0.16	0.03	0.22	1.71	6.56	0.45	2.86**
<i>Natural Gas</i>	0.33	0.92	2.67**	0.37	0.75	3.50	0.16	0.19	0.17	0.62	1.19	2.93	1.34**	17.36**
<i>Unleaded Regular Gas</i>	0.54	1.82*	0.06	20.98***	1.04	16.66**	0.06	0.06	0.00	0.24	2.49	11.43**	0.63	2.45**
<i>WTI Oil</i>	0.30*	0.92*	0.00	4.78***	2.81*	1.06	0.23	0.48	0.03	0.16	2.03	0.72	0.12	0.97
<i>Aluminum</i>	0.44*	0.84*	0.33	3.57***	2.51*	0.15	0.03	0.85*	0.50	0.21	0.33	0.02	0.00	0.12
<i>Gold</i>	0.14	0.40	0.07	3.36***	0.68	0.65	0.07	0.25	0.06	0.03	3.13**	0.39	0.08	0.90
<i>High Grade Copper</i>	0.02	0.94*	0.25	1.94**	0.09	0.00	0.14	0.26	0.13	0.02	2.95**	0.42	0.01	0.05
<i>Nickel</i>	0.00	0.81	0.21	2.94	0.34	0.40	0.11	0.04	1.24	1.67	1.00	1.33	0.05	0.02
<i>Palladium</i>	0.39	0.40	0.06	1.37	0.04	1.94	2.09***	0.69	2.44**	3.76	3.76	2.35	0.99*	0.29
<i>Platinum</i>	0.09	0.14	0.00	0.20	0.05	0.34	0.05	0.00	0.43	0.18	1.00	0.24	0.00	1.13
<i>Silver</i>	0.03	0.13	0.02	2.04**	0.90	0.36	0.03	0.25	0.06	0.01	3.33**	0.03	0.00	0.00
<i>Tin</i>	0.39*	0.53	0.27	0.00	0.06	2.39	0.53**	0.33	1.07**	0.00	3.25**	1.11	0.07	0.03
<i>Zinc</i>	0.35*	1.31**	0.01	1.26*	1.01	1.50	0.25	0.01	1.56**	0.95	1.11	4.60**	0.33	0.00
													0.06	0.71

Table C.5: In-Sample Return Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	dy			ep			erp			
	Exp	eExp	lExp	lRec	Rec	eRec	lRec	Rec	eRec	lRec
Butter	0.01	0.00	0.00	1.48*	0.01	0.00	0.00	1.05	0.04	0.04
Cocoa	0.02	0.26	0.11	0.14	0.00	0.18	0.20	0.04	0.12	0.12
Coffee Arabica	0.04	0.00	0.02	0.32	0.18	4.17**	0.04	10.27**		
Corn Oil	0.31	0.84*	0.14	0.84	0.03	0.27	1.28	5.39**	0.18	0.18
Cotton	0.49**	0.80**	0.41	0.00	0.13	0.31	0.08	0.09	0.00	0.00
Live Cattle	0.10	0.03	0.22	0.00	0.08	0.04	0.01	0.01	0.02	0.11
Lean Hog	0.00	0.00	0.00	0.03	0.09	0.20	0.01	0.06	0.00	0.00
Milk	0.29*	0.33	0.19	0.03	0.27	0.32	0.18	0.05	0.26	0.23
Oranges	0.42**	0.12	0.61*	0.08	1.67	0.03	0.21	0.01	0.32	0.01
Soybean Oil	0.44*	1.01**	0.12	1.80**	0.00	0.07	0.03	0.32	0.85	0.00
Soybeans	0.07	0.06	0.07	1.20*	0.47	0.05	0.31	0.02	0.78	0.51
Soybean Meal	0.00	0.00	0.02	0.19	0.91	0.17	0.31	0.09	0.79	0.03
Sugar	0.00	0.02	0.02	0.52	1.19*	0.19	0.00	0.00	0.36	0.08
Wheat	0.00	0.08	0.02	0.00	0.14	0.06	0.01	0.03	0.03	0.02
Wood	0.44**	0.14	0.82**	1.84**	6.65**	0.32	0.10	2.00	1.05**	2.26**
Yellow Corn	0.02	0.15	0.00	0.21	0.63	0.03	0.00	0.06	0.11	0.01
Cool	0.03	0.64	0.06	0.13	4.11*	5.17**	0.06	0.06	0.42	0.19
Heating Oil	0.55	2.92**	0.02	0.34	0.22	19.64**	0.07	1.07	0.04	0.04
Natural Gas	1.46**	2.55**	0.52	0.42	1.97	0.01	0.92	1.88*	0.27	2.38
Unleaded Regular Gas	0.76	2.66**	0.09	0.07	1.05	9.06*	0.20	0.88	0.02	2.15
WTI Oil	0.15	0.12	0.22	0.00	0.07	1.12*	0.09	0.17	0.01	0.07
Aluminium	0.00	0.08	0.10	0.00	0.25	1.08	0.01	0.45	0.50	0.01
Gold	0.06	0.74**	0.04	0.74**	2.55**	0.01	0.07	2.41**	0.71*	1.63**
High Grade Copper	0.01	0.08	0.01	0.26	0.60	0.00	0.00	0.01	0.00	1.89**
Nickel	0.05	2.59*	0.54	0.00	0.05	0.00	0.03	0.59	0.13	4.53
Palladium	1.07**	0.00	1.22	2.50	2.15	1.49	0.37	0.00	0.60	0.36
Platinum	0.00	0.02	0.08	0.03	0.00	1.77	0.02	0.24	0.07	0.28
Silver	0.00	0.12	0.15	0.12	0.66	0.00	0.10	0.21	0.92**	0.45
Tin	0.09	0.05	0.71**	0.14	1.28*	0.23	0.12	0.00	0.95**	0.66*
Zinc	0.05	0.39	0.03	0.11	0.00	0.77	0.00	0.07	0.13	1.12**

Table C.5: In-Sample Return Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	<i>in/fl</i>				<i>tr</i>				<i>ty</i>							
	Exp	eExp	lExp	Rec	eRec	lRec	Rec	eRec	lExp	Exp	eExp	lExp	Rec	eRec	lRec	
<i>Butter</i>	0.04	0.45	0.00	1.38**	0.24	1.34	0.01	0.24	0.47	0.14	0.78*	0.01	5.47**	0.00	0.26	0.01
<i>Cocoa</i>	0.03	0.10	0.02	0.20	0.34	0.00	0.25	0.05	0.46**	0.10	0.12	1.38**	0.13	0.11	1.83	1.43
<i>Coffee Arabica</i>	0.16	1.74**	0.16	0.33	0.24	4.69	2.11**	0.00	0.49	0.41	0.10	0.58	0.01	0.11	0.19	0.11
<i>Corn Oil</i>	0.11	0.59	0.13	0.21	0.02	1.46	0.90*	1.53	0.01	0.45*	0.17	1.53	0.38*	0.11	0.08	0.01
<i>Cotton</i>	0.56**	0.40	0.86**	0.31	0.55	0.04	0.18	1.40**	0.77	0.27	1.32**	0.79*	5.75**	0.25	0.21	0.14
<i>Live Cattle</i>	0.00	0.00	0.01	1.16**	1.47**	1.16*	0.18	0.09	0.10	0.18	0.09	0.49	0.00	0.19	0.07	1.65
<i>Lean Hog</i>	0.05	0.06	0.08	0.14	0.89	0.06	0.20	0.02	0.14	0.20	0.02	1.49**	0.44	0.10	0.18	0.18
<i>Milk</i>	0.22	0.30	0.38	2.98***	2.14**	3.00**	0.47**	0.67**	1.92	0.44	1.04	1.92	0.86	0.03	0.01	0.00
<i>Oranges</i>	0.00	0.07	0.01	0.04	0.01	0.61	0.16	0.12	5.19***	0.80	0.80	0.53	0.80	0.01	0.06	0.04
<i>Soybean Oil</i>	0.56**	1.16**	0.08	0.69	0.88	0.61	0.23	0.00	0.04	0.11	1.52	0.33*	0.11	0.18	0.68	0.01
<i>Soybeans</i>	0.01	0.00	0.00	0.30	0.60	0.22	0.16	0.03	0.01	1.52	0.01	0.61	0.01	0.14	0.03	0.03
<i>Soybean Meal</i>	0.37	0.20	0.76*	0.01	0.30	0.01	0.01	0.00	0.06	0.18	0.06	0.04	0.06	0.04	0.08	1.10
<i>Sugar</i>	0.03	0.16	0.00	2.58***	5.32***	0.45	0.11	0.46	0.03	0.09	0.49	0.09	0.22	0.03	0.00	1.27
<i>Wheat</i>	0.23	0.27	0.16	0.02	0.41	0.51	0.00	0.14	0.36	0.41	0.32	0.78*	0.41	0.02	0.12	0.02
<i>Wool</i>	0.50**	0.30	0.81**	0.13	0.20	0.01	0.93***	2.08***	0.06	7.93***	0.36	4.51***	0.41	0.23	0.28	0.15
<i>Yellow Corn</i>	0.02	0.07	0.02	0.15	0.01	0.29	0.00	0.06	0.10	0.91	0.56	1.47***	0.02	0.01	0.00	0.01
<i>Cool</i>	0.15	0.16	0.06	3.60***	3.51*	2.62	0.23	0.80*	0.07	0.13	0.43*	2.14***	0.04	0.22	0.00	0.52
<i>Heating Oil</i>	0.47	1.42*	0.45	3.75*	0.35	11.80**	0.37	0.66	1.34	0.38	0.42	1.13	0.08	0.08	0.30	1.28
<i>Natural Gas</i>	0.82	0.11	1.55*	0.14	0.91	0.01	0.12	0.26	0.44	2.13	1.13**	2.60**	0.23	0.18	0.80	0.10
<i>Unleaded Regular Gas</i>	1.26**	1.66	1.65	0.20	0.13	0.87	2.04***	1.42	2.65**	0.11	0.70	1.36	0.33	0.30	1.19	0.08
<i>WTI Oil</i>	0.00	0.01	0.00	1.62***	0.07	4.23***	0.94***	1.23**	2.64*	3.04*	0.17	1.08**	0.06	0.33	2.76*	0.27
<i>Aluminium</i>	0.02	0.25	0.00	2.48***	2.03*	2.12*	0.89***	1.48**	1.67	0.32	0.01	0.01	0.02	0.00	0.00	0.01
<i>Gold</i>	0.01	0.02	0.17	0.01	0.01	0.18	0.16	0.54	0.29	2.03	0.31	2.35***	0.28	0.02	1.98	4.64**
<i>High Grade Copper</i>	0.09	0.08	0.00	0.04	0.04	0.21	0.04	0.11	0.66	0.66	0.39*	1.87***	0.01	0.01	0.00	0.10
<i>Nickel</i>	0.43	2.50*	0.05	0.68	2.65	0.10	0.01	0.40	0.08	7.18	0.17	1.77	0.16	0.80	0.68	5.48
<i>Palladium</i>	0.21	2.14**	0.05	3.78*	9.51**	3.39	0.03	0.17	0.54	0.38	1.02**	0.05	1.61*	0.55	0.36	0.69
<i>Platinum</i>	0.67**	0.73*	0.63*	0.11	0.05	0.57	0.01	0.12	0.25	0.00	0.38*	0.88**	0.09	0.18	0.98	0.22
<i>Silver</i>	0.12	0.03	0.24	0.04	0.20	0.03	0.04	0.07	0.11	0.30	0.17	1.86***	0.42	0.45	1.61	0.11
<i>Tin</i>	0.03	0.05	0.07	0.32	0.30	0.36	0.36*	1.07**	0.51	0.24	1.14***	2.27***	0.10	0.00	0.62	1.12
<i>Zinc</i>	0.06	0.05	0.27	0.25	0.35	0.38	0.33	0.31	0.47	0.80	0.33*	1.90***	0.08	0.05	0.03	0.09

Table C.5: In-Sample Return Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	svar						tbl						tms					
	Exp	eExp	IExp	Rec	eRec	IRec	Exp	eExp	IExp	Rec	eRec	IRec	Exp	eExp	IExp	Rec	eRec	IRec
Butter	0.00	0.01	0.00	0.88**	0.84	0.56	0.16	0.85**	0.05	0.02	1.27	0.02	0.01	0.01	0.15	0.09	4.94**	0.01
Cocoa	0.22	0.80**	0.00	0.57	2.13**	0.06	1.03**	0.47	1.15**	0.24	0.31	1.76	0.45*	0.49	0.02	0.19	0.72	0.04
Coffee Arabica	0.02	0.01	0.10	0.05	0.36	2.86	1.03**	0.40	0.08	0.00	1.16	4.47	2.38***	2.05**	0.17	0.31	4.75	8.95**
Corn Oil	0.69**	2.69***	0.03	1.19	0.04	1.90	0.34	1.09**	0.01	0.11	0.08	0.02	0.00	0.20	0.20	0.01	0.03	0.01
Cotton	0.39**	1.54***	0.00	0.02	0.73	0.71	0.41*	1.54***	0.59	0.72	0.24	0.65	0.12	0.00	0.01	1.27*	0.11	1.27
Live Cattle	0.55**	1.23***	0.17	1.08**	1.91**	1.40*	0.78**	2.39***	0.02	0.26	0.01	2.10	0.25	0.01	0.78*	0.12	0.17	0.33
Lean Hog	0.10	0.60*	0.07	0.01	0.14	0.40	0.19	0.62	0.00	0.05	0.50	0.09	0.00	0.03	0.02	0.97	1.95	0.05
Milk	0.00	0.02	0.00	0.70	0.00	1.62*	0.55**	2.78***	0.00	0.40	0.03	0.65	0.02	0.00	0.17	1.81**	0.06	4.29***
Oranges	0.01	0.00	0.04	0.73	1.56	0.08	0.13	0.42	0.03	0.06	0.50	0.03	0.01	0.02	0.05	0.01	0.00	0.00
Soybean Oil	1.14***	3.01***	0.12	1.13*	1.14	1.13	0.84***	1.96***	0.03	0.10	0.71	0.06	0.87*	0.36	0.87*	0.01	0.22	0.14
Soybeans	1.30***	2.38***	0.48	1.37**	0.54	1.13	1.06***	1.42***	0.59	0.00	0.13	0.19	0.58**	0.11	1.29**	0.25	0.00	0.45
Soybean Meal	0.39*	0.20	0.65	0.02	0.25	0.01	0.59**	0.69	0.66	0.18	0.03	1.25	0.34	0.06	1.42**	0.63	0.07	0.23
Sugar	0.10	0.16	0.09	0.05	0.05	0.29	0.23	0.93**	0.00	0.00	0.10	2.43	0.18	0.24	0.56	0.14	0.85	1.67
Wheat	0.12	0.02	0.42	0.13	0.10	0.00	0.37*	0.96**	0.00	0.10	0.00	0.12	0.02	0.00	0.18	0.27	0.79	1.64
Wool	1.28***	4.30***	0.03	0.34	0.35	0.13	0.95***	1.37***	0.41	0.99	0.97	0.58	0.79**	0.25	1.48**	2.59**	2.98*	0.97
Yellow Corn	0.45**	0.55*	0.45	0.65*	0.55	0.40	0.54**	1.27**	0.18	0.03	0.00	0.03	0.00	0.16	0.59	0.08	0.00	0.03
Coal	0.20	0.01	0.60	1.24	1.04	1.25	0.51*	4.23***	0.06	0.70	0.01	2.04	0.05	1.63**	0.04	1.94*	0.01	6.34**
Heating Oil	0.00	1.12	0.10	5.96**	6.36**	5.90	0.14	1.21	0.03	0.38	0.13	1.38	0.07	0.32	0.01	1.03	0.04	0.34
Natural Gas	0.05	2.43**	0.02	10.01**	11.36**	28.52**	0.61	2.30**	0.04	0.06	1.06	0.34	0.02	0.34	0.14	0.08	1.22	2.16
Unleaded Regular Gas	0.02	0.03	0.11	4.06*	0.06	2.07	0.30	1.23	0.27	0.06	0.60	0.00	0.06	0.21	0.01	0.25	0.04	0.84
WTI Oil	0.05	0.79**	0.13	1.15**	0.01	1.38	0.08	1.41**	0.16	0.23	1.88	0.54	0.06	0.03	0.22	0.00	0.03	0.47
Aluminium	0.02	0.00	0.10	0.65	0.18	1.09	0.15	0.27	0.13	0.07	0.10	0.05	0.34*	0.81*	0.32	0.41	0.99	0.19
Gold	0.66**	2.64***	0.04	0.56	0.17	2.82**	0.50**	4.96***	0.45	0.00	1.56	3.14*	0.15	1.78***	0.31	0.20	0.03	0.33
High Grade Copper	1.42***	0.64*	2.31***	1.01**	0.34	0.53	0.61**	2.47***	0.01	0.10	0.03	0.50	0.16	0.05	0.17	0.40	0.25	0.94
Nickel	0.64*	0.86	0.56	0.97	2.65	1.72	0.65	1.72	0.24	0.67	0.75	3.54	0.69	0.42	2.60*	0.13	0.57	0.50
Palladium	0.03	1.26	0.13	0.11	0.29	0.36	0.57	0.16	2.03***	0.35	1.73	0.04	0.02	0.30	0.44	0.00	5.68	1.89
Platinum	0.04	0.26	0.07	0.02	0.25	0.12	0.34*	0.73*	0.22	0.06	1.97	0.22	0.00	0.10	0.30	0.11	3.25**	0.00
Silver	0.05	0.50**	0.03	0.06	0.00	0.53	0.11	2.76***	0.73*	1.15	1.31	0.03	0.01	0.23	0.54	1.88**	0.04	1.59
Tin	0.71**	2.42***	0.00	0.68*	2.12**	0.00	1.68***	3.38***	0.17	0.06	0.88	1.95	0.31	0.18	0.15	0.31	0.74	0.93
Zinc	0.00	0.05	0.02	0.36	0.29	3.08***	0.37*	1.33**	0.00	0.04	0.17	0.48	0.02	0.48	0.60	0.00	3.33**	0.97

Table C.5: In-Sample Return Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	<i>unrate</i>					
	Exp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	0.02	0.16	0.00	0.00	1.37	5.80*
<i>Cocoa</i>	0.06	2.05**	1.71**	0.67	0.13	5.49*
<i>Coffee Arabica</i>	0.78**	0.65	0.01	0.18	0.06	8.05*
<i>Corn Oil</i>	0.00	0.00	0.74	0.05	0.74	0.08
<i>Cotton</i>	0.17	0.07	2.56***	0.30	1.40	1.11
<i>Live Cattle</i>	0.01	0.47	1.97**	0.09	0.01	0.08
<i>Lean Hog</i>	0.51*	0.10	0.61	0.50	0.00	4.10
<i>Milk</i>	0.04	0.38	0.03	0.45	2.96	0.85
<i>Oranges</i>	0.12	0.37	0.01	0.05	0.18	0.55
<i>Soybean Oil</i>	0.21	0.21	0.64	0.87	2.77	0.09
<i>Soybeans</i>	0.17	0.09	0.45	0.16	1.79	0.07
<i>Soybean Meal</i>	0.08	0.08	0.32	0.01	0.15	0.12
<i>Sugar</i>	0.00	0.00	0.39	1.09	1.90	0.01
<i>Wheat</i>	0.01	0.06	0.60	0.17	1.88	0.01
<i>Wool</i>	0.10	0.01	0.44	0.28	2.02	0.06
<i>Yellow Corn</i>	0.00	0.06	0.99*	2.15*	4.87*	1.08
<i>Coal</i>	0.73**	3.56***	0.08	0.00	0.03	1.55
<i>Heating Oil</i>	0.33	1.23	0.04	0.00	1.79	11.14**
<i>Natural Gas</i>	0.80	1.14	1.10	0.23	0.32	0.14
<i>Unleaded Regular Gas</i>	0.71	1.23	0.08	0.02	3.39	7.07
<i>WTI Oil</i>	0.37	0.61	0.05	0.06	0.10	9.25**
<i>Aluminium</i>	0.03	0.44	0.01	0.00	0.12	1.29
<i>Gold</i>	0.07	1.48**	0.91*	0.25	4.16*	3.68
<i>High Grade Copper</i>	0.13	0.81	0.02	0.47	1.87	4.37
<i>Nickel</i>	0.09	0.77	0.23	1.64	0.09	0.12
<i>Palladium</i>	0.39	0.56	0.56	1.33	0.31	1.22
<i>Platinum</i>	0.24	0.90	0.01	0.52	0.49	1.36
<i>Silver</i>	0.09	0.54	0.68	0.22	3.82	5.09*
<i>Tin</i>	0.03	1.02*	0.29	0.38	1.41	0.39
<i>Zinc</i>	0.04	0.30	0.65	0.22	1.65	3.64

Table C.6: Out-of-Sample Return Predictability and Business Cycle Stages (1 Month)

This table reports the out-of-sample R^2 's of a regression of monthly excess returns on a constant and the lagged predictive variable across business cycle stages. We predict the next month's excess return. "de" denotes the dividend-payout ratio, " $\Delta indpro$ " the growth of industrial production, and " ΔMI " the growth of money supply $M1$. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "itr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "rms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider six business cycle stages. "Exp" denotes the expansion, "eExp" the early expansion, "iExp" the late expansion, "Rec" the recession, "eRec" the early recession, "lRec" the late recession. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de						$\Delta indpro$						ΔMI					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Butter	-0.94	0.69**	-1.23	-3.98	-0.11	-0.20	-0.75	0.90**	-0.69	-0.30	-1.32	-0.61	-1.19	-0.05*	-0.37	-3.02		
Cocoa	-1.72	-0.57	-1.57	-1.62	-0.25	-2.15	-1.05	0.12*	-0.66	1.07**	-0.05*	-0.37	-3.02	-0.05*	-0.37	-3.02		
Coffee Arabica	-1.32	-2.12	-3.17				-0.73	0.09	-1.28		-1.18	-2.10	-1.23	-1.18	-2.10	-1.23		
Corn Oil	-2.79	-1.49	-3.39	-5.04			0.38***	0.69**	0.12*	-0.45	-0.34	-0.46	0.76**	-0.34	-0.46	0.76**		
Cotton	-2.31	-1.09	-2.04	-1.10	-2.49	-3.23	0.00**	-0.29	-0.77	-1.01	-1.49	-1.82	-0.14	-1.49	-1.82	-0.14		
Live Cattle	-1.72	0.44**	-1.01	-2.40	-1.46	-2.68	-0.68	-0.87	-0.30	0.07	-2.05	-2.20	-1.44	-2.05	-2.20	-1.44		
Lean Hog	-1.29	0.24**	-0.29*	-2.18	-2.32	-1.90	-1.36	-1.33	0.06*	-0.82	-0.96	-2.68	-1.33	-0.96	-2.68	-1.33		
Milk	-1.34	-4.41	-1.72	-3.71	-2.91	-7.97	-0.34	-0.65	0.06*	0.12	-1.10	-0.35	-0.80	-1.10	-0.35	-0.80		
Oranges	-1.26	-1.66	-2.62	-2.42			-0.45	-1.21	-0.21	-0.17	-0.94	-0.13	-0.60	-1.22	-0.67	-0.20		
Soybean Oil	-2.69	-1.22	-3.69	-1.74*			-0.82	1.01**	-0.51	0.77**	-0.74	-1.84	-1.27	-0.74	-1.84	-1.27		
Soybeans	-2.49	-0.69	-2.52	0.02**			-0.62	-0.38	-0.67	-0.13	-1.32	-1.72	-2.45	-1.32	-1.72	-2.45		
Soybean Meal	-2.82	-1.96	-2.47	-1.21*			-0.66	-0.21	-1.08	-0.36	-0.62	-4.29	-1.30	-0.62	-4.29	-1.30		
Sugar	-1.19	0.09**	-1.20	-2.27	0.24	0.01	-0.90	-0.34	-0.37	-0.29	-0.70	-3.17	0.71**	-0.70	-3.17	0.71**		
Wheat	-2.32	-1.06	-0.73	-2.79	-1.07	-1.97	-1.26	-0.87	-0.25	0.85*	-0.17*	-0.80	0.47**	-0.17*	-0.80	0.47**		
Wool	-3.54	-1.36	-0.97	-15.75	4.04**	-10.70	0.36***	0.35*	-1.38	-0.16	-1.28	-0.10	0.52*	-1.28	-0.10	0.52*		
Yellow Corn	-2.19	-0.38	-1.53	-1.79	0.84*	-1.81	-1.26	-0.18	-0.98	-1.46	-1.45	-0.08	-2.11	-1.45	-0.08	-2.11		
Coal	-1.23	4.23***	-0.23**	-13.82			-0.50	-0.73	-0.37	-5.52	-1.02	0.52	-1.10	-1.02	0.52	-1.10		
Heating Oil	-0.98	0.17	-0.98				-1.63	-2.90	-0.33		1.08**	1.45	2.24*	1.08**	1.45	2.24*		
Natural Gas	-0.93	-0.53	-1.41				-0.63	-0.82	0.01		-1.91	-1.53	-1.51	-1.91	-1.53	-1.51		
Unleaded Regular Gas	-1.36	-0.06	-1.77				-1.49	-3.79	-0.83		-2.02	-2.37	-0.51	-2.02	-2.37	-0.51		
WTI Oil	-2.64	-0.91	-2.29	-3.64	2.07***	1.78**	-0.73	-0.64	1.61***	0.27	-0.86	-1.42	-1.07	-0.86	-1.42	-1.07		
Aluminum	-1.29	-2.15	-1.96	-8.95	0.09		-0.41	-0.16	-0.49	1.65**	0.00*	-4.35	1.67**	0.00*	-4.35	1.67**		
Gold	-3.25	-1.23	-1.33	-2.95	-2.67	-1.63	-0.64	0.75**	-0.82	-1.22	-1.42	-2.09	-1.87	-1.42	-2.09	-1.87		
High Grade Copper	-0.70*	-0.66	-1.70	-2.60	-0.55	1.27**	-1.02	0.22*	-0.98	0.93*	-1.44			-1.44				
Nickel	-1.96						0.73*											
Palladium	-1.05	-3.12	0.30	-5.08	5.55**		-0.75	-0.99	-1.32		-0.82	-1.66	-2.52	-0.82	-1.66	-2.52		
Platinum	-1.79	-1.20	-2.01	-2.59	-2.05	-2.36	-0.66	-0.14	-0.58	0.39*	-1.76	-3.11	-1.20	-1.76	-3.11	-1.20		
Silver	-2.11	-1.18	-2.04	-2.59	-2.05	-2.36	-0.63	-0.49	-2.19	-0.96	-1.14	-3.53	0.33*	-1.14	-3.53	0.33*		
Tin	-0.59**	-3.32	-0.10**	-2.63	2.91***	1.39**	-1.01	-1.10	-0.53	-0.01	-0.62	0.68*	1.03**	-0.62	0.68*	1.03**		
Zinc	-2.08	-1.29	-1.71	-2.04	-1.49	5.63***	-0.79	-0.51	-0.64	2.24**	-1.24	-2.40	0.27**	-1.24	-2.40	0.27**		

Table C.6: Out-of-Sample Return Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	df r				df y				df p							
	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec
<i>Butter</i>	-0.94	-0.51	-0.77	-2.05	-0.62	-1.05	0.58**	-0.92	-2.11	-0.99	-2.03	-3.29	-2.11	-0.99	-2.03	-3.29
<i>Cocoa</i>	0.42***	-1.34	-1.25	-0.12	-2.20	-1.04	0.44**	-1.85	-1.84	0.07**	-0.73*	-1.10	-1.84	0.07**	-0.73*	-1.10
<i>Coffee Arabica</i>	-0.27	-0.77	2.13**		-1.62	-3.60	-0.79	-1.85	-3.31	-2.74	-2.04		-3.31	-2.74	-2.04	
<i>Corn Oil</i>	-0.02**	-3.08	0.41**	-1.52	-1.73	-1.76	-1.64	-0.78	-0.96	-0.81	-0.72	0.53	-0.96	-0.81	-0.72	0.53
<i>Cotton</i>	-1.25	-0.89	-1.41	-4.35	-0.26**	-0.95	-1.48	-0.55	-0.58**	-0.20*	-1.32	0.11**	-0.58**	-0.20*	-1.32	0.11**
<i>Live Cattle</i>	0.22**	0.47**	-0.33	-1.61	-1.82	-0.82	-2.12	1.46**	-2.37	-1.05	-3.05	-2.85	-2.37	-1.05	-3.05	-2.85
<i>Lean Hog</i>	-0.71	-0.46	-0.94	0.43	-1.62	1.06***	-1.49	-0.86	-1.55	-0.56*	-2.38	-1.98	-1.55	-0.56*	-2.38	-1.98
<i>Milk</i>	-1.05	-0.08	-0.73	-0.32	-0.92	-1.50	-1.31	2.00**	-2.62	-0.74	-0.78	-3.76	-2.62	-0.74	-0.78	-3.76
<i>Oranges</i>	-1.83	-0.41	-1.28	-2.70	-0.67	-0.97	-0.41	-1.18	-1.86	-1.18	-1.07	-0.14	-1.86	-1.18	-1.07	-0.14
<i>Soybean Oil</i>	-0.92	-1.50	-0.03	-2.64	-1.88	-2.40	-3.07	0.84*	-1.31	0.34**	0.12**	-1.67	-1.31	0.34**	0.12**	-1.67
<i>Soybeans</i>	-0.88	-0.67	-0.79	-1.20	-0.94	-0.22	-1.18	0.98*	-1.22	-1.05	-1.30	1.15**	-1.22	-1.05	-1.30	1.15**
<i>Soybean Meal</i>	-0.44	-1.68	-0.90	-2.54	-1.03	-0.67	-1.34	-2.33	-1.65	-1.94	-1.19	-0.81	-1.65	-1.94	-1.19	-0.81
<i>Sugar</i>	-1.16	-3.06	-1.36	-0.62	-1.87	-2.81	-2.15	-2.33	-2.14	-0.99	-0.97	-1.44	-2.14	-0.99	-0.97	-1.44
<i>Wheat</i>	-1.14	-1.62	-1.18	-3.88	-0.84	-2.74	-0.65	-1.14	-2.17	-1.29	-1.45	-1.84	-2.17	-1.29	-1.45	-1.84
<i>Wool</i>	-0.58	1.26***	0.18*	7.40***	1.28***	-2.96	1.66***	-4.28	-1.17	0.95***	-1.76	1.96***	-1.17	0.95***	-1.76	1.96***
<i>Yellow Corn</i>	-0.70	-1.64	-0.32	-3.19	-1.54	-1.98	-0.57	0.12	-1.66	-2.04	-1.49	-1.28	-1.66	-2.04	-1.49	-1.28
<i>Coal</i>	-0.71	1.35***	-1.28	-4.29	-0.92	0.27*	-1.24	0.12	-1.20	1.93***	-0.87	-1.13	-1.20	1.93***	-0.87	-1.13
<i>Heating Oil</i>	-1.44	2.60**	-0.90		-0.15	-0.43	-0.84		-2.29	4.66***	-1.33		-2.29	4.66***	-1.33	
<i>Natural Gas</i>	-1.12	-0.06	1.88*		-1.02	-0.09	0.13		-0.70*	0.28	-0.27		-0.70*	0.28	-0.27	
<i>Unleaded Regular Gas</i>	-0.26	2.44*	-0.52		-0.32	-0.75	-0.15		-1.01*	2.25*	-0.10		-1.01*	2.25*	-0.10	
<i>WTI Oil</i>	-2.05	-2.08	-0.81	8.59***	0.07**	-0.20*	-1.86	-1.94	-2.01	1.12***	-3.11	-2.39	-2.01	1.12***	-3.11	-2.39
<i>Aluminium</i>	-0.06**	1.64***	-0.73	1.57**	-0.26**	-1.05	-0.31	-0.03	-2.50	-1.07	-0.56*	-1.83	-2.50	-1.07	-0.56*	-1.83
<i>Gold</i>	-1.31	-2.46	-1.23	2.92***	0.63***	-1.54	-1.93	0.00	-2.58	0.85***	1.05***	-2.16	-2.58	0.85***	1.05***	-2.16
<i>High Grade Copper</i>	-0.36	-2.43	-7.86	-1.91	-0.55*	-4.40	-0.37	-1.63	-1.95	-1.15	-0.84	-1.46	-1.95	-1.15	-0.84	-1.46
<i>Nickel</i>	-1.34				1.93**				-0.10*				-0.10*			
<i>Palladium</i>	-0.82	-0.01	-3.39		-0.94	0.55	1.61**		-0.46**				-0.46**			
<i>Platinum</i>	-1.08	-1.05	-0.57	0.78*	-0.81	-1.35	-1.50	-0.66	-1.41	-1.40	-2.21	-4.30	-1.41	-1.40	-2.21	-4.30
<i>Silver</i>	-0.41	-0.74	-1.15	2.43**	-1.76	-2.16	-3.71	-0.14	-2.08	-0.28*	-0.55***	-1.18	-2.08	-0.28*	-0.55***	-1.18
<i>Tin</i>	0.01**	1.54***	0.43**	-4.39	-0.41**	1.06**	-0.14*	-3.71	-2.27	0.46**	-2.35	-2.77	-2.27	0.46**	-2.35	-2.77
<i>Zinc</i>	-1.92	-1.46	-0.61	-3.10	-0.56*	-0.35	-0.44	-3.74	-2.60	-0.61	-1.30	-5.35	-2.60	-0.61	-1.30	-5.35

Table C.6: Out-of-Sample Return Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	dy			ep			erp											
	Exp	eExp	lRec	Exp	eExp	lRec	Exp	eExp	lRec									
<i>Butter</i>	-2.22	-0.92	-2.04	-3.14	-2.22	-3.04	-1.92	-1.25	-1.36	-3.46	-2.76	-15.98	-1.08	-1.32	-0.42	0.54**	-0.43	4.19**
<i>Cocoa</i>	-2.13	-0.46*	-0.84	-1.50	-1.66	-4.42	-2.42	-0.85	-0.62	-2.13	-2.45	-6.39	-1.01	-1.16	-0.96	0.45**	4.29***	-1.60
<i>Coffee Arabica</i>	-3.17	-2.87	-2.03	-1.37	-1.38	-5.15	-2.69	-1.23	-0.39	-0.81*			-1.19	-1.04	-0.90			
<i>Corn Oil</i>	-1.02	-0.95	-0.83	-0.20*	-1.04	-2.69	-2.75	-1.00	-1.31	-1.82	-2.86	-3.52	-1.30	-1.58	-1.41	-0.95		
<i>Cotton</i>	-0.59**	-0.42*	-1.35	-0.81	-1.02	-2.38	-2.79	-0.23*	-1.95	-1.82	-1.77	-2.78	-1.12	-1.99	-0.68	1.46***	-1.11	3.78***
<i>Live Cattle</i>	-2.39	-0.83	-2.90	-2.73	-1.04	-2.69	-2.18	-0.29*	-2.58	-2.41	-1.77	-2.78	-1.12	-1.99	-0.68	0.23**	-1.49	-1.37
<i>Lean Hog</i>	-1.66	-0.81	-2.27	-1.62	-1.02	-2.38	-1.77	-0.92	-2.41	-1.40	-1.00	-1.16	-1.09	-1.28	-2.96	-1.63	-1.35	-4.26
<i>Milk</i>	-3.18	-0.85	-0.84	-3.17	-10.27	-7.86	-2.41	-3.94	-0.06**	-2.66	-7.08	-7.49	-1.81	-0.44	-0.24	-1.00	0.12	-2.44
<i>Oranges</i>	-1.84	-1.12	-1.07	-0.21			-1.32	-1.27	-0.61	-3.25			-0.47	-0.78	-0.26	-0.81		
<i>Soybean Oil</i>	-1.57	-0.07*	-0.20**	-2.06			-2.99	0.35**	-0.06*	-3.18			-0.77	-3.01	1.09***	1.05**		
<i>Soybeans</i>	-1.46	-0.69	-1.52	-0.36	-2.16	-0.18*	-2.16	-0.18*	-1.09	-2.04			-1.58	-4.61	-0.25	1.89**		
<i>Soybean Meal</i>	-1.63	-1.72	-1.27	-0.84	-1.71	-0.84	-1.71	-1.35	-1.41	-0.22*			-0.89	-0.58	-0.74	0.84*		
<i>Sugar</i>	-2.46	-1.15	-1.19	-1.58	-1.41	-1.18	-1.84	-0.59	-1.52	-1.11*	-2.31	-0.01*	-1.09	-1.18	-1.72	-1.35	-1.89	-1.82
<i>Wheat</i>	-2.21	-1.24	-1.71	-1.68	-3.67	-2.57	-2.39	-1.05	-1.76	-1.76	-2.22	-3.08	-0.81	-1.44	0.90***	-2.28	-1.86	-1.40
<i>Wood</i>	-1.24	1.54***	-1.80	1.15***	3.52***	-1.34	-2.34	-0.03*	-1.66	-3.72	-0.79	-18.47	-1.49	1.30***	-0.77	1.01**	0.75	-6.69
<i>Yellow Corn</i>	-1.97	-2.11	-1.62	-1.31	1.96**	-1.93	-1.87	-0.67	-1.63	-2.78	-0.02	-2.76	-1.01	-1.10	0.12**	-1.03	-1.39	-5.35
<i>Coal</i>	-1.38	1.96***	-1.07	-1.46			-0.77*	-1.05	-0.40	-2.61			-1.06	-1.57	-1.09	-1.41		
<i>Heating Oil</i>	-2.12	4.74**	-1.39		-2.12		-2.09	1.05	-0.93				-1.76	-1.76	0.21			
<i>Natural Gas</i>	-0.55*	0.28	-0.35		-0.18*		-0.18*	0.84	-0.23				-0.32	-0.59	-0.78			
<i>Unleaded Regular Gas</i>	-1.01*	2.98**	-0.16				-1.32	0.44	-0.09				-2.17	-1.90	-1.32			
<i>WTI Oil</i>	-1.64	1.11***	-3.42	-2.26	-1.15	-0.66	-1.52	0.81***	-5.77	-3.08	-1.82	-4.23	-2.46	-2.61	-1.82	-1.31	-2.09	-2.26
<i>Aluminium</i>	-2.04	-0.97	-0.54*	-2.09	-5.17	-2.45	-1.85	-2.20	-0.54	-3.42	-0.91	-3.65	-1.26	-1.03	-0.93	-2.34	1.44	-0.12
<i>Gold</i>	-3.17	1.19***	0.84***	-0.87	1.55**	-3.90	-3.07	0.98***	1.23***	-1.52	1.00**	-3.17	-1.32	-1.52	-1.69	-0.80	-0.03	-0.89
<i>High Grade Copper</i>	-2.45	-1.01	-0.96	-2.20	-1.20	-3.90	-0.90	-0.56	-0.66	-2.03	-2.72	-3.17	-0.24**	0.45***	-1.36	0.03**	-2.19	-0.89
<i>Nickel</i>	-0.01*						-0.15						-1.02					
<i>Palladium</i>	-0.33**	-3.11	-0.01	-2.89	-3.69		-0.61*	-3.11	-0.68	-2.59	0.53		-1.53	-0.63	-0.78	0.42		
<i>Platinum</i>	-1.49	-1.85	-2.23	-1.16	0.04	-2.82	-1.60	-0.86	-2.78	-1.40	-1.00	-4.90	-0.85	-1.02	-1.41	-1.20	0.42	
<i>Silver</i>	-2.22	-0.64	0.44***	-1.16	0.04	-2.82	-2.44	-0.89	0.69***	-1.40	-1.00	-4.90	-1.03	-0.38	-1.12	-0.41	-0.49	-1.40
<i>Tin</i>	-2.78	0.11**	-2.29	-3.13	-1.73	-2.43	-1.30	-2.89	-1.19	-2.13	-1.84	-1.89	-4.71	-3.28	-0.88	2.37***	1.05**	2.48***
<i>Zinc</i>	-2.55	-0.70	-1.36	-5.97	-2.87	-3.45	-2.75	-0.97	-1.09	-2.58	-1.34	-4.19	-0.52	-2.11	-0.53	-0.64	-1.92	-1.79

Table C.6: Out-of-Sample Return Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	<i>in,fl</i>				<i>ltr</i>				<i>ltr</i>			
	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec
<i>Butter</i>	-1.02	-0.15*	-0.70	0.39	-0.50	-0.53	-0.99	-1.54	-1.26	-1.59	-1.90	-3.55
<i>Cocoa</i>	-0.33*	1.22***	-1.05	-3.44	-0.62	-3.44	-2.15	-3.35	-0.91*	-1.24	-2.14	-3.67
<i>Coffee Arabica</i>	-0.89	-0.47	-2.41		-1.27	-1.00	1.62**		-3.88	-0.81	-1.23	
<i>Corn Oil</i>	-1.59	0.25*	-3.05	-3.95	-0.84	-2.34	-1.93	-1.63	-1.41	-3.02	-3.30	-4.33
<i>Cotton</i>	-0.84	-0.09*	-1.35	-1.04	-1.96	-0.97	-1.47	-2.78	-0.41**	-0.37	-1.06	-2.49
<i>Live Cattle</i>	-0.75	-0.75	-2.31	1.19**	-0.83	-0.90	-1.49	-3.71	-1.21	-2.89	-3.61	-4.54
<i>Lean Hog</i>	-0.33*	-2.08	-0.74	-2.52	0.09**	-0.94	2.19***	-1.77	-1.83	-2.50	-3.21	-4.02
<i>Milk</i>	0.14**	1.12***	1.11***	-2.84	0.08**	-0.12	-0.22	0.14	0.13***	-0.30*	-1.34	-2.61
<i>Oranges</i>	-1.14	-0.66	-0.19	-1.91	-0.68	-0.36	-0.75	-1.07	-1.30	-1.30	-1.19	-4.47
<i>Soybean Oil</i>	-0.96	0.04*	-0.73	-0.78	0.11**	-2.25	1.23***	-1.12	-1.16	-2.75	-2.49	-4.30
<i>Soybeans</i>	-1.45	-1.11	-2.42	-0.83	-0.57	-1.36	-0.54	-2.45	-1.28	-2.26	-3.21	-3.37
<i>Soybean Meal</i>	-1.11	-1.48	-1.81	-2.05	-0.72	-1.13	-1.57	-5.99	-1.43	-3.07	-3.59	-4.66
<i>Sugar</i>	-1.08	-0.45	-2.09	-0.06*	-0.92	-1.16	-1.98	-1.96	-1.82	-1.96	-2.78	-4.77
<i>Wheat</i>	-0.94	-0.54	-0.82	-0.82	-1.35	-1.82	-0.47	-2.13	-1.32	-1.42	-3.51	-3.04
<i>Wool</i>	-1.40	1.28***	-2.99	-0.37	-1.05	-0.64	-0.38	4.77***	-2.44	-3.08	-3.86	-1.68
<i>Yellow Corn</i>	-0.58	0.06**	-0.67	-2.87	-0.58	-1.76	-1.29	-1.37	-1.55	-2.65	-2.30	-3.18
<i>Coal</i>	-0.78	-0.90	-1.00	10.31***	-0.96	-0.04	-1.78	-0.60	-1.64	0.87**	-3.05	-2.55
<i>Heating Oil</i>	0.88**	2.60**	0.26		-1.83	0.10	-0.34		-1.78	2.06**	-0.73	
<i>Natural Gas</i>	-0.46	-1.05	0.88		-1.16	-0.41	-1.09		-1.23	1.05	-1.11	
<i>Unleaded Regular Gas</i>	2.22***	4.15***	2.87**		0.83**	0.80	2.01*		-1.62	1.89**	-0.70	
<i>WTI Oil</i>	-0.35*	0.32**	-0.44	4.60***	-0.21*	0.41**	-0.22	3.50***	-1.00	2.18***	-1.89	-1.19
<i>Aluminium</i>	0.64***	-1.03	-0.79	6.02***	0.34***	1.39***	0.03*	0.26	-0.72*	-1.67	-1.04	-1.14
<i>Gold</i>	-0.82	-0.11*	1.81***	-1.42	-0.85	-1.33	0.16	-1.49	-0.76*	0.49**	-1.00	-4.92
<i>High Grade Copper</i>	-1.04	-0.99	-0.04*	-1.37	-1.81	-0.89	-4.90	-2.28	-1.38	-1.23	-0.89	-2.88
<i>Nickel</i>	-0.97				-2.46				0.21*			
<i>Palladium</i>	-1.76	3.13**	-3.60		-1.13	-0.42	-0.79	-1.45	-0.50	-4.19	-0.18	-0.85
<i>Platinum</i>	-0.39	0.83**	-1.33	-1.40	-1.57	-3.46	-0.88	-1.45	-2.06	-1.05	-2.64	-0.85
<i>Silver</i>	-0.17**	-1.34	1.22***	-0.87	-0.73	-1.91	-1.40	-2.63	-2.83	0.02**	-1.64	-6.46
<i>Tin</i>	-0.95	-2.57	0.23**	-2.04	-0.35	0.27*	-1.07	-3.08	-0.36***	2.99***	-2.86	-2.93
<i>Zinc</i>	-0.75	-0.19*	-0.33	-1.61	-0.96	-2.30	0.31**	-0.45	-1.42	0.57***	-2.30	-4.17

Table C.6: Out-of-Sample Return Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	<i>svar</i>						<i>tbt</i>						<i>tms</i>					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	-2.54	-2.88	-0.55	-0.57	-2.63	-0.17	-1.65	-1.50	-0.93	-3.78			-1.16	-1.54	-0.45			
<i>Cocoa</i>	-18.70	-0.90	-25.35	-27.52	2.11**	-1.40	-0.68*	1.57***	-0.76	-3.00			-1.26	0.05*	-2.00			
<i>Coffee Arabica</i>	-67.91	-1.59	-0.25	-6.43			-0.79	0.45*	-0.47	-4.52			2.25***	0.91*	-2.38			
<i>Corn Oil</i>	-15.73	1.99***	-26.56	-13.25	1.10*	-3.05	-2.92	-1.84	-2.97	-1.64			-2.33	-1.70	-2.91			
<i>Cotton</i>	-3.48	-5.62	-187.24	-17.04	1.43**	-2.26	-0.42**	0.34**	-0.74	-1.64			-1.36	0.27**	-1.93			
<i>Live Cattle</i>	-5.45	-2.12	-9.51	-2.92	1.37	-2.69	-2.23	-1.83	-1.78	-3.50			-1.71	-1.19	-2.16			
<i>Lean Hog</i>	-3.72	-3.86	-5.72	-4.47	-1.37	-2.69	-1.48	-1.71	-2.19	-3.22			-1.33	-0.26	-1.24			
<i>Milk</i>	-4.88	-1.37	-6.43	-4.47	-1.80	5.29***	-1.61	0.77**	-0.08*	-0.76			-1.71	-0.26	0.09**			
<i>Oranges</i>	-11.83	-1.91	-14.13	-14.99			-2.00	-1.07	-0.63	-2.47			-1.66	-0.84	-0.85			
<i>Soybean Oil</i>	-7.42	0.30**	-2.09	-7.77			-1.32	-0.88	-2.57	-3.67			-1.29	0.27**	-1.48			
<i>Soybeans</i>	-0.69	1.19***	-19.80	-2.76	-1.16	-1.84	-1.16	-1.84	-1.42	-2.54			-1.38	-0.53	-2.68			
<i>Soybean Meal</i>	-4.26	-1.74	-4.55	-4.07			-1.60	-1.80	-1.73	-3.38			-1.31	-1.30	-0.95			
<i>Sugar</i>	-2.55	-0.55	-25.76	-45.17	-0.07	-0.04	-1.09	-1.08	-2.25	-4.94			-1.18	-0.69	-1.43			
<i>Wheat</i>	-1.66	-2.56	-18.54	-17.03	-1.24	-2.53	-1.65	-0.82	-2.46	-2.91			-1.25	-1.54	-1.72			
<i>Wool</i>	-7.89	-3.22	-3.64	-5.78	0.49	-1.02	-1.76	0.75**	-2.58	-0.96			-1.83	-1.96	-3.75			
<i>Yellow Corn</i>	-3.65	-2.51	-6.82	-1.10	0.17	-2.09	-1.55	-2.12	-1.76	-2.46			-1.66	-1.33	-1.78			
<i>Coal</i>	-2.01	-3.15	0.29*	-24.51			-1.84	2.16***	-2.92	-2.07			-1.16	-0.98	-0.90			
<i>Heating Oil</i>	-8.47	0.73	-0.06				-1.84	2.63**	0.29				-0.42	1.17*	-0.33			
<i>Natural Gas</i>	-1.12	0.12	-0.28				-2.30	0.54	-0.34				-1.10	-0.33	-1.04			
<i>Unleaded Regular Gas</i>	-43.73	-11.68	-0.06				-0.38	1.97*	0.24				-0.72	0.21	-0.24			
<i>WTI Oil</i>	-4.25	-2.20	-22.95	-8.76	-0.20	0.05	-1.36	2.15***	-0.94	-2.23			0.08**	0.38**	-1.15			
<i>Aluminium</i>	-11.54	-0.84	-22.91	2.29***	-0.06		-0.19**	-1.37	-0.13*	-1.06			0.22**	0.45**	-2.79			
<i>Gold</i>	-76.78	-0.97	-6.61	-15.48	0.19	0.48	-2.70	2.53***	-0.80	-4.10			-1.75	-0.85	-2.36			
<i>High Grade Copper</i>	-0.11**	-3.22	1.31***	-25.57	0.32	-2.51	-1.53	0.48**	-0.58	-2.39			-1.57	-2.09	-1.41			
<i>Nickel</i>	-2.81						-0.96						-0.28					
<i>Palladium</i>	-3.20	0.07	-0.09	-8.42			0.27**	-4.92	0.82*				-0.68	-3.11	-0.41			
<i>Platinum</i>	-2.17	-1.86	-22.11				-1.79	0.07**	-1.11	-1.49			-2.06	-1.53	-1.60			
<i>Silver</i>	-35.50	-1.65	-6.43	-17.21	-0.10	-1.34	-3.77	0.03**	-1.43	-5.11			-1.39	-1.75	-2.93			
<i>Tin</i>	-12.48	-3.59	-8.99	-5.44	2.71**	-2.91	-1.17	4.81***	-1.94	-4.82			-1.55	0.00*	-0.68			
<i>Zinc</i>	-11.37	-1.54	-7.84	-18.17	-0.14	1.97**	-2.18	0.11**	-1.12	-3.80			-1.57	-1.36	-1.03			

Table C.6: Out-of-Sample Return Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	<i>unrate</i>					
	Exp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	-0.90	-0.42	-1.45			
<i>Cocoa</i>	-1.25	1.13**	-0.01			
<i>Coffee Arabica</i>	0.35**	-3.21	-3.05			
<i>Corn Oil</i>	-2.04	-3.16	-0.11			
<i>Cotton</i>	-0.59	-2.97	0.96**			
<i>Live Cattle</i>	-1.28	-2.53	1.31**			
<i>Lean Hog</i>	-0.84	-0.29	-1.74			
<i>Milk</i>	-0.92	-0.26	-0.88			
<i>Oranges</i>	-1.02	-0.19	-1.37			
<i>Soybean Oil</i>	-2.20	-4.61	-1.26			
<i>Soybeans</i>	-1.26	-3.83	-1.49			
<i>Soybean Meal</i>	-1.01	-2.35	-2.73			
<i>Sugar</i>	-1.58	-2.36	-0.76			
<i>Wheat</i>	-1.18	-2.79	-2.81			
<i>Wool</i>	-1.26	1.24**	-1.33			
<i>Yellow Corn</i>	-1.55	-6.76	-0.76			
<i>Coal</i>	-0.20*	7.26***	-1.66			
<i>Heating Oil</i>	-0.62	3.29**	-0.78			
<i>Natural Gas</i>	-0.29	0.43	0.27			
<i>Unleaded Regular Gas</i>	-0.42	1.54	-0.32			
<i>WTI Oil</i>	-0.36*	1.34**	-1.35			
<i>Aluminum</i>	-1.15	-1.87	-0.79			
<i>Gold</i>	-2.12	0.04	0.03*			
<i>High Grade Copper</i>	-0.97	0.30*	-0.88			
<i>Nickel</i>	-2.05					
<i>Palladium</i>	-0.98	0.32	0.53			
<i>Platinum</i>	-1.21	-0.11	-2.07			
<i>Silver</i>	-1.84	-1.52	-0.59			
<i>Tin</i>	-0.84	1.61**	-0.06			
<i>Zinc</i>	-1.81	-1.52	-1.03			

Table C.7: In-Sample Return Predictability and Business Cycle Stages (12 Months)

This table reports the in-sample R^2 s of a regression of monthly excess returns on a constant and the lagged predictive variable across business cycle stages. We predict the next year's excess return. "de" denotes the dividend-payout ratio, "Δindpro" the growth of industrial production, and "ΔMI" the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "itr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "unrate" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider six business cycle stages. "Exp" denotes the expansion, "eExp" the early expansion, "lExp" the late expansion, "Rec" the recession, "eRec" the early recession, "lRec" the late recession, "*, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	$\Delta indpro$						ΔMI					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Butter	0.01	0.13	0.48	0.00	0.19	0.91	0.30	0.16	0.25	1.43*	0.04	2.88*
Cocoa	0.17	0.68**	0.13	0.23	2.14**	0.15	0.32	0.30	0.11	1.40*	0.02	4.59**
Cof Ice Arabica	0.93**	1.11	2.41**	0.06	12.79**	14.13**	0.11	0.11	0.17	8.63***	11.00**	9.20**
Corn Oil	0.86**	9.22***	4.39***	0.00	3.52**	1.21	0.05	0.13	0.07	0.33	0.03	0.42
Cotton	2.28***	6.49***	0.22	0.08	3.76***	0.16	1.22***	1.67**	0.20	0.48	0.47	0.00
Live Cattle	1.18***	3.96***	0.08	0.09	0.00	1.70**	0.90***	1.18**	0.08	0.02	0.00	0.03
Lean Hog	0.54**	1.11**	0.00	0.00	3.22***	3.92***	0.58**	0.84*	0.30	0.15	0.00	0.81
Milk	0.04	0.03	0.95**	0.07	0.35	3.19**	0.42*	0.82*	0.00	0.82	0.30	1.74
Oranges	0.23	0.66*	0.58	0.09	0.35	0.22	0.02	0.00	0.00	1.49*	2.52*	7.75***
Soybean Oil	0.55**	2.90***	0.79*	0.91	3.89***	10.12***	0.65**	0.92*	0.13	1.15	0.00	5.06**
Soybeans	1.03***	2.73***	0.01	0.91	23.87***	9.35***	1.45***	1.65***	0.32	1.17*	0.12	3.75*
Soybean Meal	0.56**	0.39	0.37	0.96	20.91***	12.38***	0.28	0.12	0.31	0.14	1.10	0.85
Sugar	0.13	0.25	1.99***	0.08	0.46	2.89***	0.00	0.01	0.15	0.12	0.02	0.66
Wheat	0.25	0.15	1.83***	0.00	2.88***	2.46**	0.49**	1.43**	0.09	1.28*	0.27	5.64**
Wood	0.12	0.44	0.32	4.57***	0.00	5.89***	0.97***	1.11**	0.05	0.57	0.19	5.07**
Yellow Corn	0.00	0.63*	0.02	0.09	2.21***	0.06	0.29	0.05	0.88**	0.46	0.06	2.69*
Coal	3.94***	1.48**	7.89***	2.18*	1.79	3.21	0.06	0.02	0.10	0.52	0.10	2.49
Heating Oil	4.56***	14.04***	0.13	1.59	3.02	2.75	0.05	0.12	0.71	0.70	1.73	8.34
Natural Gas	0.39	0.77	0.13	0.31	13.16**	0.82	0.30	0.02	1.61*	0.45	0.02	1.62
Unleaded Regular Gas	2.30***	5.85***	0.25	9.32**	23.37***	1.29	0.15	1.02	0.17	1.74	0.62	2.43
WTI Oil	1.86**	0.17	6.75***	1.42***	4.04***	0.84	0.39*	5.37***	0.25	2.84**	1.70	9.54***
Aluminum	1.72***	0.63*	2.04***	1.59**	0.31	1.86	0.10	0.02	0.26	0.10	0.77	0.37
Gold	1.66***	0.25	6.00***	3.29***	2.44**	14.79***	0.00	0.54	0.35	1.43*	0.03	4.50**
High Grade Copper	0.01	0.22	0.77**	2.50***	0.66	0.76	0.13	0.15	0.04	0.02	0.07	1.97
Nickel	1.38**	0.00	14.80***	0.38	8.49	17.78*	0.28	0.74	1.48	0.53	0.00	5.45
Palladium	0.78*	11.52***	2.72**	1.60	1.75	10.86*	0.62	0.03	2.00**	0.97*	2.15	9.03**
Platinum	0.05	1.03**	2.11***	3.23***	6.13***	0.10	0.20	0.18	0.21	2.61**	0.06	3.25**
Silver	1.02***	0.59*	3.55***	0.50	0.01	0.23	0.25	0.22	0.37	1.00	2.62*	1.15
Tin	0.61***	0.08	3.53***	10.09***	0.16	15.98***	0.79**	1.15**	0.06	0.00	0.75	1.30
Zinc	0.42**	4.04***	1.00**	1.53***	1.46*	0.08	0.56**	1.60**	0.01	0.01	0.00	1.61

Table C.7: In-Sample Return Predictability and Business Cycle Stages (12 Months) (continued)

Commodity	dy						ep						ertp					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
	<i>Butter</i>	0.04	0.16	0.01	2.91***	0.71	0.52	0.01	0.01	0.08	2.19***	1.13	2.01*	0.18	0.16	0.05	2.18***	0.49
<i>Cocoa</i>	0.03	0.11	0.62*	0.53	1.11*	1.07*	0.20	0.03	0.58*	0.21	0.08	0.29	0.16	0.80**	0.00	0.51*	3.13***	0.24
<i>Coffee Arabica</i>	0.35	0.39	0.91	0.31	8.35***	0.00	0.00	0.00	0.13	0.20	17.70***	1.96	0.02	0.14	0.13	1.34	6.08*	0.22
<i>Corn Oil</i>	0.21	1.14**	3.88***	0.09	0.06	0.03	1.14***	0.53	1.66***	0.00	0.78	1.51	0.17	0.34	0.20	1.90**	0.96	1.12
<i>Cotton</i>	1.62***	3.37***	0.51*	0.35	0.97	3.14***	0.12	0.00	1.54***	0.66*	0.06	2.14***	0.06	0.00	0.02	0.39	1.45**	0.00
<i>Live Cattle</i>	0.18	0.09	0.18	0.04	0.32	1.62***	0.09	1.30***	0.56*	0.17	0.00	0.17	0.00	0.10	0.01	0.46	1.37**	0.02
<i>Lean Hog</i>	0.00	0.10	0.00	0.11	0.13	0.09	0.35**	1.01**	0.01	3.87***	3.05***	3.17***	0.03	0.03	0.06	0.03	0.06	0.08
<i>Milk</i>	1.63***	2.05***	1.10**	4.96***	7.17***	0.03	2.51***	1.49***	3.96***	4.71***	8.80***	1.38	0.08	0.32	0.12	3.73***	0.84	2.33**
<i>Oranges</i>	0.00	0.30	0.20	0.27	0.14	0.50	0.08	1.07**	0.02	1.07*	0.00	2.38*	0.01	0.10	0.00	1.28*	0.24	1.58
<i>Soybean Oil</i>	0.02	2.27***	1.30**	2.46***	0.94	6.53***	0.09	0.12	0.73*	0.09	0.04	0.75	0.03	0.00	0.63*	3.03***	0.21	2.11*
<i>Soybeans</i>	0.00	0.23	0.06	0.76	5.90***	4.22**	0.40*	0.53	0.10	0.02	0.30	1.25	0.14	0.65*	0.14	1.92**	0.48	0.60
<i>Soybean Meal</i>	0.06	0.00	0.17	1.42	2.58	4.16*	0.68**	0.28	0.82*	0.01	1.96	3.41*	0.30	0.52	0.00	3.06**	1.78	2.17
<i>Sugar</i>	0.14	0.07	0.20	0.50	0.13	0.77	0.01	0.32	0.18	1.06**	1.07*	0.56	0.20	0.22	0.27	0.01	0.45	0.02
<i>Wheat</i>	0.06	0.70**	0.87**	0.13	0.05	0.44	0.02	0.32	0.05	1.59***	0.20	5.13***	0.08	0.07	0.10	0.51	0.82	0.01
<i>Wool</i>	0.01	0.05	0.04	0.45	6.49***	3.19**	0.02	0.45	0.42	1.85***	7.41***	0.44	0.00	0.00	0.04	1.49**	1.95**	0.16
<i>Yellow Corn</i>	0.00	0.36	0.07	0.08	0.75	0.17	0.00	0.00	0.05	0.03	0.02	0.55	0.01	0.09	0.09	0.57*	0.12	0.23
<i>Coal</i>	2.95***	5.88***	1.50**	2.70*	4.40*	0.17	0.48**	2.63***	0.01	8.96***	7.65**	5.11**	0.00	0.10	0.06	0.18	1.00	0.15
<i>Heating Oil</i>	4.07***	41.35***	0.18	4.64*	17.03***	15.93**	0.94*	14.17***	0.49	5.95**	21.06***	6.73	0.01	0.01	0.01	0.08	2.60	2.12
<i>Natural Gas</i>	6.13***	23.57***	0.96	4.88	42.63***	50.08***	5.13***	14.25***	0.94	5.41	52.02***	37.15***	0.21	0.75	0.01	1.44	0.59	36.69***
<i>Unleaded Regular Gas</i>	9.42***	36.59***	0.67	0.62	10.06**	20.45***	6.10***	17.02***	1.24	2.58	18.08***	16.73***	0.01	0.01	0.04	0.81	0.83	4.07
<i>WTI Oil</i>	1.50***	0.94*	1.66***	0.69*	6.41***	2.87***	0.16	1.76***	0.02	0.01	1.30*	6.62***	0.00	0.35	0.11	0.63	0.37	0.06
<i>Aluminium</i>	0.00	0.47	1.05**	1.51**	2.26*	0.00	0.88***	0.01	4.55***	0.06	4.16**	1.60	0.04	0.10	0.05	0.01	0.41	0.21
<i>Gold</i>	0.57**	4.76***	0.00	0.57**	10.50***	1.57**	0.00	6.68***	2.93***	5.53***	4.88***	6.13***	0.03	0.40	0.06	0.33	0.99	0.82
<i>High Grade Copper</i>	1.73***	0.99**	3.20***	3.21***	1.21*	1.48*	2.67***	1.95***	2.80***	0.09	0.17	0.05	0.28*	0.47**	0.00	1.38**	1.35*	0.24
<i>Nickel</i>	0.83	29.05***	1.54	2.57	0.04	57.49***	0.45	3.20***	0.46	2.97	0.17	56.88***	0.13	3.18**	0.00	0.23	0.48	9.51
<i>Palladium</i>	1.00*	0.42	0.88	13.58***	27.81***	1.20	2.43*	1.54*	0.12	8.40***	31.56***	0.07	0.72*	1.76*	0.21	0.55	4.72	0.43
<i>Platinum</i>	0.03	0.27	0.73*	0.91	4.31***	2.43*	0.14	0.07	0.06	0.31	0.25	4.39**	0.26	0.60	0.00	0.21	0.02	1.08
<i>Silver</i>	0.06	2.56***	0.12	0.98**	0.02	1.11*	0.23	4.73***	3.17***	0.11	0.02	0.30	0.03	0.22	0.45	0.54*	0.61	0.14
<i>Tin</i>	0.19	0.56*	0.15	3.00***	0.38	8.24***	0.00	0.36	0.67*	1.07**	1.01	1.14*	0.15	0.53*	0.05	0.18	0.13	0.02
<i>Zinc</i>	0.37**	0.60*	2.78***	1.50***	1.12*	0.07	1.38***	0.53*	2.01***	0.03	0.04	0.01	0.01	0.01	0.02	0.01	0.07	0.31

Table C.7: In-Sample Return Predictability and Business Cycle Stages (12 Months) (continued)

Commodity	<i>in/fl</i>										<i>ltr</i>										<i>lty</i>									
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec						
<i>Butter</i>	0.01	0.01	0.01	0.28	0.05	1.52	0.21	0.00	0.36	0.07	0.29	3.57***	11.27***	0.19	0.02	0.41	0.59	3.21***	2.33***	5.25***	0.85	3.36**	0.39							
<i>Cocoa</i>	0.70**	3.47***	0.75**	0.06	0.00	0.20	0.05	0.01	1.51*	0.45	0.25	0.05	0.13	1.51*	0.13	5.05	2.91	0.13	0.13	0.55	3.51*	5.05	2.91							
<i>Coffee Arabica</i>	0.10	1.18	1.24	1.24	17.48***	4.58	0.13	0.13	0.02	0.01	0.42	0.00	0.02	0.01	2.20**	0.04	0.69	0.08	3.10***	10.94***	0.13	0.08	2.06							
<i>Corn Oil</i>	0.04	0.00	0.03	0.00	1.24	2.21	0.00	0.00	0.21	0.14	0.85	2.02***	10.62***	1.35**	0.88	0.38	1.50	3.10***	10.94***	0.13	0.08	2.06								
<i>Cotton</i>	0.39**	0.18	1.43***	1.03**	0.27	2.60**	0.00	0.21	0.14	0.85	0.57	3.10***	10.62***	1.35**	0.88	0.38	1.50	3.10***	10.94***	0.13	0.08	2.06								
<i>Live Cattle</i>	0.30*	0.54*	0.26	0.09	0.63	2.82***	0.11	0.33	0.11	0.20	0.55	6.41***	16.81***	0.04	2.69***	0.92	7.39***	6.41***	16.81***	0.04	2.69***	0.92	7.39***							
<i>Lean Hog</i>	0.08	0.15	0.01	0.41	3.06***	1.72*	0.02	0.22	0.43	0.00	0.14	3.86***	4.63***	3.03***	2.40**	12.44***	0.25	3.86***	4.63***	3.03***	2.40**	12.44***								
<i>Milk</i>	0.79***	0.24	2.37***	0.13	1.06	1.72*	0.23	0.01	0.35	0.54	0.05	8.04***	23.64***	0.59	0.00	0.27	0.05	8.04***	23.64***	0.59	0.00	0.27	0.05							
<i>Oranges</i>	0.13	1.41**	0.03	0.10	0.03	0.06	0.09	0.20	0.01	0.07	0.26	2.91***	1.72***	4.69***	1.08	0.00	5.61***	2.91***	1.72***	4.69***	1.08	0.00	5.61***							
<i>Soybean Oil</i>	0.00	0.02	0.01	3.79***	0.00	9.00***	0.01	0.13	0.00	2.24**	0.70	1.67***	7.90***	0.63	0.52	0.00	1.28	1.67***	7.90***	0.63	0.52	0.00	1.28							
<i>Soybeans</i>	0.02	0.52	0.05	0.58	2.92*	3.23**	0.00	0.00	0.17	1.17	0.63	3.47***	7.74***	0.67	0.24	0.04	0.92	3.47***	7.74***	0.67	0.24	0.04	0.92							
<i>Soybean Meal</i>	0.79***	0.06	1.80***	0.00	12.10***	5.36**	0.08	0.67	0.66	0.97	0.02	1.76***	2.57***	1.11**	0.65	0.00	2.47	1.76***	2.57***	1.11**	0.65	0.00	2.47							
<i>Sugar</i>	0.40**	0.14	1.52***	0.01	0.00	0.06	0.21	0.58	0.01	0.03	5.17**	0.00	2.13***	4.30***	0.70	0.44	0.86	0.00	2.13***	4.30***	0.70	0.44	0.86							
<i>Wheat</i>	0.17	0.67**	0.00	0.62*	0.81	0.02	0.01	0.07	0.03	0.89	0.06	2.36***	12.08***	0.00	1.29*	0.36	1.80	2.36***	12.08***	0.00	1.29*	0.36	1.80							
<i>Wool</i>	0.11	0.02	0.45	4.61***	2.67**	2.51**	0.08	0.29	0.38	0.26	0.21	0.79**	1.26**	1.70	3.30**	1.70	4.54**	0.79**	1.26**	1.70	3.30**	1.70	4.54**							
<i>Yellow Corn</i>	0.05	0.36	0.20	0.02	0.00	0.23	0.01	0.15	0.00	1.30*	1.72	3.89***	13.31***	0.01	0.01	0.31	0.15	3.89***	13.31***	0.01	0.01	0.31	0.15							
<i>Coal</i>	0.05	0.00	0.19	7.54***	6.32**	6.36**	0.19	1.10**	0.04	0.74	0.05	0.91***	4.21***	0.03	0.02	1.01	3.15	0.91***	4.21***	0.03	0.02	1.01	3.15							
<i>Heating Oil</i>	0.07	1.59*	0.40	2.79	3.26	3.13	0.75*	0.92	0.32	0.36	4.29	8.10***	29.48***	0.32	0.48	8.83**	36.87***	8.10***	29.48***	0.32	0.48	8.83**	36.87***							
<i>Natural Gas</i>	0.07	0.34	0.02	0.05	4.50	0.16	0.06	0.01	0.28	1.07	0.02	4.25***	16.22***	0.00	15.06***	68.12***	33.15***	4.25***	16.22***	0.00	15.06***	68.12***	33.15***							
<i>Unleaded Regular Gas</i>	2.75***	6.27***	1.93*	0.53	6.24	0.03	0.73*	0.14	1.42	1.27	1.21	15.88***	32.03***	3.81***	0.30	10.78**	41.48***	15.88***	32.03***	3.81***	0.30	10.78**	41.48***							
<i>WTI Oil</i>	0.38*	0.02	1.66***	0.02	1.32*	0.02	0.08	0.04	0.06	0.17	1.72	0.07	10.83***	3.37***	0.74	5.66**	0.07	10.83***	3.37***	0.74	5.66**	0.07	5.66**							
<i>Aluminum</i>	1.32***	0.91**	0.93**	0.13	0.18	2.16*	1.01***	1.53**	0.58*	0.09	2.18	0.35*	1.51***	0.00	1.55*	7.69***	0.35	1.51***	0.00	1.55*	7.69***	0.35	7.69***							
<i>Gold</i>	0.56**	0.07	1.71***	0.95**	0.02	3.72***	0.06	0.38	0.04	0.00	2.02	0.06	4.84***	1.98***	0.73	2.98*	0.06	4.84***	1.98***	0.73	2.98*	0.06	2.98*							
<i>High Grade Copper</i>	0.10	0.01	0.49*	1.16**	1.82**	0.05	0.19	1.22**	0.00	1.24	0.03	3.74***	18.64***	0.31	3.19***	0.04	13.77***	3.74***	18.64***	0.31	3.19***	0.04	13.77***							
<i>Nickel</i>	0.01	2.25*	0.02	3.73	0.68	13.00	1.97**	1.30	3.19**	4.99	0.84	2.33***	26.13***	0.07	0.03	3.45	44.57***	2.33***	26.13***	0.07	0.03	3.45	44.57***							
<i>Palladium</i>	0.01	3.38**	0.14	1.09	12.73**	4.75	0.30	0.07	0.25	0.89	3.38	5.60***	5.56***	3.60***	1.215**	24.05***	0.30	5.60***	5.56***	3.60***	1.215**	24.05***								
<i>Platinum</i>	0.19	0.90**	0.35	1.98**	0.99	2.31*	0.06	0.15	0.02	0.00	0.63	1.29***	5.55***	0.00	1.00	0.56	6.00***	1.29***	5.55***	0.00	1.00	0.56	6.00***							
<i>Silver</i>	0.42**	0.06	1.67***	1.11**	2.66**	0.42	0.01	0.10	0.03	1.68*	0.27	0.50**	16.16***	1.56**	0.28	1.86	0.39	0.50**	16.16***	1.56**	0.28	1.86	0.39							
<i>Tin</i>	0.22	0.05	1.13**	3.26***	1.94**	3.50***	0.20	0.86*	0.11	0.17	0.08	3.54***	10.95***	0.05	4.45***	2.97*	6.69***	3.54***	10.95***	0.05	4.45***	2.97*	6.69***							
<i>Zinc</i>	0.53**	1.53***	0.00	0.05	0.40	1.47*	0.08	0.81*	0.00	1.16	3.44**	2.20***	20.58***	0.21	0.35	0.14	3.97**	2.20***	20.58***	0.21	0.35	0.14	3.97**							

Table C.7: In-Sample Return Predictability and Business Cycle Stages (12 Months) (continued)

Commodity	suar				tbl				tms			
	Exp	eExp	Rec	IRec	Exp	eExp	Rec	IRec	Exp	eExp	Rec	IRec
<i>Butter</i>	0.67**	1.84***	0.39	1.67*	5.18***	12.62***	0.70*	0.40	1.03***	0.01	1.32**	0.09
<i>Cocoa</i>	0.29*	1.38**	1.17**	2.66**	3.98***	2.88***	4.02***	0.01	0.33	0.05	0.00	0.08
<i>Coff.Fee Arabica</i>	0.22	0.10	7.67***	0.29	3.61***	2.88***	5.39**	4.89**	8.17***	7.50***	0.10	2.81*
<i>Corn Oil</i>	1.19***	4.90***	0.05	0.01	2.93***	12.88***	0.69	4.75**	0.01	0.02	1.25**	3.69*
<i>Cotton</i>	0.19	2.48***	0.61*	1.15**	4.30***	14.57***	0.34	2.62**	2.38***	0.56	1.12**	0.15
<i>Live Cattle</i>	2.57***	6.96***	0.19	5.14***	10.54***	20.49***	1.74**	2.52**	3.06***	0.07	8.21***	0.63
<i>Lean Hog</i>	0.57**	3.05***	0.27	0.07	4.56***	7.62**	1.18**	3.02***	0.25	0.89*	1.23**	1.85
<i>Milk</i>	0.96***	4.21***	0.00	2.77***	8.07***	25.15***	0.43	2.20	0.08	0.25	0.00	0.00
<i>Oranges</i>	0.08	0.01	0.22	1.52**	3.88***	3.30***	5.81***	4.22**	0.56**	0.90*	1.87***	0.36
<i>Soybean Oil</i>	0.21	1.00**	0.02	3.56***	2.49**	9.54***	0.18	1.69**	0.52**	0.03	0.39	2.26
<i>Soybeans</i>	2.36***	6.88***	0.23	2.23**	5.48***	8.37***	2.01***	5.92**	1.55***	0.02	3.25***	2.30*
<i>Soybean Meal</i>	0.22	0.36	0.09	2.04**	2.95***	2.25***	2.30***	1.65*	1.16***	0.23	2.76***	3.70**
<i>Sugar</i>	0.02	0.00	0.07	0.01	0.00	3.50***	4.42***	1.12*	0.00	0.52	0.60	0.12
<i>Wheat</i>	0.48**	1.12**	0.30	3.61***	3.42***	14.60***	0.22	4.50**	0.69**	0.06	1.55**	0.09
<i>Wool</i>	0.34*	0.24	0.32	3.39***	2.46***	1.49***	1.94***	2.99**	2.36***	0.00	6.49***	3.60**
<i>Yellow Corn</i>	2.28***	5.59***	0.48	1.61*	4.26***	12.74***	0.57	1.43	0.12	0.57	2.70***	17.18***
<i>Coal</i>	0.28	0.19	0.41	0.00	0.86**	7.92***	0.22	1.61	0.00	2.60***	0.74*	31.25***
<i>Heating Oil</i>	0.03	1.07	0.36	0.08	3.80***	23.45***	0.25	6.21**	0.53	0.94	0.00	21.68***
<i>Natural Gas</i>	0.09	1.93*	0.00	0.20	3.15***	11.18***	0.00	15.67***	0.03	0.10	0.01	44.84***
<i>Unleaded Regular Gas</i>	0.14	2.28**	0.01	2.14	9.36***	23.14***	3.49**	2.84	0.10	0.55	0.24	6.06*
<i>WTI Oil</i>	0.16	2.70***	0.16	0.07	0.03	12.23***	3.62***	1.21*	0.75**	0.01	0.62	10.06**
<i>Aluminium</i>	0.00	0.32	0.39	0.02	1.32***	3.65***	0.51	1.05	1.51***	1.71***	3.19***	0.09
<i>Gold</i>	0.01	3.04***	0.79**	10.75***	0.05	9.48***	2.98***	3.90***	0.00	2.68***	1.72***	6.01***
<i>High Grade Copper</i>	0.72***	0.87***	0.50*	2.59**	7.23***	22.90***	0.41	5.39***	3.22***	0.11	7.82***	2.04
<i>Nickel</i>	3.32**	14.71***	2.06*	2.82	4.40***	24.57***	3.09**	0.16	2.14**	5.15***	14.30***	4.62***
<i>Palladium</i>	0.22	4.76***	0.19	6.12**	3.90***	4.62***	8.33***	17.32***	0.00	2.29**	5.59***	0.58
<i>Platinum</i>	0.00	0.00	0.00	1.05*	2.50***	6.49***	0.50	2.27**	1.07***	0.00	3.16***	3.98*
<i>Silver</i>	0.00	2.48***	0.38*	0.55	0.43*	24.86***	1.68***	2.70***	0.01	2.34***	0.35	33.58***
<i>Tin</i>	0.34*	1.95***	0.11	9.31***	4.15***	11.09***	0.00	10.33***	0.19	0.37	0.31	11.65***
<i>Zinc</i>	0.61**	0.69**	0.54*	1.28	4.07***	15.56***	0.60	0.51	1.71***	4.15***	9.24***	0.31
												2.55**
												0.15

Table C.7: In-Sample Return Predictability and Business Cycle Stages (12 Months) (continued)

Commodity	<i>unrate</i>					
	Exp	eExp	Exp	Rec	eRec	Rec
<i>Butter</i>	0.14	4.15***	0.00	2.76*	0.28	0.63
<i>Cocoa</i>	0.15	9.91***	4.92***	0.85	24.81***	1.86
<i>Coffee Arabica</i>	6.38***	3.20***	0.01	0.40	0.13	0.52
<i>Corn Oil</i>	0.08	0.04	0.09	0.34	1.35	0.62
<i>Cotton</i>	0.67**	0.00	5.86***	2.48	2.26	0.16
<i>Live Cattle</i>	0.13	3.17***	8.47***	3.82**	8.23**	18.45***
<i>Lean Hog</i>	5.20***	3.10***	9.89***	1.49	13.95***	0.48
<i>Milk</i>	0.85**	10.23***	0.01	1.47	0.85	0.11
<i>Oranges</i>	0.01	0.82	0.08	0.64	2.70	23.45***
<i>Soybean Oil</i>	0.49*	2.38***	1.97***	0.01	7.35**	2.82
<i>Soybeans</i>	0.21	0.22	0.88*	0.46	19.64***	3.28
<i>Soybean Meal</i>	0.02	1.46**	0.10	0.08	12.36***	9.31**
<i>Sugar</i>	0.17	1.71**	1.80**	1.53	7.32**	4.99
<i>Wheat</i>	0.40	6.14***	1.72**	1.28	14.67***	0.10
<i>Wood</i>	1.22***	0.02	3.02***	0.05	3.94	0.30
<i>Yellow Corn</i>	0.77**	6.42***	2.86***	1.26	15.58***	22.98***
<i>Coal</i>	0.75**	4.94***	0.46	2.35*	0.52	14.06***
<i>Heating Oil</i>	4.27***	15.58***	0.18	0.67	0.26	25.52***
<i>Natural Gas</i>	2.99***	10.35***	3.00**	4.64	35.50***	28.76**
<i>Unleaded Regular Gas</i>	9.78***	20.38***	2.41**	0.20	0.32	32.35***
<i>WTI Oil</i>	1.74***	5.30***	1.04*	1.84	3.82*	30.74***
<i>Aluminium</i>	0.10	0.86	3.02***	0.94	2.88	14.27***
<i>Gold</i>	0.00	4.91***	6.16***	4.01**	3.69	2.98
<i>High Grade Copper</i>	0.27	9.05***	3.96***	0.05	6.08**	0.75
<i>Nickel</i>	0.32	11.23***	8.01***	0.07	0.16	25.07**
<i>Palladium</i>	1.34**	1.70*	0.17	8.82**	1.56	16.44**
<i>Platinum</i>	0.01	4.73***	2.94***	0.96	0.05	1.39
<i>Silver</i>	0.40	9.66***	3.52***	7.46***	0.08	20.65***
<i>Tin</i>	0.20	1.15*	2.81***	1.75	18.08***	0.32
<i>Zinc</i>	0.43	4.03***	6.24***	0.05	5.67*	1.04

Table C.8: Out-of-Sample Return Predictability and Business Cycle Stages (12 Months)

This table reports the out-of-sample R^2 's of a regression of monthly excess returns on a constant and the lagged predictive variable across business cycle stages. We predict the next year's excess return. "de" denotes the dividend-payout ratio, " $\Delta indpro$ " the growth of industrial production, and " ΔMI " the growth of money supply $M1$. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bonds and the 3-month Treasury bill rate. "ep" is the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "itr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider six business cycle stages. "Exp" denotes the expansion, "eExp" the early expansion, "lRec" the late recession, "Rec" the recession, "eRec" the early recession, and "lRec" the late recession. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de						$\Delta indpro$						ΔMI					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Butter	4.13***	4.26***	3.10***	0.09*	-0.97	-0.63	-1.20	-0.92	-0.12	10.20***	-0.13*	3.32***	-0.13*	3.32***	-0.35			
Cocoa	1.29***	5.29***	2.94***	-3.10	4.77***	-3.47	-1.32	1.02**	-0.17	1.31*	-0.14*	-0.64	-0.14*	-0.64	2.87***			
Coffee Arabica	-0.94	-8.86	-1.29				-0.37	-1.21	-0.96		1.33***	-3.37	1.33***	-3.37	-2.22			
Corn Oil	-0.33**	5.14***	3.47***	-0.39			-1.11	1.45***	-0.70	-0.79	-1.24	-1.80	-1.24	-1.80	0.46*			
Cotton	-2.73	4.07***	1.73***	0.49**	-6.13	0.13	0.10**	1.10***	-1.94	6.47***	-0.26	-2.28	-0.26	-2.28	3.15***			
Live Cattle	-2.00	7.78***	1.84***	-0.61	1.25**	2.68**	-1.32	1.25***	-1.42	4.33***	-2.31	-3.45	-2.31	-3.45	-2.54			
Lean Hog	1.95***	6.65***	3.77***	-5.26	13.81***	0.95*	-1.45	-1.53	-1.56	-0.26	-0.60	-7.30	-0.60	-7.30	-1.08			
Milk	0.96***	-4.76	7.13***	3.22***	-11.03	-18.78	-0.37	1.91***	-0.09*	9.55***	-2.23	-0.49	-2.23	-0.49	2.01***			
Oranges	3.62***	0.03*	3.77***	-1.92			-1.20	-0.69	-1.00	2.66**	-1.40	-1.76	-1.40	-1.76	-0.15			
Soybean Oil	-3.78	0.63**	-2.22	2.53***			0.29***	1.70***	-0.75	0.46	-0.79	0.31	-0.79	0.31	4.32***			
Soybeans	-4.19	2.02***	7.77***	-5.98			-0.30*	2.21***	-0.60	0.09	-0.75	-0.71	-0.75	-0.71	1.71***			
Soybean Meal	-4.39	-3.64	5.47***	11.71***			-1.83	0.61**	-0.36	2.12*	-1.20	-1.40	-1.20	-1.40	1.29**			
Sugar	-12.82	0.93***	-0.54	-1.25	-2.68	3.87***	-0.65	0.79***	-0.38	-0.05	-0.48	-3.33	-0.48	-3.33	-1.63			
Wheat	-3.79	-0.25*	6.55***	2.94***	0.64*	7.81***	-0.27*	1.05***	-1.59	-2.89	-0.31	-3.23	-0.31	-3.23	4.44***			
Wool	-3.25	-2.41	-0.24*	4.90***	0.12	5.23**	-0.34	0.39**	-1.03	7.25	0.15**	-0.83	0.15**	-0.83	0.97**			
Yellow Corn	-4.12	-2.93	3.53***	-1.12	3.50***	0.39	-1.35	0.25*	-0.77	0.39	-1.14	3.87***	-1.14	3.87***	2.70***			
Coal	-3.04	2.23***	10.69***	-13.15			-0.33	0.27**	-0.37	0.88	-2.17	0.16*	-2.17	0.16*	-0.60			
Heating Oil	-5.10	21.35***	-7.37				-0.63	-1.60	-3.82		-0.59	6.96***	-0.59	6.96***	2.95***			
Natural Gas	-3.41	-0.76	-2.94				-0.22	-0.70	1.80*		-0.92	8.92***	-0.92	8.92***	-1.94			
Unleaded Regular Gas	-8.02	10.03***	-13.88				-1.19	0.01	-2.55		-0.39	2.24**	-0.39	2.24**	-2.19			
WTI Oil	-1.08	4.83***	-5.66	-0.68	-0.55	-5.29	-1.03	0.20*	-0.99	1.29*	-0.94	1.52**	-0.94	1.52**	1.27**			
Aluminum	-4.84	-7.61	-11.75	-34.98	-0.16		-1.92	-0.26	-1.49	0.57	-0.08*	-1.31	-0.08*	-1.31	0.53*			
Gold	-1.21	2.21	6.88***	13.31***	-2.52	21.95***	-1.83	0.90**	-0.45	0.23	1.10***	-4.72	1.10***	-4.72	7.64***			
High Grade Copper	-0.99	1.12***	-4.22	-3.74	-1.01	5.19***	-1.64	1.17***	-2.00	1.65**	3.03***	-0.05	3.03***	-0.05	6.94***			
Nickel	-0.98						-7.69				-2.09		-2.09					
Palladium	-1.71	-22.35	-5.08				0.21*	-2.31	1.49*		18.61***	-1.84	18.61***	-1.84	-5.96			
Platinum	-3.17	1.38	4.12***	-2.10	-9.66		-1.76	0.54**	0.00*	5.36***	0.89***	-1.98	0.89***	-1.98	3.69***			
Ptitanium	-2.20	1.07***	-0.38*	3.15***	-4.18	0.99*	-1.23	2.27***	-0.93	2.86***	-1.06	-1.62	-1.06	-1.62	2.51***			
Silver	-4.36	-0.23	7.25***	24.02***	-1.67	26.39***	-0.36	1.07**	-0.88	-2.93	-1.52	2.30**	-1.52	2.30**	2.24**			
Tin	-0.01***	-0.68	-2.29	-10.80	-1.40	-0.19	-0.98	0.37*	-1.73	-1.15	-2.15	-4.64	-2.15	-4.64	-1.27			
Zinc																		

Table C.8: Out-of-Sample Return Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	dfr				dfy				dp				
	Exp	eExp	Rec	eRec	Exp	eExp	Rec	eRec	Exp	eExp	Rec	eRec	
<i>Butter</i>	-0.93	-0.53	-1.03	-0.87	-3.47	2.24***	4.47***	-1.13	0.06***	7.48***	0.35**	1.12***	-2.62
<i>Cocoa</i>	-0.66	-0.67	-0.75	-1.19	-2.80	-23.30	-4.10	-2.84	-9.00	-3.78	-0.79*	-4.30	-2.68
<i>Coffee Arabica</i>	-0.81	-0.78	-0.30		0.12**	-16.78	-1.42		-6.55	-3.69	-4.39		
<i>Corn Oil</i>	-1.80	-0.90	-0.23	-1.47	-1.25	4.96***	-0.54	0.10	0.18	9.26***	-1.85	-13.66	
<i>Cotton</i>	-1.33	-0.63	-0.15	-0.91	8.33***	-0.99	-2.75	-9.15	0.05***	8.84***	-2.44	1.92***	8.78***
<i>Live Cattle</i>	-0.93	-0.47	-1.30	-0.43	2.37***	3.95***	1.31***	11.86***	-2.11	-3.03	-0.60	-2.25	-2.13
<i>Lean Hog</i>	-1.44	-1.29	-2.44	-0.43	2.37***	14.44***	-6.12	-4.12	0.89***	-3.70	-6.87	1.97***	-2.10
<i>Milk</i>	-0.65	-0.69	-1.44	-0.74	3.40***	7.10***	-0.46	2.68**	3.19***	15.66***	7.88***	5.83***	-23.96
<i>Oranges</i>	-1.81	-0.57	-2.20	-0.99	2.29***	-17.35	-3.80	-29.06	-7.68	-3.96	5.74***	0.62*	
<i>Soybean Oil</i>	-1.35	-0.49	-0.13	-1.09	2.03***	-5.58	-5.68	-17.06	-4.27	-0.07**	-4.27	1.53**	
<i>Soybeans</i>	-0.85	-0.54	-1.51	-0.43	7.94***	1.71***	0.08*	-31.40	-0.92*	4.65***	-3.66	-39.64	
<i>Soybean Meal</i>	-0.79	-0.51	-2.09	-0.45	2.14***	-0.30	-0.67	-0.06	1.57***	-0.37*	-1.70	-0.87	
<i>Sugar</i>	-0.50	-0.71	-0.62	-1.19	2.52	-7.38	9.30	-1.64	3.34	0.66***	4.73***	-4.86	0.23
<i>Wheat</i>	-0.62	-0.40	-0.86	-0.60	7.27***	9.29***	-1.92	-12.84	-3.16	1.48***	-0.01**	1.78***	-1.85
<i>Wool</i>	-0.36	-1.26	-0.66	-1.01	1.74***	-2.78	5.95***	-2.10	-0.58**	-0.32*	-2.94	6.97***	-9.37
<i>Yellow Corn</i>	-1.01	-1.30	-0.81	-0.20	6.74***	9.82***	2.25***	-1.26	-3.30	-0.43*	-3.16	0.11**	-4.45
<i>Coal</i>	-1.21	-0.14	-0.18	-1.83	11.66***	0.04*	5.67***	7.76**	0.57***	18.62***	0.59**	4.79**	
<i>Heating Oil</i>	-1.33	1.06	-1.67		10.02***	4.98***	-12.67		-2.82	60.49***	-6.96		
<i>Natural Gas</i>	-0.38	-0.02	1.77*		0.13*	-0.37	0.16		5.24***	23.77***	-2.40		
<i>Unleaded Regular Gas</i>	-0.72	0.20	-3.14		6.22***	1.59*	4.57**		-0.42**	49.59***	-8.87		
<i>WTI Oil</i>	-1.12	-2.28	-0.52	-1.45	7.70***	5.43***	-7.98	-1.00	-1.85	12.65***	-2.51	-10.21	-25.75
<i>Aluminium</i>	0.68***	0.60**	-0.63	-1.13	2.68***	-2.44	4.10***	1.77**	-6.66	-0.71	-2.38	4.67***	-2.79
<i>Gold</i>	-1.00	-1.97	-0.36	-1.80	8.34***	-10.80	-9.12	-3.21	2.29***	2.13***	9.91***	1.09***	8.07***
<i>High Grade Copper</i>	-0.19*	-0.74	-0.62	-1.23	8.99***	-4.95	3.99***	-13.70	1.56***	12.60***	-1.63	-4.65	4.15***
<i>Nickel</i>	0.51*				19.95***				-10.82				
<i>Palladium</i>	-1.05	-0.14	0.08	0.23	1.97***	-5.66	11.51***	-0.06	9.27***	-69.04	-13.16	-13.58	20.59***
<i>Platinum</i>	-1.00	-3.04	-0.33	-1.03	0.40***	1.72***	2.77***	7.50***	2.96***	0.19**	-8.94	1.45***	-3.58
<i>Silver</i>	-0.43	-1.69	-0.18	-1.03	4.31***	7.32***	-5.92	-46.56	1.05***	15.58***	4.61***	2.43***	2.38**
<i>Tin</i>	-0.07**	-0.06	-0.26	-1.80	10.03***	-1.08	4.67***	-17.19	-0.09***	8.67***	-8.52	1.92**	14.81***
<i>Zinc</i>	-0.91	-1.27	-0.35	-1.47	-1.01	-1.83	-0.11*	-17.19	-3.19	5.43***	-0.05**	-2.46	-2.01

Table C.8: Out-of-Sample Return Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	<i>dy</i>				<i>ep</i>				<i>erp</i>										
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	
<i>Butter</i>	-0.01***	7.18***	-0.13**	1.54***	-7.79	-5.61	-1.88	-3.30	-1.88	2.09***	2.09***	-1.32	3.45***	3.45***	-1.32	0.22*	3.32**	3.32**	3.36**
<i>Cocoa</i>	-8.69	-4.52	-0.64*	-3.91	-5.61	-3.30	-1.88	-3.30	-1.88	-0.13**	1.54***	-7.79	-5.61	-1.88	-3.30	-1.88	2.09***	2.09***	-1.32
<i>Coffee Arabica</i>	-8.83	-4.05	-3.80	-13.59	-5.38	8.49***	-5.38	8.49***	-5.38	3.32***	3.32***	-1.64	-1.76	-1.60	-1.78	-0.60	-0.60	-0.60	-0.60
<i>Corn Oil</i>	0.38***	8.79***	-2.37	2.55***	-4.87	-2.55	-1.88	-2.55	-1.88	0.90***	0.90***	-0.40	0.64**	0.64**	-0.40	0.36	0.36	0.36	0.36
<i>Cotton</i>	-1.97	-2.14	-10.01	-1.82	-4.87	-2.55	-1.88	-2.55	-1.88	-1.63	4.59***	-6.06	0.90***	0.90***	-0.40	0.36	0.36	0.36	0.36
<i>Live Cattle</i>	1.36***	-4.05	-7.32	1.74***	-2.93	-1.88	-2.55	-1.88	-2.55	0.25***	0.25***	0.70***	0.70***	0.70***	-1.18	-1.18	-1.18	-1.18	-1.18
<i>Lean Hog</i>	3.35***	15.12***	2.35***	8.09***	5.65***	-21.26	-21.26	-21.26	-21.26	0.70***	0.70***	2.79***	2.79***	2.79***	-0.15	10.44***	10.44***	4.19**	4.19**
<i>Milk</i>	-7.12	-3.75	5.98***	0.30	5.65***	-21.26	-21.26	-21.26	-21.26	-2.63	-4.58	-0.14*	-0.14*	-0.14*	-0.14*	-1.25	-0.20	-0.20	-0.20
<i>Oranges</i>	-3.62	-0.43*	-4.32	2.70***	-4.43	-4.43	-4.43	-4.43	-4.43	5.80	2.35***	0.55**	0.55**	0.55**	-1.12	-1.12	-1.12	-1.12	-1.12
<i>Soybean Oil</i>	0.20***	2.84***	-3.76	-4.61	-4.43	-4.43	-4.43	-4.43	-4.43	-4.46	6.07***	-2.30	-10.34	-10.34	-1.70	-2.06	-2.06	-2.06	-2.06
<i>Soybeans</i>	1.50***	-0.30	-1.73	2.63**	-1.79	-0.01	-0.01	-0.01	-0.01	1.38	0.81	-3.48	-8.85	-8.85	-0.58	-0.60	-0.60	-0.60	-0.60
<i>Soybean Meal</i>	-2.60	1.14***	4.39***	-5.03	-1.79	-0.01	-0.01	-0.01	-0.01	-5.37	1.34***	3.56***	3.56***	3.56***	-1.87	-2.92	-2.92	-2.92	-2.92
<i>Sugar</i>	-2.47	1.41***	-0.31**	2.75***	-0.66	-2.78	-2.78	-2.78	-2.78	0.60**	0.60**	-2.69	-2.69	-2.69	-0.38*	0.30**	0.30**	0.30**	0.30**
<i>Wheat</i>	-0.61**	0.02**	-3.01	8.97***	8.50***	-19.12	-19.12	-19.12	-19.12	-1.84	-3.38	-4.46	-4.46	-4.46	-0.79	-0.71	-0.71	-0.71	-0.71
<i>Wood</i>	-3.08	0.16**	-3.04	0.21**	0.49*	-4.28	-4.28	-4.28	-4.28	-1.09	1.54***	-3.53	-3.53	-3.53	-0.95	-0.87	-0.87	-0.87	-0.87
<i>Yellow Corn</i>	0.59***	17.77***	0.51**	1.67	1.67	-4.28	-4.28	-4.28	-4.28	-0.52*	8.74***	1.77***	1.77***	1.77***	-0.28*	-0.30	-0.30	-0.30	-0.30
<i>Coal</i>	-2.53	59.55***	-7.36	5.57***	24.58***	-2.36	-2.36	-2.36	-2.36	-10.66	19.38***	-9.59	-9.59	-9.59	-1.13	-0.76	-0.76	-0.76	-0.76
<i>Heating Oil</i>	5.57***	24.58***	-2.36	5.57***	24.58***	-2.36	-2.36	-2.36	-2.36	6.73***	15.43***	-1.42	-1.42	-1.42	-0.61	0.44	0.44	0.44	0.44
<i>Natural Gas</i>	-0.82*	48.68***	-9.98	-10.16	-29.16	-7.07	-7.07	-7.07	-7.07	-5.35	21.67***	-11.52	-11.52	-11.52	-1.24	-0.98	-0.98	-0.98	-0.98
<i>Unleaded Regular Gas</i>	-1.79	11.77***	-2.97	-10.16	-29.16	-7.07	-7.07	-7.07	-7.07	-3.12	7.15***	0.05**	0.05**	0.05**	-1.15	-2.31	-2.31	-2.31	-2.31
<i>WTI Oil</i>	-5.95	-0.29*	-2.21	4.70***	-5.14	-5.14	-5.14	-5.14	-5.14	-1.79	3.55***	-4.46	-4.46	-4.46	-0.86	4.80**	4.80**	4.80**	4.80**
<i>Aluminium</i>	2.19***	2.14***	9.69***	-0.31*	8.59***	5.29***	5.29***	5.29***	5.29***	-1.01	2.32***	12.31***	12.31***	12.31***	10.52***	6.68***	6.68***	6.68***	6.68***
<i>Gold</i>	0.86***	12.15***	-1.74	-3.95	-3.95	5.29***	5.29***	5.29***	5.29***	-0.29***	5.81***	0.08**	0.08**	0.08**	-7.61	-4.03	-4.03	-4.03	-4.03
<i>High Grade Copper</i>	-10.56	8.60**	-66.76	-0.37*	15.04***	4.58***	4.58***	4.58***	4.58***	-4.34	5.79***	-13.69	-13.69	-13.69	0.69**	4.81**	4.81**	4.81**	4.81**
<i>Nickel</i>	8.60**	-66.76	-0.37*	15.04***	4.58***	4.58***	4.58***	4.58***	4.58***	5.79***	-13.69	-13.69	-13.69	-13.69	-0.04**	-0.06*	-0.06*	-0.06*	-0.06*
<i>Palladium</i>	2.86***	15.04***	4.58***	4.58***	4.58***	4.58***	4.58***	4.58***	4.58***	-2.75	14.68***	6.38***	6.38***	6.38***	-1.79	-2.21	-2.21	-2.21	-2.21
<i>Platinum</i>	1.15***	7.21***	-8.55	2.84***	1.44**	13.57***	13.57***	13.57***	13.57***	-4.99	6.29***	-4.44	-4.44	-4.44	0.86**	1.61**	1.61**	1.61**	1.61**
<i>Silver</i>	-0.35***	7.21***	-8.55	2.84***	1.44**	13.57***	13.57***	13.57***	13.57***	-1.90	2.37***	-1.49	-1.49	-1.49	-6.61	-4.61	-4.61	-4.61	-4.61
<i>Tin</i>	-3.37	5.14***	-0.17**	-2.21	-2.23	-2.21	-2.21	-2.21	-2.21	-1.90	2.37***	-1.49	-1.49	-1.49	-6.61	-4.61	-4.61	-4.61	-4.61
<i>Zinc</i>	-3.37	5.14***	-0.17**	-2.21	-2.23	-2.21	-2.21	-2.21	-2.21	-1.90	2.37***	-1.49	-1.49	-1.49	-6.61	-4.61	-4.61	-4.61	-4.61

Table C.8: Out-of-Sample Return Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	<i>in/f</i>				<i>tr</i>				<i>ty</i>			
	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec
Butter	-1.03	0.12**	-1.23	0.58**	-0.56	-0.70	-1.41	-0.13	-0.16**	14.91***	-2.85	-25.18
Cocoa	1.97***	6.66***	1.17***	1.19***	-0.76	-0.13	-1.88	-1.61	0.30***	-8.18	5.56***	-5.78
Coffee Arabica	-2.58	-0.75	-0.85		-0.76	-1.85	1.48**		-11.39	6.21***	-0.17	
Corn Oil	-1.99	-1.31	-3.53	0.28	-0.26	-0.34	-0.92	1.58**	4.35***	13.72***	1.51***	-2.94
Cotton	-1.03	-1.07	-2.32	1.62***	-0.73	-1.68	-0.54	0.79	13.61***	5.35***	-5.57	-4.39
Live Cattle	1.31***	1.40***	-0.57	-0.20*	-0.48	1.11***	-2.02	-1.01	-1.32	1.79***	-3.08	-25.02
Lean Hog	-0.87	-0.74	1.70***	1.93***	-1.45	2.33***	-1.49	-1.69	-7.73	-15.09	-4.72	8.27***
Milk	1.56***	-1.03	1.30***	1.16**	0.22**	-0.86	-0.65	0.48	12.81***	25.75***	-0.47	-20.15
Oranges	-1.61	1.80***	-0.31	-0.55	-0.48	-0.07	-1.04	-0.28	1.83***	-4.30	3.71***	-118.89
Soybean Oil	-1.73	-1.07	-6.02	4.78***	0.07**	-0.15	-0.92	0.34	6.45***	4.15***	-7.25	1.68**
Soybeans	-2.72	-0.12	-3.19	1.32**	-0.81	-0.91	-0.13	-0.94	9.49***	0.20**	-1.26	7.46***
Soybean Meal	-1.62	-3.00	-3.37	-4.46	-1.07	0.08*	0.35*	-0.41	5.24***	-9.49	-0.92	1.21*
Sugar	-0.55	1.30***	7.96***	1.43	-0.72	-1.19	-2.32	-4.91	-3.33	-2.58	-1.77	-3.61
Wheat	-1.88	1.09***	-3.69	1.35***	-0.38	-0.84	-0.63	-0.40	9.89***	9.02***	-3.77	5.99***
Wool	-2.83	-0.81	-3.61	5.02***	-0.41	-0.24	-0.14	-1.38	0.65***	-7.54	-4.40	7.99***
Yellow Corn	-1.09	1.17***	-3.12	-1.21	-1.16	-2.06	-1.25	-0.13	6.99***	8.06***	1.30***	-13.73
Coal	0.04**	0.41**	0.57**	-19.22	-1.14	-0.31	-0.74	0.46	11.84***	14.95***	7.25***	-24.60
Heating Oil	-0.92	-0.58	0.20		-0.44	0.24	0.05		3.09***	43.38***	-2.16	
Natural Gas	-1.50	-1.21	-2.52		-1.38	-0.23	0.06		2.78***	16.79***	-1.56	
Unrefined Regular Gas	1.41**	6.86***	4.80**		-0.46	-1.18	0.31		3.92***	39.76***	-5.12	
WTI Oil	3.20***	1.31***	5.96***	-2.33	0.39	-2.43	-0.95	-4.03	7.70***	34.70***	-4.73	-2.42
Aluminium	-1.09	-1.67	-1.15	-2.27	1.03***	1.48***	-0.04	-1.41	3.548**	-0.34*	-1.95	-0.38
Gold	1.49***	-0.14*	16.58***	3.78***	-0.88	-1.67	-0.86	-3.98	12.58***	-0.89	4.67***	-4.42
High Grade Copper	-1.14	1.50***	-1.04	0.41**	-0.90	-0.96	-0.82	-1.00	11.70***	31.81***	-0.61	-1.05
Nickel	0.23*				1.86***				16.51***			
Palladium	0.48**	-16.05	-15.98		-0.66	-1.50	-0.05		11.50***	-48.95	-0.78	
Platinum	-0.31*	0.64**	2.42***	0.61*	-1.08	-1.85	0.24*	-6.09	-2.04	6.11***	6.73***	-52.46
Silver	0.63***	2.47***	7.42***	1.24***	-0.69	-1.97	-0.78	-5.74	-0.91	33.42***	2.17***	-30.12
Tin	-0.70	-1.05	1.98***	9.00***	-0.76	-0.37	-0.27	-5.79	12.88***	18.47***	1.09***	22.40***
Zinc	-0.68	0.44**	-2.06	-2.49	-1.11	-0.81	-0.91	0.17	4.55***	18.66***	-1.40	-0.67

Table C.8: Out-of-Sample Return Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	star				tbl				tms			
	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec
Butter	-18.01	-3.71	-19.53	-18.09	0.19	2.50**	0.19	2.50**	-5.44	12.33***	-2.05	-13.04
Cocoa	-0.21**	2.36***	-84.96	-41.91	-0.35	1.12*	-0.35	1.12*	-4.02	6.19***	5.75***	4.83***
Coffee Arabica	-1.75	-22.17	-0.18						-1.94	12.13***	1.99**	
Corn Oil	-0.64	4.70***	-2.56	1.21*	19.17***	-0.52	19.17***	-4.85	2.20***	10.72***	-0.73	-28.13
Cotton	-6.40	-2.09	0.27**	-8.39	8.20***	14.37***	-4.42	-28.13	0.43***	8.49***	-9.47	-10.35
Live Cattle	-17.96	5.90***	0.74**	-66.72	5.22***	10.20***	-3.42	-2.38	0.85***	11.68***	-4.51	-3.33
Lean Hog	-18.96	3.10***	-188.85	-10.24	-0.68	2.08**	-10.74	8.15***	-5.69	0.98**	9.88	8.15***
Milk	-12.74	-0.90	-24.98	-10.59	-1.02	2.08**	-1.02	2.08**	4.41***	23.57***	-1.74	-7.62
Oranges	-0.18**	-0.22	-6.42	-0.87					-9.54	3.93***	3.57***	-28.81
Soybean Oil	-18.18	-0.52	-0.96	-0.17	4.63***	5.10***	-3.28	-8.14	4.63***	5.10***	-3.28	-8.14
Soybeans	-10.53	3.70***	-45.46	-11.99	5.88***				1.15	-3.24	0.88**	-7.44
Soybean Meal	-2.58	-2.49	-66.43	5.88***	-0.03	-0.03	-0.18	4.49**	-1.15	0.96***	-0.64	-5.84
Sugar	-67.89	-11.03	-63.73	-11.19	-4.13	5.51***	-4.13	5.51***	-1.88	1.96***	-1.80	-15.56
Wheat	-9.16	-5.18	-18.05	-29.18	3.59**				7.56***	14.04***	-1.80	-15.56
Wood	-39.66	-0.21	-16.54	-10.96	0.52	3.59**	0.52	3.59**	-6.67	-3.19	-2.66	4.93***
Yellow Corn	-6.37	4.28***	1.82***	-42.39	-17.10	2.25**	-17.10	2.25**	4.31***	11.63***	0.99***	-17.15
Cool	0.08**	0.23*	-95.21	-9.36					-0.13**	16.93***	0.86**	-19.67
Heating Oil	-48.50	-8.26	-0.66						-3.07	36.34***	-0.59	0.79*
Natural Gas	0.00	-7.18	-0.11						-3.30	11.54***	-1.27	
Unleaded Regular Gas	-50.11	-2.22	-0.08						5.36***	31.86***	6.62***	
WTI Oil	-9.34	-1.50	-168.06	-14.47	-4.54	0.02	-4.54	0.02	0.75***	25.99***	-2.55	-16.31
Aluminum	-110.27	-6.55	-568.31	-1.08	0.00	0.00	0.00	0.00	7.71***	4.11***	0.38**	-1.33
Gold	-187.68	-8.10	-2.88	10.67***	20.52***	0.62*	20.52***	0.62*	2.24***	4.22***	6.33***	-13.91
High Grade Copper	-15.67	-1.32	-86.77	-52.92	-12.47	-2.13	-12.47	-2.13	15.97***	32.85***	0.69**	-18.73
Nickel	2.04**								4.61***			
Palladium	-47.98	-9.03	0.00	-2.28	-1.91	-1.91	-1.91	-1.91	12.83***	-52.72	13.56***	-57.08
Platinum	-79.13	2.98***	-11.02	-19.69	2.57**	-2.54	2.57**	-2.54	1.68***	12.62***	5.07***	-33.50
Silver	-16.40	-11.56	-77.00	7.76***	33.76***	-0.18	33.76***	-0.18	-1.95	43.45***	2.54***	-33.50
Tin	-4.66	1.04***	-62.96	-34.46	-0.40	-0.40	-0.40	-0.40	4.02***	18.13***	2.09***	-21.58
Zinc	-34.32	-3.61	-27.08	-34.46	-5.53	-5.53	-5.53	-5.53	4.54***	22.33***	4.84***	-6.10

Table C.8: Out-of-Sample Return Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	<i>unrate</i>			
	Exp	eExp	lExp	lRec
Butter	0.27***	5.22***	1.37***	
Cocoa	-2.27	10.70***	7.72***	
Cof fee Arabica	8.40***	-2.54	-1.93	
Corn Oil	-5.16	-9.23	-4.81	
Cotton	0.81***	-4.06	-6.38	
Live Cattle	-1.03	1.43***	5.56***	
Lean Hog	-2.34	2.00***	4.59***	
Milk	-1.40	9.82***	3.63***	
Oranges	-3.14	-0.51	-0.84	
Soybean Oil	-6.62	-13.09	-13.91	
Soybeans	-3.51	-5.20	-11.10	
Soybean Meal	-4.64	-0.75	-13.08	
Sugar	5.90***	1.05**	-2.00	
Wheat	0.96***	12.09***	-7.94	
Wool	-6.35	0.59*	-3.33	
Yellow Corn	3.32***	-1.19	-5.02	
Coal	-3.54	12.33***	3.78***	
Heating Oil	3.15***	34.80***	-1.74	
Natural Gas	-0.32	14.03***	1.54	
Unleaded Regular Gas	2.14***	32.24***	-22.79	
WTI Oil	2.87***	21.08***	-1.99	
Aluminium	1.56***	-8.12	-0.01	
Gold	-10.73	6.46***	4.41***	
High Grade Copper	6.71***	16.00***	0.22*	
Nickel	1.24**			
Palladium	-7.46	24.48***	-7.05	
Platinum	-9.86	6.36***	0.29*	
Silver	-7.18	19.42***	2.97***	
Tin	-0.68	6.69***	1.87***	
Zinc	1.81***	6.68***	4.27***	

Table C.9: In-Sample Volatility Predictability and Business Cycle Stages (1 Month)

This table reports the in-sample ΔR^2 's of a regression of monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable across business cycle stages. We predict the next month's volatility. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔMI" the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "suar" the stock variance, and "tbl" the 3-month Treasury bill rate. "trns" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider six business cycle stages. "Exp" denotes the expansion, "eExp" the early expansion, "lExp" the late expansion, "Rec" the recession, "eRec" the early recession, "lRec" the late recession, "de", "dfy", "dfr", "dy", "erp", "infl", "ltr", "tbl", "trns", "unrate", "de", "dfy", "dfr", "dy", "erp", "infl", "ltr", "tbl", "trns", "unrate" indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de						Δindpro						ΔMI					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Butter	0.02	-0.02	0.12	0.01	-0.25	0.35	-0.03	-0.05	-0.04	-0.16	-0.35	-0.49	0.37***	0.35*	0.39***	0.61*	-0.51	2.15*
Coconut	0.65***	1.03***	0.87***	-0.06	0.98**	0.13	-0.02	-0.14	0.17	0.54*	0.04	-0.07	0.07	0.08	0.33	0.41	-0.83	4.00*
Coffee Arabica	0.43**	0.00	0.81**	-0.57	0.66	-0.99	-0.06	-0.09	0.21	-0.96	-1.82	-2.26	-0.07	-0.11	-0.21	0.03	-1.64	1.33
Corn Oil	-0.06	-0.16	-0.17	-0.13	2.44**	-0.65	-0.05	0.34*	1.06***	0.78*	1.12*	1.18*	-0.07	-0.12	-0.14	0.22	-0.57	-0.96
Cotton	-0.05	-0.07	-0.01	-0.06	-0.06	-0.01	-0.03	0.03	-0.11	-0.22	0.91	-0.49	0.03	-0.15	-0.17	-0.27	-0.57	-0.88
Live Cattle	-0.04	-0.02	-0.16	-0.02	-0.10	0.04	0.87***	1.07**	0.14	0.50	0.22	0.72	0.23	0.59*	0.02	0.25	-0.84	-0.15
Lean Hog	-0.01	0.63**	1.07***	-0.14	-0.23	-0.32	-0.07	-0.12	-0.03	-0.21	-0.35	-0.65	0.16	-0.31	0.23	0.45	-0.25	-0.39
Milk	-0.01	0.02	0.00	0.43**	0.23	1.00*	-0.04	-0.07	-0.07	1.02***	0.30	0.80*	0.16**	-0.09	0.55**	-0.28	-0.51	-0.23
Oranges	0.37***	0.13	0.61**	-0.23	-0.23	-0.13	-0.05	-0.11	-0.07	-0.08	-0.51	0.32	0.00	-0.15	0.17	0.67	-0.23	-0.04
Soybean Oil	-0.02	-0.10	0.20	0.39**	0.95*	-0.05	-0.04	0.27*	1.04***	-0.08	1.15**	-0.49	-0.05	-0.11	-0.19	-0.29	-0.71	-0.04
Soybeans	0.06	-0.13	0.36*	-0.20	0.18	-0.39	0.07	0.41**	-0.09	-0.21	0.10	-0.51	-0.05	-0.02	-0.16	-0.36	-0.81	-1.09
Soybean Meal	0.16*	0.16	0.07	-0.21	-0.20	-0.86	0.00	0.44*	0.27*	-0.25	1.05	-0.46	-0.08	0.05	-0.16	-0.43	-1.17	-1.22
Sugar	0.10**	0.14**	0.10*	0.16**	0.45**	0.01	-0.01	-0.06	0.00	-0.09	0.12	-0.24	0.11**	0.07	-0.07	-0.10	-0.48	-0.58
Wheat	-0.02	-0.08	0.01	0.11	-0.19	0.92**	0.01	-0.08	-0.06	-0.17	0.67*	-0.48	0.29*	0.29*	0.21	-0.17	-0.51	-0.69
Wool	0.02	0.20	1.15***	2.54***	1.34**	5.97***	0.32**	1.32***	-0.12	-0.17	1.14*	-0.48	-0.08	0.13	-0.18	-0.18	1.09	-0.21
Yellow Corn	0.00	0.65**	-0.08	0.37*	0.56	0.70*	0.13	0.04	0.28	0.55*	-0.70	-0.26	-0.10	-0.03	0.09	1.34*	-1.00	-0.72
Coal	3.04***	4.32***	2.09***	2.47**	0.92	5.62**	-0.12	-0.25	-0.21	0.65	-0.90	-0.30	-0.07	1.08**	-0.21	-0.50	-1.08	-1.36
Heating Oil	0.14	-0.29	0.20	1.07	0.97	0.99	0.47**	1.29**	-0.22	0.68	-1.27	0.11	0.07	0.42	-0.28	0.09	-1.28	0.50
Natural Gas	0.49**	-0.35	2.33***	-0.61	8.70**	0.72	0.37**	-0.03	1.63**	-0.62	1.37	5.01**	0.45*	-0.18	1.10**	-0.37	-1.63	-0.73
Unleaded Regular Gas	1.39**	-0.46	0.97*	15.50***	10.24*	17.89**	0.11	-0.11	-0.42	-1.23	4.03	-2.43	0.51*	-0.22	0.14	-1.23	-3.21	-2.66
WTI Oil	-0.02	-0.01	0.02	0.13*	0.01	0.12	-0.02	0.00	0.11*	-0.09	-0.07	-0.26	0.02	0.03	0.07	0.29	0.17	2.04**
Aluminum	0.14**	-0.01	0.14*	-0.12	0.10	-0.24	-0.01	0.06	-0.05	-0.04	0.11	-0.13	-0.04	0.03	-0.04	0.57*	-0.75	0.54
Gold	0.29***	0.10*	0.82***	0.11*	0.44**	-0.02	-0.01	0.05	-0.03	-0.07	-0.17	-0.18	0.00	-0.06	-0.04	-0.13	-0.53	0.39
High Grade Copper	0.09*	0.00	0.10	-0.08	0.89**	-0.13	0.33***	0.97***	-0.03	-0.06	1.03*	-0.34	0.37**	0.37**	-0.09	1.04**	1.10	1.17**
Nickel	1.24**	10.26***	-0.30	10.85**	2.53	7.82	-0.29	-0.51	-0.56	14.06***	9.71*	-1.04	0.63*	4.03***	-0.60	5.87**	-4.76	-0.23
Palladium	0.14	-0.16	1.14*	-0.33	-2.31	-0.65	-0.03	0.43	-0.46	2.56*	13.27**	0.88	-0.12	0.00	1.72**	-0.83	5.97*	-2.31
Platinum	-0.05	-0.05	-0.07	-0.05	-0.13	0.05	-0.03	-0.11	-0.03	0.00	0.63	0.01	0.23**	-0.17	0.26	-0.03	0.72	-0.88
Silver	0.59***	0.32**	1.48***	0.04	1.05***	-0.19	-0.04	-0.09	-0.06	-0.18	0.06	-0.41	0.23**	0.43**	-0.04	-0.31	0.47	-1.06
Tin	0.01	-0.08	1.20***	0.05	0.00	0.15	0.21**	0.04	0.00	0.45*	0.31	-0.22	0.00	-0.17	-0.12	2.34***	-0.63	3.95**
Zinc	0.19***	-0.03	0.73***	-0.12	0.57*	-0.03	-0.03	-0.07	-0.09	0.16	-0.62	-0.31	-0.06	0.91**	-0.06	0.17	-0.56	0.73

CHAPTER 4. PREDICTABILITY IN COMMODITY MARKETS:
EVIDENCE FROM MORE THAN A CENTURY

Table C.9: In-Sample Volatility Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	df _r				df _y				df _p				
	Exp	eExp	lExp	Rec	lRec	eRec	Rec	Exp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	-0.02	-0.09	0.04	0.17	0.07	-0.38	-0.13	-0.05	0.02	0.95***	-0.05	-0.23	-0.03
<i>Cocoa</i>	-0.08	-0.16	-0.16	-0.28	-0.19	-0.55	-0.21	2.08***	-0.01	-0.15	2.08***	0.92*	-0.47
<i>Coffee Arabica</i>	-0.11	-0.19	-0.06	1.04	0.18	0.84	-0.62	0.02	-0.08	-0.20	-0.62	-1.16	-2.15
<i>Corn Oil</i>	0.01	0.23	-0.15	-0.17	0.39	-0.37	0.49***	0.78**	0.49***	0.78**	-0.04	-0.16	-0.32
<i>Cotton</i>	-0.07	-0.13	0.59**	0.30	0.08	0.88	1.25**	1.26***	0.57***	0.32*	1.26***	1.09*	0.69
<i>Live Cattle</i>	-0.09	-0.19	0.04	0.20	-0.43	2.00*	1.19***	0.93**	1.19***	0.93**	1.95***	-0.62	4.03***
<i>Lean Hog</i>	0.02	0.02	-0.16	-0.28	0.11	-0.78	0.79***	0.98***	0.79***	0.98***	-0.18	-0.16	-0.51
<i>Milk</i>	0.12**	0.14	0.09	-0.18	0.63	-0.53	0.09*	0.11	0.05	0.22	0.08	0.51	-0.08
<i>Oranges</i>	0.13*	-0.14	0.44**	-0.15	0.43	-0.49	0.44***	0.61**	0.19**	0.23*	0.14	-0.52	0.09
<i>Soybean Oil</i>	-0.06	-0.07	-0.16	0.04	-0.41	-0.44	0.19**	0.50**	0.37***	0.05	0.02	0.00	-0.08
<i>Soybeans</i>	0.31**	0.74**	0.10	0.61*	-0.44	0.08	0.37***	1.03***	-0.05	-0.13	-0.23	-0.42	-0.57
<i>Soybean Meal</i>	0.09	0.14	-0.08	0.63*	-0.40	-0.47	-0.05	-0.09	-0.15	-0.22	-1.05	-0.59	-0.06
<i>Sugar</i>	0.03	0.01	-0.05	0.23*	0.55*	0.09	-0.02	0.01	-0.05	-0.07	-0.01	-0.16	0.08**
<i>Wheat</i>	0.11*	0.07	-0.06	-0.19	0.44	-0.47	0.96***	2.29***	0.17	0.04	0.37	1.11*	0.20
<i>Wool</i>	0.79***	1.57***	0.36*	3.54***	0.60	3.65***	-0.03	-0.03	-0.14	0.32	-0.19	-0.15	0.02
<i>Yellow Corn</i>	0.12	0.04	-0.16	1.52**	-0.25	0.90	0.75***	1.22***	0.89**	0.60*	1.55*	1.10	0.15
<i>Coal</i>	-0.12	-0.26	-0.22	-0.47	0.47	-0.72	-0.11	-0.26	-0.18	1.84**	-0.93	0.94	2.45
<i>Heating Oil</i>	-0.14	-0.18	-0.16	-0.09	-0.97	0.26	-0.09	-0.23	0.50	0.57	-0.96	0.62	-1.13
<i>Natural Gas</i>	-0.13	-0.04	0.19	3.93***	0.98	1.35	0.26	-0.25	0.87*	-0.47	-1.03	1.39	2.97
<i>Unleaded Regular Gas</i>	0.87***	-0.44	0.23	-1.16	-0.38	-2.17	0.68*	3.75***	0.18	-0.20	4.10	0.82	0.41
<i>WTI Oil</i>	0.06**	-0.02	-0.05	-0.11	-0.09	0.19	0.06*	0.21**	0.19**	-0.09	-0.03	0.11	-0.11
<i>Aluminum</i>	-0.03	0.06	-0.05	0.26*	-0.23	-0.09	-0.03	0.03	-0.04	-0.10	-0.24	-0.21	1.49***
<i>Gold</i>	0.06	0.18*	0.01	0.21	-0.09	0.47	-0.01	-0.01	-0.04	-0.07	0.36	-0.21	0.50**
<i>High Grade Copper</i>	0.04	-0.11	-0.03	-0.07	-0.50	-0.17	-0.03	0.22*	0.03	0.11	-0.48	-0.32	0.43*
<i>Nickel</i>	0.74*	-0.29	1.09*	-2.12	-3.55	0.21	0.11	2.20**	0.14	-0.07	-4.12	-3.10	8.44
<i>Palladium</i>	-0.12	-0.36	-0.34	-1.02	3.74	0.30	0.15	0.85*	0.48	1.05	0.36	2.55	-2.39
<i>Platinum</i>	-0.05	0.14	-0.11	-0.03	-0.41	-0.66	-0.05	-0.13	0.25*	0.31	0.37	-0.42	0.55
<i>Silver</i>	-0.05	-0.04	-0.11	-0.20	0.23	-0.35	0.04	-0.01	-0.09	-0.18	0.32	-0.48	0.88**
<i>Tin</i>	-0.04	-0.11	0.00	-0.19	-0.49	0.43	0.00	0.11	-0.01	1.46***	0.26	1.42**	0.01
<i>Zinc</i>	0.24**	0.16	0.18*	0.11	-0.30	0.37	-0.03	-0.10	-0.09	0.44	0.94	-0.03	0.03

Table C.9: In-Sample Volatility Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	dy				ep				epP			
	Exp	eExp	Rec	lRec	Exp	eExp	Rec	lRec	Exp	eExp	Rec	lRec
<i>Butter</i>	0.36***	-0.07	0.34*	-0.02	0.29***	0.04	0.67**	0.76*	0.01	0.02	-0.06	-0.12
<i>Cocoa</i>	0.15*	0.11	-0.07	0.02	-0.11	-0.04	-0.09	-0.19	-0.05	-0.05	-0.11	0.22*
<i>Coffee Arabica</i>	-0.06	-0.21	0.29	-0.14	-0.10	-0.20	0.56	1.41	0.29***	-0.15	0.29	-0.32
<i>Corn Oil</i>	0.61***	0.53***	-0.24	-0.06	0.63***	0.37*	-0.19	-0.63	-0.05	-0.02	-0.16	-0.22
<i>Cotton</i>	-0.03	-0.05	-0.11	-0.25	-0.03	-0.09	0.05	-0.14	-0.05	-0.09	-0.08	0.06
<i>Live Cattle</i>	0.62***	0.54***	2.58***	1.77***	0.50***	0.08	1.39***	0.70*	0.09	0.03	-0.04	0.59**
<i>Lean Hog</i>	0.01	0.03	-0.10	0.57*	0.19**	-0.03	-0.13	0.24	-0.02	-0.06	-0.12	0.41*
<i>Milk</i>	-0.04	-0.07	-0.13	-0.24	-0.02	-0.02	0.16	0.10	0.10*	0.03	0.07	-0.13
<i>Oranges</i>	0.93***	0.73**	1.67***	3.90***	0.30**	0.03	0.59*	0.54	0.35***	1.06***	0.13	-0.52
<i>Soybean Oil</i>	-0.05	-0.09	-0.11	0.39*	0.01	-0.03	-0.13	-0.17	0.01	-0.04	-0.14	1.08***
<i>Soybeans</i>	-0.06	0.04	0.12	0.95*	-0.01	0.09	-0.09	0.13	0.00	-0.13	0.12	-0.21
<i>Soybean Meal</i>	-0.06	0.26	-0.10	-0.31	0.16*	0.85**	-0.15	-0.37	-0.08	-0.15	-0.09	-0.34
<i>Sugar</i>	0.08**	0.04	0.10*	-0.01	-0.01	-0.04	0.03	0.02	-0.02	0.00	0.03	0.20**
<i>Wheat</i>	-0.04	-0.08	-0.02	0.32	-0.04	-0.10	-0.10	0.35	-0.04	-0.09	-0.40	0.37**
<i>Wool</i>	0.46***	0.05	0.67***	5.97***	0.40***	0.82***	3.95***	1.76**	0.26**	0.74**	0.06	0.15
<i>Yellow Corn</i>	-0.04	0.11	-0.08	-0.29	-0.06	-0.10	-0.13	-0.23	0.01	-0.09	-0.08	1.40***
<i>Coal</i>	2.68***	1.60***	1.21*	5.18**	0.67***	-0.22	3.58***	2.11*	0.18	0.64*	-0.21	0.43
<i>Heating Oil</i>	0.60**	1.10*	-0.32	-1.07	0.27*	1.01**	1.01	-1.28	-0.09	-0.26	-0.19	-0.33
<i>Natural Gas</i>	3.92***	4.50***	1.59	0.54	2.06***	3.88***	1.56**	-0.93	0.29*	1.25**	-0.29	5.40***
<i>Unleaded Regular Gas</i>	3.96***	5.84***	0.47	-1.15	1.85***	3.36***	1.29*	12.38***	-0.23	-0.40	-0.43	1.37
<i>WTI Oil</i>	0.15***	-0.04	-0.04	-0.08	0.20***	0.03	0.36**	-0.01	0.02	-0.06	0.00	-0.04
<i>Aluminum</i>	0.07*	-0.01	1.01***	2.12**	-0.02	-0.08	0.57***	0.86*	-0.02	-0.07	-0.04	0.21*
<i>Gold</i>	0.08**	0.01	0.16**	0.38**	-0.02	-0.04	-0.03	-0.05	0.00	-0.01	-0.01	0.36**
<i>High Grade Copper</i>	0.00	0.02	0.04	0.41*	-0.04	-0.08	-0.05	-0.22	0.00	-0.02	-0.01	-0.08
<i>Nickel</i>	0.18	8.24***	-0.06	-0.73	-0.29	0.32	0.80	15.25***	-0.28	-0.40	-0.55	-2.14
<i>Palladium</i>	0.75**	0.67	1.45**	1.26	0.27	0.05	0.49	1.40	-0.20	0.06	-0.02	0.31
<i>Platinum</i>	0.02	-0.06	-0.03	0.31	0.05	0.10	-0.08	0.46*	0.19**	0.08	0.04	1.48***
<i>Silver</i>	0.38***	0.15*	0.27**	0.81**	0.00	-0.07	0.09	-0.08	0.06	-0.01	-0.02	-0.04
<i>Tin</i>	-0.04	-0.05	-0.06	0.15	-0.03	-0.08	-0.04	0.07	-0.02	0.29**	-0.07	0.31**
<i>Zinc</i>	0.02	-0.05	0.39**	0.63*	-0.02	-0.02	-0.01	0.02	-0.01	-0.05	0.17*	-0.15

CHAPTER 4. PREDICTABILITY IN COMMODITY MARKETS:
EVIDENCE FROM MORE THAN A CENTURY

Table C.9: In-Sample Volatility Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	<i>in fl</i>				<i>ltr</i>				<i>lty</i>								
	Exp	eExp	lExp	lRec	eRec	lRec	lExp	lRec	eRec	lRec	lExp	lRec	eRec	lRec			
<i>Butter</i>	0.08*	0.34**	-0.05	0.27*	-0.22	1.19**	-0.04	0.02	0.65**	-0.26	1.04*	-0.03	-0.07	-0.06	-0.16	-0.37	-0.48
<i>Cocoa</i>	0.03	0.12	-0.11	0.13	-0.22	-0.12	-0.05	0.26	-0.05	-0.36	1.07	0.43**	0.53**	0.32*	0.01	0.12	-0.37
<i>Coffee Arabica</i>	-0.11	-0.11	-0.24	1.09	8.01**	-1.71	0.36**	0.21	0.38	1.46	2.95	0.06	-0.18	1.10**	-0.42	-0.38	-2.11
<i>Corn Oil</i>	1.77***	1.22***	2.23***	1.50***	1.37*	2.19**	0.23**	-0.13	1.20***	-0.20	1.62**	0.49***	0.86**	-0.10	0.77*	0.91	0.62
<i>Cotton</i>	0.62***	0.39**	0.85***	-0.13	0.35	-0.26	0.07	0.28*	0.13	-0.09	0.20	0.28**	-0.01	1.89***	0.16	1.02*	-0.30
<i>Live Cattle</i>	0.08	0.07	0.17	0.15	-0.12	-0.09	-0.10	0.04	0.01	-0.23	0.90	0.07	-0.20	0.76**	0.03	0.30	-0.65
<i>Lean Hog</i>	0.14*	0.24*	-0.05	-0.08	-0.11	0.33	-0.08	-0.14	-0.17	-0.28	1.62*	-0.01	0.17	-0.09	-0.26	-0.53	-0.62
<i>Milk</i>	-0.01	-0.02	-0.07	-0.01	-0.25	0.93**	0.02	-0.10	0.30**	-0.13	-0.57	-0.02	-0.07	-0.06	-0.15	-0.35	-0.38
<i>Oranges</i>	-0.06	-0.13	-0.10	-0.01	-0.49	0.16	0.01	-0.11	0.48**	-0.21	0.49	-0.05	-0.10	-0.11	-0.18	-0.45	-0.17
<i>Soybean Oil</i>	0.28**	0.02	0.69**	0.15	0.73*	-0.14	-0.04	0.00	-0.14	-0.14	-0.20	0.12*	0.19	-0.07	0.10	-0.09	0.07
<i>Soybeans</i>	0.09	-0.07	0.01	0.39*	0.45	0.24	-0.03	0.02	-0.13	-0.20	-0.41	-0.06	-0.13	-0.09	-0.18	-0.36	-0.58
<i>Soybean Meal</i>	1.27***	2.79***	-0.02	1.14**	0.38	3.07**	-0.06	0.07	-0.09	-0.25	-0.83	-0.06	0.01	-0.12	-0.31	-1.04	-0.62
<i>Sugar</i>	-0.02	-0.04	-0.02	0.31***	0.45**	0.77**	-0.02	0.08	0.08	0.19*	-0.16	0.49	0.44***	0.60***	0.33**	0.24	0.55
<i>Wheat</i>	-0.01	-0.05	0.33**	0.11	-0.05	0.58**	-0.02	-0.08	0.42**	0.07	0.38	0.05	-0.02	0.03	-0.06	-0.20	-0.36
<i>Wool</i>	-0.01	0.10	-0.08	-0.16	-0.10	-0.33	-0.02	0.17	-0.14	1.05**	0.08	-0.06	-0.01	-0.12	-0.23	-0.49	-0.39
<i>Yellow Corn</i>	0.21**	0.44**	-0.06	-0.10	-0.22	-0.16	-0.04	-0.16	-0.13	-0.32	-0.52	-0.05	0.22	0.10	-0.30	-0.64	-0.70
<i>Coal</i>	0.26*	0.41	0.25	-0.41	-0.75	-1.11	0.08	1.07**	-0.24	1.25*	-0.86	9.73***	0.59**	0.79**	0.16	-0.45	-0.93
<i>Heating Oil</i>	0.06	0.59*	-0.23	4.73***	4.49*	8.43***	-0.12	-0.34	-0.19	-1.23	-1.23	-0.02	-0.20	-0.21	0.14	-1.28	0.14
<i>Natural Gas</i>	0.29*	-0.37	1.89***	0.50	-1.99	0.33	0.07	-0.36	0.57*	-0.63	-1.54	-0.66	2.98***	2.75**	4.07***	2.04*	4.45
<i>Unleaded Regular Gas</i>	0.13	1.60**	-0.19	-0.66	1.98	2.00	-0.25	-0.29	-0.47	1.04	3.82	7.26**	4.17***	4.87***	2.55**	9.71***	6.83*
<i>WTT Oil</i>	0.06*	0.02	0.04	0.11*	0.10	0.01	0.29***	0.33***	0.04	-0.06	0.91**	-0.36	0.07*	-0.01	0.55***	-0.05	0.08
<i>Aluminium</i>	-0.03	-0.07	-0.03	-0.11	-0.19	-0.22	-0.03	-0.09	-0.02	0.04	-0.14	-0.05	0.36***	0.51**	0.04	0.41	0.21
<i>Gold</i>	-0.01	-0.04	-0.01	-0.02	-0.07	-0.05	0.12**	0.22**	-0.03	-0.10	3.23***	0.68*	1.41***	1.28***	0.83***	0.48*	0.65*
<i>High Grade Copper</i>	0.03	0.07	-0.06	-0.03	-0.02	-0.15	-0.04	-0.11	-0.07	0.21	4.97***	-0.39	0.15**	0.75**	0.04	0.27	-0.09
<i>Nickel</i>	1.57**	0.48	1.14*	6.44**	9.16*	5.63	0.17	-0.38	-0.17	0.87	-0.49	-0.56	0.50	8.24***	16.28***	-3.84	18.61**
<i>Palladium</i>	1.11**	0.18	0.43	-0.64	-2.18	-1.96	0.01	-0.37	0.51	-0.97	12.68**	-2.41	-0.02	0.40	-0.05	3.75	-2.32
<i>Platinum</i>	0.03	0.26*	-0.10	0.06	-0.21	-0.33	-0.06	-0.11	-0.12	0.09	0.19	-0.37	0.00	-0.13	0.45**	-0.32	-0.29
<i>Silver</i>	0.00	0.08	-0.09	0.25**	0.18	0.50**	-0.05	-0.10	-0.13	-0.21	0.41	2.11**	2.25***	2.78***	1.59***	1.81***	1.09*
<i>Tin</i>	0.05	-0.02	0.08	-0.06	0.64*	-0.14	-0.05	-0.02	-0.13	-0.08	-0.47	-0.34	-0.03	-0.10	0.44**	-0.14	0.09
<i>Zinc</i>	-0.01	-0.05	-0.04	-0.07	0.00	-0.26	0.39***	0.08	0.48***	-0.13	-0.70	-0.36	0.20**	0.05	0.38**	0.00	-0.59

Table C.9: In-Sample Volatility Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	star					tbl					tms					
	Exp	eExp	Rec	eRec	lRec	Exp	eExp	Rec	eRec	lRec	Exp	eExp	Rec	eRec	lRec	
<i>Butter</i>	0.04	0.18*	-0.02	0.48**	0.21	-0.01	0.14	-0.06	-0.17	-0.38	0.01	0.31**	-0.06	-0.17	-0.37	-0.46
<i>Cocoa</i>	-0.04	-0.04	-0.09	1.26***	0.17	0.20*	0.13	0.70***	-0.15	-0.27	0.03	0.43*	0.51***	-0.09	-0.31	-0.47
<i>Cof fec Arabica</i>	-0.02	-0.07	-0.15	-0.47	-0.30	-0.10	-0.17	-0.16	0.23	0.25	0.46**	0.49*	1.64***	-0.47	-0.04	-1.79
<i>Corn Oil</i>	0.14	0.94***	-0.11	-0.25	0.30	0.41**	0.64**	0.10	0.68*	0.68	-0.08	-0.01	0.40*	-0.18	-0.47	-0.28
<i>Cotton</i>	0.42***	0.60**	0.07	-0.05	-0.31	0.03	1.31***	0.11	1.15*	1.15*	0.25**	0.30*	-0.14	-0.23	0.01	-0.49
<i>Live Cattle</i>	0.14*	0.35*	-0.16	0.69**	-0.37	1.82**	-0.20	0.35	0.05	0.19	-0.03	-0.21	-0.10	-0.22	-0.51	0.44
<i>Lean Hog</i>	0.36**	1.05***	-0.14	0.08	-0.24	0.02	0.29*	-0.08	-0.22	-0.31	-0.06	-0.12	-0.17	-0.07	1.31*	-0.01
<i>Milk</i>	-0.04	-0.05	-0.08	-0.13	-0.11	-0.01	0.02	-0.06	-0.16	-0.35	-0.03	0.15	-0.08	-0.12	-0.34	-0.12
<i>Oranges</i>	0.11*	-0.05	0.16*	0.44*	1.01*	-0.04	-0.14	-0.08	-0.22	-0.38	-0.06	-0.02	0.00	0.94**	0.94	-0.15
<i>Soybean Oil</i>	0.08	0.89***	0.01	-0.14	-0.19	-0.03	-0.13	-0.13	0.13	-0.12	0.45	0.46**	-0.09	-0.09	-0.32	0.04
<i>Soybeans</i>	0.04	1.32***	0.10	0.00	-0.06	0.19	-0.06	-0.13	-0.23	-0.46	0.11	0.49**	-0.05	0.10	0.01	-0.56
<i>Soybean Meal</i>	-0.02	0.12	-0.15	-0.38	-0.92	-0.06	0.04	-0.14	-0.29	-0.99	0.24	-0.08	-0.17	-0.34	-0.82	2.67*
<i>Sugar</i>	-0.02	-0.02	-0.01	-0.05	-0.10	0.43***	0.68***	0.49***	0.61***	0.42	-0.02	-0.06	-0.02	0.31**	0.08	-0.22
<i>Wheat</i>	-0.04	-0.03	-0.09	0.65**	-0.09	2.67***	-0.12	-0.04	-0.13	-0.26	0.07	0.26*	-0.12	-0.12	-0.38	-0.29
<i>Wool</i>	0.16*	0.60**	-0.10	0.16	-0.32	0.13	0.71**	-0.11	-0.12	-0.54	0.04	1.13***	-0.12	0.23	-0.50	0.49
<i>Yellow Corn</i>	0.04	0.06	-0.10	0.60**	-0.39	1.38**	0.29*	-0.15	-0.24	-0.72	0.03	-0.16	0.43*	0.07	-0.38	-0.63
<i>Coal</i>	-0.10	0.30	-0.18	1.10*	-0.90	0.84***	0.84**	0.40	-0.37	-0.95	0.04	-0.26	0.25	-0.11	-0.94	2.32
<i>Heating Oil</i>	-0.14	1.06**	-0.21	1.05	-1.28	3.04*	-0.26	-0.16	0.91	-1.17	0.06	-0.34	-0.24	1.39*	-0.26	2.62
<i>Natural Gas</i>	-0.11	0.03	-0.28	5.67***	-1.86	1.88	1.56**	1.56**	2.63*	7.75*	-0.09	-0.21	-0.18	1.08	7.58**	-0.79
<i>Unleaded Regular Gas</i>	-0.17	-0.43	-0.54	9.97***	9.51*	10.35**	0.59*	0.30	7.68***	4.69	21.73***	1.45***	0.44	0.33	-1.61	9.51**
<i>WTI Oil</i>	0.05*	0.12*	0.00	0.14	0.05	0.38	-0.05	0.51***	-0.10	-0.31	-0.02	0.06	0.02	-0.11	-0.22	0.00
<i>Aluminum</i>	0.06*	-0.03	0.35**	-0.10	-0.21	0.16**	0.09	0.13*	-0.06	-0.13	0.05	0.62***	0.10*	-0.07	0.14	0.00
<i>Gold</i>	0.04*	-0.01	0.05	0.02	-0.03	0.97***	0.61***	1.56***	0.42**	0.28	-0.02	0.26**	0.01	-0.09	-0.20	-0.08
<i>High Grade Copper</i>	-0.02	-0.03	-0.07	1.77***	-0.20	2.33***	0.07*	-0.01	-0.06	-0.05	-0.28	0.76***	-0.07	-0.06	-0.46	0.09
<i>Nickel</i>	-0.23	-0.38	-0.60	8.25***	-3.75	-2.67	6.01***	-0.16	20.82***	-3.67	-0.24	-0.63	0.27	15.27***	-3.52	13.90**
<i>Palladium</i>	0.36*	0.05	0.32	-1.09	-1.93	-1.00	-0.18	0.17	2.25*	2.98	-0.16	-0.05	1.17*	6.14**	-1.31	2.36
<i>Platinum</i>	-0.05	-0.10	-0.11	0.28*	-0.25	0.02	-0.06	-0.10	0.05	-0.17	0.18**	0.12	0.24*	-0.11	0.28	-0.19
<i>Silver</i>	-0.04	-0.07	-0.08	-0.03	-0.18	-0.06	1.24***	1.03***	1.12**	0.85*	0.15**	0.73***	-0.12	-0.17	-0.33	-0.45
<i>Tin</i>	0.08*	0.09	-0.09	1.78***	0.04	1.78***	-0.04	-0.10	0.63**	-0.28	-0.05	-0.12	0.14	0.01	-0.40	-0.08
<i>Zinc</i>	-0.03	-0.04	-0.04	0.75**	0.03	2.61***	0.09*	0.25*	-0.26	-0.60	0.00	0.47**	-0.09	0.45	0.40	0.33

Table C.9: In-Sample Volatility Predictability and Business Cycle Stages (1 Month) (continued)

Commodity	<i>umrate</i>					
	Exp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	-0.01	-0.15	-0.08	-0.13	-0.51	-0.78
<i>Cocoa</i>	0.92***	0.48	-0.26	-0.55	-1.13	-1.54
<i>Coffee Arabica</i>	0.20	-0.07	3.38***	-0.69	-1.31	-1.91
<i>Corn Oil</i>	0.79***	1.48***	-0.23	-0.34	-0.50	-0.99
<i>Cotton</i>	0.30**	0.33	2.26***	0.32	0.59	-0.49
<i>Live Cattle</i>	1.19***	1.34**	2.12***	-0.33	-0.76	-1.12
<i>Lean Hog</i>	-0.08	0.12	-0.16	0.08	-0.66	0.32
<i>Milk</i>	0.05	-0.10	-0.01	-0.28	-0.59	0.80
<i>Oranges</i>	0.07	-0.02	-0.02	-0.45	-0.74	0.14
<i>Soybean Oil</i>	0.24*	0.78**	-0.22	-0.13	-0.72	1.24
<i>Soybeans</i>	-0.08	-0.13	-0.11	-0.40	-0.61	-0.49
<i>Soybean Meal</i>	-0.10	-0.23	-0.13	-0.49	-1.34	0.41
<i>Sugar</i>	0.06	0.21*	0.05	-0.23	-0.44	-0.79
<i>Wheat</i>	0.15*	0.51**	0.12	0.00	-0.38	-0.78
<i>Wool</i>	0.08	0.17	-0.16	-0.10	-0.12	-0.02
<i>Yellow Corn</i>	-0.08	0.19	1.41***	0.20	-0.01	-1.35
<i>Coal</i>	-0.15	-0.26	0.00	-0.34	-0.54	-1.19
<i>Heating Oil</i>	0.31*	0.10	-0.13	0.25	-0.17	-0.40
<i>Natural Gas</i>	1.67***	1.74**	2.52***	0.33	-0.39	2.93
<i>Unleaded Regular Gas</i>	5.07***	9.61***	0.07	-0.38	5.80	-2.69
<i>WTI Oil</i>	-0.03	-0.07	0.28**	-0.14	-0.45	1.12
<i>Aluminium</i>	-0.04	-0.15	0.11	-0.23	-0.75	0.12
<i>Gold</i>	0.50***	0.95***	0.73***	0.15	-0.49	-0.38
<i>High Grade Copper</i>	-0.05	0.28	-0.05	0.39	-0.89	-0.60
<i>Nickel</i>	1.53**	6.22***	-0.44	-1.74	-3.80	-1.32
<i>Palladium</i>	-0.20	0.40	1.68**	0.39	-1.95	2.19
<i>Platinum</i>	0.04	-0.07	1.87***	-0.22	-0.75	-0.76
<i>Silver</i>	0.67***	1.52***	0.51**	0.30	-0.55	-0.70
<i>Tin</i>	-0.07	0.30	0.13	0.07	-0.51	-0.66
<i>Zinc</i>	-0.07	-0.14	-0.03	-0.32	-0.74	-0.59

Table C.10: Out-of-Sample Volatility Predictability and Business Cycle Stages (1 Month)

This table reports the out-of-sample R^2 's of a regression of monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable across business cycle stages. We predict the next month's volatility. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "trns" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider six business cycle stages. "Exp" denotes the expansion, "eExp" the early expansion, "lExp" the late expansion, "Rec" the recession, "eRec" the early recession, "lRec" the late recession. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de						Δindpro						ΔM1					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Baifer	1.08***	5.45***	-1.97	-3.31	-2.20	-6.72	-0.42	0.37*	0.30*	-0.16	0.27**	3.91***	0.28	-0.62	-2.90	0.21	-0.62	-2.90
Cocoa	0.27***	1.72***	-0.14	-4.65	-0.26	-1.48	-0.10	-0.52	1.77***	-1.57	-0.95	-1.19	-1.86	-0.95	-1.19	-1.86	-0.95	-1.19
Coffee Arabica	1.14**	-4.53	-0.97	-15.25	-1.05	-2.22	-0.37	-1.76	1.70***	0.30	-0.40	-3.67	-2.00	-0.40	-3.67	-2.00	-0.40	-3.67
Corn Oil	-0.23	1.03**	-2.78	-5.11	-0.91	-2.26	0.18**	0.73**	-0.41	-1.36	-1.97	2.87***	-1.84	-1.97	2.87***	-1.84	-1.97	2.87***
Cotton	-1.57	-2.38	-1.29	-5.11	-0.91	-2.26	0.18**	0.73**	-0.41	-1.36	-1.97	2.87***	-1.84	-1.97	2.87***	-1.84	-1.97	2.87***
Live Cattle	1.78***	2.52***	0.13*	-0.11	-2.86	-1.80	-1.12	-0.02	-0.33	-2.68	-0.90	0.95**	0.28	-0.90	0.95**	0.28	-0.90	0.95**
Lean Hog	0.51***	2.34***	-1.87	-2.59	-2.86	-1.80	-1.12	-0.02	-0.33	-2.68	-0.90	0.95**	0.28	-0.90	0.95**	0.28	-0.90	0.95**
Milk	-0.74	-1.67	-1.23	-2.67	1.75**	2.16*	-0.93	0.36**	-0.91	0.76*	-0.92	-0.66	0.78*	-0.92	-0.66	0.78*	-0.92	-0.66
Oranges	-2.01	-0.63	0.08*	-4.06	-1.43	-1.30	-1.43	0.21**	-1.30	-1.06	-0.74	-2.01	-0.57	-0.74	-2.01	-0.57	-0.74	-2.01
Soybean Oil	-1.01	0.33*	-2.03	-5.69	-1.35	-1.06	-0.49	0.81**	-1.35	-1.06	-0.74	-2.01	-0.57	-0.74	-2.01	-0.57	-0.74	-2.01
Soybeans	0.75***	3.39***	-1.83	-9.35	-1.75	-1.75	-0.45	0.25*	-0.34	-1.75	-0.56	-1.82	-1.16	-0.56	-1.82	-1.16	-0.56	-1.82
Soybean Meal	-0.43	0.34*	-1.57	-14.98	0.85*	-1.54	-0.48	-0.04	-0.25	-2.15	-0.80	-1.14	-2.68	-0.80	-1.14	-2.68	-0.80	-1.14
Sugar	-1.31	-0.30	-2.45	-3.34	-1.12	1.10**	-0.58	-0.48	-0.09	0.17	-1.19	-0.80	-2.80	-1.19	-0.80	-2.80	-1.19	-0.80
Wheat	-1.01	-0.16	-1.38	-4.48	-1.12	1.10**	-0.61	0.33*	-0.30	-0.62	-0.98	-1.32	-0.65	-0.98	-1.32	-0.65	-0.98	-1.32
Wool	-0.33	0.73**	-0.87	0.55***	1.80**	7.83***	-0.25	-1.37	-0.46	0.04	-0.91	-0.38	-1.21	-0.91	-0.38	-1.21	-0.91	-0.38
Yellow Corn	-0.52	1.51***	-1.34	-3.45	-1.49	0.63*	-0.88	-0.26	-0.23	-1.55	-1.14	-0.85	-0.70	-1.14	-0.85	-0.70	-1.14	-0.85
Coal	-0.11	0.13*	-0.41	-6.79	-1.12	15.65***	-0.30	0.72**	-0.20	15.65***	-1.12	1.23**	-3.07	-1.12	1.23**	-3.07	-1.12	1.23**
Heating Oil	-1.66	-1.26	-2.80	-6.79	-1.12	15.65***	-0.11	-0.12	-0.52	-1.03	0.62	-3.07	-3.07	-1.03	0.62	-3.07	-1.03	0.62
Natural Gas	-1.96	6.59**	-0.81	-6.79	-1.12	15.65***	0.08	3.90**	-0.26	-0.34	-1.55	0.98	0.98	-1.55	0.98	0.98	-1.55	0.98
Unleaded Regular Gas	0.76**	-0.39	-0.81	-6.79	-1.12	15.65***	-1.39	-1.15	-0.26	-0.34	-1.55	0.98	0.98	-1.55	0.98	0.98	-1.55	0.98
WTI Oil	-1.25	-0.43	-1.08	-5.04	-3.05	-0.34	-0.06	0.71**	-0.20	-0.85	-0.48	-0.88	-0.88	-0.48	-0.88	-0.48	-0.88	-0.48
Aluminium	-1.06	-3.04	1.01	-2.13	2.09**	-1.82	-0.19	0.19*	-0.02	-2.37	-1.01	-1.60	-1.43	-1.01	-1.60	-1.43	-1.01	-1.60
Gold	1.70***	0.13*	-2.78	-3.85	2.09**	-1.82	-1.05	-0.04	-0.24	0.01	-0.75	-2.20	0.50*	-0.75	-2.20	0.50*	-0.75	-2.20
High Grade Copper	-2.14	0.23**	-1.35	-5.17	-2.86	-1.92	-0.33	0.06	-0.82	-0.34	-0.37	-0.69	-0.85	-0.37	-0.69	-0.85	-0.37	-0.69
Nickel	-0.27	-0.27	1.01	-2.13	-2.86	-1.92	-0.98	-0.74	-0.74	-0.74	-2.04	-0.36	-1.65*	-2.04	-0.36	-1.65*	-2.04	-0.36
Palladium	-1.48	-3.93	1.01	-2.13	2.09**	-1.82	-0.67	0.89**	-0.27	-0.76	0.04*	-0.36	1.65*	0.04*	-0.36	1.65*	0.04*	-0.36
Platinum	-1.04	-0.65	-1.33	-1.04*	0.87*	-1.48	-0.58	0.13*	-0.71	-0.09	-0.81	-0.34	-1.52	-0.81	-0.34	-1.52	-0.81	-0.34
Silver	-2.68	0.58**	-1.37	-6.23	-2.88	-1.91	-0.74	-0.58	-0.68	-0.62	0.09*	-1.63	0.31	0.09*	-1.63	0.31	0.09*	-1.63
Tin	-0.94	-0.96	-0.28*	-2.88	-1.91	-1.31	-0.74	-0.58	-0.68	-0.79	-0.86	-0.66*	-3.40	-0.86	-0.66*	-3.40	-0.86	-0.66*
Zinc	-0.08*	-5.40	-2.05	-4.01	-1.02	-1.31	-0.74	-0.58	-0.68	-0.79	-0.86	-0.66*	-3.40	-0.86	-0.66*	-3.40	-0.86	-0.66*

Table C.10: Out-of-Sample Volatility Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	<i>dfr</i>				<i>dfy</i>				<i>dp</i>					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec		
<i>Butter</i>	-0.86	-1.01	-0.30	-0.80	-2.05	4.03***	2.00***	-2.36	0.55***	1.65***	3.51***	1.23***	-3.82	-0.06
<i>Cocoa</i>	-1.60	-5.90	-0.76	-1.05	1.94***	1.01***	1.15***	0.57*	-1.07	-3.27	-2.82	-1.11	-1.23	-1.12
<i>Coff fee Arabica</i>	-1.16	-1.26	-2.48		0.53***	-0.24	1.58**		-1.28	-3.29	-3.86			
<i>Corn Oil</i>	-1.75	-0.16	-1.24	-2.32	1.94***	3.62***	-0.72	-4.14	0.31**	-1.42	-0.30	-8.40	-4.18	-2.28
<i>Cotton</i>	-2.16	-0.36	-3.54	-2.50	-1.57	2.92***	2.94***	0.63*	1.14***	-2.68	-1.03	-0.26	-3.75	4.15***
<i>Live Cattle</i>	-1.67	-3.40	-1.54	-0.64	-4.68	3.27***	1.19**	-4.35	-1.62	-2.71	2.45***	1.68***	0.57*	-2.36
<i>Lean Hog</i>	-1.10	-1.20	-0.07	-1.87	-3.05	-1.53	-2.91	-1.57	0.01**	-0.89	2.40***	-2.26	-16.21	-3.33
<i>Milk</i>	-0.60	-0.70	-0.38	-3.01	-0.84	0.90**	0.37*	0.41	3.61***	-13.83	-3.61	-1.98		
<i>Oranges</i>	-0.16	-0.84	0.30*	-0.42	-0.39	1.34***	0.47**	-0.76	-1.26	-1.12	1.42***	0.43		
<i>Soybean Oil</i>	-1.89	-1.65	-2.47	-0.51	-0.24	0.09	-2.32	-0.97	-0.67	-1.48	-1.86	-2.55		
<i>Soybeans</i>	-1.09	-1.70	0.40*	-0.01	0.59***	-3.42	-0.74	-0.70	-1.91	1.28***	-0.99	-0.90		
<i>Soybean Meal</i>	-0.54	-1.32	-1.07	-15.85	-1.77	-2.49	-0.90	-1.32	-1.71	0.95**	-1.49	-3.85		
<i>Sugar</i>	0.53***	-0.56	-1.16	0.50	-0.05*	-0.21	0.44*	-0.79	-1.85	-0.71	-0.21	-1.24	-0.77	-1.41
<i>Wheat</i>	-0.38	-0.77	-1.28	-2.61	0.18**	4.55***	0.20*	-3.36	-1.23	-0.54	-2.23	-1.24	0.41*	-3.22
<i>Wood</i>	0.01*	-3.24	0.41*	6.54***	-0.92	-2.95	-0.52	-2.25	1.17***	2.03***	-4.75	-2.04	4.73***	-3.73
<i>Yellow Corn</i>	-0.54	-0.25	-1.74	1.34*	-2.77	1.38***	2.56***	1.59**	-0.14	-1.80	-1.99	0.44**	-1.35	0.17
<i>Coal</i>	-1.80	-10.13	-2.21	-5.27	-2.11	-2.71	-6.42	10.59***	-2.12	-0.58	1.94***	1.60		
<i>Heating Oil</i>	-0.73	0.70	-2.85		-1.46	-1.01	-3.06		-3.54	1.73*	-2.43			
<i>Natural Gas</i>	0.44*		0.02		2.34***		-3.08		3.47***		3.55*			
<i>Unleaded Regular Gas</i>	-0.25	-1.81	0.95		-2.35	3.27**	-0.53		0.21**	0.99*	1.49*			
<i>WTI Oil</i>	-1.01	-4.92	-2.59	-1.64	-0.96	0.98**	-2.19	-2.24	-0.60	-2.75	-0.80	0.78**	-2.76	0.05
<i>Aluminium</i>	-0.45	-1.10	-0.75	-1.08	-1.23	3.84***	-0.41	0.90*	-0.96	-3.96	-0.46	1.78**	0.76*	2.68**
<i>Gold</i>	-0.61	-1.49	-0.69	0.34	1.08***	2.07***	0.37*	-0.24	2.53***	-0.84	-0.66	0.26*	-1.86	-2.06
<i>High Grade Copper</i>	-0.82	-0.81	-0.90	-4.07	-0.49	3.01***	-2.40	2.49**	-2.34	-2.65	-1.49	-1.37		
<i>Nickel</i>	-5.78				-1.01				-1.90					
<i>Palladium</i>	-0.07	0.02	-1.62	-1.54	-0.23	3.30**	2.26**	0.76*	4.73***	3.26**	0.78	1.89**	0.46	0.83*
<i>Platinum</i>	-0.69	-0.11	-2.62	-1.01	-1.65	-3.49	1.28***	0.30	-0.49	-2.89	-2.17	-0.26	-5.29	-4.05
<i>Silver</i>	-1.32	-1.35	-0.59	-3.29	-0.95	3.46***	1.30***	2.17**	-2.06	-0.61	-2.29	0.25**	-6.23	-4.77
<i>Tin</i>	-1.72	-2.54	-1.72	-0.65	-2.05	-1.90	-1.90	1.93**	-0.87	-1.26	0.17*	-2.37		
<i>Zinc</i>	-0.81	-2.91	-1.17		-2.99	1.72***	0.49*		-0.79	0.58**				

Table C.10: Out-of-Sample Volatility Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	<i>dy</i>				<i>ep</i>				<i>erp</i>									
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	0.24**	1.50***	3.52***	1.04**	-3.51	-7.56	-0.58	-0.74	4.46***	-1.46	-0.55	-0.94	-1.47	-1.05	-1.04	-0.08	-0.73	-0.39
<i>Cocoa</i>	-1.17	-2.60	-2.83	-1.40	-1.13	-0.68	0.56***	-1.60	-3.57	-3.46	-2.07	-0.43	-0.86	-0.42	-1.36	-0.26	-0.74	-0.93
<i>Coff/Tea Arabica</i>	-0.94	-3.08	-4.11				0.78**	-2.30	-1.29				-0.04	-0.96	0.06			
<i>Corn Oil</i>	0.49***	-1.17	-0.48	-7.81			1.08***	0.65**	0.09*	-2.90	-1.88	-3.16	-1.39	-0.93	-1.64	-1.09		
<i>Cotton</i>	1.41***	-2.85	-1.21	0.08*	-4.83	-2.65	-0.64	-1.81	-0.35	-2.02	-1.88	-3.16	-1.25	-1.31	-1.08	-1.27	-0.38	-3.16
<i>Live Cattle</i>	-1.32	-3.04	2.53***	0.34**	-4.04	2.34**	1.26***	-0.70	2.80***	0.17**	-0.66	1.04**	-0.40	-0.38	-1.01	-0.29	-1.74	0.40
<i>Lean Hog</i>	-0.07*	-0.70	2.05***	-2.53	0.97**	-2.43	-1.36	0.04*	2.45***	-2.37	-0.38	-3.01	-1.20	-0.38	0.72**	-0.76	-1.07	-5.44
<i>Milk</i>	4.04***	-13.16	-4.82	-1.27	-16.29	-3.73	-1.04	-1.75	-0.54	-2.95	-10.68	-3.53	-1.72	-4.17	-2.77	-0.49	-0.94	-1.23
<i>Oranges</i>	-1.15	-1.07	1.74***	0.50			-0.35	-0.60	0.71**	-0.22**			0.26**	1.06**	-0.04	-0.73		
<i>Soybean Oil</i>	-1.34	-1.79	-2.09	-1.23			-1.39	-0.31	-1.07	-2.53			-0.66	0.24**	-1.04	1.66**		
<i>Soybeans</i>	-2.47	1.02**	-0.96	-1.06			-1.40	1.44***	-1.54	-2.43			-0.99	-0.30	-0.48	-0.76		
<i>Soybean Meal</i>	-1.69	0.68**	-1.48	-4.40			-2.06	0.99**	-1.32	-8.50			-1.21	-1.26	-1.31	-0.96		
<i>Sugar</i>	-1.38	-0.57	-0.02*	-1.36	-0.80	-1.51	-1.69	0.46**	-3.54	-1.15	0.13	-3.45	-0.61	-2.03	-0.71	-1.99	-0.67	-4.30
<i>Wheat</i>	-1.48	-0.24	-2.30	-1.34	0.09	-3.67	-1.11	-0.92	-2.89	-1.02	0.25	-0.07	-2.02	-2.00	-1.38	-0.02	-0.85	-0.52
<i>Wool</i>	1.56***	3.44***	-5.16	-2.55	4.73***	-5.08	-0.32	2.47***	-2.83	4.30***	-1.24	6.65**	0.15**	0.19*	-0.31	-0.79	-0.99	2.16**
<i>Yellow Corn</i>	-0.22	-1.95	-2.02	0.14*	-1.10	-0.18	-0.28	-0.39	-1.85	-1.11	-1.07	-0.47	-0.77	-2.53	-0.46	0.92***	-0.15	-0.42
<i>Coal</i>	-2.91	-0.95	1.68***	2.29			-2.01	-2.21	2.44***	7.46**			-0.63	0.69**	-1.06	0.70		
<i>Heating Oil</i>	-3.72	1.69*	-2.65				-4.46	3.96**	-1.03				-0.44	-0.78	-0.34			
<i>Natural Gas</i>	4.11***		3.53**				2.30***		-0.48				-0.27		-0.35			
<i>Unleaded Regular Gas</i>	0.41**	0.68	1.80*				-1.57	1.98*	-1.58				-0.39	-1.01	-0.19			
<i>WTI Oil</i>	-1.09	-2.88	-1.17	0.86***	-3.32	0.26	-2.43	-2.08	1.39***	1.62***	0.12	1.18*	-1.29	-2.30	-0.21	-1.13	-0.70	-2.16
<i>Aluminium</i>	-0.40	-4.14	-0.30	2.59**			0.10**	-2.46	-1.39	1.10**			-1.90	0.00	-2.83	1.01**		
<i>Gold</i>	2.51***	-0.96	-0.86	0.02	1.35**	2.05**	2.41***	0.65**	0.88**	-1.32	-0.54	-2.06	-1.29	-1.36	-1.06	-0.43	1.31**	-0.08
<i>High Grade Copper</i>	-2.21	-2.27	-1.55	-1.26	-1.15	-2.05	-1.41	-3.13	-0.87	-3.44	-2.30	-3.65	-0.71	-0.28	-2.23	-1.59	1.52**	-1.73
<i>Nickel</i>	-1.95						-4.24											
<i>Palladium</i>	4.67***	2.47**	1.48*				5.36***	2.01**	-1.08				-1.14	0.91	0.06			
<i>Platinum</i>	-0.92	-3.27	-2.02	4.30***			-0.71	-2.19	-1.97	-3.44	-1.43	-0.23	-0.25	-0.70	-0.07	-4.65		
<i>Silver</i>	-2.52	-0.70	-2.18	-0.38	0.62*	0.71*	-1.97	0.87***	-2.17	-1.73	-1.43	-0.23	-1.11	-0.77	-0.80	-0.96	-0.97	-1.37
<i>Tin</i>	-0.94	-0.44	-2.19	-0.39	-3.02	-3.38	-1.40	-2.24	-1.19	-0.22*	-0.48	-0.51	-1.98	-0.66	-1.80	-0.21	-0.69	-1.87
<i>Zinc</i>	-0.91	0.23*	-0.20	-1.35	-5.16	-5.06	0.80***	-0.36	-0.51	-0.88	-1.25	-4.89	-0.98	-1.05	-0.16	-1.39	-2.48	-3.06

Table C.10: Out-of-Sample Volatility Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	<i>infl</i>				<i>ltr</i>				<i>lty</i>					
	Exp	eExp	IExp	Rec	eRec	IRec	Exp	eExp	IExp	Rec	eRec	IRec		
Butter	-0.39	1.04***	-0.77	-1.80	-0.33	0.38	-1.22	-0.52	-0.77	1.70*	0.27**	0.93**	-1.34	-3.84
Cocoa	-0.30	0.94***	-1.22	-0.18	-3.96	-2.18	-1.35	-2.51	-0.88	-2.47	-3.38	-2.62	0.12*	-4.50
Coffee Arabica	-0.06	-1.14	-1.93				0.10	0.62	1.65**		0.47**	-2.72	-3.54	-1.30
Corn Oil	-2.50	1.07**	0.32*	1.55**			0.20**	-2.33	3.45***	-5.65	1.49***	1.32**	-2.16	-4.36
Cotton	0.07**	-0.70	1.19***	-0.84	-0.35	-1.84	-0.84	-0.01	-0.47	-2.83	-0.59	1.38***	0.40**	-4.11
Live Cattle	0.12**	-0.56	0.54**	-2.51	-5.96	-0.06	-1.47	-1.81	-1.73	-3.33	-5.44	-3.20	4.74***	-4.11
Lean Hog	0.73***	1.97***	1.01***	-0.99	-0.26	1.34**	-2.18	-1.86	-1.75	-2.63	-0.85	-1.87	-1.68	-4.97
Milk	-0.22	0.08*	-0.64	-3.22	-1.62	4.03**	-1.39	-0.39	-0.40	-2.76	0.83***	2.54***	4.45***	-12.96
Oranges	-0.87	-1.14	-0.75	-1.07			0.22**	-1.73	0.27*	-3.14	-1.13	-0.87	-2.41	-2.41
Soybean Oil	-1.08	-0.43	-0.04	2.59***			-0.56	-1.47	-3.84	-2.27	1.17***	-4.48	-5.47	-4.87
Soybeans	-0.59	1.12**	0.06	-0.18			-1.27	-1.78	-1.76	-2.56	-0.60	-5.59	-2.60	-4.44
Soybean Meal	1.13***	1.50**	0.32*	-2.91			-0.75	-0.46	-2.08	-1.51	-1.39	-4.16	-2.54	-13.63
Sugar	-1.45	-0.80	-2.51	1.21***	2.12**	1.51**	-0.85	-1.41	-0.66	-0.09	-2.03	-0.52	-0.36	-0.77
Wheat	-0.61	-0.69	-2.23	-0.60	-1.47	0.19	-0.73	-1.59	0.66**	-2.38	-0.27	-2.77	-0.94	-4.19
Wool	-0.44	-0.06	-1.75	-1.16	0.51	-1.50	-0.87	-2.98	-0.87	1.07*	1.06***	-0.79	-1.79	-1.31
Yellow Corn	0.18**	1.82***	-0.39	-2.04	0.32	-1.28	-0.71	-1.51	-1.62	-2.33	-2.46	-1.01	-0.07	-4.92
Cool	-0.30	-1.31	0.27*	0.01			-1.39	-1.56	-2.79	0.96	0.40**	-2.32	-3.16	0.41
Heating Oil	-3.08	0.65	-2.60				-0.54	-2.60	-2.03		-4.50	2.08**	-4.99	
Natural Gas	-1.02	-0.37	4.61**				1.52**		1.28		2.76***		8.33***	
Unleaded Regular Gas	-2.12	-0.37	-2.36				-0.62	-0.89	-0.74		-1.43	8.21***	3.59**	
WTI Oil	-0.52	1.06***	0.69**	-2.70	-1.48	0.97*	0.62***	-1.56	-0.49	-2.77	-3.44	-1.47	-2.20	-6.26
Aluminium	-0.42	-1.21	-1.14	-1.94			-0.54	-1.08	-0.82	-0.41	-0.65	-1.96	-0.47	-1.95
Gold	0.89***	0.03	1.36***	-1.04	-0.24	-0.35	-0.70	-1.90	-1.38	-2.96	6.84***	-2.27	-0.72	1.31*
High Grade Copper	-1.87	-1.27	-1.43	-1.65	-1.11	-1.36	-0.65	-1.91	-1.78	-1.61	-1.11	-1.00	-1.21	-2.72
Nickel	-1.60						-0.80				-0.19			
Palladium	1.50***	1.30	-6.02				-1.06	-1.16	-0.66		-0.50	2.96**	-0.49	
Platinum	0.04*	1.97***	0.46**	1.25**			-1.34	-1.32	-1.48	-1.17	-2.25	-4.20	1.95***	-1.33
Silver	-0.87	0.04	0.39**	-2.73	0.25	0.61*	-1.46	-3.31	-1.54	-4.54	-0.07*	5.50***	0.63**	-1.12
Tin	-2.59	-1.14	-0.72	-2.18	0.10	-1.78	-0.88	-3.00	-1.75	-1.29	-1.76	-0.10*	-1.35	-4.71
Zinc	-2.30	-1.36	-1.55	-1.83	-0.30	-1.11	-0.50	-6.38	1.69***	-1.39	-2.56	2.22***	1.18**	-8.53

Table C.10: Out-of-Sample Volatility Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	svol				tbl				tms			
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Butter	-1.71	-4.47	-21.18	-3.31	0.54	-1.54	-3.88	0.88**	0.23*	-1.87	-1.65	-3.28
Cocoa	-21.23	-0.76	-31.32	-1.03	-0.99	3.32**	-4.21	-3.38	0.88**	-5.96	-1.62	-4.49
Coffee Arabica	-49.04	-0.84	-0.12	-1.84			0.84**	-1.27	-0.55	-0.30	-1.18	
Corn Oil	-3.48	-0.38	-148.58	-5.38	-1.16	-4.91	-2.04	1.36***	-1.77	-2.38	-0.93	-4.06
Cotton	-6.62	1.18***	-56.03	-25.40	-0.10	4.24***	-1.53	-0.90	-0.86	-4.69	-2.82	-6.32
Live Cattle	-10.81	0.82***	-7.37	-0.08	-0.21	-3.02	-2.41	-3.34	2.07***	-7.45	-1.45	-6.25
Lean Hog	-2.58	-4.21	-1.51	-50.94	-2.26	-1.57	0.13**	1.34***	1.69***	-2.38	-1.61	-4.59
Milk	-1.76	-1.81	-10.42	-0.73			-3.35	-1.72	-0.32	-1.27	0.10	-1.75
Oranges	-7.76	-2.67	-17.77	-7.42			-1.22	-4.82	-5.66	-2.68	-3.69	-1.82
Soybean Oil	-3.08	1.96***	-48.04	-5.15			-2.33	-2.60	-1.79	-3.06	-1.23	-1.24
Soybeans	-38.57	1.14**	-18.56	-24.34			-0.77	-4.34	-1.25	-0.94	-1.87	-1.29
Soybean Meal	-10.52	-5.80	-16.90	-2.70	-0.20	5.64***	-2.06	0.40*	-0.44	3.84***	-3.52	0.50
Sugar	-25.01	0.26**	-1.89	-4.86	-1.30	-3.00	-3.20	1.59***	-3.74	-1.02	-1.94	-2.77
Wheat	-2.20	-1.08	-90.60	-4.32	-3.08	4.03***	-2.49	-0.98	-0.24	-5.00	-0.40	-0.77
Yellow Corn	-2.52	-0.46	-30.14	-2.54			0.68***	-0.70	1.24**	0.19	0.80**	-3.16
Coal	-0.61	-20.30	0.23				-3.60	-0.73	-3.39		-2.85	
Heating Oil	-0.38		0.04				-1.59		2.26*		2.29*	
Natural Gas	-0.22	-7.58	0.06				-3.19	4.01**	1.95*		-3.66	-0.34
Unleaded Regular Gas	-0.55	-4.70	-11.39	-1.10	-0.47	-0.58	-3.18	-2.13	-2.12	-3.92	-1.76	-3.10
WTI Oil	-25.53	-2.41	-92.87	-16.90			-0.21	-2.04	-1.70	-1.50	0.09*	-0.01
Aluminum	-62.72	-5.39	-82.08	-2.40	-0.20	-1.50	3.70***	-1.23	1.04**	2.46**	-5.66	-1.19
Gold	-4.92	-4.58	0.24**	3.22***	-0.46	6.13***	-2.91	-0.04	-2.93	-2.79	-0.60	-2.65
High Grade Copper	-1.03						-0.93					
Nickel	-136.41	-10.41	0.20				-1.04	3.10**	-2.21	-1.02	-1.48	1.08*
Palladium	-82.85	-5.31	-39.93	-1.73	-0.12	-1.58	-2.16	-3.22	-0.89	-1.05	-0.19	-2.14
Platinum	-3.29	-2.59	-1.03	-0.23	-1.15	5.50***	1.36***	1.38***	0.19*	1.05*	0.21*	-2.90
Silver	-57.05	-3.93	-43.62	1.80***	-2.25	1.05	-2.87	0.07*	-1.85	-4.15	-1.45	-0.23
Tin							-3.15	4.27***	-0.76	-3.48	0.55**	-1.09
Zinc												1.81**

Table C.10: Out-of-Sample Volatility Predictability and Business Cycle Stages (1 Month)
(continued)

Commodity	<i>unrate</i>			
	Exp	eExp	lExp	lRec
<i>Butter</i>	0.80***	4.49***	1.34**	
<i>Cocoa</i>	-0.18	-0.03	0.42*	
<i>Coffee Arabica</i>	0.65**	-1.93	-2.54	
<i>Corn Oil</i>	0.91***	4.00***	-1.24	
<i>Cotton</i>	-0.27	1.67**	1.66**	
<i>Live Cattle</i>	-0.19	-0.17	8.35***	
<i>Lean Hog</i>	0.47**	1.00**	1.10**	
<i>Milk</i>	-1.33	0.27	3.47***	
<i>Oranges</i>	-2.13	-0.18	1.56**	
<i>Soybean Oil</i>	0.30**	0.98**	-2.60	
<i>Soybeans</i>	-1.55	-1.58	-0.70	
<i>Soybean Meal</i>	-2.73	-1.63	-2.13	
<i>Sugar</i>	-0.45	-0.07	-5.24	
<i>Wheat</i>	-0.50	-0.62	0.36*	
<i>Wool</i>	-1.21	-1.02	0.72*	
<i>Yellow Corn</i>	-0.36	0.36	2.24***	
<i>Coal</i>	-2.02	-1.36	-5.28	
<i>Heating Oil</i>	0.17*	1.18	-1.81	
<i>Natural Gas</i>	0.40*		4.81**	
<i>Unleaded Regular Gas</i>	1.96***	11.80***	-0.37	
<i>WTI Oil</i>	1.89***	-0.34	-1.83	
<i>Aluminium</i>	-0.82	-0.84	-0.88	
<i>Gold</i>	1.03***	3.80***	0.90**	
<i>High Grade Copper</i>	-2.06	2.71***	-2.09	
<i>Nickel</i>	-2.33			
<i>Palladium</i>	1.06**	-6.27	2.00**	
<i>Platinum</i>	-0.43	-3.74	4.32***	
<i>Silver</i>	-2.14	4.36***	0.34*	
<i>Tin</i>	-1.17	1.69**	0.27*	
<i>Zinc</i>	0.10*	2.46***	2.53***	

Table C.11: In-Sample Volatility Predictability and Business Cycle Stages (12 Months)

This table reports the in-sample ΔR^2 's of a regression of monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable across business cycle stages. We predict the next year's volatility. "de" denotes the dividend–payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfjr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "inft" the inflation rate, "itr" the long-term U.S. government bond returns, "ity" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "4ms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider six business cycle stages. "Exp" denotes the expansion, "eExp" the early expansion, "lExp" the late expansion, "Rec" the recession, "eRec" the early recession, "lRec" the late recession. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de						Δindpro						ΔM1					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Butter	0.00	0.02*	0.00	0.01	0.04	-0.05	0.00	-0.01	-0.01	-0.07	-0.19	-0.21	0.00	0.02*	-0.01	0.02	-0.45	-0.37
Cocoa	0.00	0.00	0.00	-0.01	-0.05	-0.04	0.00	0.00	0.01	-0.04	0.97***	-0.30	0.00	0.02	-0.03	-0.11	-0.43	-0.82
Coffee Arabica	0.02*	0.03	-0.02	-0.13	-0.14	-0.78	0.00	-0.02	-0.02	-0.07	3.73***	-0.66	0.01*	0.04*	0.00	-0.13	1.98**	-0.67
Corn Oil	0.00	-0.02	-0.03	-0.05	-0.19	-0.15	-0.01	-0.01	0.04	0.06	0.52*	0.48	0.00	0.03	0.04	-0.04	0.00	-0.32
Cotton	0.00	0.01	0.01	-0.01	-0.05	-0.04	0.00	-0.01	-0.02	-0.02	0.91***	-0.07	0.01*	-0.02	-0.04	-0.07	-0.24	-0.19
Live Cattle	0.00	-0.02	0.00	-0.01	-0.02	-0.01	0.01*	0.01	0.00	0.15**	1.07***	0.67*	0.02**	-0.03	0.12**	-0.11	-0.25	-0.61
Lean Hog	0.00	0.01	0.00	-0.02	-0.06	-0.08	0.00	0.01	-0.02	-0.02	0.23	-0.11	-0.01	-0.01	-0.02	-0.14	0.82*	-0.73
Milk	0.00	0.00	0.00	-0.01	-0.02	-0.03	0.00	0.00	0.04**	0.02	0.01	0.00	0.00	0.00	-0.01	0.26**	-0.16	0.55
Oranges	0.00	0.00	0.00	-0.01	-0.04	-0.15	0.00	-0.01	-0.01	0.05	0.18	0.02	0.00	-0.01	-0.01	-0.07	-0.28	-0.21
Soybean Oil	0.00	-0.01	-0.02	-0.03	-0.12	-0.18	0.00	-0.02	0.03	-0.02	0.33*	-0.18	0.00	-0.01	-0.01	-0.07	-0.04	-0.35
Soybeans	0.00	0.00	-0.02	-0.06	-0.20	-0.35	0.00	-0.01	0.00	-0.06	0.47*	0.34	0.00	-0.02	0.00	-0.11	0.28	-0.41
Soybean Meal	-0.01	-0.01	0.00	-0.10	-0.35	-0.27	0.00	0.00	-0.01	-0.11	0.59	-0.57	0.00	-0.01	-0.01	-0.08	0.01	-0.21
Sugar	0.00	0.00	0.01	0.03*	0.10	0.06	0.00	0.00	0.08**	-0.03	0.52***	-0.16	0.00	0.01	-0.02	-0.07	1.07***	-0.32
Wheat	0.00	0.00	-0.02	-0.01	-0.05	-0.07	0.00	-0.01	-0.01	-0.04	0.90***	-0.15	0.01***	0.02	-0.01	-0.08	0.29	-0.46
Wool	0.01*	-0.02	0.03*	-0.02	-0.09	0.13	0.00	-0.02	0.00	-0.02	1.06***	-0.16	0.00	0.06*	0.00	-0.08	-0.14	-0.14
Yellow Corn	0.00	0.02	-0.02	-0.01	0.00	-0.22*	0.00	-0.01	-0.02	-0.03	1.82***	-0.01	0.00	-0.02	-0.02	-0.10	0.15	-0.52
Coal	0.00	-0.01	0.05	-0.01	-0.14	-0.25	0.00	-0.03	-0.02	-0.06	-0.15	-0.28	-0.01	-0.02	-0.02	-0.06	0.11	-0.20
Heating Oil	0.01	0.10*	-0.03	0.34	-0.26	-0.24	-0.01	-0.01	-0.05	-0.23	-0.37	-0.21	0.00	0.03	-0.01	-0.10	-0.55	-0.28
Natural Gas	0.04***	0.06	-0.02	-0.16	0.39	1.82	0.00	-0.03	-0.02	-0.19	-0.28	-1.43	0.07***	0.35***	0.06*	-0.19	-0.24	-1.86
Unleaded Regular Gas	-0.01	-0.01	0.03	0.20	-0.43	4.57	-0.01	-0.04	-0.06	-0.17	-0.44	-0.53	-0.01	-0.02	-0.02	-0.16	-0.26	-2.40
WTTOil	0.00	0.01	0.03*	-0.01	-0.01	-0.02	0.00	-0.01	-0.01	-0.05	0.14	-0.16	0.00	0.00	-0.01	0.12	-0.11	0.33
Aluminium	0.00	0.00	0.00	-0.01	0.01	-0.06	0.00	0.00	0.00	-0.02	0.04	-0.19	0.00**	0.06***	0.00	0.07	-0.05	0.15
Gold	0.00*	0.01*	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.05	-0.05	0.13	0.00	-0.02	-0.01	-0.08	1.05***	-0.31
High Grade Copper	0.00	0.01	0.00	0.00	0.05	-0.04	0.00	-0.01	-0.01	-0.01	0.71**	0.07	0.00	-0.04	0.00	-0.07	1.75***	-0.23
Nickel	0.02	0.13*	0.37**	0.57	-1.31	-3.02	-0.02	-0.01	-0.06	-0.48	-0.10	-0.54	-0.02	-0.01	-0.02	-0.44	-1.26	-3.28
Palladium	0.04*	0.03	-0.01	-0.20	-0.31	-1.08	0.02	-0.21**	-0.05	-0.22	-0.39	-1.10	0.04*	0.10*	0.00	-0.21	-0.51	-1.10
Platinum	0.00	-0.02	-0.02	-0.02	-0.08	-0.03	0.02**	0.06*	-0.01	0.00	0.51**	-0.17	0.00	-0.03	-0.01	0.01	0.06	-0.36
Silver	0.00	0.00	0.02	0.05*	0.19**	0.09	0.00	-0.02	0.03*	0.01	0.00	0.01	0.00	-0.01	0.01	-0.12	2.06***	-0.43
Tin	0.02**	0.01	0.04	-0.01	-0.07	-0.07	0.01	-0.01	-0.02	0.00	1.50***	-0.12	-0.01	-0.01	0.00	-0.04	-0.12	-0.48
Zinc	0.00	0.00	-0.01	-0.03	-0.08	-0.07	0.00	0.04**	-0.01	0.00	0.72*	0.41	0.00	0.01	-0.01	-0.05	-0.08	-0.11

Table C.11: In-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	df _r			df _y			df _p			IRec	IRExp							
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp			Rec	eRec					
<i>Butter</i>	0.00	-0.01	0.00	-0.06	-0.17	-0.28	0.00	0.02*	0.00	-0.06	-0.20	0.00	0.04*	0.00	-0.04	-0.13	0.00	
<i>Cocoa</i>	0.00	-0.02	-0.02	-0.02	-0.26	-0.15	0.01	0.00	0.06	0.03	0.29	0.01**	0.04*	0.03	0.01	0.09	0.01	-0.78
<i>Coffee Arabica</i>	0.00	0.00	-0.02	-0.09	-0.24	-0.78	-0.01	-0.01	0.09**	-0.04	-0.71	0.00	0.00	-0.01	-0.07	-0.47	0.01	-0.08
<i>Corn Oil</i>	0.00	-0.02	-0.01	-0.04	-0.02	-0.23	0.00	0.00	0.01	-0.06	-0.32	0.01	-0.01	-0.01	0.07	0.40	-0.04	-0.08
<i>Cotton</i>	0.00	0.00	0.04	0.07	0.27	-0.07	0.00	-0.02	0.09**	-0.01	-0.11	-0.07	0.00	-0.01	0.01	0.05	0.05	-0.04
<i>Live Cattle</i>	0.00	-0.01	-0.02	0.09	-0.11	0.40	0.00	-0.01	0.01	-0.04	-0.19	0.00	-0.01	-0.01	-0.01	-0.05	-0.04	-0.05
<i>Lean Hog</i>	0.01	-0.01	0.08*	-0.07	0.37*	-0.04	-0.01	-0.01	0.00	-0.07	0.52*	0.01	0.01	0.07**	0.08*	0.70***	-0.05	-0.05
<i>Milk</i>	0.00	0.02*	0.01*	-0.04	-0.11	-0.22	0.00	-0.01	-0.01	0.00	-0.03	-0.03	0.00	0.00	0.01	0.00	0.04	0.04
<i>Oranges</i>	0.00	0.00	0.02*	0.10*	-0.15	0.22	0.00	-0.01	0.00	-0.03	-0.13	0.02*	0.04	0.01	-0.03	-0.10	-0.06	-0.06
<i>Soybean Oil</i>	0.00	-0.03	0.05*	-0.03	0.12	-0.09	0.03***	0.05	0.04	0.08	0.49*	0.03	0.05	0.06*	0.19**	0.72***	0.29	0.29
<i>Soybeans</i>	0.00	-0.01	-0.02	-0.03	0.40	0.01	0.00	-0.02	-0.02	-0.03	-0.30	0.00	0.00	0.03	0.05	0.97**	-0.29	-0.29
<i>Soybean Meal</i>	0.02*	0.00	-0.01	-0.08	0.26	-0.32	-0.01	-0.01	-0.02	0.15	1.04*	0.79	0.00	0.00	0.02	0.25*	0.48	-0.37
<i>Sugar</i>	0.00	0.01	-0.01	0.01	-0.07	0.01	0.00	0.00	0.01	0.02	0.71***	0.00	0.00	0.00	0.01	0.03	0.02	0.02
<i>Wheat</i>	0.00	-0.01	0.00	-0.04	0.37*	0.00	0.01**	-0.02	-0.01	-0.04	-0.07	-0.18	-0.02	-0.02	0.04	0.04*	0.13	-0.07
<i>Wool</i>	0.00	-0.01	-0.01	-0.04	0.07	-0.20	0.00	-0.02	-0.01	-0.04	-0.14	0.30	0.01*	-0.01	0.03	0.36*	-0.05	-0.05
<i>Yellow Corn</i>	0.00	-0.02	-0.02	-0.05	0.03	0.05	-0.01	-0.02	0.01	-0.05	-0.16	-0.16	0.01	-0.01	0.03	0.12	0.01	0.01
<i>Coal</i>	0.03**	0.02	-0.01	-0.02	-0.08	0.07	0.01**	0.09*	0.04*	0.15*	0.78	0.01	0.19**	0.02	0.67***	1.60***	0.54	0.54
<i>Heating Oil</i>	0.00	-0.02	0.21**	-0.22	0.25	-0.41	0.01	0.00	-0.01	0.80*	0.64	-0.01	-0.02	-0.04	0.06	-0.49	-0.51	-0.51
<i>Natural Gas</i>	0.01	-0.02	-0.02	-0.19	-0.48	-1.33	0.02**	0.05	-0.02	-0.09	3.09	0.02	-0.02	0.04	0.17	-0.41	5.30*	5.30*
<i>Unleaded Regular Gas</i>	-0.01	0.12*	-0.03	0.49*	-0.24	0.57	0.06**	0.04	-0.06	0.08	-2.77	-0.01	-0.01	-0.06	0.13	0.04	2.78	2.78
<i>WTI Oil</i>	0.00	0.00	0.07**	-0.05	0.45*	-0.22	0.00	0.00	0.00	-0.03	-0.14	-0.12	0.01*	0.00	0.05*	-0.02	-0.02	-0.02
<i>Aluminium</i>	0.00	0.01*	0.02***	-0.01	0.01	-0.22	0.00	-0.01	0.01	-0.03	-0.07	-0.18	0.00	0.00	0.01	0.06	0.01	-0.06
<i>Gold</i>	0.01**	-0.01	0.01	-0.04	-0.05	-0.15	0.00*	0.01	0.02*	-0.02	0.28**	-0.08	0.00	0.00	0.06**	0.18**	0.04	0.04
<i>High Grade Copper</i>	0.00	-0.02	0.00	-0.04	0.07	-0.17	0.02**	0.08**	0.00	-0.01	0.82**	-0.10	0.01	0.00	0.11***	0.81***	0.09	0.09
<i>Nickel</i>	-0.02	-0.01	-0.06	0.50	-0.85	-0.28	-0.02	-0.02	0.23*	-0.44	0.75	2.82	0.00	0.04	0.00	-0.34	-1.39	1.11
<i>Palladium</i>	0.02	0.01	0.04	0.13	-0.69	-0.63	-0.01	-0.03	0.28**	-0.19	-0.68	-1.05	0.02	-0.04	0.06	-0.13	0.07	-1.09
<i>Platinum</i>	0.00	-0.02	-0.02	-0.02	0.00	-0.29	0.00	-0.01	0.03	-0.02	0.21*	-0.13	0.00	-0.01	0.11*	0.36*	-0.21	-0.21
<i>Silver</i>	0.02**	0.01	0.06**	-0.06	-0.14	-0.25	0.00	-0.01	0.04*	-0.02	0.64**	-0.20	0.00	0.00	0.16***	0.49***	0.16	0.16
<i>Tin</i>	0.00	-0.02	-0.02	-0.03	0.01	-0.10	0.01*	0.04*	-0.02	-0.02	-0.09	-0.14	0.02*	0.01	0.05*	0.31**	-0.07	-0.07
<i>Zinc</i>	0.00*	0.01	-0.01	-0.08	-0.24	-0.11	0.00	-0.01	-0.01	-0.07	-0.26	-0.26	0.00	-0.01	0.09*	0.64***	-0.06	-0.06

Table C.11: In-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	<i>dy</i>			<i>ep</i>			<i>erp</i>						
	Exp	eExp	IEExp	Rec	eRec	IRec	Exp	eExp	IEExp	Rec	eRec	IRec	
<i>Butter</i>	0.00	0.04*	0.00	-0.04	-0.14	0.06	0.00	0.00	0.01	0.01	0.06	0.22	0.00*
<i>Cocoa</i>	0.01**	0.04*	0.03	0.01	0.08	0.02	0.01**	0.02	0.02	0.01	0.08	-0.03	0.00
<i>Coffee Arabica</i>	0.00	0.00	-0.02	-0.07	-0.30	-0.79	0.00	0.03	0.00	-0.08	-0.79	-0.79	-0.01
<i>Corn Oil</i>	0.01	-0.01	-0.01	0.10	0.39	0.05	0.01	-0.01	0.00	0.17*	0.30	0.62	0.00
<i>Cotton</i>	0.00	-0.01	-0.02	0.02	0.07	-0.03	0.00	-0.01	-0.02	0.00	0.03	-0.04	0.00
<i>Live Cattle</i>	0.00	-0.01	-0.01	-0.01	-0.05	-0.05	0.00	-0.01	-0.02	0.00	-0.02	-0.04	0.00
<i>Lean Hog</i>	0.01*	0.01	0.08**	0.12**	0.75***	0.01	0.03**	0.04**	0.05*	0.15**	0.66***	0.00	0.00
<i>Milk</i>	0.00	0.00	0.00	0.01	0.00	0.05	0.00	-0.01	0.00	0.02	0.07	0.00	0.00
<i>Oranges</i>	0.01*	0.03	0.01	-0.04	-0.13	-0.15	0.01*	0.00	0.02	-0.04	-0.12	-0.08	0.02**
<i>Soybean Oil</i>	0.03***	0.05	0.06	0.20**	0.69**	0.35	0.03***	0.01	0.11**	0.19**	0.71**	0.32	0.00
<i>Soybeans</i>	0.02**	0.02	0.05	0.17*	0.92**	-0.29	0.04***	0.07**	0.10**	0.27**	1.07**	-0.29	0.00
<i>Soybean Meal</i>	0.00	0.00	0.03	0.21	0.40	-0.40	0.01	0.00	0.09**	0.30*	0.61	-0.56	0.00
<i>Sugar</i>	0.00	0.00	0.00	0.01	0.04	0.02	0.00	-0.01	-0.01	-0.01	-0.04	-0.06	0.00
<i>Wheat</i>	0.02**	-0.02	0.04	0.04*	0.12	-0.07	0.01*	0.00	0.05*	0.03	0.11	-0.07	0.00
<i>Wool</i>	0.01*	-0.01	0.02	0.05	0.39*	-0.06	0.00	-0.01	0.00	0.08*	0.44**	-0.06	0.00
<i>Yellow Corn</i>	0.01	-0.01	0.03	0.02	0.10	-0.02	0.01*	0.02	0.04*	0.06*	0.43**	-0.03	0.00
<i>Coal</i>	0.02	0.21**	0.03	0.62***	1.53***	0.51	0.01	0.08*	-0.01	0.68***	1.42***	0.52	0.01
<i>Heating Oil</i>	-0.01	-0.02	-0.05	-0.03	-0.45	-0.51	-0.01	0.01	-0.03	0.33	-0.34	-0.48	-0.01
<i>Natural Gas</i>	0.02	-0.02	0.03	0.22	-0.56	6.70**	0.00	0.00	0.02	0.11	0.35	5.39*	0.00
<i>Unleaded Regular Gas</i>	-0.01	0.00	-0.05	0.09	0.10	2.53	-0.01	-0.04	-0.07	0.37	0.22	5.43	-0.01
<i>WTI Oil</i>	0.01*	0.00	0.05*	0.00	-0.02	-0.02	0.00	-0.01	0.01	0.00	-0.02	-0.02	0.00
<i>Aluminium</i>	0.00	0.00	0.01	0.05	0.03	-0.08	0.01**	0.00	0.01*	0.00	-0.07	-0.16	0.00
<i>Gold</i>	0.00	0.00	0.00	0.05**	0.24***	0.04	0.00	-0.01	0.00	0.03*	0.08*	-0.03	0.00
<i>High Grade Copper</i>	0.00	0.02	-0.01	0.11**	0.85***	0.08	0.00	-0.02	-0.01	0.06*	0.48***	0.07	0.00
<i>Nickel</i>	0.00	0.04	0.00	-0.39	-1.41	1.82	0.07*	0.10***	-0.05	-0.04	-1.31	-1.11	-0.02
<i>Palladium</i>	0.01	-0.04	0.03	-0.14	-0.08	-1.10	-0.01	-0.05	0.03	-0.18	0.17	-1.10	0.01
<i>Platinum</i>	0.00	-0.02	-0.01	0.10*	0.28*	-0.19	0.00	-0.01	0.00	0.09*	0.35*	-0.23	0.01*
<i>Silver</i>	0.00	0.00	0.01	0.15***	0.57***	0.11	0.00	-0.01	-0.01	0.03*	0.15*	-0.07	0.00
<i>Tin</i>	0.01*	0.00	0.03	0.05*	0.28**	-0.07	0.00	-0.02	0.00	0.02	0.29**	-0.04	0.00
<i>Zinc</i>	0.00	-0.01	0.01	0.07*	0.61***	-0.06	0.01	0.01	0.01	0.12**	0.73***	-0.05	0.00

Table C.11: In-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	in fl			ltr			lty					
	Exp	eExp	IExp	Exp	eExp	IExp	Exp	eExp	IExp			
<i>Butter</i>	0.00	0.02*	0.00	0.00	-0.01	-0.01	0.00	-0.01	0.01	-0.08	-0.20	-0.16
<i>Cocoa</i>	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	-0.28	0.95*	-0.05	-0.17	-0.21
<i>Coffee Arabica</i>	0.00	-0.02	0.03	0.00	-0.02	-0.02	0.00	3.26**	1.94*	0.17	-0.29	0.15
<i>Corn Oil</i>	0.02**	0.05*	-0.03	0.00	-0.01	-0.03	0.00	0.35*	0.11	-0.02	-0.04	0.05
<i>Cotton</i>	0.00	-0.01	-0.02	0.00	-0.01	0.02	0.00	0.30**	0.03	0.02	0.06	-0.05
<i>Live Cattle</i>	0.00	0.03*	0.00	0.00	-0.02	-0.02	0.00	0.60*	0.00	-0.01	-0.04	-0.20
<i>Lean Hog</i>	0.01	0.00	-0.01	0.00	-0.01	-0.02	0.05	0.51*	0.25	-0.01	-0.05	-0.19
<i>Milk</i>	0.00	-0.01	0.01	0.00	0.02*	-0.01	-0.03	-0.09	-0.04	0.00	0.03	-0.02
<i>Oranges</i>	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.13*	-0.11	0.49*	0.00	0.05	0.39
<i>Soybean Oil</i>	0.00	0.07*	-0.01	0.00	-0.03	-0.02	0.13*	0.01	3.15***	0.00	-0.04	-0.15
<i>Soybeans</i>	0.00	-0.02	-0.01	0.00	0.03	-0.02	0.08	0.03	4.82***	0.00	-0.07	-0.21
<i>Soybean Meal</i>	0.00	0.00	0.00	0.00	0.03*	-0.02	-0.01	0.09	2.42**	0.00	-0.08	-0.33
<i>Sugar</i>	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.02	0.79***	1.46***	0.00	0.00	-0.07
<i>Wheat</i>	0.00*	-0.02	0.00	0.00	0.00	0.00	0.07	-0.03	1.85***	0.00	-0.04	-0.10
<i>Wool</i>	0.00	-0.01	0.01	0.00	-0.02	-0.01	-0.03	-0.05	-0.11	0.00	-0.03	-0.01
<i>Yellow Corn</i>	0.00	0.02	0.00	0.00	-0.02	-0.02	-0.03	-0.20	1.06**	-0.01	-0.05	-0.19
<i>Coal</i>	0.00	-0.03	-0.01	0.00	-0.02	-0.01	-0.06	0.08	2.48***	0.00	0.00	-0.01
<i>Heating Oil</i>	0.02*	-0.02	-0.03	0.00	-0.01	-0.05	-0.16	-0.54	0.01	0.09	-0.09	-0.56
<i>Natural Gas</i>	0.00	-0.02	0.00	0.00	-0.01	-0.02	-0.20	-0.56	-1.08	0.00	0.55	1.80
<i>Unleaded Regular Gas</i>	0.03**	-0.04	-0.07	0.00	-0.01	-0.07	-0.10	-0.40	-2.28	-0.01	-0.04	0.38
<i>WTI Oil</i>	0.00	0.00	-0.01	0.00	0.00	0.00	-0.03	0.07	-0.16	0.01	0.03	0.13***
<i>Aluminium</i>	0.00	0.01	0.00	0.00	0.02**	0.01**	-0.03	-0.01	-0.08	0.00	0.00	0.22
<i>Gold</i>	0.00	0.00	0.00	0.00	-0.01	0.01*	0.00	1.03***	0.18	0.00	0.00	0.13
<i>High Grade Copper</i>	0.00	-0.01	0.00	0.00	-0.02	-0.01	0.11**	0.69**	0.07	0.00	-0.01	-0.13
<i>Nickel</i>	-0.02	0.00	-0.05	0.00	-0.01	-0.05	1.38**	5.11**	-1.39	0.02	0.06*	-1.20
<i>Palladium</i>	0.01	-0.02	-0.05	0.00	0.00	-0.04	0.05	-0.68	0.29	0.00	0.02	0.21
<i>Platinum</i>	0.03***	-0.01	-0.01	0.00	0.00	-0.02	-0.03	0.00	-0.11	0.00	0.00	-0.07
<i>Silver</i>	0.00	0.01	-0.01	0.00	-0.02	-0.01	-0.04	1.49***	0.43*	0.00	0.02	-0.12
<i>Tin</i>	0.01*	0.04*	0.03	0.00	-0.01	-0.01	-0.01	-0.15	-0.07	0.00	-0.01	-0.02
<i>Zinc</i>	0.00	0.02	0.00	0.00	0.00	0.00	-0.09	-0.24	-0.41	0.00	0.01	-0.15

Table C.11: In-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	star				tbl				tms							
	Exp	eExp	lExp	Rec	lRec	Exp	eExp	lExp	Rec	lRec	Exp	eExp	lExp	Rec	lRec	
<i>Butter</i>	0.00	-0.01	-0.01	-0.04	-0.13	-0.08	0.00	0.01	-0.08	-0.23	-0.13	0.00	0.00	-0.08	-0.26	-0.19
<i>Cocoa</i>	0.00	0.00	-0.01	0.01	0.00	-0.05	-0.01	-0.02	-0.05	-0.21	-0.23	0.00	-0.02	-0.06	-0.16	-0.31
<i>Coffee Arabica</i>	0.00	-0.02	-0.01	0.66**	1.93**	0.82	0.09*	0.14	0.00	0.63	0.00	0.08***	0.26***	-0.11	0.23	0.89
<i>Corn Oil</i>	-0.01	-0.02	-0.03	-0.02	-0.18	-0.32	0.01	-0.03	-0.06	-0.04	-0.33	0.03**	0.19***	-0.01	-0.20	-0.31
<i>Cotton</i>	0.00	-0.01	-0.02	-0.01	-0.08	-0.03	0.01	0.01	-0.02	0.05	-0.04	0.00	0.14**	-0.03	-0.09	-0.06
<i>Live Cattle</i>	0.00	-0.01	-0.02	0.02	-0.10	0.15	0.00	-0.01	-0.05	-0.20	-0.21	0.01	0.03	-0.02	-0.01	-0.15
<i>Lean Hog</i>	0.02**	0.08***	-0.02	-0.03	-0.09	-0.11	-0.01	-0.02	-0.05	-0.19	0.00	-0.01	-0.01	-0.08	-0.16	-0.21
<i>Milk</i>	0.00	-0.01	-0.01	-0.01	-0.03	-0.02	0.00	-0.01	0.00	0.00	0.03	0.00	-0.01	-0.01	-0.07	-0.02
<i>Oranges</i>	0.00	-0.01	-0.01	-0.04	-0.11	-0.16	0.00	-0.01	0.01	-0.12	0.12	0.01*	0.04**	-0.03	0.09	0.03
<i>Soybean Oil</i>	0.00	-0.02	-0.02	-0.01	-0.06	-0.12	0.00	-0.03	-0.04	-0.15	-0.20	0.03***	-0.01	-0.02	-0.04	-0.13
<i>Soybeans</i>	0.00	0.01	-0.02	-0.06	-0.17	-0.34	0.00	0.00	-0.01	-0.06	-0.21	-0.02	0.00	0.00	-0.10	-0.35
<i>Soybean Meal</i>	-0.01	0.00	-0.02	0.01	-0.23	0.26	0.00	-0.01	-0.09	-0.36	-0.42	0.02*	0.01	-0.10	-0.36	0.32
<i>Sugar</i>	0.00	-0.01	-0.01	-0.01	-0.05	-0.02	0.00	0.00	-0.01	-0.08	0.22	0.00	-0.01	0.02	-0.02	0.04
<i>Wheat</i>	0.00	-0.02	-0.02	-0.03	-0.07	-0.09	0.01**	-0.01	-0.04	-0.13	-0.04	0.03***	0.00	-0.01	-0.05	-0.15
<i>Wool</i>	0.00	-0.02	-0.01	-0.02	-0.04	0.28*	0.00	-0.02	-0.04	-0.14	-0.14	0.00	0.00	-0.01	-0.03	0.08
<i>Yellow Corn</i>	0.00	-0.01	-0.02	-0.03	-0.03	-0.11	-0.01	0.02	-0.05	-0.19	-0.18	-0.01	-0.02	-0.05	-0.15	-0.03
<i>Coal</i>	0.00	-0.03	-0.01	-0.05	-0.12	-0.03	0.00	-0.01	-0.02	0.01	0.02	0.02**	0.00	-0.01	-0.04	0.84*
<i>Heating Oil</i>	-0.01	-0.01	-0.04	-0.20	1.10*	-0.51	-0.01	-0.02	0.06	0.55	-0.03	0.01	-0.01	1.59**	2.70*	2.10*
<i>Natural Gas</i>	0.00	0.10*	-0.02	-0.20	-0.54	-1.38	0.00	-0.01	-0.02	0.33	2.08	0.02**	0.20**	-0.15	0.12	-1.84
<i>Unleaded Regular Gas</i>	-0.01	-0.04	-0.07	0.48*	-0.47	2.37	0.03*	0.02	-0.02	0.70**	0.54	0.08**	0.24***	0.60*	1.11*	-1.35
<i>WTI Oil</i>	0.00	-0.01	-0.01	-0.02	-0.08	-0.08	0.00	0.02	-0.04	0.10	0.06	0.00	0.01	0.02	-0.10	-0.13
<i>Aluminum</i>	0.00**	-0.01	0.01**	-0.03	-0.07	-0.05	0.00	0.00	-0.02	0.04	0.30	0.01***	0.03***	0.00	0.01	0.03
<i>Gold</i>	0.00	-0.01	0.00	-0.01	0.00	-0.03	0.00	0.00	0.00	-0.06	-0.04	0.00	0.03**	0.00	0.12	-0.09
<i>High Grade Copper</i>	0.00	0.00	-0.01	-0.03	-0.02	-0.05	0.00	0.01	-0.01	-0.03	-0.12	0.09	0.04	-0.03	0.36*	-0.15
<i>Nickel</i>	0.04*	0.03*	0.07	-0.16	0.09	2.30	0.04	0.11**	-0.06	0.27	-1.14	-2.77	0.06**	1.42**	-1.28	-2.02
<i>Palladium</i>	-0.01	0.00	-0.05	0.15	1.56*	0.26	0.00	-0.05	0.07	-0.19	0.55	0.15***	0.53***	-0.03	0.39	-0.98
<i>Platinum</i>	0.01*	0.03	-0.02	-0.01	-0.08	0.00	0.00	0.00	0.01	-0.02	-0.08	0.00	-0.02	0.04	0.02	-0.27
<i>Silver</i>	0.00*	0.00	0.00	-0.01	-0.02	-0.06	0.00	0.04	-0.01	0.01	0.68*	0.00	-0.01	-0.01	-0.03	0.28
<i>Tin</i>	0.00	-0.01	-0.01	-0.02	0.02	-0.10	0.00	-0.01	-0.01	-0.02	-0.04	0.00	-0.02	-0.03	-0.13	-0.14
<i>Zinc</i>	0.00	-0.01	-0.01	-0.04	-0.07	-0.09	0.00	0.00	-0.07	-0.21	-0.10	0.01*	0.01	0.00	-0.13	-0.29

Table C.11: In-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	unrate					
	Exp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	0.00	0.00	0.01	-0.17	-0.43	-0.55
<i>Cocoa</i>	0.00	0.01	-0.03	0.53**	-0.32	1.58
<i>Coffee Arabica</i>	0.01	-0.02	0.05	-0.12	-0.41	-0.55
<i>Corn Oil</i>	0.00	0.06**	-0.01	0.01	-0.26	0.09
<i>Cotton</i>	0.01*	0.03	0.22**	-0.04	-0.20	-0.11
<i>Live Cattle</i>	0.00	-0.03	0.08*	0.06	-0.05	0.62
<i>Lean Hog</i>	-0.01	-0.03	0.02	-0.13	-0.18	0.38
<i>Milk</i>	0.00	0.00	0.00	0.10	0.35	-0.13
<i>Oranges</i>	-0.01	-0.02	-0.01	-0.07	-0.16	0.65
<i>Soybean Oil</i>	0.01*	-0.03	-0.02	0.16*	-0.07	0.26
<i>Soybeans</i>	0.00	-0.01	-0.02	0.35*	0.09	-0.25
<i>Soybean Meal</i>	0.00	-0.02	-0.01	0.36*	0.36	-0.21
<i>Sugar</i>	0.00	0.00	-0.01	-0.08	-0.11	-0.28
<i>Wheat</i>	0.02***	0.01	-0.02	-0.03	-0.19	-0.23
<i>Wool</i>	0.00	-0.03	-0.02	-0.06	-0.34	-0.63
<i>Yellow Corn</i>	0.00	0.00	0.06*	0.05	-0.26	-0.02
<i>Coal</i>	0.03**	0.01	-0.02	0.20*	0.05	0.99*
<i>Heating Oil</i>	-0.01	0.00	0.00	0.67*	0.06	1.64*
<i>Natural Gas</i>	0.03***	0.08	0.00	-0.11	-0.34	-0.24
<i>Unleaded Regular Gas</i>	-0.01	0.02	-0.06	0.33	-0.32	1.16
<i>WTI Oil</i>	0.00	-0.01	0.09**	0.43**	0.27	2.06**
<i>Aluminium</i>	0.01**	0.03**	0.04**	0.26**	0.33	1.02
<i>Gold</i>	0.00	-0.01	-0.01	-0.06	-0.15	-0.35
<i>High Grade Copper</i>	0.00	-0.03	0.00	-0.07	-0.27	-0.11
<i>Nickel</i>	-0.02	0.00	0.34**	-0.15	-0.73	0.19
<i>Palladium</i>	0.11***	0.09	-0.02	-0.15	-0.45	-1.10
<i>Platinum</i>	0.00	-0.01	0.23***	-0.06	-0.08	-0.54
<i>Silver</i>	0.00	0.00	0.00	-0.08	-0.05	-0.30
<i>Tin</i>	0.01	0.03	0.00	-0.06	-0.15	-0.57
<i>Zinc</i>	0.00	0.00	0.02*	-0.10	-0.30	0.09

Table C.12: Out-of-Sample Volatility Predictability and Business Cycle Stages (12 Months)

This table reports the out-of-sample R^2 's of a regression of monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable across business cycle stages. We predict the next year's volatility. "de" denotes the dividend-payout ratio, "Δndpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dty" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dip" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "4ms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. We consider six business cycle stages. "Exp" denotes the expansion, "eExp" the early expansion, "iExp" the late expansion, "Rec" the recession, "eRec" the early recession, "iRec" the late recession. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	de						Δndpro						ΔM1					
	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec	Exp	eExp	lExp	Rec	eRec	lRec
Butter	-0.82	-0.30	-1.47	-2.01	-0.70	0.09	-1.40	-0.48	-0.79	-0.38	-0.38	0.11*	-0.26	0.31*	-1.38	-0.19	-1.18	-1.19
Cocoa	-1.86	-1.66	-1.55	-0.86	-0.79	-0.74	-1.07	-0.12	-0.76	-2.65	-2.65	-1.58	-1.69	-1.02	-0.75	-2.92	-2.92	-2.92
Coffee Arabica	-4.18	-0.38	-4.51	-0.86	-0.79	-0.74	-1.07	-0.12	-0.76	-2.65	-2.65	-1.58	-1.69	-1.02	-0.75	-2.92	-2.92	-2.92
Corn Oil	-2.50	-2.55	-1.28	-2.63	-0.66	-1.94	-0.47	-1.32	-1.03	1.17**	1.17**	-0.38	-0.62	1.31**	-0.38	0.61	-1.18	0.61
Cotton	0.21**	-1.56	-1.76	-0.80	-0.66	-1.94	-0.70	-0.57	-0.22	-0.57	-0.57	-0.08	-0.74	-0.82	-0.08	-0.82	-0.08	-0.82
Live Cattle	-1.74	-1.89	-1.00	-3.15	-0.40	-1.44	-1.22	-0.28	-0.40	-1.84	-1.84	-0.04*	-2.46	3.12***	0.04*	0.20	-0.49	0.20
Lean Hog	-0.09*	-0.26	-1.88	-0.28	-1.46	-1.57	-1.42	-0.71	-0.14	-1.64	-1.64	-1.02	-1.06	0.20	-1.02	-0.43	-1.02	-0.43
Milk	-1.56	-0.18	-3.33	-1.33	-4.20	-6.72	0.45***	0.18*	-0.22	-0.90	-0.90	-0.91	-3.10	-0.43	-0.91	-1.09	-0.77	-0.95
Oranges	-2.49	-0.38	-0.84	0.06	-0.74	0.20*	-0.74	0.20*	0.67**	0.23	0.23	-0.91	-0.20	-1.09	-0.91	-1.09	-0.77	-0.95
Soybean Oil	-0.64	-1.46	-2.06	0.14	-0.87	-2.03	-0.87	-0.73	-2.03	-0.04	-0.04	-0.91	-0.13	0.84**	-0.91	0.84**	-0.77	-0.95
Soybeans	-2.69	1.95***	-1.68	0.05	-0.88	-0.18	-0.88	-0.18	-0.48	-0.22	-0.22	-0.54	-1.15	1.05**	-0.54	1.05**	-0.77	-0.95
Soybean Meal	-3.28	-1.89	-1.91	5.72**	0.51*	0.27	-0.57	1.13**	-0.56	-0.49	-0.49	-0.12	0.19	0.54*	-0.12	0.54*	-0.77	-0.95
Sugar	-1.96	-1.56	-2.76	-0.86	-0.73	-1.12	-0.15	-0.33	-0.20	-0.20	-0.20	-0.68	-2.15	-0.47	-0.68	-2.15	-0.77	-0.95
Wheat	-2.31	-1.84	0.34**	-1.59	-0.73	-1.12	-0.44	-0.04	-0.24	-0.06	-0.06	0.62***	-1.72	0.07	0.62***	0.07	-0.77	-0.95
Wool	-1.04	-2.02	-7.22	-0.31	-1.03	-0.27	-0.42	0.03	-1.12	0.80*	0.80*	-0.48	-0.77	-0.95	-0.48	-0.77	-0.77	-0.95
Yellow Corn	-1.11	0.75***	-1.04	-0.55	-0.46	-0.85	-1.63	-0.18	0.25*	-0.94	-0.94	-0.70	-1.54	-0.09	-0.70	-1.54	-0.77	-0.95
Cool	-4.31	-1.23	-3.52	-0.55	-0.46	-0.85	-0.86	-1.20	-0.67	-0.67	-0.67	-0.86	-1.20	-0.67	-0.86	-1.20	-0.77	-0.95
Heating Oil	-5.10	10.80**	-10.31	-0.55	-0.46	-0.85	-0.73	0.70	-5.30	-0.60	-0.60	-0.73	6.74***	-2.92	-0.73	6.74***	-0.77	-0.95
Natural Gas	2.17***	-0.82	-0.82	-0.55	-0.46	-0.85	-1.88	0.75	-2.59	-0.63*	-0.63*	5.49***	-0.99	-0.21	5.49***	-0.21	-0.77	-0.95
Unleaded Regular Gas	-3.04	6.47	-3.58	-1.17	-1.46	-0.47	-0.92	-2.95	-2.95	0.00	0.00	-1.18	-0.38	0.33*	-1.18	-0.38	-0.77	-0.95
WTI Oil	-2.12	0.04	-1.01	-0.46	-0.47	-1.14	-0.33	0.02	-0.15	0.19	0.19	-0.33	0.39*	0.33*	-0.33	0.39*	-0.77	-0.95
Aluminium	3.01***	-2.01	-6.15	0.06	-0.47	-1.14	-2.01	-0.51	-0.30	0.13	0.13	1.32***	2.81***	-1.09	1.32***	-1.09	-0.77	-0.95
Gold	-3.26	-0.54	-2.46	0.46**	0.10	0.23	-1.28	-0.46	-0.60	0.63*	0.63*	-0.99	-1.18	-0.21	-0.99	-1.18	-0.77	-0.95
High Grade Copper	-2.27	-1.15	-2.90	-1.17	-1.46	-0.47	-0.56	-0.88	-0.59	0.00	0.00	-1.37	-0.94	0.78**	-1.37	-0.94	-0.77	-0.95
Nickel	4.76***	-0.17	-1.22	0.59	-0.46	-0.50	-0.99	0.75	-2.47	-0.46	-0.46	-0.11	-0.37	-0.40	-0.11	-0.37	-0.77	-0.95
Palladium	-4.62	0.17	-1.22	0.59	-0.46	-0.50	-0.16	0.57	-2.47	-0.46	-0.46	4.33	-3.07	-0.40	4.33	-3.07	-0.77	-0.95
Platinum	-1.07	-3.10	-2.54	0.59	0.46	-0.50	-1.13	-2.02	-0.34	-4.90	-4.90	-1.13	-0.52	-0.58	-1.13	-0.52	-0.77	-0.95
Silver	-2.17	-0.91	-2.69	-0.55	0.46	-0.50	-0.27	-0.26	-0.35	0.62*	0.62*	-0.98	-0.64	-0.61	-0.98	-0.64	-0.77	-0.95
Tin	-2.63	-0.90	-0.78	-2.57	-1.35	-0.37	-0.46	-1.55	-1.30	0.46	0.46	-0.74	-1.78	-1.55	-0.74	-1.78	-0.77	-0.95
Zinc	-1.32	-2.97	-2.61	-0.63	-0.64	-0.29	-0.68	0.26*	-0.46	-1.43	-1.43	-0.99	-1.80	-0.55	-0.99	-1.80	-0.77	-0.95

Table C.12: Out-of-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	dfr				dfr				dp					
	Exp	eExp	lExp	Rec	eRec	lRec	Rec	eRec	lExp	eExp	lExp	Rec	eRec	lRec
<i>Butter</i>	-0.95	-1.14	-0.58	-0.64	-0.92	-0.56	-0.66	-0.53	-0.41	-1.62	-0.41	-1.43	-2.45	-3.15
<i>Cocoa</i>	-1.12	-1.08	-2.30	0.27	-2.21	-1.10	-1.34	0.47	0.84***	-0.61	-0.33	-0.82	1.06*	0.51
<i>Coffee Arabica</i>	-3.68	-1.56	-2.33		-0.67	-2.43	-1.02		-4.43	-4.76	-7.10			
<i>Corn Oil</i>	-4.71	-1.11	-3.74	-0.74	-0.93	-5.02	-2.84	-1.47	-1.86	-9.64	-0.33	-5.89		
<i>Cotton</i>	-3.57	-0.13	-3.11	0.23	-0.30	-2.64	-2.22	-0.18	-2.08	-3.08	0.13*	-0.31	-1.23	-2.60
<i>Live Cattle</i>	-1.85	-0.58	-2.38	0.17	-3.54	-4.06	-2.75	-0.32	-3.36	-1.80	0.01*	-2.30	-1.31	-0.99
<i>Lean Hog</i>	-3.21	-2.45	-1.17	-1.85	1.02***	-4.58	-1.70	-0.84	-1.51	-3.65	-0.28	-1.65	1.49**	-1.71
<i>Milk</i>	0.03*	-0.20	0.13*	-1.60	-0.17	-0.57	-2.97	-3.16	-0.53	-9.48	-6.93	0.68**	-0.56	0.71
<i>Oranges</i>	-0.70	-1.17	-0.55	2.55**	-2.26	-0.36	-0.27	-0.19	-0.39	-1.76	0.16	-1.39		
<i>Soybean Oil</i>	-1.72	-1.39	-2.07	-1.39	-7.45	-7.17	-2.69	1.46*	-5.39	-1.02	-4.70	-0.87		
<i>Soybeans</i>	-1.96	-1.68	-3.20	-2.30	-0.54	-0.47	-4.53	0.03	-2.97	-9.18	-0.89	-1.17		
<i>Soybean Meal</i>	-2.68	-0.55	-2.95	-13.24	-3.10	-2.95	-2.88	-1.81	-5.07	-9.25	-0.58	-20.17	-1.92	-0.95
<i>Sugar</i>	-1.00	-0.65	-1.19	0.77*	-3.65	-1.95	-1.52	0.60	-2.45	-2.21	0.09*	-0.99	1.44**	-1.74
<i>Wheat</i>	-3.85	-1.04	-3.64	-1.89	-2.61	-5.37	-0.77	0.06	-4.25	-2.87	-5.36	-0.22	1.88*	-3.65
<i>Wool</i>	-1.48	-1.45	-3.96	-0.98	-2.94	-1.07	-1.25	-2.69	-1.92	-3.64	-1.60	0.14	1.88*	-3.65
<i>Yellow Corn</i>	-1.76	-1.21	-3.45	-1.99	-5.00	-5.07	0.44**	0.06	-2.61	-1.45	-1.62	-1.67	0.57*	-1.13
<i>Coal</i>	-2.24	-0.71	-1.38		-1.39	-0.82	-2.89		-2.83	-2.80	-0.85			
<i>Heating Oil</i>	-6.38	-2.87	-30.78		-2.34	1.54*	-5.75		-4.25	-27.67	-6.36			
<i>Natural Gas</i>	1.31**		-0.27		3.50***		-1.55		0.10		0.58			
<i>Unleaded Regular Gas</i>	-0.50	3.25**	-1.99		-1.74	-2.61	-0.76		-4.89	-3.52	0.03			
<i>WTI Oil</i>	-4.57	-2.26	-3.55	-1.65	-2.70	-1.30	-5.14	-1.32	-3.22	-4.44	0.72**	-0.29	-0.10	-1.44
<i>Aluminium</i>	-1.82	-0.98	-0.62	-0.91	-0.41	-1.61	-1.70	-0.26	-5.10	-6.58	-1.45	0.06		
<i>Gold</i>	-3.55	-0.80	-2.56	-0.71	-0.47	-1.21	-1.61	-0.36	-28.48	8.10***	-1.88	0.35**	2.03**	0.60
<i>High Grade Copper</i>	-1.40	-0.81	-1.16	-0.89	-2.54	-4.76	-2.98	0.18	-3.01	-4.04	-1.70	0.59**	5.00***	-0.23
<i>Nickel</i>	-0.97				4.49***				-10.44					
<i>Palladium</i>	0.48**	0.03	-0.34		-2.90	-0.98	0.40		-0.73	-3.53	-0.70			
<i>Platinum</i>	-0.75	-1.83	-2.09	0.60	-4.38	-4.32	-4.74	-1.44	-2.11	-2.31	-3.30	3.20**		
<i>Silver</i>	-2.55	-0.69	-0.71	-0.51	-5.36	-2.22	-0.66	-0.36	-3.91	-2.37	-1.44	0.88**	3.21***	-0.56
<i>Tin</i>	-1.41	-1.68	-1.50	-1.50	-3.75	-3.70	-5.68	-1.40	-0.38	-0.88	-3.35	-1.37	1.77**	-0.54
<i>Zinc</i>	-2.24	-2.07	-2.42	-2.65	-0.70	-2.56	-1.97	-1.12	-4.15	-5.81	-5.60	0.01	0.47*	-1.29

Table C.12: Out-of-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	<i>dy</i>				<i>ep</i>				<i>erp</i>					
	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec	eRec	lRec
<i>Butter</i>	-2.76	-1.39	-0.36	-3.38	-2.64	-2.50	-0.12	-0.98	-0.43	-0.43	-0.33	-0.99	0.34	-0.03
<i>Cocoa</i>	0.39***	-0.51	-0.24	0.38	-2.09	-1.57	-0.22	-0.91	0.08***	0.08***	-2.59	-1.24	-1.15	-1.24
<i>Coffee Arabica</i>	-4.19	-3.78	-6.37		-5.58	-2.22	-6.80			-2.89	0.64**			
<i>Corn Oil</i>	-1.92	-9.32	-0.24	-5.80	-2.18	-5.91	0.34*	-1.06	-0.81	-1.47	0.64***	-1.83		
<i>Cotton</i>	-1.83	-2.42	0.06*	-0.36	-1.20	-3.22	0.10*	-0.11	-0.33	-2.75	-0.65	0.05	-0.76	-0.67
<i>Live Cattle</i>	-3.33	-1.98	0.03*	-2.38	-1.26	-4.69	0.06*	-0.97	-0.68	-2.03	-0.75	-0.90	-0.74	-0.89
<i>Lean Hog</i>	-1.30	-2.75	-0.31	-1.52	-1.13	-0.62	-0.25	1.77***	-0.85	-3.20	-0.43	1.08***	-1.15	0.10
<i>Milk</i>	-0.49	-8.93	-5.69	0.67*	-2.28	-1.59	-3.62	-0.97	1.77**	-2.17	-1.95	-2.78	-3.68	-0.66
<i>Oranges</i>	-0.74	-1.40	-0.15	-1.06	-0.19	-1.87	0.98***	-2.00	-0.13	0.38***	0.44*	0.35		
<i>Soybean Oil</i>	-4.44	-1.05	-4.56	-1.13	-2.87	-1.11	-3.03	1.03*		-0.27	-1.13	-0.76		
<i>Soybeans</i>	-2.69	-8.21	-0.67	-1.21	-4.09	-4.27	0.45*	0.76*		-1.44	-0.24	-0.34		
<i>Soybean Meal</i>	-4.05	-9.61	-0.61	-21.91	-7.44	-9.57	1.06***	-1.26	-0.46	-0.75	-0.87	2.08*		
<i>Sugar</i>	-2.66	-1.82	-0.02	-1.29	-1.98	-1.37	-1.12	-1.12	-2.53	-2.26	-0.65	-1.16	-0.31	-1.74
<i>Wheat</i>	-3.86	-2.49	-4.61	-0.56	-3.29	-3.19	-0.31	0.92***	1.99***	-3.02	-2.97	-1.03	-0.79	-0.83
<i>Wool</i>	-1.70	-3.33	-1.96	-3.45	-1.34	-2.33	-2.80	1.04**	3.19***	-1.14	-1.43	-1.03	-0.66	-0.29
<i>Yellow Corn</i>	-2.37	-0.92	-1.48	-1.79	-0.26	-0.70	-1.23	0.73**	2.37***	-1.09	-1.83	-1.25	-1.10	-1.75
<i>Coal</i>	-2.69	-2.69	-0.92		-5.65	-1.58	-0.98			-0.84	-0.49	-0.28		
<i>Heating Oil</i>	-4.66	-22.21	-6.79		-5.55	-16.68	-11.14			-1.08	-3.40	0.90*		
<i>Natural Gas</i>	0.64		0.72		-0.05		0.24			-0.36		-2.36		
<i>Unleaded Regular Gas</i>	-4.97	-1.35	0.27		-3.33	-1.18	-1.83			-0.83	-2.64	1.83*		
<i>WTI Oil</i>	-3.17	-3.15	0.55**	-0.60	-1.88	-1.97	1.33***	1.47***	-0.56	-2.64	-4.31	-0.41	-0.43	-1.53
<i>Aluminium</i>	-5.32	-4.25	-1.54	0.02	0.24*	-4.98	-2.63	0.49*		-0.94	-1.87	-0.87		
<i>Gold</i>	-22.51	7.66***	-1.82	0.38**	-16.16	0.71**	-2.05	-0.22	0.83*	-7.14	-0.10	-0.57	1.41**	-0.27
<i>High Grade Copper</i>	-2.53	-3.84	-1.74	0.74**	-1.39	-3.26	-1.41	-0.45	1.92**	-1.80	-0.30	-0.98	-0.90	-3.15
<i>Nickel</i>	-9.46				-2.16					-0.24				
<i>Palladium</i>	-1.32	-3.21	-0.86		-4.46	-1.07	0.97			-0.76	-0.10	0.14		
<i>Platinum</i>	-1.99	-1.52	-2.52	2.79**	-1.68	-3.00	-2.32	2.95**		-0.08	-1.32	-2.61	-1.08	
<i>Silver</i>	-3.79	-1.91	-1.32	0.94***	-4.16	-1.42	-1.21	-0.73	0.51*	-0.55	-0.68	-0.63	0.22	-0.33
<i>Tin</i>	-0.19	-0.52	-3.33	-0.64	-1.21	-3.17	-3.18	-0.74	1.93**	-2.32	-1.18	-0.96	-1.90	-2.76
<i>Zinc</i>	-3.29	-4.83	-5.10	0.03	-1.42	-2.51	-1.50	-0.39	1.41**	-2.21	-2.55	-2.67	-1.16	-5.41

Table C.12: Out-of-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	<i>infl</i>				<i>tr</i>				<i>ty</i>			
	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec	Exp	eExp	lExp	lRec
<i>Butter</i>	-0.80	-0.76	-0.28	0.13*	-0.33	-2.86	-0.45	-1.54	-0.33	-4.10	0.46*	-0.82
<i>Cocoa</i>	-2.79	-2.12	0.22**	-0.40	-1.00	-1.11	-4.24	-5.16	-3.48	-1.91	-2.66	-2.73
<i>Coffee Arabica</i>	-1.48	-0.93	-5.36		-0.71	-1.41	-0.97		-5.19	-0.16	-2.92	
<i>Corn Oil</i>	-1.66	-1.10	-0.77	-1.99	-0.21	-3.11	-2.91	-10.36	-1.06	-3.71	0.76**	-5.15
<i>Cotton</i>	-0.24	-1.23	-0.81	-1.09	-1.38	-1.43	-0.51	-9.29	-0.76	-1.43	-1.52	-6.65
<i>Live Cattle</i>	-1.39	-1.01	-0.27	-0.69	-1.01	-1.45	-1.29	-10.32	-4.90	-3.64	-1.79	-5.61
<i>Lean Hog</i>	-0.33	-0.25	1.22***	-1.72	-1.36	-2.08	-1.14	-8.20	0.53***	-2.80	-0.87	-4.55
<i>Milk</i>	-1.02	-1.47	-0.28	-1.67	1.06	-1.10	-0.96	-2.72	-1.54	0.08	-0.42	-0.64
<i>Oranges</i>	-0.85	-0.52	0.20*	-0.87	-0.93	-0.92	-1.78	0.43	0.35**	-1.92	-1.09	-3.41
<i>Soybean Oil</i>	-3.80	-0.25	-0.87	-0.27	-1.25	-2.82	-2.97	-4.96	-0.93	-2.17	-6.87	-3.84
<i>Soybeans</i>	-3.74	-2.27	-1.06	-1.19	-0.92	0.04	-1.12	-8.81	-1.35	-4.92	-2.62	-2.85
<i>Soybean Meal</i>	-2.10	-1.27	-1.74	-2.45	-1.13	-0.51	-0.89	-25.42	-3.81	-5.30	-1.14	3.14
<i>Sugar</i>	-0.42	-1.47	-2.00	0.51**	-0.96	-1.21	-3.43	-3.64	-5.15	-1.21	-4.77	-1.57
<i>Wheat</i>	-1.22	-0.62	-0.25	-1.60	-1.35	-1.19	-0.57	-9.77	-4.37	-5.25	0.11	-3.91
<i>Wool</i>	-0.79	-0.61	-0.85	-1.01	-0.70	-2.22	-1.84	-4.16	-3.11	-4.33	-4.91	-1.91
<i>Yellow Corn</i>	-1.13	-0.22	-1.38	-1.28	-1.33	-2.65	-2.00	-7.11	-2.77	-1.73	-0.85	-4.04
<i>Cool</i>	-1.69	-1.36	-1.20		-1.06	-2.53	-1.12		-2.68	-0.17	-2.60	
<i>Heating Oil</i>	-0.71	1.14*	2.47**		-0.79	1.27*	0.14		-2.42	-12.88	-17.39	
<i>Natural Gas</i>	-2.29		-1.93		-0.05	0.09			-2.36		-0.45	
<i>Unleaded Regular Gas</i>	-1.33	-0.68	-3.56		-0.80	2.91**	-0.54		-4.51	-4.42	-1.76	
<i>WTI Oil</i>	0.49**	-1.06	-0.58	-0.11	-0.82	-0.97	-0.37	-5.42	-3.61	-3.74	-0.56	-2.81
<i>Aluminum</i>	0.21**	-1.65	-2.63	0.31	-1.46	-1.17	0.80**	-2.16	-4.42	-4.01	-5.99	-2.55
<i>Gold</i>	1.60***	2.07***	-0.37	0.48**	-0.35	-0.74	0.04	-5.22	-0.51	-3.45	-2.90	-1.35
<i>High Grade Copper</i>	-0.76	-1.22	0.57***	-3.04	-1.22	-2.60	-2.91	-0.82	-2.18	-4.03	-0.27	-5.23
<i>Nickel</i>	-1.30				-1.19				0.45			
<i>Palladium</i>	-1.09	-0.47	-1.41	-0.40	-1.13	-0.72	-0.61	-0.72	-2.47	-1.00	-1.79	-3.02
<i>Platinum</i>	0.28**	-1.51	-1.42	0.40**	-1.83	-0.90	-1.08	-0.72	-4.02	-2.63	-3.72	-0.20
<i>Silver</i>	-0.82	0.28**	-0.74	0.40**	-0.76	-0.89	-0.95	-2.80	-5.79	-1.34	0.20	-2.70
<i>Tin</i>	-1.09	-0.03*	-0.75	-4.48	-1.30	-2.04	-2.77	-8.60	-1.96	0.31*	-8.28	-5.04
<i>Zinc</i>	-0.24	-0.84	0.16*	-2.49	-1.17	-0.94	-1.64	-5.65	-3.45	-0.95	-3.52	-2.06

Table C.12: Out-of-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	<i>svar</i>				<i>tbl</i>				<i>tms</i>			
	Exp	eExp	Rec	eRec	Exp	eExp	Rec	eRec	Exp	eExp	Rec	eRec
<i>Butter</i>	-6.13	-1.45	-2.77	-2.74	-5.97	-2.68	1.07**	-0.33	-4.39	-2.51	-2.29	-1.58
<i>Cocoa</i>	-12.69	-1.74	-1.87	-0.66	-10.31	-1.36	-2.59	-1.86	-4.30	-1.31	-3.83	-2.26
<i>Coffee Arabica</i>	-40.42	-4.49	0.36*		-1.34	-0.88	-4.96		2.03***	6.39***	-5.05	
<i>Corn Oil</i>	-10.36	-2.43	-5.54	-0.14	-2.10	-5.03	-0.35	-5.99	-0.32	-0.67	-1.47	-3.71
<i>Cotton</i>	-7.19	-1.51	-52.30	-0.80	-1.69	-2.54	0.77**	-3.59	-0.24	-1.38	-0.38	-0.80
<i>Live Cattle</i>	-1.62	-0.75	-0.55	-1.20	-2.84	-2.60	-1.18	-2.77	-6.65	-1.81	-0.93	0.38
<i>Lean Hog</i>	-2.49	0.05*	-0.63	-7.12	-0.93	-6.03	-1.12	-0.94	1.35***	-3.98	-1.50	-0.18
<i>Milk</i>	-3.03	-3.81	-3.93	-53.44	-3.37	-1.58	-0.43	-1.09	-1.20	-1.26	-0.94	-0.64
<i>Oranges</i>	-1.44	-1.96	-0.65	-2.53	-3.50	-2.67	-0.52	-1.78	-2.69	-3.78	0.51**	0.12
<i>Soybean Oil</i>	-29.97	-0.90	-4.85	-0.07	-0.88	-4.57	-8.96	-3.87	-1.85	-5.00	-8.36	-3.51
<i>Soybeans</i>	-1.34	0.81**	-116.80	-0.17	-4.72	-1.34	-1.63	-2.75	-1.98	-2.25	-2.14	-2.50
<i>Soybean Meal</i>	-5.64	-0.09	-180.40	-1.62	-7.01	-3.62	-1.69	2.75	-3.82	-4.29	-3.31	-5.05
<i>Sugar</i>	-18.07	-0.84	-0.42	-0.96	-4.33	-0.69	-1.57	-1.70	-1.66	-1.86	0.84**	-2.54
<i>Wheat</i>	-12.39	-1.38	-0.58	-1.78	-0.63	-4.91	0.48*	-2.94	1.53***	-3.87	-1.37	-2.44
<i>Wood</i>	-2.23	-0.60	-15.19	-3.33	-3.91	-3.78	-6.20	-0.95	-3.26	-1.84	-4.15	-2.45
<i>Yellow Corn</i>	-33.26	-0.75	-12.39	-0.29	-3.29	-2.64	-2.35	-1.66	-6.51	-0.97	-4.13	-1.28
<i>Coal</i>	-53.06	-1.11	-4.19		-3.76	0.16	-2.14		0.72***	-2.11	-1.53	
<i>Heating Oil</i>	-96.33	-31.49	0.12		-2.10	-8.97	-4.83		-2.78	1.77*	-8.96	
<i>Natural Gas</i>	-0.60	-0.09			0.85***		-0.73		3.48***		-1.14	
<i>Unleaded Regular Gas</i>	-0.33	-24.01	-0.09		-0.02	0.30	-0.81		1.15**	8.65***	-5.57	
<i>WTI Oil</i>	-48.01	-7.05	-21.91	-0.99	-1.54	-2.86	-2.09	-1.30	-1.02	0.19*	-1.88	2.72***
<i>Aluminium</i>	-42.03	-0.32	-11.33	-0.86	-5.80	-3.42	-8.07	-1.55	-0.75	-1.14	-2.34	0.31
<i>Gold</i>	-12.52	-1.37	-1.12	0.70***	-3.38	-5.29	0.68**	-0.93	-2.63	-3.08	-1.61	-3.58
<i>High Grade Copper</i>	-6.40	-2.41	-77.68	-15.58	-4.41	-5.66	-0.62	-2.79	-2.24	-3.10	-3.75	0.48
<i>Nickel</i>	0.30*				0.20				2.01**			
<i>Palladium</i>	0.27*	-1.39	-0.15		-4.08	-1.57	0.56		-2.60	1.74*	-0.93	
<i>Platinum</i>	-3.17	-0.19	-5.74	-0.72	-5.65	-2.43	-2.96	-1.60	-4.90	-1.92	-3.09	2.04**
<i>Silver</i>	-7.26	-0.40	-65.27	0.33**	-4.90	-2.70	-0.04	-0.10	-1.75	-3.70	-2.70	-2.64
<i>Tin</i>	-25.20	-1.44	-2.08	-4.80	-5.81	-4.27	-10.32	-3.48	-2.52	-4.16	-0.92	-2.51
<i>Zinc</i>	-0.95	-3.07	-0.80	-18.24	-8.17	-0.77	-1.41	-0.63	-3.73	-0.92	-0.29	2.92**

Table C.12: Out-of-Sample Volatility Predictability and Business Cycle Stages (12 Months)
(continued)

Commodity	<i>unrate</i>			
	Exp	eExp	lExp	lRec
Butter	-0.22	-0.04	-0.28	
Cocoa	-3.18	-0.82	-4.47	
Coffee Arabica	0.74**	-1.86	-2.65	
Corn Oil	0.09*	-1.51	-0.62	
Cotton	-0.28	-1.87	-3.67	
Live Cattle	-3.05	-0.46	0.00	
Lean Hog	-1.32	-2.44	-1.43	
Milk	-1.23	-1.05	-1.04	
Oranges	-2.61	-0.60	0.67*	
Soybean Oil	-3.37	-3.11	-1.85	
Soybeans	-2.26	-7.63	-2.20	
Soybean Meal	-3.52	-7.62	-0.99	
Sugar	-0.63	-6.93	-9.36	
Wheat	1.75***	-3.16	-0.70	
Wool	-0.99	-4.23	0.67*	
Yellow Corn	-2.25	-1.59	-0.01	
Coal	-0.94	-1.53	-2.08	
Heating Oil	-1.22	6.14**	-6.56	
Natural Gas	3.07***		0.27	
Unleaded Regular Gas	0.26	1.11	-2.69	
WTI Oil	-1.40	-0.57	0.68*	
Aluminium	-0.57	-0.82	-4.96	
Gold	-3.70	-0.42	-0.62	
High Grade Copper	-0.77	1.19**	2.46***	
Nickel	2.73**			
Palladium	-2.67	-2.79	-1.07	
Platinum	-0.44	-0.95	-4.10	
Silver	-3.03	-0.23	-0.18	
Tin	-0.23	-8.22	-2.86	
Zinc	0.07*	-4.02	-0.22	

Table C.13: Restricted Return Predictability

This table reports the out-of-sample R^2 's of predicting monthly excess returns on a constant and the lagged predictive variable after imposing an economically motivated restriction. We predict the next month's and the next year's excess return. Statistical inferences are based on a bootstrapped distribution. Following Campbell & Thompson (2008), we impose the restriction that we set the out-of-sample slope estimate equal to zero whenever it is different to that of the in-sample estimate. All data are sampled at the monthly frequency. "de" denotes the dividend-payout ratio, " $\Delta indpro$ " the growth of industrial production, and " $\Delta M1$ " the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "itr" the long-term U.S. government bond returns, "ity" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Horizon	de	$\Delta indpro$	$\Delta M1$	dfr	dfy	dp	dy	ep	erp	infl	itr	ity	svar	tbl	tms	unrate
Butter	1 Month	-4.33*	-0.42	0.60***	-0.15	-1.65	-7.59***	-13.02***	-19.99**	-0.10*	-0.32	-0.64	-8.50	-0.39	-4.28	-5.00	-12.15
	12 Months	-56.02	-0.14	-0.10*	0.11**	-13.98	-659.74	-865.36	-327.87	0.66***	-0.42	-0.79	-85.35	-11.27	-20.03	-42.56	-35.34
Cocoa	1 Month	-32.21	-0.21	-0.99	0.23**	-5.62	-67.26*	-82.80	-49.79	-0.26	-0.53	-0.53	-10.72	-9.42	-1.58*	-8.47	-9.30
	12 Months	-115.50	1.11***	-2.05	-0.19	-16.09	-349.76	-352.36	-189.27	-1.35	-10.22	-0.89	-53.27	-11.54	-9.71	-67.96	-92.87
Coffee Arabica	1 Month	-4.56	-0.35	-1.52	-0.03	-6.04	-303.77	-334.46	-68.26	-0.64	-0.79	-0.55	-36.18	-1.62	-1.58	0.93***	-2.10**
	12 Months	-27.96	-0.10	-2.59	-0.28	-25.12	-2,541.46	-2,430.51	-116.20	-0.41	-3.34	0.20**	-100.11	-6.80	1.17***	11.11***	1.98***
Corn	1 Month	-6.04	-0.09*	-0.88	-0.01*	-6.20	-96.70	-128.40	-32.83	-1.78	-2.60	-0.55	-3.39*	-6.30	-5.16	-14.01	-13.57
	12 Months	-72.90	0.67***	0.52***	-0.64	-23.86	-212.13	-218.08	-150.88	-0.53	0.25**	-0.61	-28.99	-10.81	-7.94	-73.19	-75.66
Cotton	1 Month	-18.50	-0.25	-0.55	-1.01	-2.54	-41.13**	-157.55	-69.43	0.62***	-0.75	-0.68	-16.11	-1.19	-1.56	-13.21	-2.28***
	12 Months	-44.59	-0.24	-0.86	-0.38	-2.15	-1,969.98	-1,947.59	-1,130.09	-0.42	-6.43	-0.34	-64.64	-3.89	3.03***	-49.42	-3.72**
Live Cattle	1 Month	-6.70	0.24**	-0.77	0.03*	-6.67	-36.36**	-45.93**	-61.77	-0.38	-3.06	-1.09	-4.22	-4.26	-2.41	-8.38	-6.43*
	12 Months	-52.39	1.12***	-0.12	-0.29	-24.82	-152.73	-194.00	-189.94	-0.36	-2.04	0.04**	-11.33	-23.33	0.37***	-27.76	-47.32
Lean Hog	1 Month	-5.16*	-0.64	-0.28	-0.32	-5.03	-22.62***	-15.57***	-56.84	-1.25	-0.50	-0.06*	-8.16	-2.00	-2.39	-3.52	-2.07***
	12 Months	-41.53	-0.66	-0.68	-0.08*	-21.58	-119.19	-176.18	-347.41	-0.01**	-1.37	-0.24	-82.60	-10.81	-24.71	-19.35	-54.85
Milk	1 Month	-4.93*	1.00***	0.45***	-0.64	-0.36***	-32.14**	-194.45	-55.99	-0.15*	1.59***	-0.05*	-6.90	0.69***	-2.45	-1.55	-7.46*
	12 Months	-36.64	-0.08*	-0.60	0.77***	-7.61	-593.00	-523.95	-283.62	1.02***	-1.06	-0.14	-24.66	-4.75	-3.20	-82.57	-25.70
Oranges	1 Month	-6.61	-0.54	-0.47	-1.77	-1.69	-14.29***	-9.62***	-7.82***	-0.83	-0.89	-0.44	-12.79	-1.54	-4.28	-4.97	-4.01**
	12 Months	-40.78	-0.18	-1.45	-1.18	2.61***	-34.61**	-19.66**	5.52***	-0.33	-1.51	0.52***	-47.54	0.87***	-26.28	-73.04	-26.02
Soybean Oil	1 Month	-12.74	0.88***	-1.22	-1.11	-3.65	-69.54	-69.79	-35.95	0.43***	-1.04	-0.40	-6.54	-4.46	-4.32	-13.42	-24.37
	12 Months	-126.18	0.33***	-1.56	-0.33	-28.02	-3,585.18	-3,655.07	-75.57	-0.67	-0.18	-0.39	-47.40	-42.79	-1.87	-85.02	-101.25
Soybeans	1 Month	-5.84*	0.35***	-0.54	-0.56	-3.71	-35.63**	-38.87**	-13.24**	1.29***	-0.78	-0.72	-4.40	-1.61	-1.18*	-5.83	-7.22*
	12 Months	-23.53	0.91***	-1.28	-0.30	-3.64	-284.70	-333.68	-51.57	0.04**	0.69***	-0.38	-49.36	-20.97	-2.38	-21.31	-16.93
Soybean Meal	1 Month	-10.07	-1.12	-0.55	-0.85	-1.57	-25.19**	-44.14*	-8.90**	-0.40	-1.18	-0.33	-2.15**	-1.71	-0.95**	-9.90	-1.92**
	12 Months	-49.99	-1.10	-1.96	-0.27	-20.17	-156.87	-155.86	-57.49	0.11**	-0.81	-0.37	-34.80	-13.18	-11.81	-35.88	-11.11

CHAPTER 4. PREDICTABILITY IN COMMODITY MARKETS:
EVIDENCE FROM MORE THAN A CENTURY

Table C.13: Restricted Return Predictability (continued)

Commodity	Horizon	de	$\Delta \ln \text{dopro}$	$\Delta M1$	dfr	dfl	dp	dy	ep	erp	infl	ltr	lty	svar	tbl	tms	unrate
Sugar	1 Month	-5.47*	-0.94	-1.19	-0.76	-12.64	-241.52	-546.95	-82.48	-0.87	0.06**	-0.55	-8.54	-1.88	-3.82	-3.66	-4.18**
	12 Months	-124.41	-0.91	-0.79	-0.76	-47.45	-2,168.23	-1,497.37	-534.08	-1.20	0.17***	-0.82	-73.02	-2.07	-29.24	-11.23	-27.11
Wheat	1 Month	-9.90	-0.66	-1.19	-1.42	-4.78	-79.93*	-61.97**	-45.08	-0.26	-0.94	-0.99	-11.21	-2.08	-2.44	-5.87	-16.61
	12 Months	-98.06	2.58***	-1.30	-0.39	-31.94	-658.70	-649.53	-394.82	-0.49	-1.59	-0.27	-83.64	-7.84	-1.98	-26.83	-94.31
Wool	1 Month	-55.23	1.82***	-0.31	0.67***	-25.70	-42.80**	-52.23*	-27.39*	2.10***	-2.55	0.93***	24.58	-2.89	-2.27	-2.72	-4.16*
	12 Months	-45.01	0.75***	-0.42	0.11**	-6.19	-247.28	-369.82	-134.45	0.00**	-2.07	-0.40	-34.82	-5.76	-6.00	-2.57	-14.79
Yellow Corn	1 Month	-7.38	-0.09*	-0.48	-0.80	-3.49	-66.05*	-63.82**	-74.35	-0.77	-1.14	-0.24	-4.01	-1.29	-1.91	-7.64	-16.48
	12 Months	-64.54	0.33***	0.80***	-0.64	-17.81	-356.76	-393.05	-628.47	-0.52	-2.12	-0.30	-71.04	-19.48	-0.15***	-22.56	-91.88
Coal	1 Month	-6.81	-1.36	-1.26	-0.29	-4.86	-160.65	-155.43	-44.23	-0.09	1.04***	-0.43	-16.00	0.37***	-0.18***	-2.12	-17.72
	12 Months	-24.75	-0.18	0.42**	-0.72	-85.10	-720.66	-851.49	-349.71	-0.44	2.88***	-0.55	-65.19	-12.19	-12.23	-15.12	-184.07
Heating Oil	1 Month	-1.83	-0.16	-0.94	0.59**	-0.48	-25.50*	-12.88**	-23.43	0.13*	-1.12	-0.74	-8.59	-0.23	-1.56	-1.07	-0.98***
	12 Months	-42.78	-0.20	-0.88	-0.36	-67.25	-153.29	-183.88	-136.14	-0.45	0.04	-0.41	-7.10	-5.61	-10.87	-9.17	-26.26
Natural Gas	1 Month	-4.18	2.35***	-2.43	-1.58	-2.79	-23.04	-13.99	-4.64*	-1.08	-2.51	-0.33	-12.52	-6.45	-3.41	-0.28	-1.92**
	12 Months	-33.72	-0.93	-0.14	-0.21	-33.30	-114.46	-104.52	-54.13	-0.48	-0.75	-0.62	-156.93	-0.79	-5.00	-3.74	1.08***
Unleaded Regular Gas	1 Month	-5.37	-1.90	-2.69	0.54**	-8.41	-4.59**	-19.65	-9.45	-0.14	-2.09	-1.13	-6.87	-2.10	-2.16	-0.83	-2.11**
	12 Months	-32.89	-1.71	-0.18	-0.45	-83.97	-216.60	-290.85	-94.09	-0.86	3.97***	-0.53	10.06***	-4.11	0.50**	-2.79	-45.94
WTI Oil	1 Month	-2.59***	0.23**	-1.02	-0.17	-9.71	-232.92	-246.75	-87.73	-0.41	-0.11**	1.40***	-19.19	-0.26*	-2.99	-3.38	-2.16***
	12 Months	-33.92	0.82***	-1.39	-0.46	-30.96	-668.42	-662.03	-249.03	-0.26	0.61***	-0.94	-48.14	-2.70	-39.62	-15.91	-26.89
Aluminium	1 Month	-15.11	-0.31	-0.53	0.14**	-5.18	-73.76	-56.69*	-38.50	-0.56	-0.56	-0.03*	-20.53	0.70***	-4.76	-0.34**	-7.45*
	12 Months	-91.40	-1.49	-1.69	-0.06*	-35.46	-698.40	-3,451.18	-164.21	-0.70	-0.98	0.39***	-71.45	-10.41	-27.87	2.93***	-30.17
Gold	1 Month	-8.16	-0.84	-1.04	-0.48	-14.27	-189.34	-261.72	-102.91	-0.80	-0.78	-0.61	-5.21	-0.22*	0.06***	-1.64	-70.04
	12 Months	-38.21	0.68***	0.28**	-0.53	-170.01	-715.10	-703.16	-324.97	-0.07**	-1.10	-0.64	-49.45	-11.31	2.73***	-7.19	-540.53
High Grade Copper	1 Month	-3.36**	-0.08*	-1.07	-0.61	-5.07	-52.94**	-54.26**	-16.48***	0.76***	-0.32	-0.98	-8.37	-5.31	-0.27***	-2.46	-19.08
	12 Months	-16.17	0.03**	0.62***	-0.83	-9.92	-981.72	-1,050.91	-68.13	0.31***	0.05**	-0.56	-6.85	-1.96	9.19***	-7.19	-46.19
Nickel	1 Month	-1.79	-0.11	-0.92	-1.29	-14.75	-181.14	-279.74	-32.42	-1.00	-0.81	-1.27	-11.87	-1.36	-2.49	-1.92	-26.64
	12 Months	-23.92	-4.72	-1.11	-1.32	6.07***	-1,452.39	-1,442.26	-29.39	-0.31	0.28*	-1.24	-4.63	1.69***	-16.21	-5.77	-97.05
Palladium	1 Month	-19.11	-0.87	-1.25	-0.38	-4.68	-64.49	-70.38	-29.36	-0.58	-0.21	-0.88	-21.31	-14.38	-4.34	-1.13	-40.29
	12 Months	-15.22	-3.56	-2.46	-0.04	-79.11	-3,197.18	-3,662.42	-201.04	-0.19	-0.43	-2.27	-61.95	-7.85	-1.07	-3.34	-181.47
Platinum	1 Month	-7.28	0.15**	-1.64	0.23**	-5.74	-36.15**	-38.26**	-6.01***	-0.58	-0.14*	-1.15	-14.71	-7.56	-2.14	-10.60	-7.27*
	12 Months	-24.71	-0.38	-0.52	-0.92	-43.53	-623.77	-677.37	-26.22*	-0.97	-1.51	-0.96	-44.13	-4.52	3.08***	-49.22	-118.77
Silver	1 Month	-7.87	-0.63	-0.95	0.30**	-4.62	-185.54	-267.73	-83.51	-0.59	-1.46	-0.72	-5.22	-1.78	-1.94	-3.55	-19.81
	12 Months	-37.86	-0.29	-2.40	-0.45	-19.39	-1,561.80	-1,478.33	-409.32	-0.51	-1.72	-0.49	-41.81	-4.46	-7.65	-13.83	-211.19
Tin	1 Month	-3.54***	-0.81	0.43**	-0.34	-8.81	-78.51	-138.53	-75.11	0.50***	-0.94	-0.55	-16.23	-2.91	-1.11**	-4.01	-18.86
	12 Months	-41.30	0.35***	0.56***	-0.30	-7.09	-1,226.67	-1,490.01	-175.33	-0.52	-0.76	-0.74	-78.17	-3.08	6.46***	-6.33	-26.37
Zinc	1 Month	-5.08**	-1.00	-0.37	-1.04	-7.23	-91.25	-162.25	-33.18*	0.72***	-0.67	-0.27	-11.57	-5.18	-2.20	-8.18	-14.61
	12 Months	-18.68	-0.98	-0.94	-0.82	-7.25	-1,307.80	-1,312.07	-127.85	-1.03	-0.48	-0.84	-33.51	-4.73	0.19***	-9.71	-71.80

Table C.14: Restricted Volatility Predictability

This table reports the out-of-sample R^2 s of predicting monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable after imposing an economically motivated restriction. We predict the next month's and the next year's volatility. Statistical inferences are based on a bootstrapped distribution. Following Campbell & Thompson (2008), we impose the restriction that we set the out-of-sample slope estimate equal to zero whenever it is different to that of the in-sample estimate. All data are sampled at the monthly frequency. "de" denotes the dividend-payout ratio, " $\Delta indpro$ " the growth of industrial production, and " $\Delta M1$ " the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "swar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency.

Commodity	Horizon	de	$\Delta indpro$	$\Delta M1$	dfr	dfy	dp	dy	ep	erp	infl	ltr	lty	swar	tbl	tms	unrate
Butter	1 Month	-9.42	0.01	-2.18	-0.63	-9.26	-376.03	-490.25	-241.99	-0.83	0.18**	-0.52	-63.66	-2.02	-14.25	-4.92	-1.23
	12 Months	-77.31	-0.39	0.17*	-0.70	-10.08	-1,085.76	-1,209.26	-915.19	-0.55	0.05	-0.83	-171.99	-5.76	-17.09	-16.84	-60.60
Cocoa	1 Month	-8.41	-0.56	-1.31	-0.56	-5.23	-731.29	-814.25	-493.59	-0.51	-0.01	-0.73	-105.08	-0.70	-11.97	-10.96	-9.76
	12 Months	-67.18	-0.77	-2.26	-0.29	-30.61	-270.32	-266.84	-223.58	-0.56	-1.18	-0.67	-196.15	-13.50	-15.68	-45.77	-34.70
Coffee Arabica	1 Month	-0.37	-0.86	-0.41	0.08	-35.84	-244.57	-236.61	-56.40	-0.21	-0.25	-0.12	-78.47	-5.33	-9.25	-0.60	-39.90
	12 Months	-36.34	-0.80	-1.17	-0.62	-36.74	-365.36	-399.80	-178.60	-0.74	-0.76	-0.60	-25.49	-47.41	-2.62	2.33***	-8.80
Corn Oil	1 Month	-62.05	-0.13	-3.34	-0.28	-0.36	-308.30	-253.18	-235.84	0.00	-2.18	-0.29	-77.04	-0.20	-5.06	-4.20	-5.45
	12 Months	-204.90	0.36***	-0.82	-0.96	-5.96	-226.81	-257.16	-227.05	-0.74	-1.70	-0.87	-31.16	-33.13	-15.30	-13.07	-57.68
Cotton	1 Month	-71.16	-0.49	0.47***	-0.71	-5.47	-145.08	-168.46	-49.40	-0.49	-0.44	-0.08	-48.15	-2.04	-8.98	-2.41	-7.96
	12 Months	-159.45	0.29**	0.34***	-0.46	-9.50	-405.05	-348.88	-282.66	-0.11	-0.29	-0.77	-287.55	-8.54	-41.01	-3.01	-15.13
Live Cattle	1 Month	-190.69	-0.73	-0.58	-0.03	-6.45	-88.68	-128.53	-186.96	-0.16	-3.89	-0.49	-136.08	-9.92	-10.33	-53.96	-48.34
	12 Months	-20.00	-0.16	-0.24	-0.61	-7.94	-734.73	-802.09	-333.04	-0.22	-2.23	-0.45	-32.42	-13.47	-5.87	-64.34	-84.35
Lean Hog	1 Month	-35.76	-0.97	-0.96	-0.72	-5.80	-628.86	-579.82	-304.53	-0.47	0.36***	-1.40	-38.95	-2.09	-17.80	-2.80	-4.33
	12 Months	-14.06	-1.03	-0.75	-0.49	-37.46	-212.50	-209.59	-281.05	0.00	-0.71	-0.96	-86.69	-3.54	-2.31	-5.54	-5.73
Milk	1 Month	-12.16	-0.62	-0.03	-0.54	-5.60	-786.28	-138.38	-68.65	-0.42	-1.21	-0.57	-226.83	-3.00	-5.20	-7.15	-7.47
	12 Months	-39.77	-0.83	-0.44	-0.34	-13.92	-628.86	-723.06	-536.87	-0.82	-1.08	-0.83	-244.81	-4.69	-7.22	-4.16	-5.94
Oranges	1 Month	-9.44	-1.25	-1.45	-0.61	-1.57	-12.43	-9.80	-9.68	0.39***	-0.79	-0.80	-27.16	-1.50	-3.43	-5.80	-11.37
	12 Months	-35.38	-0.92	-1.18	-0.29	-17.05	-65.95	-76.85	-9.40	-0.28	-1.61	-0.26	-23.87	-0.91	-10.03	-3.04	-53.09
Soybean Oil	1 Month	-6.14	-0.55	-1.22	-0.90	-7.02	-123.63	-748.81	-83.64	-0.78	-0.55	-0.84	-94.03	-1.15	-7.19	-4.28	-9.92
	12 Months	-63.28	-0.81	-0.88	-0.90	-9.59	-196.78	-249.34	-85.34	-0.68	0.18**	-0.72	-37.90	-18.71	-9.38	-24.54	-44.07
Soybeans	1 Month	-3.34	-0.78	-0.98	-0.71	-4.30	-276.93	-176.31	-84.45	0.79***	-0.42	-0.30	-44.27	-3.24	-4.75	-2.93	-24.62
	12 Months	-5.24	0.08*	-0.07	-0.28	-12.57	-207.55	-235.38	-72.66	-0.16	-1.38	0.12*	-19.80	-11.55	-2.86	-3.99	-20.24
Soybean Meal	1 Month	-1.97	-0.38	-0.95	-0.65	-3.68	-122.80	-160.20	-31.49	-0.60	1.14***	-0.38	-22.94	0.27**	-8.92	-4.02	-31.58
	12 Months	-257.35	0.21**	-0.07	-0.54	-11.43	-395.07	-484.53	-261.60	-0.75	-0.67	-0.17	-29.14	4.19***	-9.44	-25.24	-32.68

CHAPTER 4. PREDICTABILITY IN COMMODITY MARKETS:
EVIDENCE FROM MORE THAN A CENTURY

Table C.14: Restricted Volatility Predictability (continued)

Commodity	Horizon	de	$\Delta \ln dpro$	ΔMI	df _r	df _y	dp	dy	ep	erp	infl	ltr	lty	svar	tbl	tms	umrade
Sugar	1 Month	-5.51	-0.01	0.25**	-0.33	-5.98	-328.80	-330.36	-61.38	-0.23	-1.85	-0.18	-31.17	-5.74	-7.79	-4.36	-8.55
	12 Months	-132.45	-0.08	-1.02	-0.89	-22.35	-1,665.31	-2,144.84	-287.61	-0.83	0.26***	-0.83	-200.52	-1.55	-27.12	-8.86	-56.26
Wheat	1 Month	-52.33	-1.00	0.39**	-0.78	-2.20	-232.52	-215.73	-85.16	-0.81	-3.92	-0.29	-15.94	-1.77	-3.08	-0.62	-3.40
	12 Months	-101.09	-0.07	-0.76	-0.87	-3.19	-666.81	-641.21	-241.23	-0.38	-2.56	-1.05	-247.23	-1.46	-19.30	-10.35	2.86***
Wool	1 Month	-12.79	-0.01	-1.92	1.90***	-3.20	-421.28	-586.82	-34.36	0.36***	0.28***	-0.90	-21.32	-1.54	-3.78	-4.00	-6.08
	12 Months	-69.43	1.00***	0.84***	-0.29	-5.39	-968.93	-842.44	-187.43	-0.16	-0.52	-0.72	-164.31	-1.83	-10.59	-7.26	-7.74
Yellow Corn	1 Month	-27.38	-1.07	-0.38	-0.06	-5.55	-116.73	-142.01	-128.02	-0.29	0.43***	-0.45	-45.24	-0.40	-7.29	-3.45	-19.44
	12 Months	-40.22	-2.73	-0.69	-0.20	-11.43	-754.06	-736.34	-220.30	-1.07	-0.32	0.06	-369.12	-8.68	-1.76	-88.01	-50.53
Coal	1 Month	-27.29	-0.79	-3.79	-0.75	-0.27	-2,334.74	-2,407.17	-172.71	-0.68	-0.21	-0.71	-83.64	0.81***	2.18***	-1.07	-17.40
	12 Months	-23.71	-0.31	-1.92	-1.40	-3.42	-277.31	-215.74	-135.95	-0.37	-0.90	-1.08	-58.74	-35.33	-6.17	-1.37	-32.99
Heating Oil	1 Month	-57.24	0.31*	-0.10	-0.17	1.47***	-429.44	-435.15	-61.80	-0.65	-1.70	-0.17	-25.35	-0.20	-39.29	-2.07	-1.81
	12 Months	-191.05	-0.79	-0.66	-0.35	1.74***	-351.43	-462.84	-74.48	-1.70	-0.21	1.06***	-71.95	-69.28	-31.96	-14.38	-3.21
Natural Gas	1 Month	-19.80	-0.47	-2.96	-0.56	-13.64	-221.80	-79.34	1.97***	2.62***	-2.94	-0.66	0.49*	2.91***	-6.78	1.67***	-5.68
	12 Months	3.30***	0.01	2.92***	-1.44	7.70***	0.70	-1.01	4.11***	-0.63	-0.36	-2.24	-10.47	2.94***	5.35***	5.57***	1.63*
Unleaded Regular Gas	1 Month	-15.52	2.14***	-0.37	1.13***	4.37***	-868.00	-805.62	-53.92	1.69***	-1.65	0.23*	-6.17	1.83***	-13.51	-0.57	-6.01
	12 Months	-20.68	-0.66	0.15	-0.40	3.99***	-420.00	-367.45	-24.95	-0.64	-3.12	0.02	-72.46	-54.46	-8.75	-4.31	-9.60
WTI Oil	1 Month	-41.98	-0.22	-0.76	-0.41	-4.35	-867.08	-842.69	-363.66	-1.15	-1.10	0.48***	-78.08	0.26***	-11.41	-4.46	-95.32
	12 Months	-98.86	-0.34	0.63***	0.10*	-1.73	-1,226.40	-1,054.91	-279.70	-1.00	0.15**	0.09**	-203.06	-41.79	-39.09	-8.91	-3.89
Aluminium	1 Month	-8.31	0.42***	1.18***	-0.90	-24.48	-2,165.14	-2,292.31	-462.27	-0.98	0.46***	-0.52	-69.55	-0.48	-4.64	-8.71	-124.55
	12 Months	-28.44	-0.90	0.38**	-0.65	-14.73	-46.25	-47.53	-55.87	-0.49	-6.83	-0.85	-262.87	-13.03	-86.59	-3.47	-35.66
Gold	1 Month	-9.10	0.39***	-1.46	-1.23	3.14***	-2,055.69	-2,209.92	-370.46	-1.30	0.37***	0.07	-57.19	-28.33	1.95***	-17.61	-2.00
	12 Months	-297.15	-0.96	0.70***	-0.41	-13.83	-1,952.87	-1,940.73	-445.08	-0.55	-0.27	-1.05	-35.28	-7.61	-2.14	-7.64	-8.88
High Grade Copper	1 Month	-12.59	-0.78	-2.02	-0.56	-1.96	-566.80	-514.03	-170.42	-0.45	-1.44	-1.06	-30.78	-6.33	-2.52	-7.79	-63.37
	12 Months	-49.84	-0.55	-3.58	-0.44	-6.85	-745.00	-607.07	-458.87	-0.22	-0.72	-0.03	-197.52	-15.53	-12.96	-4.49	-48.48
Nickel	1 Month	-4.43	1.74***	0.53**	-0.92	-1.67	-606.30	-682.05	-381.36	1.47***	2.45***	1.34***	-23.01	2.87***	-18.08	-1.58	-39.38
	12 Months	-6.73	-0.68	-0.42	-1.19	-35.61	-169.49	-137.29	-11.86	-0.35	-2.10	-0.60	-2.47	-4.25	-0.75	0.46	-109.64
Palladium	1 Month	-49.25	1.90***	-0.51	-1.49	1.03**	-310.03	-301.06	-21.04	-0.33	-0.84	-0.78	-11.88	-1.12	-2.18	0.48**	-0.07
	12 Months	-34.65	0.23*	-2.28	-1.19	-23.39	-969.33	-1,288.03	-22.41	-0.62	-1.72	-0.04	-3.34	-0.37	0.92**	0.54*	-13.33
Platinum	1 Month	-16.76	-0.34	0.15*	-0.27	-7.03	-150.42	-178.22	-24.97	0.66***	0.07*	-0.43	-120.95	-1.40	-6.37	-6.20	-30.74
	12 Months	-18.37	-0.53	-0.51	-0.96	-16.62	-461.00	-504.64	-219.88	-1.05	-0.27	-1.30	-258.24	-8.96	-14.60	-56.87	-36.16
Silver	1 Month	-8.70	-0.96	-0.69	-0.71	-4.06	-625.22	-712.71	-166.43	-0.58	-0.49***	-0.60	-76.82	-28.13	-1.55	-6.24	2.56***
	12 Months	-28.75	-1.27	-2.57	-0.40	-12.46	-1,318.34	-1,548.13	-164.88	-0.25	-0.19	-1.39	-9.90	-3.86	-12.34	-6.51	-49.39
Tin	1 Month	-3.20	-0.89	2.60***	-0.75	-21.23	-694.33	-714.26	-221.53	-0.65	-1.22	-0.98	-51.60	-2.36	-11.52	-4.16	-10.97
	12 Months	-34.24	-1.10	-0.62	-0.78	-18.94	-226.25	-229.43	-404.69	-0.55	-1.36	-0.90	-374.51	-14.58	-8.71	-15.19	-72.92
Zinc	1 Month	-6.50	-0.67	-0.51	-0.43	-7.07	-769.05	-731.14	-359.84	-0.76	-0.58	-0.18	-82.85	-15.94	-8.61	-18.89	-16.24
	12 Months	-7.04	-1.11	-1.00	-0.61	-12.51	-520.88	-496.93	-143.33	-1.13	-1.41	0.32**	-120.64	-2.19	-14.17	-30.52	-70.24

C. APPENDIX

Table C.15: Summary Return and Volatility Predictability from 1950

This table reports a summary of the regression results of monthly excess returns on a constant and the lagged predictive variable (Panel (A) and (B)), and the regression results of monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable (Panel (C) and (D)). In Panel (A) and (B), we report the percentage of significant in-sample and out-of-sample R^2 s across the variables of predicting the next month's and next year's excess return. In Panel (C) and (D), we report the percentage of significant in-sample F -statistics of the difference between the adjusted R^2 s of the unrestricted and restricted model, and out-of-sample R^2 s across the variables of predicting the next month's and next year's volatility. "de" denotes the dividend–payout ratio, " $\Delta indpro$ " the growth of industrial production, and " $\Delta M1$ " the growth of money supply $M1$. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend–price ratio, "dy" the dividend yield, "ep" the earnings–price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. All data are sampled at the monthly frequency. The sample period is from January 1950 to December 2015.

Panel (A): Return Predictability (1 Month)				Panel (B): Return Predictability (12 Months)			
In-Sample		Out-of-Sample		In-Sample		Out-of-Sample	
dfr	50.00	dfr	20.00	lty	90.00	tbl	73.33
svar	36.67	$\Delta indpro$	16.67	ep	86.67	dfy	53.33
$\Delta indpro$	33.33	$\Delta M1$	10.00	tbl	86.67	lty	50.00
ltr	30.00	infl	10.00	dp	76.67	infl	36.67
$\Delta M1$	26.67	ltr	10.00	dy	73.33	tms	36.67
tbl	23.33	erp	6.67	tms	60.00	de	26.67
infl	16.67	svar	3.33	unrate	53.33	$\Delta M1$	26.67
tms	16.67	tms	3.33	de	50.00	dy	26.67
de	13.33	de	0.00	infl	50.00	unrate	26.67
erp	13.33	dfy	0.00	$\Delta indpro$	40.00	ep	23.33
dp	10.00	dp	0.00	dfy	33.33	dp	20.00
dy	10.00	dy	0.00	svar	33.33	erp	16.67
ep	6.67	ep	0.00	$\Delta M1$	26.67	$\Delta indpro$	13.33
dfy	3.33	lty	0.00	dfr	26.67	dfr	6.67
lty	3.33	tbl	0.00	erp	13.33	ltr	3.33
unrate	0.00	unrate	0.00	ltr	13.33	svar	0.00

Panel (C): Volatility Predictability (1 Month)				Panel (D): Volatility Predictability (12 Months)			
In-Sample		Out-of-Sample		In-Sample		Out-of-Sample	
dp	66.67	infl	43.33	de	50.00	tms	23.33
dy	66.67	dp	40.00	dfy	40.00	dfy	20.00
ep	60.00	dy	40.00	tms	40.00	ep	16.67
infl	60.00	lty	40.00	svar	36.67	dp	13.33
dfy	56.67	dfy	36.67	tbl	3.33	tbl	13.33
unrate	53.33	unrate	26.67	unrate	26.67	unrate	13.33
svar	50.00	erp	23.33	dp	23.33	de	10.00
lty	46.67	$\Delta indpro$	20.00	dy	23.33	$\Delta indpro$	10.00
tbl	46.67	ep	20.00	$\Delta indpro$	20.00	ltr	10.00
de	43.33	tbl	20.00	dfr	16.67	$\Delta M1$	6.67
tms	33.33	de	16.67	$\Delta M1$	13.33	dy	6.67
erp	30.00	$\Delta M1$	6.67	ep	13.33	infl	6.67
$\Delta M1$	26.67	ltr	6.67	erp	13.33	svar	6.67
$\Delta indpro$	20.00	svar	6.67	infl	13.33	dfr	0.00
dfr	13.33	dfr	3.33	ltr	13.33	erp	0.00
ltr	10.00	tms	3.33	lty	0.00	lty	0.00

Table C.16: Return Predictability from 1950 (1 Month)

This table reports the regression results of monthly excess returns on a constant and the lagged predictive variable(s). We predict the next month's excess return. Statistical inferences are based on a bootstrapped distribution. "de" denotes the dividend-payout ratio, "Δindpro" the growth of industrial production, and "ΔM1" the growth of money supply M1. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "suar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. "MSA" and "MFC" denote the model selection approach and mean forecast combination. R^2 and R_{OOS}^2 are the in-sample and out-of-sample R^2 , respectively. We report the t-statistics in parentheses. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency. The sample period is from January 1950 to December 2015.

Commodity	Statistic	de	Δindpro	ΔM1	dfr	dfy	dp	dy	ep	erp	infl	ltr	lty	suar	tbl	tms	unrate	MSA	MFC	
Butter	R^2	0.35*	0.00	1.40***	0.03	0.14	0.52**	0.42*	0.09	0.47*	0.82**	0.01	0.10	0.62**	0.11	0.02	0.00			
	R_{OOS}^2	-1.49	-0.98	0.54***	-0.75	-1.35	-2.62	-2.51	-1.84	-0.71	0.00**	-1.93	-2.15	-1.11	-1.34	-0.77	-1.62	-17.55	-0.41	
	t-stat	(-1.68)	(0.02)	(-3.35)	(0.47)	(-1.05)	(-2.02)	(-1.83)	(-1.98)	(-0.84)	(1.98)	(2.55)	(-0.32)	(-0.87)	(-2.21)	(-0.95)	(0.37)	(-0.09)		
Cocoa	R^2	0.11	0.37*	0.15	0.24	0.02	0.03	0.05	0.17	0.10	0.00	0.04	0.26	0.00	0.49*	0.28	0.01			
	R_{OOS}^2	-2.83	-1.36	-1.25	-0.96	-2.35	-1.98	-1.97	-2.83	-1.43	-2.56	-1.11	-2.19	-2.84	-0.55**	-0.42*	-1.36	-18.56	-1.49	
	t-stat	(0.92)	(1.72)	(-1.09)	(1.37)	(-0.43)	(-0.32)	(-0.62)	(-1.14)	(-0.90)	(0.12)	(0.59)	(-1.48)	(-0.13)	(-1.96)	(1.49)	(-0.32)			
Coffee Arabica	R^2	0.07	0.56*	0.01	0.34	0.00	0.00	0.00	0.05	0.00	0.12	0.13	0.01	0.00	0.43*	0.38	0.00			
	R_{OOS}^2	-1.77	-0.60	-2.20	-0.30	-1.65	-2.32	-2.43	-2.75	-0.81	-1.23	-1.05	-1.76	-0.87	-1.09	0.85***	-0.76*			
	t-stat	(0.68)	(1.94)	(0.23)	(1.51)	(0.00)	(-0.09)	(-0.11)	(-0.58)	(-0.02)	(0.88)	(-0.93)	(-0.25)	(-0.57)	(-1.71)	(3.21)	(1.59)			0.46**
Corn Oil	R^2	0.01	0.21	0.00	1.05***	0.07	0.01	0.00	0.03	0.22	0.00	0.43*	0.09	0.15	0.08	0.00	0.00			
	R_{OOS}^2	-3.77	-2.61	(0.02)	-0.76	-2.27*	-1.66	-1.42	-2.22	-1.23	-0.60	-1.62	-2.49	-8.17	-2.59	-2.80	-2.63	-18.02	-2.28	
	t-stat	(0.32)	(1.30)	(0.02)	(2.89)	(-0.77)	(-0.29)	(-0.16)	(-0.50)	(1.32)	(-0.08)	(-1.84)	(-0.85)	(-1.10)	(-0.81)	(0.11)	(0.03)			
Cotton	R^2	0.01	0.11	0.18	0.00	0.12	0.01	0.00	0.04	0.55**	0.00	0.06	0.12	0.00	0.31	0.30	0.14			
	R_{OOS}^2	-3.46	-0.40	-1.23	-2.25	-1.16	-1.70	-1.85	-2.67	-0.64	-1.18	-1.00	-1.45	-4.36	-0.71*	-1.08	-1.09	-17.22	-1.42	
	t-stat	(0.34)	(0.92)	(-1.19)	(-0.08)	(0.97)	(-0.31)	(-0.11)	(-0.53)	(2.09)	(-0.13)	(0.71)	(-0.97)	(-0.15)	(-1.57)	(1.55)	(1.06)			
Live Cattle	R^2	0.16	0.00	0.10	0.72**	0.02	0.17	0.15	0.02	0.07	0.03	0.16	0.18	0.08	0.45*	0.10	0.10			
	R_{OOS}^2	-2.07	-1.01	-1.04	-0.08*	-2.42	-2.40	-2.42	-2.71	-0.64	-0.48	-1.62	-1.89	-1.30	-1.09	-0.67	-1.04	-17.14	-1.47*	
	t-stat	(-1.14)	(-0.05)	(0.91)	(2.39)	(-0.42)	(-1.15)	(-1.08)	(-0.35)	(0.76)	(0.45)	(-1.13)	(-1.18)	(-0.78)	(-1.89)	(1.84)	(0.88)			
Lean Hog	R^2	0.04	0.00	0.00	0.12	0.01	0.07	0.09	0.02	0.08	0.04	0.04	0.04	0.08	0.09	0.06	0.02			
	R_{OOS}^2	-2.05	-0.79	-1.03	-0.70	-3.22	-2.77	-2.36	-3.39	-1.11	-0.11*	-0.65	-2.81	-2.24	-1.47	-1.00	-1.34	-16.64	-2.39	
	t-stat	(0.55)	(0.07)	(-0.06)	(0.99)	(-0.22)	(-0.77)	(-0.84)	(-0.73)	(0.81)	(-0.54)	(-0.78)	(-0.54)	(-0.57)	(-0.78)	(0.71)	(-0.35)			
Milk	R^2	0.41*	0.42*	1.18***	0.48**	0.82***	0.19	0.13	0.00	0.67**	1.09***	1.09***	0.27	1.41***	0.16	0.02	0.00			
	R_{OOS}^2	-2.27	0.06**	0.28***	-0.83	-0.28**	-1.60	-1.78	-2.02	0.04**	0.02**	0.02**	-2.80	0.52***	-1.70	-1.06	-1.45	-9.26**	3.00***	
	t-stat	(-1.80)	(1.83)	(-3.07)	(1.96)	(-2.55)	(-1.24)	(-1.01)	(0.02)	(2.31)	(4.45)	(-2.96)	(-4.46)	(-3.36)	(-1.11)	(-0.42)	(0.09)			
Oranges	R^2	0.08	0.02	0.00	0.03	0.05	0.57**	0.63**	0.31	0.18	0.01	0.06	0.04	0.00	0.03	0.00	0.08			
	R_{OOS}^2	-2.37	-0.90	-1.02	-1.88	-1.37	-1.84	-2.28	-1.47	-1.84	-1.46	-0.56	-1.89	-2.41	-1.61	-1.74	-1.73	-12.96	-0.72	
	t-stat	(0.77)	(-0.38)	(-0.17)	(0.46)	(-0.64)	(-2.13)	(-2.24)	(-1.56)	(-1.19)	(-0.23)	(-0.67)	(-0.54)	(-0.09)	(-0.50)	(0.04)	(-0.78)			
Soybean Oil	R^2	0.00	0.14	0.02	0.01	0.09	0.03	0.04	0.03	0.18	0.11	0.02	0.05	0.01	0.09	0.05	0.00			
	R_{OOS}^2	-3.16	-1.43	-1.48	-2.30	-2.81	-2.33	-1.92	-3.09	-1.04	-1.65	-0.41	-2.62	-5.46	-1.60	-1.69	-2.96	-18.64	-0.50	
	t-stat	(0.04)	(1.07)	(0.37)	(0.32)	(-0.82)	(-0.45)	(-0.57)	(-0.46)	(-1.19)	(0.92)	(-0.40)	(-0.61)	(-0.31)	(-0.83)	(0.63)	(-0.06)			
Soybeans	R^2	0.02	0.00	0.05	0.06	0.00	0.06	0.06	0.09	0.08	0.05	0.07	0.18	0.11	0.43*	0.37**	0.02			
	R_{OOS}^2	-4.05	-1.25	-1.00	-1.28	-1.38	-1.78	-1.73	-3.41	-0.58	-1.75	-0.68	-1.66	-1.56	-0.55**	-0.27**	-1.72	-16.07	-2.38	
	t-stat	(0.35)	(0.01)	(0.61)	(0.66)	(0.17)	(-0.63)	(-0.71)	(-0.85)	(-0.77)	(-0.63)	(-0.75)	(-1.20)	(-0.93)	(-1.85)	(1.71)	(-1.71)			
Soybean Meal	R^2	0.03	0.03	0.21	0.01	0.07	0.02	0.02	0.06	0.00	0.13	0.02	0.18	0.07	0.36*	0.22	0.03			
	R_{OOS}^2	-4.09	-1.39	-0.92	-1.21	-1.17	-2.25	-2.21	-1.19	-0.96	-1.78	-0.81	-2.19	-2.50	-1.20	-0.10**	-1.28	-16.54	-3.23*	
	t-stat	(0.46)	(-0.40)	(1.30)	(0.29)	(0.76)	(-0.37)	(-0.40)	(-0.67)	(-0.17)	(-1.02)	(-0.42)	(-1.20)	(-0.73)	(-1.68)	(1.32)	(-0.92)			

Table C.17: Return Predictability from 1950 (12 Months) (continued)

Table with columns: Commodity, Statistic, de, Δndpro, ΔMI, dfr, dfy, dp, dy, ep, err, infl, ltr, lty, svar, tbl, tms, unrate, MSA, MFC. Rows include commodities like Sugar, Wheat, Wool, Yellow Corn, Coal, Heating Oil, Natural Gas, Unleaded Regular Gas, WTI Oil, Aluminum, Gold, High Grade Copper, Nickel, Palladium, Platinum, Silver, Tin, and Zinc, each with multiple statistical values and significance markers.

Table C.18: Volatility Predictability from 1950 (1 Month) (continued)

Table with columns: Commodity, Statistic, de, Δindpro, ΔM1, dfr, dfy, dp, dy, ep, erp, infl, ltr, lty, svar, tbl, tms, unrate, MSA, MFC. Rows are grouped by commodity (Soybean Meal, Sugar, Wheat, Wood, Yellow Corn, Coal, Heating Oil, Natural Gas, Unleaded Regular Gas, WTI Oil, Aluminum, Gold, High Grade Copper, Nickel, Palladium, Platinum, Silver, Tin, Zinc) and include sub-rows for ΔR2, R2, and t-stat.

Table C.19: Volatility Predictability from 1950 (12 Months)

This table reports the regression results of monthly volatilities on a constant, the lagged volatility, and the lagged predictive variable(s). We predict the next year's volatility. Statistical inferences are based on a bootstrapped distribution. "de" denotes the dividend-payout ratio, " Δindpro " the growth of industrial production, and " $\Delta M1$ " the growth of money supply M1. "dfr" is the default return ratio, "spread" the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default return spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dp" is the dividend-price ratio, "dy" the dividend yield, "ep" the earnings-price ratio, "erp" the market risk premium, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, "svar" the stock variance, and "tbl" the 3-month Treasury bill rate. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. "MSA" and "MFC" denote the model selection and restricted model, and the combination. ΔR^2 and R_{cons}^2 are the in-sample difference between the adjusted R^2 s of the unrestricted and restricted model, and the out-of-sample R^2 , respectively. We report the t-statistics of the respective predictive variables in parentheses. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. We split the commodities into the agricultural, energy, and metal sector. All data are sampled at the monthly frequency. The sample period is from January 1950 to December 2015.

Commodity	Statistic	de	Δindpro	$\Delta M1$	dfr	dfy	dp	dy	ep	erp	infl	ltr	lty	svar	tbl	tms	unrate	MSA	MFC
Badder	ΔR^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-17.50*	-1,422.60**
	R_{cons}^2	-5.12	-1.50	-0.90	-2.05	-2.61	-2.51	-1.87	-0.66	-1.53	-0.92	-0.63	-2.69	-8.12	-6.86	-2.22	-6.86		
	t-stat	(-0.75)	(0.65)	(-0.34)	(-1.44)	(-0.56)	(-0.43)	(0.11)	(0.87)	(0.26)	(0.41)	(-0.01)	(-0.87)	(-0.35)	(-0.76)	(0.45)			
Cocoa	ΔR^2	0.02**	0.00	0.00	0.00	0.01**	0.01**	0.01**	0.01**	0.01**	0.00	0.00	0.00	0.00	0.01	0.01**	0.01	-24.16***	-2,421.84
	R_{cons}^2	-2.60	-0.49	-1.58	-0.34	-4.25	-1.05	-0.49	-1.78	-0.21	-1.65	-0.26	-2.68	-26.56	-1.73	-1.67	-1.67		
	t-stat	(-2.77)	(0.47)	(-0.20)	(-0.65)	(-1.14)	(-2.46)	(-2.63)	(-0.49)	(-1.91)	(-0.54)	(-1.00)	(1.07)	(1.05)	(1.91)	(-2.03)	(-1.85)		
Coffee Arabica	ΔR^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01*	0.04***	0.00	-35.07***	-2,084.13
	R_{cons}^2	-3.42	-1.06	-1.81	-1.01	-2.30	-2.74	-2.74	-6.21	-0.77	-1.08	-1.40	-4.35	-48.20	-2.23	2.33***	0.51**		
	t-stat	(0.50)	(-0.38)	(1.22)	(-0.11)	(-0.95)	(0.76)	(0.67)	(0.34)	(-0.68)	(-0.38)	(-0.44)	(-0.27)	(-0.68)	(-2.08)	(3.95)	(1.29)		
Corn Oil	ΔR^2	0.02***	0.01*	0.00	0.00	0.01**	0.01**	0.01**	0.01**	0.01**	0.00	0.00	0.00	0.00*	0.01	0.02***	0.00	-14.97***	-2,115.78
	R_{cons}^2	1.94***	-0.11	-0.65	-1.49	2.16***	-1.10	-1.72	2.82***	-1.62	-0.90	-1.35	-2.27	-45.81	0.31**	2.43***	-1.32		
	t-stat	(3.55)	(1.88)	(-0.11)	(0.61)	(-1.60)	(-2.34)	(-2.26)	(0.28)	(0.52)	(1.50)	(-1.07)	(0.07)	(-1.85)	(1.94)	(-3.61)	(-1.03)		
Cotton	ΔR^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-19.17*	-1,535.01
	R_{cons}^2	-1.32	-0.49	-0.75	-1.32	-0.79	-1.20	-1.22	-1.09	-0.82	-0.97	-1.11	-2.98	-14.60	-1.93	-0.84	-0.84		
	t-stat	(-1.05)	(1.23)	(-0.58)	(-0.82)	(0.33)	(-0.68)	(-0.63)	(0.06)	(0.40)	(-1.14)	(0.50)	(1.05)	(-1.01)	(1.05)	(-0.35)	(0.35)		
Live Cattle	ΔR^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-37.91**	-2,442.92
	R_{cons}^2	-5.10	-0.99	-0.08	-1.18	-3.29	-1.60	-1.62	-4.13	-0.85	-1.14	-1.06	-4.54	-36.06	-2.99	-3.57	-1.32		
	t-stat	(0.37)	(-0.24)	(1.27)	(-0.22)	(-1.18)	(-1.34)	(-1.24)	(-1.68)	(0.85)	(-1.20)	(-0.67)	(-0.04)	(-1.42)	(-0.61)	(1.15)	(0.03)		
Lean Hog	ΔR^2	0.00	0.00	0.00	0.01*	0.00	0.01	0.01	0.01*	0.00	0.01*	0.00	0.00	0.00	0.00	0.00	0.00	-19.42**	-1,470.64
	R_{cons}^2	-1.81	-1.29	-1.26	-0.91	-1.39	-1.09	-1.84	-1.14	-0.59	-0.71	-1.03	-1.28	-5.43	-0.90	-1.34	-1.18		
	t-stat	(0.30)	(-0.23)	(0.20)	(1.91)	(-0.91)	(-2.02)	(-1.92)	(-2.13)	(1.49)	(-1.68)	(-1.16)	(-0.78)	(-1.03)	(-0.88)	(0.30)	(-0.20)		
Milk	ΔR^2	0.00	0.00	0.00	0.00	0.01**	0.01**	0.01**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00*	0.00	-22.80*	-1,887.37
	R_{cons}^2	-2.60	0.14**	-0.77	-0.49	-2.82	-2.86	-2.90	-3.53	-0.88	-1.23	-1.49	-2.45	-4.04	-2.15	-2.23	-2.92		
	t-stat	(-0.83)	(-0.62)	(0.77)	(1.58)	(-0.17)	(-2.80)	(-2.70)	(-1.58)	(-1.58)	(0.09)	(0.14)	(-0.48)	(0.80)	(0.48)	(-2.01)	(-1.95)		
Oranges	ΔR^2	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02***	0.00	0.01*	0.00	0.00	0.00	0.01*	0.00	-24.80**	-1,197.41
	R_{cons}^2	-4.12	-1.76	-1.17	-1.35	-3.98	-3.26	-2.71	-2.31	-0.53	-0.91	-0.43	-2.70	-3.22	-2.82	-2.80	-3.00		
	t-stat	(-0.59)	(1.10)	(-0.38)	(0.27)	(-0.19)	(-1.86)	(-1.54)	(-1.26)	(2.72)	(1.11)	(-1.64)	(0.72)	(-0.40)	(-0.25)	(1.91)	(0.11)		
Soybean Oil	ΔR^2	0.01*	0.00	0.00	0.00	0.02***	0.01*	0.01*	0.00	0.00	0.00*	0.00	0.00	0.00	0.00	0.01***	0.02***	-11.52**	-3,176.54
	R_{cons}^2	-2.21	-1.11	-0.93	-1.83	-2.99	3.67***	2.94***	4.27***	-2.02	-1.20	-1.52	-6.48	-17.17	0.53**	-1.98	-3.68		
	t-stat	(-2.22)	(0.83)	(-0.13)	(0.88)	(-3.35)	(-2.65)	(-2.70)	(-1.09)	(-0.48)	(1.71)	(-0.52)	(-0.03)	(-1.15)	(1.28)	(-2.75)	(-3.62)		
Soybeans	ΔR^2	0.00	0.00	0.00	0.00	0.01	0.01*	0.01*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-23.60**	-2,375.58
	R_{cons}^2	-2.84	-0.45	-0.30	-0.54	-1.84	0.25*	-0.24	1.22***	-1.02	-2.49	-0.33	-7.82	-5.97	-2.09	-1.03	-1.67		
	t-stat	(-1.03)	(0.14)	(0.78)	(-0.88)	(-0.34)	(-2.28)	(-2.40)	(-1.52)	(-1.19)	(-1.30)	(-0.55)	(-0.29)	(0.06)	(-0.68)	(0.91)	(-1.60)		

Chapter 5

Return Predictability in Metal Futures Markets: Is it there?*

5.1 Introduction

Are returns predictable? This question has been analyzed at least since one century. Initial attempts to predict stock returns were already performed by Dow (1920). Numerous studies have tackled the question of return predictability and provided evidence either in favor or against predictability. Goyal & Welch (2008) argue that the historical mean is a tough benchmark to beat and that the so far observed predictability is mainly driven by the period of the oil crises. In contrast, Campbell & Thompson (2008) provide evidence in favor of return predictability when including two economically motivated restrictions. Cochrane (2008) shows that return predictability results from the time-variation of expected returns rather than dividend growth, and thus contradicts the random walk hypothesis. Overall, return

*This chapter is based on the Working Paper “Return Predictability in Metal Futures Markets: Is it there?” authored by Björn Tharann, 2018.

predictability is challenging and the answer of it is still inconclusive.

We accept this challenge and analyze the predictability of metal futures returns. From a practical standpoint, to have knowledge about future price developments of commodities goes along with an improved investment performance. Investors may better select assets for their asset allocations. Due to the performance of commodities, investors have detected commodities as a new investment class (e.g., Bessembinder, 1992; Gorton & Rouwenhorst, 2006). Erb & Harvey (2006) show that commodity portfolios have similar average returns than stock and bond portfolios. Further, commodities exhibit advantageous properties that improve the portfolio performance. For instance, commodities are used for diversification due to the low correlation with stocks and bonds, and commodities serve as hedge against inflation (e.g., Gorton & Rouwenhorst, 2006, Symeonidis et al., 2012).

The main goal of this study is to provide evidence on return predictability of metal commodity futures. In doing so, we make two contributions. First, we analyze not only the predictability in-sample, but also out-of-sample. Here, we use five distinct time series of metal futures and 12 variables that are supposed to predict stock returns. Moreover, we focus on several sample periods and use different techniques to identify years of high predictability. We also use forecast combinations to improve the out-of-sample predictability. In addition, we do not only analyze the return predictability, but also the economic value that arises if an investor can utilize knowledge about future price movements.

Second, we introduce and analyze the Aruoba–Diebold–Scotti (ADS) index, developed by Aruoba, Diebold, & Scotti (2009), to examine the potential effects on metal futures returns and on the behavior over business cycles. The ADS index claims to accurately measure business conditions in real-time. As a consequence, the index should incorporate information that

5.1. INTRODUCTION

are relevant for metal commodities.

We find excessive evidence for predictability for the next year's excess return across all metal commodities, both in- and out-of-sample. The best performing variable is the long-term government bond yield, indicated by an out-of-sample R^2 of 37.90 % in the case of gold. The mean forecast combination approach provides evidence for an improved and especially stable out-of-sample predictability, in particular for gold and platinum, indicated by out-of-sample R^2 s up to 18.57 %. Gold returns seem to be best predictable out-of-sample. A timing strategy leads to utility gains of 2.18 % p.a., when using aggregated information in predicting gold returns.

The ADS index shows remarkable correlations with metal futures returns, particularly in recessions. We also find that the ADS index strongly predicts gold returns, indicated by an out-of-sample R^2 of 8.21 %.

Our study directly relates to the literature on stock return predictability. Initial studies used aggregated valuation ratios as the dividend–price ratio (e.g., Rozeff, 1984; Fama & French, 1988b), short-term interest rates (e.g., 1987, Campbell; Ang & Bekaert, 2007), and the consumption–wealth ratio (e.g., Lettau & Ludvigson, 2001). Campbell & Shiller (1988, 1998) introduced and comprehensively examined the earnings–price ratio, and provide evidence that this ratio especially predicts long-term stock returns. Goyal & Welch (2003, 2008) analyze numerous financial and macroeconomic variables, re-examine previous studies and identify the years of the oil crises as the main drivers for predictability. Campbell & Thompson (2008) show that there exists predictability when imposing two economically motivated restrictions. Rapach et al. (2010) and Rapach & Zhou (2013) document that combination forecasts might lead to out-of-sample improvements.

Our study also relates to the literature on commodities and commodity return predictability. Fama & French (1988a) analyze the behavior of metal spot and futures prices over business cycles and provide evidence that the

prices are affected by the level of inventory and the business cycle stage. Numerous papers examine aggregated valuation ratios known from the stock return predictability literature, e.g., Bessembinder (1992), Bailey & Chan (1993), and Bjornson & Carter (1997). De Roon et al. (2000) use hedging pressure as predictive variable. Gargano & Timmermann (2014) use commodity spot indices to analyze the predictability of commodities over a longer time period. Nguyen, Prokopczuk, & Wese Simen (2017) show that gold returns are predictable by the jump tail premium and variance risk premium. Jordan, Vivian, & Wohar (2018) analyze metal commodities in the G7 countries. Prokopczuk, Tharann, & Wese Simen (2018) examine the return predictability of commodities using spot prices of more than 140 years, and find evidence particularly for longer horizons.

The remainder of this chapter is structured as follows. Section 5.2 describes the data, the computation of the variables, and the methodology. Section 5.3 provides the main empirical results. Section 5.4 shows the results related to the ADS index. Finally, Section 5.5 concludes.

5.2 Data & Methodology

5.2.1 Data

We obtain our data from several sources. We use monthly settlement prices of five continuously rolled metal futures retrieved from Datastream: high grade copper (NHGCS00), gold (NGCCS00), palladium (NPACS20), platinum (NPLCS00), and silver (NSLCS00). The commodities are traded on exchanges in the U.S. and are denominated in U.S. Dollar (USD). Table 5.1 provides an overview about the metal futures. Our sample period spans from August 1988 to December 2017. Moreover, to gain insights about the

behavior of metal commodities over business cycles, we use the ADS index.¹

5.2.2 Variables

Metal Futures Excess Returns To base our analysis on the most conservative procedure, we compute the log-return on a fully collateralized futures contract (Gorton et al., 2012; Bakshi, Gao, & Rossi, 2017) as:

$$r_{t+1} = \log \left(\frac{F_{t+1,T}}{F_{t,T}} \right) + rf_t, \quad (5.1)$$

where $F_{t+1,T}$ and $F_{t,T}$ are the settlement prices on the continuous futures contract with maturity T at the end of month $t + 1$ and t , respectively. The interest rate on a fully collateralized position is denoted by rf_t . The corresponding futures excess return, i.e. er_{t+1} , is then defined as:

$$er_{t+1} = r_{t+1} - rf_t. \quad (5.2)$$

Predictors To analyze the predictability of metal futures, we use 12 variables that appear to have predictive power for stock returns. Following Goyal & Welch (2008), we take: the monthly dividend–payout ratio (de) as the difference between the log of dividends and the log of earnings², the monthly default return spread (dfr) as the difference between long-term corporate bond returns and long-term government bond returns, the monthly default yield spread (dfy) as the difference between BAA- and AAA-rated corporate bond yields, the monthly dividend yield (dy) as the difference between the log of dividends and the log of lagged prices, the monthly earnings–price ratio (ep) as the difference between the log of earnings and the log of prices, the monthly inflation rate ($infl$) as the return on the U.S. consumer price index, the monthly long-term rate of returns

¹The ADS index can be obtained from the Federal Reserve Bank of Philadelphia.

²The dividends (earnings) are usually defined as the 12-months moving sums of dividends (earnings) on the S&P 500 stock index.

on U.S. government bonds (*ltr*), the monthly long-term U.S. government bond yields (*lty*), the monthly stock variance (*svar*) as the sum of squared daily returns on the S&P 500, and the monthly term spread (*tms*) as the difference between long-term U.S. government bond yields and the 3-month U.S. Treasury bill rate.³

Moreover, we follow Gargano & Timmermann (2014) and use the change in industrial production ($\Delta Indpro$) as the log difference between monthly industrial production, and the unemployment rate (*unrate*).⁴

5.2.3 In- and Out-of-Sample Return Predictability

In-Sample Analysis To evaluate the in-sample predictive power of a variable, we follow Rapach & Wohar (2006) and estimate the next year's excess return as:

$$er_{t+12} = \alpha + \beta X_t + \epsilon_{t+12}, \quad (5.3)$$

where er_{t+12} is the 12-months' ahead excess return from month t to $t + 12$.⁵ α , β , and ϵ_{t+12} are the intercept and the slope parameters, respectively, and the error term over the next year. X_t represents the predictor at month t .

In detail, to assess the in-sample predictability, we impose the null hypothesis of no predictability (H_0), i.e.,

$$er_{t+12} = \alpha + \epsilon_{t+12}, \quad (5.4)$$

defining the restricted model, where $\beta = 0$. Thus, under H_0 the excess return cannot be predicted using X_t , and we would expect that the slope

³We use the extended data set of Goyal & Welch (2008) that can be found at <http://www.hec.unil.ch/agoyal/>. Further variables known to predict stock returns are the dividend-price ratio and the 3-month U.S. Treasury bill rate. However, due to high correlations with *dy* (99 %) and *tms* (-63 %), respectively, we do not include these variables into our set of potential predictors.

⁴We obtain industrial production (INDPRO) and the unemployment rate (UNRATE) from the Federal Reserve Bank of St. Louis (FRED).

⁵At each point in time t , we sum up the monthly excess returns from month t to $t + 12$, thus, we end up with overlapping annual excess returns.

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estimate is not significantly different from zero. In that case, the excess return follows a random walk process, and the best estimate of the future excess return is just its historical mean. Under the alternative hypothesis of predictability (H_1), defined as the unrestricted model in Equation (5.3), the excess return can be predicted using X_t . Thus, we would expect that β is significantly different from zero.

To evaluate the significance of predictability, we use the bootstrap algorithm, proposed by Rapach & Wohar (2006), in order to obtain reliable statistical inferences.⁶ As a consequence, we avoid the well known statistical issues of a small sample bias (Stambaugh, 1999) and serial correlation in the error terms (Richardson & Stock, 1989).

Out-of-Sample Analysis Our out-of-sample analysis is based on the methodology used by, e.g., Goyal & Welch (2003, 2008). To obtain the first out-of-sample forecast, we proceed as follows: First, we estimate Equation (5.3) using an initial training window of 10 years.⁷ We then use the obtained estimated parameters and the most recent observation of the predictor to calculate the corresponding forecast. Third, we repeat that procedure by rolling the window by one observation ahead and estimate the next year's excess return.

To assess the out-of-sample predictability, we follow Campbell & Thompson (2008) and compute the out-of-sample R^2 , i.e.,

$$R_{oos}^2 = 1 - \frac{MSE_u}{MSE_r}, \quad (5.5)$$

where MSE_u and MSE_r are the mean squared errors of the unrestricted and restricted model, respectively. The R_{oos}^2 represents a relative measure

⁶A detailed description of the procedure can be found in Section D.1 in the Appendix to this chapter.

⁷Here, we follow Çakmaklı & van Dijk (2016) and use a rolling training window of 10 years to capture the average length of a business cycle. Thus, we also take care about potential structural breaks in the time series.

of two competing nested models. Thus, by using that measure we ask the question: How large is the improvement of the predictive power using the variable X_t in relation to the predictive power using the historical mean as naive benchmark? A variable is considered to have predictive power, if it is associated with a positive and significant R_{oos}^2 . Since that measure represents a point estimate, we have to carefully assess the degree of significant predictability.⁸ In doing so, we follow McCracken (2007) and compute the $MSE - F$ statistic, i.e.,

$$MSE - F = (N - k + 1) \cdot \left(\frac{MSE_r - MSE_u}{MSE_u} \right), \quad (5.6)$$

where N is the number of out-of-sample forecasts. k is the degree of overlap, thus, in our case 12. In accordance to the previous section, under H_0 the restricted model performs at most as well as the unrestricted model ($MSE_r \leq MSE_u$).

To further analyze the predictive (in- and out-of-sample) performance of the variable X_t over time, we plot and analyze the cumulative differences in squared forecast errors (CDSFE). The in-sample performance is the difference between the cumulative squared demeaned excess return from the restricted model and the cumulative squared regression residual from the unrestricted model, whereas the out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error of the unrestricted model.

Similar to the R_{oos}^2 , the CDSFE also go along with a relative interpretation. Whenever the variable X_t has superior (inferior) predictive power relative to the historical mean benchmark, we expect an increase (a decrease) in the CDSFE. Thus, an absolute increase (decrease) in the CDSFE is not interpretable. Moreover, the CDSFE allow an analysis of the

⁸For more detailed information, see Section D.2 in the Appendix to this chapter.

time-varying predictability of variable X_t to time periods of high and low predictability, respectively (Goyal & Welch, 2008).⁹

5.3 Main Results

5.3.1 Summary Statistics

Before discussing our main empirical results, it is instructive to look at some summary statistics and correlations. Table 5.1 provides summary statistics on the annual metal futures excess returns. We observe that the average return ranges between 2 % for platinum and 8 % for palladium, which is consistent with former studies of, e.g., Gorton et al. (2012). We also notice that gold exhibits the smallest standard deviation of 14 %, whereas copper has a standard deviation of 28 %.

Table 5.2 shows correlations between the metal futures excess returns. We observe that gold and silver exhibit a high correlation of 0.75, further, silver and platinum of 0.61, and gold and platinum of 0.54, which is not surprising given that these commodities belong to the class of precious metals. Moreover, copper exhibits a high correlation with platinum of 0.70. Tables 5.3 and 5.4 report summary statistics on and correlations between the predictive variables, which are consistent with, e.g., Goyal & Welch (2008).

⁹The sign of the final value of the out-of-sample CDSFE is equal to the sign of the estimated R_{oos}^2 . In our CDSFE plots, we standardize the in-sample CDSFE to zero at the date of the first out-of-sample forecast, by shifting the curve vertically downwards. Due to the apparent sensitivity of the forecasting accuracy of the R_{oos}^2 s, it is necessary to additionally assess the degree of significance rather than relying on the absolute amount of the R_{oos}^2 s only.

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Table 5.1: Summary Statistics Metal Futures Excess Returns

This table summarizes (annualized) key statistics for metal futures excess returns. "Mean", "Std Dev", "Skew", and "Kurt" denote the mean, standard deviation, skewness, and kurtosis, respectively. The next three columns show the first-order autoregressive coefficient and the p-value of the Jarque-Bera and Augmented Dicky Fuller test, respectively. "First Obs." and "Nobs" denote the first observation of the time series and the number of observations. All data are sampled at the monthly frequency.

Commodity	Mean	Std Dev	Skew	Kurt	AR(1)	JB p-value	ADF p-value	First Obs.	Nobs
Copper	0.03	0.28	0.21	3.76	0.93	<0.01	<0.05	31.08.1988	342
Gold	0.04	0.14	0.30	2.94	0.90	<0.1	<0.05	31.08.1988	342
Palladium	0.08	0.41	-0.38	2.71	0.93	<0.05	0.26	28.02.1995	264
Platinum	0.02	0.21	-0.20	3.46	0.91	<0.1	<0.01	31.08.1988	342
Silver	0.04	0.24	0.68	3.75	0.89	<0.01	<0.01	31.08.1988	342

Table 5.2: Correlation Matrix Metal Futures Excess Returns

This table reports the correlations among all annual metal futures excess returns. All data are sampled at the monthly frequency.

Commodity	Copper	Gold	Palladium	Platinum	Silver
Copper					
Gold	0.47				
Palladium	0.54	0.10			
Platinum	0.70	0.54	0.59		
Silver	0.55	0.75	0.43	0.61	

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Table 5.3: Summary Statistics Predictive Variables

This table summarizes (non-annualized) key statistics about the predictive variables. "de" denotes the dividend-payout ratio, " Δ Indpro" the growth of industrial production. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dy" the dividend yield, "ep" the earnings-price ratio, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, and "svar" the stock variance. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. "Mean", "Std Dev", "Skew", and "Kurt" denote the mean, standard deviation, skewness, and kurtosis, respectively. The next three columns show the first-order autoregressive coefficient and the p-value of the Jarque-Bera and Augmented Dicky Fuller test, respectively. "First Obs." and "Nobs" denote the first observation of the time series and the number of observations. All data are sampled at the monthly frequency.

Predictor	Mean	Std Dev	Skew	Kurt	AR(1)	JB p-value	ADF p-value	First Obs.	Nobs
de	-0.8024	0.4042	2.7791	13.6839	0.9847	<0.01	<0.01	31.08.1988	353
Δ Indpro	0.0015	0.0063	-1.6432	12.3151	0.2256	<0.01	<0.01	31.08.1988	353
dfr	0.0000	0.0157	-0.4845	11.3621	0.0275	<0.01	<0.01	31.08.1988	353
dfy	0.0095	0.0039	3.2061	17.1986	0.9638	<0.01	<0.01	31.08.1988	353
dy	-3.8813	0.2924	0.1077	2.4746	0.9857	<0.1	0.66	31.08.1988	353
ep	-3.0854	0.3696	-1.9176	9.1496	0.9757	<0.01	<0.1	31.08.1988	353
infl	0.0021	0.0033	-0.9453	8.4420	0.4723	<0.01	<0.01	31.08.1988	353
ltr	0.0070	0.0285	0.0073	5.3642	0.0386	<0.01	<0.01	31.08.1988	353
lty	0.0534	0.0196	0.1278	2.1312	0.9887	<0.01	<0.01	31.08.1988	353
svar	0.0025	0.0045	7.3680	76.5853	0.7072	<0.01	<0.01	31.08.1988	353
tms	0.0234	0.0128	-0.1236	1.9339	0.9763	<0.01	0.48	31.08.1988	353
unrate	0.0596	0.0152	0.9967	3.1889	0.9969	<0.01	0.98	31.08.1988	353

Table 5.4: Correlation Matrix Predictive Variables

This table reports the correlations among all predictive variables. “de” denotes the dividend–payout ratio, and “ Δ Indpro” the growth of industrial production. “dfr” is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. “dfy” is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. “dy” is the dividend yield, “ep” the earnings–price ratio, “infl” the inflation rate, “ltr” the long-term U.S. government bond returns, “lty” the long-term U.S. government bond yields, and “svar” the stock variance. “tms” is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. “unrate” is the unemployment rate. All data are sampled at the monthly frequency.

Predictor	de	Δ Indpro	dfr	dfy	dy	ep	infl	ltr	lty	svar	tms	unrate
de												
Δ Indpro	-0.24											
dfr	0.15	0.05										
dfy	0.61	-0.43	0.11									
dy	0.47	-0.11	0.05	0.24								
ep	-0.72	0.18	-0.17	-0.46	0.27							
infl	-0.06	0.03	-0.02	-0.20	0.06	0.11						
ltr	-0.01	-0.04	-0.50	0.01	0.04	0.06	-0.20					
lty	0.12	0.12	-0.03	-0.25	0.39	0.17	0.23	0.00				
svar	0.30	-0.24	-0.24	0.59	-0.01	-0.29	-0.31	0.15	-0.10			
tms	0.39	0.01	0.09	0.27	0.19	-0.28	-0.08	-0.11	-0.15	0.11		
unrate	0.30	0.01	0.09	0.37	0.39	-0.03	-0.06	0.01	-0.18	0.08	0.69	

5.3.2 Return Predictability

We start by analyzing the performance of variables predicting the next year’s excess return on the basis of univariate regressions. Table 5.5 reports the in-sample and out-of-sample results.

In-Sample Results We find an extensive degree of predictability across all metal commodities. In particular, *de*, *dfy*, and *ep* exhibit significant predictive power across all metals, indicated by their significant *t*-statistics, among others, of 4.46, 4.85, and -8.13 in the case of platinum. It is also worth analyzing the predictive power of the individual variables. We observe highly significant in-sample R^2 s of 5.55 %, 6.48 %, and 16.33 %, respectively.

Table 5.5: Return Predictability: Univariate Regressions

This table reports the regression results of monthly excess returns [name in row] on a constant and the lagged predictive variable [name in column]. We predict the next year's excess return. Statistical inferences are based on a bootstrapped distribution following Rapach & Wohar (2006). "de" denotes the dividend-payout ratio, "ΔIndpro" the growth of industrial production. "dfr" is the default return spread as the difference between long-term U.S. corporate bond returns and long-term U.S. government bond returns. "dfy" is the default yield spread as the difference between U.S. BAA- and AAA-rated corporate bond yields. "dy" the dividend yield, "ep" the earnings-price ratio, "infl" the inflation rate, "ltr" the long-term U.S. government bond returns, "lty" the long-term U.S. government bond yields, and "svar" the stock variance. "tms" is the term spread as the difference between the long-term yield on U.S. government bonds and the 3-month Treasury bill rate. "unrate" is the unemployment rate. R^2 and R^2_{oos} are the in-sample and out-of-sample R^2 , respectively. We report the t -statistics in parentheses. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency.

Commodity	Statistic	de	Δ Indpro	dfr	dfy	dy	ep	infl	ltr	lty	svar	tms	unrate
Copper	R^2	6.23***	0.31	1.00*	9.21***	0.01	6.63***	1.49**	0.10	1.18*	3.06***	3.54***	0.86*
	R^2_{oos}	2.47***	-1.87	-0.76	5.87***	-7.68	0.86**	0.11	-1.78	10.99***	-9.30	5.06***	-6.62
	t -stat	(4.75)	(-1.03)	(1.85)	(5.86)	(0.21)	(-4.93)	(-2.26)	(-0.59)	(-2.01)	(3.27)	(3.53)	(1.72)
Gold	R^2	3.07***	1.50**	0.12	9.59***	1.88***	8.42***	0.62	0.00	2.86***	4.71***	2.69***	1.20**
	R^2_{oos}	-2.26	0.88**	-0.94	10.99***	-3.97	0.79**	-1.03	-1.12	37.90***	-5.12	-2.09	-1.33
	t -stat	(3.28)	(-2.27)	(0.63)	(6.00)	(-2.55)	(-5.58)	(-1.45)	(0.10)	(-3.16)	(4.09)	(3.06)	(2.03)
Palladium	R^2	5.92***	1.47**	0.65	2.47**	5.63***	2.44***	1.55**	0.20	0.00	0.66	0.03	2.51***
	R^2_{oos}	2.82***	-14.89	-3.76	-9.61	19.58***	-5.88	0.76*	-3.47	-20.84	-22.74	-1.35	2.69***
	t -stat	(4.05)	(1.97)	(1.31)	(2.57)	(3.94)	(-2.55)	(-2.03)	(-0.72)	(0.09)	(1.32)	(-0.29)	(2.59)
Platinum	R^2	5.55***	0.02	0.22	6.48***	3.52***	16.33***	3.05***	0.08	0.04	5.37***	1.38**	0.01
	R^2_{oos}	1.16**	-2.83	-1.96	5.10***	1.15***	13.75***	1.16**	-1.21	11.02***	0.34*	-2.80	-6.35
	t -stat	(4.46)	(0.28)	(0.86)	(4.85)	(-3.52)	(-8.13)	(-3.26)	(-0.51)	(-0.36)	(4.39)	(2.17)	(0.21)
Silver	R^2	3.17***	0.06	0.00	4.85***	0.16	4.98***	2.41***	0.47	0.71	3.53***	5.60***	3.35***
	R^2_{oos}	2.59***	-0.81	-1.72	4.79***	-1.22	-1.15	0.13	-1.15	14.29***	-4.03	3.45***	3.19***
	t -stat	(3.33)	(-0.45)	(-0.09)	(4.16)	(-0.75)	(-4.21)	(-2.89)	(-1.27)	(-1.56)	(3.52)	(4.48)	(3.43)

Further variables showing substantial predictive power are, among others, $\Delta Indpro$ in the case of gold ($R^2 = 1.50\%$), dy in the case of palladium ($R^2 = 5.63\%$), $infl$ in the case of platinum ($R^2 = 3.05\%$), lty in the case of gold ($R^2 = 2.86\%$), $svar$ in the case of platinum ($R^2 = 5.37\%$), tms in the case of silver ($R^2 = 5.60\%$), and $unrate$ in the case of silver ($R^2 = 3.35\%$). We take note that dfr and ltr do not have significant power in predicting next year's metal futures excess returns.

Out-of-Sample Results Now, we translate our analysis to the out-of-sample predictability and examine whether the strong in-sample predictability also holds out-of-sample. Table 5.5 shows a high degree of return predictability by the variables. This is true for all variables, except dfr and ltr . Among many others, we find strong predictive power for tms in the case of copper ($R_{oos}^2 = 5.06\%$), dfy in the case of gold ($R_{oos}^2 = 10.99\%$), ep in the case of platinum ($R_{oos}^2 = 13.75\%$), dy in the case of palladium ($R_{oos}^2 = 19.58\%$), and lty in the case of gold ($R_{oos}^2 = 37.90\%$). These results are interesting, given that, e.g., Goyal & Welch (2008) argue that the historical mean is a tough benchmark to beat in the case of stock return predictability.

Overall, we find a substantial degree of predictability across all metal commodities for almost all variables. We do not only find evidence for in-sample predictability, but also strong evidence for out-of-sample predictability. The results are consistent with those in Fama & French (1989) who argue that tms , dfy , and dy are appropriate predictors, because tms is related to short-term business cycles, whereas dfy and dy to long-term business cycles.

5.3.3 Model Selection Approach

Next, we examine the return predictability based on a model selection approach. In particular, we ask the question: Is it possible to improve the return predictability when aggregating the information of variables? The results are presented in Table 5.6. We do not only analyze the full sample, but also three further sub-samples. First, we analyze the post financialization time period, i.e., the time after December 2000. Here, the release of the Commodity Futures Modernization Act (CFMA) took place. As a consequence, the trading of commodity futures has been facilitated. Second, we analyze expansions and recessions separately. According to Gorton & Rouwenhorst (2006) and Gorton et al. (2012), commodities behave differently over the business cycle, and commodity futures returns shall be better predictable during recessions.¹⁰

In-Sample Results To select specific variables for predicting the next year's futures excess return, we proceed as follows. First, we run a kitchen sink regression by including all variables. In doing so, we are able to identify the variables that have significant predictive power for future excess returns, at least at the 10 % significance level. Afterwards, employed with the significant variables, we run a multiple predictive regression and extract the adjusted in-sample R^2 , i.e., \bar{R}^2 . To determine the corresponding significance, we use an F -test.

Table 5.6 shows a solid predictability across all metal futures over all time periods. Analyzing the full sample, we find \bar{R}^2 s ranging from 7.46 % for silver to 19.51 % for platinum. By analyzing the post financialization period, we notice an improvement in the predictability for all metals, except

¹⁰Due to limited data availability, we cannot provide out-of-sample results for recessions.

for copper. The \bar{R}^2 s span from 12.49 % for silver to 28.31 % for gold. When differentiating between expansions and recessions, we observe a substantial improvement in return predictability, except for palladium in recessions. In particular, we find a superior performance for copper and platinum in recessions, indicated by \bar{R}^2 s of 79.63 % and 64.62 %, respectively.

Table 5.6: Return Predictability: Model Selection Approach

*This table reports the regression results of monthly excess returns [name in row] on a constant and the lagged predictive variable(s) based on a model selection approach. We predict the next year's excess return. Statistical inferences are based on an F-test (in-sample), and on the MSFE-adjusted test statistic with robust Newey & West (1987) standard errors (12 lags) following Clark & West (2007) (out-of-sample). For the in-sample analysis, we run a multiple predictive regression containing all significant variables (at least at the 10 % significance level) determined by a prior kitchen sink regression. For the out-of-sample analysis, we first run a kitchen sink regression to determine the significant variables (at least at the 10 % significance level). Subsequently, we use a mean forecast combination approach using all significant variables. \bar{R}^2 and R^2_{oos} are the in-sample adjusted and out-of-sample R^2 , respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency.*

Commodity	Statistic	Full Sample	Post Financialization	Expansion	Recession
Copper	\bar{R}^2	11.05***	2.34**	42.30***	79.63***
	R^2_{oos}	3.13	-5.06	12.56	
Gold	\bar{R}^2	9.33***	28.31***	49.09***	44.96***
	R^2_{oos}	14.38**	18.57*	18.00**	
Palladium	\bar{R}^2	17.52***	19.05***	28.79***	0.00***
	R^2_{oos}	14.26	-13.92	-12.20	
Platinum	\bar{R}^2	19.51***	26.46***	34.53***	64.62***
	R^2_{oos}	2.31*	3.30*	3.81	
Silver	\bar{R}^2	7.46***	12.49***	40.97***	40.47***
	R^2_{oos}	14.17	-1.06	14.77**	

Out-of-Sample Results Analogously to the in-sample analysis, we proceed out-of-sample similarly. In the first step, we run a kitchen sink regression to determine the variables that are significant at at least the 10 %

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significance level. Afterwards, we use a mean forecast combination approach to determine the out-of-sample forecast and the corresponding R_{oos}^2 .

Following Rapach et al. (2010), forecast combinations might lead to an improvement of the out-of-sample predictability. On the one hand, forecast combinations aggregate information of multiple variables, and thus, providing more stable out-of-sample forecasts by reducing the forecast volatility. On the other hand, forecast combinations incorporate information about the state of the real economy. The authors argue that mean forecast combinations provide evidence for a superior performance, despite its simplicity.¹¹ In doing so, we compute the combined out-of-sample forecast as:

$$\widehat{er}_{t+12}^{c, oos} = \frac{1}{M} \sum_{m=1}^M \widehat{er}_{t+12}^{m, oos}, \quad (5.7)$$

where $\widehat{er}_{t+12}^{c, oos}$ is the combined out-of-sample forecast, and $\widehat{er}_{t+12}^{m, oos}$ the individual out-of-sample forecast of the (at the at least 10 % level significant) predictor m , where $m = 1, \dots, M$. To determine the significance of the R_{oos}^2 , we use the MSFE-adjusted test statistic of Clark & West (2007).¹²

In Table 5.6, we find a substantial improvement of the out-of-sample predictability, in particular for gold, indicated by R_{oos}^2 s of 14.38 % and 18.57 % analyzing the full sample and the post financialization period, respectively. Moreover, platinum provides evidence for a strong return predictability, indicated by R_{oos}^2 s of 2.31 % and 3.30 %, respectively. In the case of silver, we observe a notable predictive power in expansions ($R_{oos}^2 = 14.77$ %).

¹¹Further alternatives are the median and trimmed mean forecast combination approaches. We obtain similar results, when using these approaches rather than the mean forecast combination approach.

¹²Further information about the MSFE-adjusted test statistic can be found in Section D.2 in the Appendix to this chapter.

Overall, the model selection approaches provide evidence for an improved performance predicting the next year's futures excess return. The findings suggest that aggregated information might lead to a superior performance, especially in the case of gold and platinum.

CDSFE Figure 5.1 shows the in- and out-of-sample CDSFE plots for each metal commodity based on the model selection approaches. Here, the dashed (blue) curve represents the in-sample performance, whereas the solid (red) curve the out-of-sample one. For all metal commodities, we observe both an increasing in- and out-of-sample performance over time, indicating the superior performance of the unrestricted model relative to the historical mean as naive benchmark. We also notice that during recessions a decline is observable, however, short-lasting only.

Overall, the CDSFE plots provide evidence for return predictability over the entire time period, on average. In particular in the time periods between crises, we observe years of high and stable predictability. This finding is a result of the aggregation of the information incorporated in different variables, justifying the application of the mean forecast combination approach. Accordingly, our findings do not confirm the previous results of Goyal & Welch (2008) who argue that return predictability is mainly driven by crises.

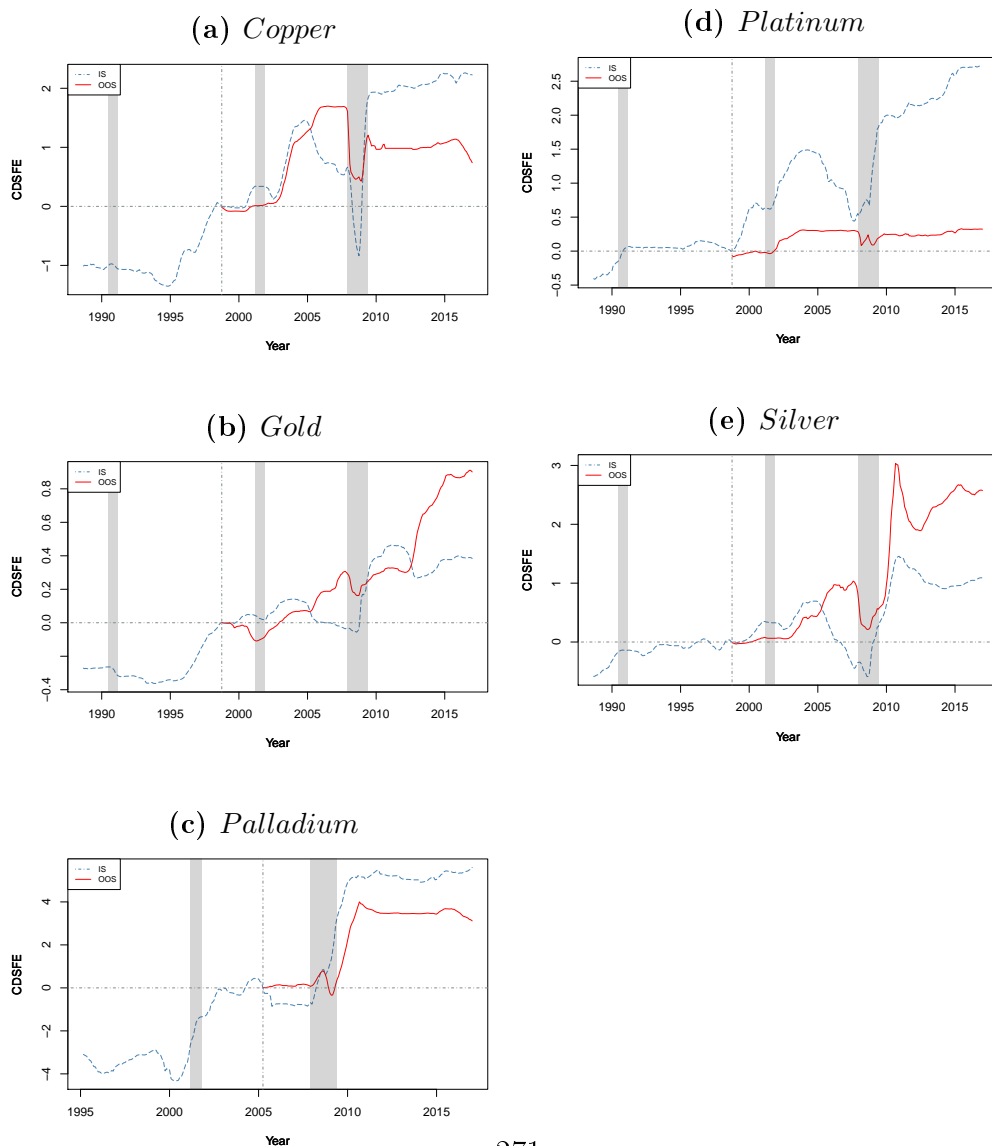
5.3.4 Economic Value Analysis

Next, we examine whether return predictability also translates to economic gains. The results are presented in Table 5.7 for different sample periods. In doing so, we assume an investor with mean–variance preferences who decides to allocate a fraction ω_t of her wealth to the risky portfolio and the remainder, i.e. $1 - \omega_t$, to the risk-free asset. The investor's objective

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Figure 5.1: Return Predictability (Model Selection Approach)

This figure plots the in- and out-of-sample performances predicting the next year's excess return based on a model selection approach. For the in-sample analysis, we run a multiple predictive regression containing all significant variables (at least at the 10 % significance level) determined by a prior kitchen sink regression. For the out-of-sample analysis, we first run a kitchen sink regression to determine the significant variables (at least at the 10 % significance level). Subsequently, we use a mean forecast combination approach using all significant variables. On the ordinate, there are the cumulative differences in squared forecast errors (CDSFE). The in-sample performance is the difference between the cumulative squared demeaned excess return from the restricted model and the cumulative squared regression residual from the unrestricted model, whereas the out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error of the unrestricted model. The grey bars indicate the U.S. recessions, published by the NBER. The sample period spans from August 1988 to December 2017. All data are sampled at the monthly frequency.



function reads as follows:

$$\max_{w_t} E_t \left(R_{p,t+12} - \frac{\gamma}{2} \sigma_{p,t+12}^2 \right), \quad (5.8)$$

where $E_t(\cdot)$ is the expectation operator, $\sigma_{p,t+12}^2$ the conditional variance of the portfolio from t to $t+12$, and γ is the coefficient of relative risk-aversion. $R_{p,t+12}$ is the next-period's (simple) return on the investor's portfolio. To address the fact that our analysis is based on log rather than simple returns, we use a second-order Taylor expansion to convert the returns.¹³ Thus, we can express the objective function as follows:

$$\max_{w_t} E_t \left(r_{p,t+12} - \frac{\gamma - 1}{2} \sigma_{p,t+12}^2 \right), \quad (5.9)$$

where $r_{p,t+12}$ is the log-return on the portfolio, and σ_{t+12}^2 is estimated using a five-year rolling window.

Optimizing Equation (5.9), we obtain the optimal weight invested in the risky asset (Jordan et al., 2014):

$$\omega_t = \frac{E_t(er_{t+12} + \frac{1}{2}\sigma_{t+12}^2)}{\gamma E_t(\sigma_{t+12}^2)} = \frac{E_t(er_{t+12})}{\gamma E_t(\sigma_{t+12}^2)} + \frac{1}{2\gamma}, \quad (5.10)$$

Equation (5.10) shows that the optimal weight depends on the expected futures excess return, the coefficient of relative risk-aversion, and the expected variance.

For each month in our out-of-sample analysis, we compute the weight ω_t and also the realized return of the portfolio. We impose the restriction that whenever the forecast of the market excess return in Equation (5.10) equals zero, we set the portfolio weight equal to $1/(2\gamma)$. Further, following Campbell & Thompson (2008) and Jordan et al. (2017), we impose the restriction that ω_t has to be between 0 and 1.5.¹⁴ Finally, we compute the

¹³The second-order Taylor expansion leads to the following relationship: $r_t \approx R_t - \frac{1}{2}\sigma_t^2$, where r_t , R_t , and σ_t^2 are the log-return, simple return, and variance at time t , respectively. Accordingly, we use the log-return and variance to express the simple return.

¹⁴In doing so, we avoid short-selling and an extensive leverage of the risky asset.

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certainty equivalent return (CER) as:

$$CER = \bar{R}_p - \frac{\gamma}{2}\sigma_p^2, \quad (5.11)$$

where \bar{R}_p is the average return on the portfolio, and σ_p^2 is the variance of the portfolio returns. Further, we define the utility gain (ΔCER) as the difference between the CER of a strategy assuming that excess returns are predictable using X_t , and the CER of the benchmark strategy that assumes that returns are unpredictable.

Table 5.7 provides the results for different coefficients of relative risk-aversion. Assuming $\gamma = 3$, we find positive utility gains for all metals ranging from 0.65 % p.a. for silver to 2.18 % p.a. for gold. Copper represents an exception by showing a slightly negative ΔCER for the full sample. Examining the post financialization period, we find that all metals, except palladium, provide evidence for positive utility gains up to 1.55 % p.a. for gold. Moreover, in expansions, all metal commodities exhibit positive utility gains up to 4.41 % p.a. for silver.

Table 5.8 reports the utility gains taking transaction costs into account. Here, we follow Balduzzi & Lynch (1999) and assume transaction costs of 50 basis points per transaction proportional to the asset's traded size $|\omega_{t+12} - \omega_{t+}|$, where ω_{t+} is the portfolio weight before re-balancing at $t + 12$. We observe that our main results are almost unchanged when taking transaction costs into account. E.g., an investor relying on the aggregated information when predicting gold excess returns, would earn an utility gain of now 2.14 % p.a. (rather than 2.18 % p.a.).

Overall, the results provide evidence that return predictability also translates to economic gains. When relying on the aggregated information, investors might earn substantial utility gains. We notice that transaction costs do not systematically affect our results.

Table 5.7: Economic Value

This table reports utility gains based on the mean forecast combination approach, assuming that the combined forecast predicts excess returns. The historical mean return serves as naive benchmark. ΔCER is the (annualized) utility gain relative to a naive strategy that assumes that excess returns are unpredictable. All data are sampled at the monthly frequency.

Panel A: $\gamma = 3$

Commodity	Statistic	Full Sample	Post Financial.	Expansion	Recession
Copper	ΔCER	-0.04	0.48	1.99	–
Gold	ΔCER	2.18	1.55	3.92	–
Palladium	ΔCER	1.42	-0.36	0.09	–
Platinum	ΔCER	1.00	0.09	1.75	–
Silver	ΔCER	0.65	0.54	4.41	–

Panel B: $\gamma = 6$

Commodity	Statistic	Full Sample	Post Financial.	Expansion	Recession
Copper	ΔCER	-0.65	0.23	0.90	–
Gold	ΔCER	1.93	2.98	1.99	–
Palladium	ΔCER	0.62	-0.16	0.03	–
Platinum	ΔCER	0.38	0.04	0.81	–
Silver	ΔCER	-4.97	0.12	2.04	–

Panel C: $\gamma = 9$

Commodity	Statistic	Full Sample	Post Financial.	Expansion	Recession
Copper	ΔCER	-0.53	0.15	0.58	–
Gold	ΔCER	0.78	2.29	1.26	–
Palladium	ΔCER	0.39	-0.10	0.02	–
Platinum	ΔCER	0.23	0.03	0.52	–
Silver	ΔCER	-3.78	0.07	1.27	–

Panel D: $\gamma = 12$

Commodity	Statistic	Full Sample	Post Financial.	Expansion	Recession
Copper	ΔCER	-0.43	0.11	0.43	–
Gold	ΔCER	0.04	1.64	0.92	–
Palladium	ΔCER	0.29	-0.07	0.01	–
Platinum	ΔCER	0.16	0.02	0.38	–
Silver	ΔCER	-3.01	0.05	0.91	–

5.3. MAIN RESULTS

Table 5.8: Economic Value and Transaction Costs

This table reports utility gains based on the mean forecast combination approach, assuming that the combined forecast predicts excess returns. We assume transaction costs of 50 basis points per transaction proportional to the asset's traded size. The historical mean return serves as naive benchmark. ΔCER is the (annualized) utility gain relative to a naive strategy that assumes that excess returns are unpredictable. All data are sampled at the monthly frequency.

Panel A: $\gamma = 3$

Commodity	Statistic	Full Sample	Post Financial.	Expansion	Recession
Copper	ΔCER	-0.08	0.48	2.00	–
Gold	ΔCER	2.14	1.50	3.82	–
Palladium	ΔCER	1.39	-0.37	0.09	–
Platinum	ΔCER	0.97	0.09	1.69	–
Silver	ΔCER	0.61	0.50	4.35	–

Panel B: $\gamma = 6$

Commodity	Statistic	Full Sample	Post Financial.	Expansion	Recession
Copper	ΔCER	-0.67	0.24	0.90	–
Gold	ΔCER	1.90	2.94	1.93	–
Palladium	ΔCER	0.61	-0.16	0.03	–
Platinum	ΔCER	0.37	0.05	0.79	–
Silver	ΔCER	-5.01	0.09	1.99	–

Panel C: $\gamma = 9$

Commodity	Statistic	Full Sample	Post Financial.	Expansion	Recession
Copper	ΔCER	-0.54	0.16	0.58	–
Gold	ΔCER	0.74	2.27	1.22	–
Palladium	ΔCER	0.39	-0.11	0.02	–
Platinum	ΔCER	0.22	0.03	0.50	–
Silver	ΔCER	-3.81	0.05	1.24	–

Panel D: $\gamma = 12$

Commodity	Statistic	Full Sample	Post Financial.	Expansion	Recession
Copper	ΔCER	-0.44	0.12	0.43	–
Gold	ΔCER	0.02	1.61	0.89	–
Palladium	ΔCER	0.28	-0.08	0.01	–
Platinum	ΔCER	0.15	0.02	0.37	–
Silver	ΔCER	-3.03	0.04	0.89	–

5.4 Predictability by the ADS Index

In this section, we analyze the relationship between metal futures excess returns and the ADS index. In the first step, we introduce the ADS index, and in the second one we examine the informative value.

5.4.1 ADS Index

The ADS index is developed by Aruoba et al. (2009) and represents a measure of macroeconomic activity, and thus of business conditions in real-time. The importance to have aggregated business conditions in real-time arises from the fact that economic agents make decisions in real-time. This includes, among many others, policy makers, central banks, and investors.

Using a variety of information, the authors are able to track business conditions over time. In doing so, they use a dynamic factor model to deal with potential co-movements of business cycles with related variables. Moreover, they employ business conditions indicators, measured at low and high frequencies, to extract relevant information, e.g., about asset prices, the term premium, the payroll employment, initial jobless claims, and the GDP. The index is zero on average, thus, a positive (negative) value represents business conditions above (below) the average conditions.

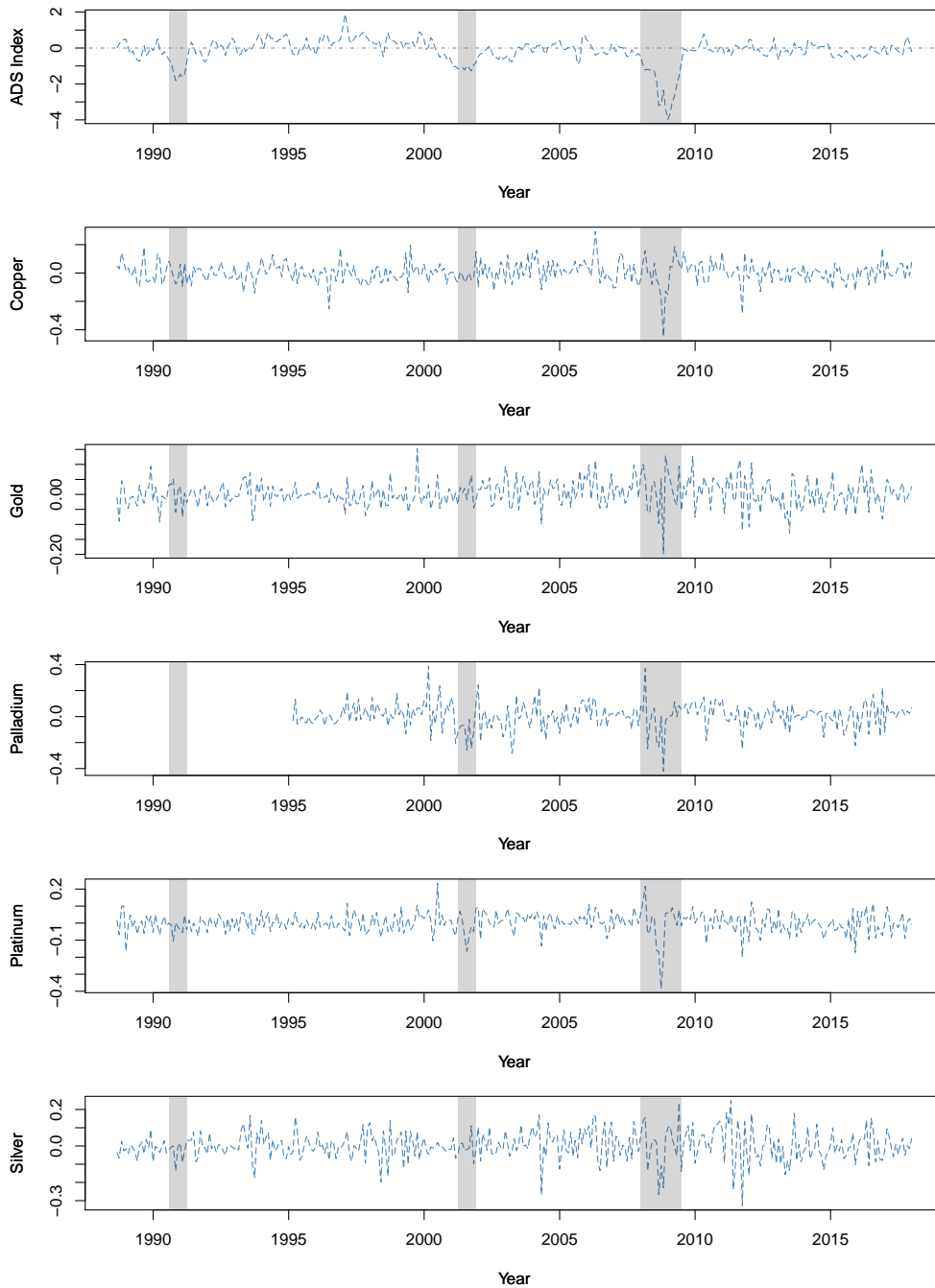
5.4.2 Informative Value of the ADS Index for Metal Futures Returns

Figure 5.2 shows the monthly development of the ADS index and of the metal futures excess returns. We observe that particularly in crises, the metal excess returns move into the same direction as the ADS index. To

5.4. PREDICTABILITY BY THE ADS INDEX

Figure 5.2: Development of ADS Index and Metal Futures Excess Returns

This figure plots the development of the ADS index and the development of the monthly metal futures excess returns over time. The grey bars indicate the U.S. recessions, published by the NBER. The sample period spans from August 1988 to December 2017. All data are sampled at the monthly frequency.



deepen the analysis, Panel A of Table 5.9 reports the correlations between the ADS index and the metal excess returns over different sample periods.

Table 5.9: Correlations and Return Predictability of ADS Index

*This table reports results related to the ADS index. Panel A shows the correlations between the ADS index and the annual metal futures excess returns over different time periods. Panel B shows the regression results of monthly excess returns [name in column] on a constant and the lagged ADS index. We predict the next year's excess return. Statistical inferences are based on a bootstrapped distribution following Rapach & Wohar (2006). R^2 and R^2_{oos} are the in-sample and out-of-sample R^2 , respectively. *, **, *** indicate the significance at the 10 %, 5 %, and 1 % significance levels, respectively. All data are sampled at the monthly frequency.*

Panel A: Correlations					
Time Period	Copper	Gold	Palladium	Platinum	Silver
Full Sample	-0.03	-0.28	0.21	0.02	-0.05
Post Financial.	-0.01	-0.13	0.06	-0.05	-0.02
Expansion	-0.04	-0.41	0.54	-0.04	-0.06
Recession	-0.53	-0.45	-0.60	-0.45	-0.57

Panel B: Return Predictability (Full Sample)					
Statistic	Copper	Gold	Palladium	Platinum	Silver
R^2	0.89*	7.69***	2.50**	0.06	0.72
R^2_{oos}	-5.26	8.21***	-47.42	-3.68	-0.74
t -stat	(-1.74)	(-5.31)	(2.59)	(-0.47)	(-1.57)

In the case of copper, platinum, and silver we observe small negative correlations with the ADS index in the range of -0.01 and -0.06 over the full sample, the post financialization period, and in expansions. Gold exhibits a strong negative correlation of -0.28 (full sample), -0.13 (post financialization), and -0.41 in recessions. In contrast, palladium shows a slight positive correlation over the post financialization period (0.06), but strong positive correlations over the full sample (0.21) and in expansions (0.54). Interestingly, all metal commodities have in common a strong

5.4. PREDICTABILITY BY THE ADS INDEX

negative correlation with the ADS index in recessions ranging from -0.45 for gold and platinum, to -0.60 for palladium. Thus, the results show that the ADS index has most explanatory power for metal future excess returns during recessions.

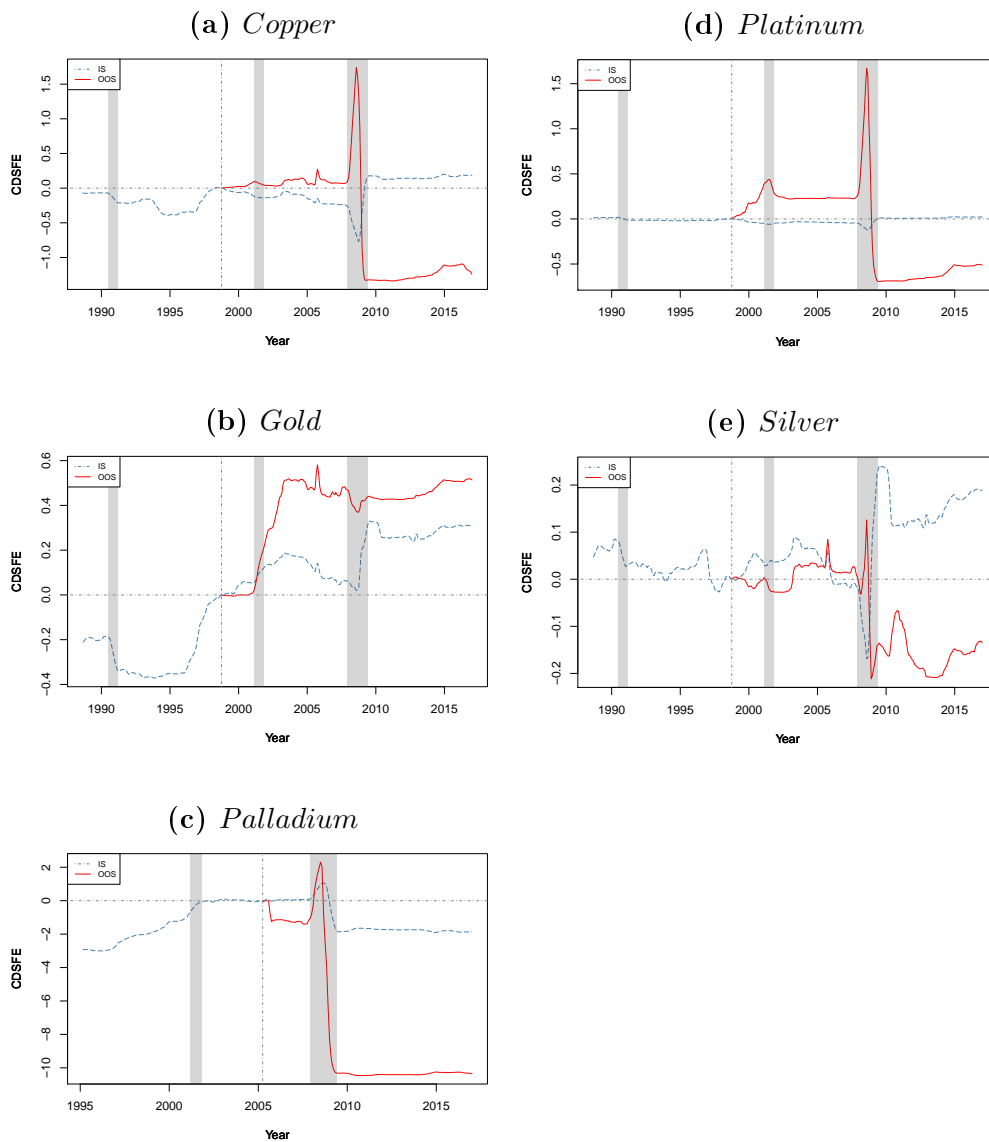
Panel B of Table 5.9 reports the in-sample and out-of-sample results predicting the next year's excess return based on the ADS index. In doing so, we use the same methodology as in our previous section, however, using the ADS index as predictive variable. In-sample, we observe significant R^2 s in the case of copper ($R^2 = 0.89\%$), palladium ($R^2 = 2.50\%$), and gold ($R^2 = 7.69\%$). For platinum and silver, we find positive but insignificant R^2 s. Thus, the ADS index seems to have in-sample predictive power for at least three of five metal commodities.

Analyzing the return predictability out-of-sample, we find that the ADS index has strong predictive power for gold excess returns, indicated by an R^2_{oos} of 8.21% . The results suggest that the ADS index is a reliable predictor, at least for gold excess returns.

Figure 5.3 plots the in- and out-of-sample performances related to the ADS index. In particular in the case of gold, we observe a superior predictive power, indicated by increasing CDSFE curves. Moreover, in the case of copper, palladium, platinum, and silver we notice a sharp decline during the global financial crisis, indicating an inferior performance of the unrestricted relative to the restricted model.

Figure 5.3: Return Predictability (ADS Index)

This figure plots the in- and out-of-sample performances predicting the next year's excess return based on the ADS index. On the ordinate, there are the cumulative differences in squared forecast errors (CDSFE). The in-sample performance is the difference between the cumulative squared demeaned excess return from the restricted model and the cumulative squared regression residual from the unrestricted model, whereas the out-of-sample performance is the difference between the cumulative squared forecast error from the restricted model and the cumulative squared forecast error of the unrestricted model. The grey bars indicate the U.S. recessions, published by the NBER. The sample period spans from August 1988 to December 2017. All data are sampled at the monthly frequency.



5.5 Conclusion

This chapter performs a comprehensive study of metal futures excess return predictability using 12 variables that are supposed to predict stock returns. We also focus on the identification of years of high and low predictability. We find a substantial degree of predictability both in- and out-of-sample. Mean forecast combinations provide evidence for an improved out-of-sample predictability. Gold returns appear to be best predictable. A timing strategy leads to utility gains of 2.18 % p.a.

Moreover, we analyze the ADS index, which captures business conditions in real-time, to examine the potential effects on metal returns and on the behavior over business cycles. We find that the ADS index incorporates relevant information for metal returns. It turns out to be a strong predictor for gold returns.

D Appendix

In this section, we provide additional material for Chapter 5: “Return Predictability in Metal Futures Markets: Is it there?”.

D.1 Bootstrap Procedure

To implement the bootstrap algorithm, we follow Rapach & Wohar (2006). In doing so, we assume a data generating process under the null hypothesis of no predictability, i.e.:

$$er_t = a_0 + \epsilon_{r,t}, \quad (\text{D.1})$$

$$X_t = b_0 + b_1 X_{t-1} + \epsilon_{u,t}, \quad (\text{D.2})$$

where er_t and X_t are the excess return and the predictive variable at month t , respectively. a_0 , b_0 and b_1 are the intercept and slope parameters, respectively. $\epsilon_t = (\epsilon_{r,t}, \epsilon_{u,t})'$ is a vector of errors that are assumed to be independently and identically distributed. We assume that the predictive variable follows an AR(1) process (Goyal & Welch, 2008).

Next, we estimate Equations (D.1) and (D.2) via OLS and obtain the corresponding residuals, i.e., $\hat{\epsilon}_t = (\hat{\epsilon}_{r,t}, \hat{\epsilon}_{u,t})'$. Afterwards, we generate a series of pseudo errors $\{\hat{\epsilon}_t^*\}_{t=1}^{T+100}$, by drawing randomly with replacement $T+100$ times from the OLS residuals. To retain the contemporaneous structure between the errors, we draw from the OLS residuals in tandem.

To compute our pseudo sample of $T+100$ observations for er_t and X_t , i.e., $\{er_t^*, X_t^*\}_{t=1}^{T+100}$, we proceed as follows. First, we define \hat{a}_0 , \hat{b}_0 , and \hat{b}_1^A as the OLS estimates of the intercept and slope parameters in Equations (D.1) and (D.2), respectively, where the bias adjustments in Shaman & Stine (1988) are used. Second, we take the estimates and $\{\hat{\epsilon}_t^*\}_{t=1}^{T+100}$, and using Equations (D.1) and (D.2) to compute our pseudo sample. Here, we

D.2. MSFE-ADJUSTED TEST STATISTIC

set the initial values in Equation (D.2) equal to zero. Third, we drop the first 100 observations of our pseudo sample to obtain the same size as our original sample.

Next, using our pseudo sample, we compute the (in-sample) t -statistic of the unrestricted model, and the (out-of-sample) $MSE - F$ statistic. We repeat the algorithm 1,000 times obtaining an empirical distribution of the respective statistic. Finally, to compute the p-values, we also calculate the in- and out-of-sample statistics using the original sample. The corresponding p-value is defined as the proportion of the respective bootstrapped statistic that is greater than the real statistic.

D.2 MSFE-adjusted Test Statistic

The R_{oos}^2 is a point estimate, thus, the forecast accuracy is sensitive, among others, to the sample size (Zhu & Zhu, 2013). To test whether the unrestricted and the restricted models are statistically different, we can use the MSFE-adjusted test statistic, developed by Clark & West (2007). The statistic is an adjusted version of the Diebold & Mariano (1995) and West (1996) statistic and examines the null hypothesis that $R_{oos}^2 \leq 0$. Thus, the statistic is applicable for nested models. The asymptotic distribution of the nested model forecasts can be well approximated by the standard normal distribution. Moreover, in finite samples the MSFE-adjusted test statistic also performs quite well (Rapach & Zhou, 2013).

Following Rapach & Zhou (2013), we divide the number of total observations T into an in-sample estimation period comprising the first R observations and an out-of-sample period comprising the last $N = T - R$ observations, where $s = 1, \dots, N$. To compute the MSFE-adjusted test

statistic, we first define:

$$\tilde{d}_{R+s} = \hat{\epsilon}_{r,R+s}^2 - [\hat{\epsilon}_{u,R+s}^2 - (\bar{e}r_{R+s} - \hat{e}r_{u,R+s})^2], \quad (\text{D.3})$$

where, $\hat{\epsilon}_r^2$ and $\hat{\epsilon}_u^2$ are the squared out-of-sample errors from the restricted and unrestricted model, respectively. $\bar{e}r$ is the average excess return, and $\hat{e}r_u$ the forecast of the excess return of the unrestricted model based on predictor X_t . Finally, we regress \tilde{d}_{R+s} on a unit vector of length N without intercept. The MSFE-adjusted test statistic is then equal to the corresponding t -statistic, considered as one-sided test.

Chapter 6

The Economic Sources of Return Anomalies: Evidence from Commodity Futures Markets*

6.1 Introduction

Do equity market anomalies also exist in commodity markets? This question is far less trivial than it sounds at first glance. There are substantial institutional differences between equity and commodity markets, which we make use of to uncover the economic sources of these anomalies.

Harvey et al. (2016) document 316 anomalies in the cross-section of stock returns. Many of these anomalies are based on ad hoc measures

*This chapter is based on the Working Paper “The Economic Sources of Return Anomalies: Evidence from Commodity Futures Markets” authored by Fabian Hollstein, Marcel Prokopczuk, and Björn Tharann, 2018.

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without stringent theoretical motivation. Among those that are theoretically motivated, they can be broadly sorted into three main categories. Part of the anomalies can be explained (i) rationally as reflecting some underlying form of systematic risk (e.g., Fama & French, 1993; Berk et al., 1999; Johnson, 2002; Liu & Zhang, 2008; Fama & French, 2015), others are motivated (ii) by irrational behavior, mostly of individual investors (e.g., De Long et al., 1990a; Daniel et al., 1998; Hong & Stein, 1999; Daniel et al., 2002; Diether et al., 2002; Baker & Wurgler, 2006; Hirshleifer et al., 2006; Baker et al., 2007; Hirshleifer & Jiang, 2010), and with (iii) limits to arbitrage (e.g., Jarrow, 1980; Mayshar, 1981; Shleifer & Vishny, 1997; Mitchell et al., 2002; Acharya et al., 2011; Baker et al., 2011; Ljungqvist & Qian, 2016). Typically, for behavioral price impact to prevail in the market, one needs both (ii) (behavioral biases of investors) and (iii) (limits to arbitrage).

The main contribution of this chapter is to organize the anomaly zoo, by examining the underlying causes of the subset of anomalies that constitutes, in our view, the most relevant issues. To do so, we examine whether the anomalies found in equity markets are also present in commodity futures markets. Using the specific features of commodity futures markets, we are able to evaluate how likely the different theoretical explanations, suggested in the previous literature, can be seen as causes for the respective anomalies.

In general, individual investors are considered to be more heavily affected by behavioral biases than institutional investors (e.g., Long, Shleifer, Summers, & Waldmann, 1990; Lee, Shleifer, & Thaler, 1991; Yu & Yuan, 2011; Stambaugh, Yu, & Yuan, 2012). Thus, the larger the fraction of traders (and actual trades) of retail investors in the market, the higher the likelihood that market prices will be affected by these cognitive biases. Among many others, De Bondt & Thaler (1985), Long, Shleifer, Summers, & Waldmann (1991), Barberis, Shleifer, & Vishny (1998), and Boyer, Mitton, & Vorkink (2009) argue and demonstrate how investors'

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behavioral biases can impact equity prices. In order for those effects to be sustained in the market, behavioral finance typically has, beside cognitive biases, a second cornerstone: limits to arbitrage. In the real world, for several reasons, making use of price deviations from fundamental values is not as easy as theory might suggest. First, there is fundamental risk, i.e., the risk that the fundamental value of an asset may change while the “arbitrage” position is still open. Second, due to noise trader risk (e.g., De Long et al., 1990a; Shleifer & Summers, 1990) the price may deviate even further from the fundamental value in the short-term, and, third, there are costs of implementing an arbitrage trade. These implementation costs consist of initial short-selling constraints. On the one hand, there are direct costs to shorting (D’Avolio, 2002) and, on the other, since short positions can be recalled at any time, such forced liquidation poses a severe challenge for arbitrageurs, especially in the interaction with noise trader risk (Shleifer & Vishny, 1997). Furthermore, many institutional investors acting in equity markets, such as pension funds, face charters that prohibit them from taking short positions, even when there are only small costs and risks associated with a potential arbitrage trade.

While the above issues facilitate the behavioral biases that are reflected in stock markets, each of these issues can be attenuated or even vanish entirely in the case of commodity futures markets. First, there are far more institutional investors relative to individual investors that trade in

6.1. INTRODUCTION

commodity markets.¹ Thus, it is far less likely that commodity futures prices will incorporate any price deviations caused by these cognitive biases. Furthermore, hedgers and speculators usually face no institutional restrictions on taking short positions in commodity futures markets. Second, commodity futures markets are also likely to be much less populated with noise traders, who are typically assumed to consist of uninformed (or wrongly-informed) retail traders.² Finally, the limits to arbitrage are considerably less severe for commodity futures markets. Commodity prices are typically strongly mean-reverting (Bessembinder, Coughenour, Seguin, & Smoller, 1995), which clearly reduces the fundamental risk of an arbitrage strategy.³ Furthermore, as opposed to equities, commodities are very easy to short. Short-selling does not require the borrowing of a commodity from an institutional investor. One simply takes the short position in the futures contract. Thus, there are only small direct trading costs and essentially no (external) risk that one has to close the position in an adverse market

¹The Commodity Futures Trading Commission (CFTC) reveals information about traders in commodity markets. Based on the size of their open interest, the CFTC classifies traders into reportable and non-reportable traders. The first category is further classified into commercial (hedgers) and non-commercial (speculators) traders, which account for 70–90 % of the total open interest across commodity markets. The CFTC has an institutionalized system for classifying the traders that imposes “strict requirements”. Thus, individual investors, which constitute a part of the non-reportable traders, represent only a small fraction in commodity futures markets and should have a negligible effect on futures prices. On the other hand, for the equity market, Blume & Keim (2017) report that the ownership of institutional investors made up to 67 % at the end of 2010. Moreover, one has to bear in mind that institutional investors in equity markets consist of a large share of passive index investors who do not participate actively in the price building mechanism at all. In commodity markets, on the other hand, all institutional investors have to trade since the futures expire regularly.

²Additionally, Palomino (1996) shows that, especially in markets populated by only few investors, noise traders can have severe impacts on prices, making arbitrageurs unwilling to trade in these markets at all. For commodity futures, beside likely fewer noise traders, there are typically far more active traders than for most single stocks in equity markets.

³Erb & Harvey (2016) further show that the correlation of commodity index returns with roll yields is very high in the long run. Bessembinder (2018) argues that this finding is consistent with mean-reversion in spot prices: roll yields should have substantial ex-post explanatory power for futures returns in the long run.

situation. The fact that commodity futures markets are highly efficient is also underlined by Roll (1984), who shows that the futures prices for frozen concentrated orange juice provide better weather forecasts for the main production region in central Florida than the National Weather Service.

Commodity futures markets thus provide an ideal testing ground to examine whether return anomalies are caused by behavioral mechanisms or if it is more likely that rational risk-based explanations are the primary channel. If we find equity anomalies that do not prevail in commodity futures markets, this indicates that cognitive biases may drive them.⁴ On the other hand, if we find these anomalies with a similar magnitude in commodity futures markets, it is likely that the sorting characteristics employed somehow represent exposure to underlying aggregate risk factors.

To set the stage, we first show that the presence of non-institutional investors, among which we typically suspect noise traders, is essentially unrelated to sentiment in commodity futures markets. Reassured by this, we then test and compare all anomalies with those of previous studies in the equity literature and evaluate different theories for the causes. Using simple portfolio sorts with a holding period of one month, we find distinct patterns in the anomalies we study. For many anomalies detected in the equity literature, we do not detect significant return premia in commodity futures markets. The main anomalies for which this is the case are downside beta, idiosyncratic volatility, and the MAX measure. Thus, it is very likely that behavioral theories suggested for explaining these anomalies (Ang, Chen, & Xing, 2006a; Boehme, Danielsen, Kumar, & Sorescu, 2009; Bali, Cakici, & Whitelaw, 2011), are the underlying causes. On the other hand, we find

⁴Gromb & Vayanos (2010) argue that institutional frictions are another potential mechanism, beside behavioral biases, that can generate demand shocks which lead to mispricing. Following their logic, it is possible that effects that we flag as behaviorally-based are in fact generated by these frictions. However, it is hard to come up with compelling examples. We regard it as unlikely that institutional frictions systematically affect the cross-section of stock returns (aligned with certain anomaly characteristics).

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anomaly returns of similar magnitude for jump risk, skewness, momentum, and volatility-of-volatility. These findings indicate that there are systematic risk-based explanations for these anomalies.

We test the robustness of our results in several dimensions. Using cross-sectional Fama & MacBeth (1973) regressions, we reach very similar conclusions. We also obtain largely similar results when building different numbers of portfolios (2, 3, 4, or 5) and for several subsample periods. Interestingly, for the post-financialization period, it seems that the MAX measure is much more strongly priced.⁵ Finally, we examine a longer holding period of 1 year, which also generates very similar results. One intriguing exception is momentum, which works far less well for an annual compared to a monthly holding period.

One might argue in the spirit of, e.g., Akbas, Armstrong, Sorescu, & Subrahmanyam (2015) and Edelen, Ince, & Kadlec (2016) that part of the institutional investors are also prone to behavioral biases.⁶ This does not run counter to our main argumentation. Even if behavioral biases affect commodity futures prices, due to the lack of short-selling constraints, some smart arbitrageurs among the institutional investors suffice to eliminate these and make markets efficient.

It is also possible that the holding costs, as opposed to direct trading costs are a major concern impeding arbitrage. Holding costs consist of opportunity costs of capital and idiosyncratic risk (Pontiff, 2006). Since futures only require a limited amount of direct collateral (margins), the major source of holding costs in commodity futures markets is idiosyncratic volatility. We cannot entirely rule out that idiosyncratic volatility may affect

⁵The post-financialization period starts with the introduction of the Commodity Futures Modernization Act (CFMA) in December 2000.

⁶The introduction of many commodity-related exchange traded funds (ETFs) also provides retail investors with exposure to commodity markets. However, these instruments provide symmetric exposure to the entire commodity market and do not constitute cross-sectional differences in commodity returns.

our results. Thus, our tests provide an upper bound of rational anomalies. It remains possible that anomalies that we flag as rational are in fact behaviorally based. However, the fact that idiosyncratic volatility is not priced in commodity markets re-assures us in our main interpretations.⁷

Other studies try to answer somewhat similar research questions to ours by examining whether return anomalies are particularly strong in times of high sentiment. Stambaugh et al. (2012) examine several equity anomalies and document that these are stronger, in particular due to the short leg, following periods of high sentiment. As opposed to theirs, our examination is model-free in that it does not require measurement of the inherently hard-to-capture “sentiment”. We also show that the share of institutional investors in commodity markets is essentially unrelated to sentiment.

Related to the above, Cochrane (2005b) argues that one can simply check if an anomaly is based on behavioral biases by testing if the asset returns can be explained by an anomaly-factor. If these assets move together, the pattern is not exploitable without taking systematic risk. On the other hand, Kozak, Nagel, & Santosh (2017) argue that part of the mispricing created by behavioral biases is related to factor-created common movement in returns and cannot be easily arbitrated away without exposure to factor risk. Thus, this simple factor-based approach is less suitable to examine our main research question.

Drechsler & Drechsler (2014) show that investors require a compensation for shorting stocks, the shorting premium, and that equity anomalies are stronger the higher the lending fees are. Engelberg, Reed, & Ringgenberg (2018) also demonstrate that short-selling risk represents a substantial limit

⁷In the stock market, idiosyncratic risk is priced negatively. Stocks with high idiosyncratic volatility appear to be overpriced. One potential explanation is that this overpricing is not arbitrated away due to high holding costs induced by idiosyncratic volatility. Apart from the question why only overpricing and not also underpricing is not arbitrated away, this logic does not apply to commodity markets, where we cannot detect any return premium for exposure to idiosyncratic volatility.

6.1. INTRODUCTION

to arbitrage in stock markets. Stocks facing higher short-selling risk are associated with lower expected returns, a lower degree of market efficiency, and go along with less short-selling activity.⁸

Our study also relates to the commodity futures literature. Previous studies document that commodity-specific variables can predict cross-sectional variation in returns. These variables include the average commodity return (e.g., Yang, 2013), the shape of the term structure, the hedging pressure (e.g., De Roon et al., 2000; Basu & Miffre, 2013), or a combination of these (e.g., Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006; Szymanowska, Roon, Nijman, & Goorbergh, 2014; Bakshi et al., 2017; Fernandez-Perez, Frijns, Fuertes, & Miffre, 2018).

Some authors also examine the performance of strategies applied in equity markets on commodity markets. Momentum-based strategies generate substantial average returns in futures markets by going long (short) a portfolio with the highest (lowest) 12-months performance (e.g., Gorton & Rouwenhorst, 2006; Erb & Harvey, 2006; Asness, Moskowitz, & Pedersen, 2013). Szymanowska et al. (2014) also show that liquidity is positively priced in the cross-section of commodity futures returns. Acharya et al. (2013) show that when speculators face capital constraints, there are limits to hedging, i.e., higher costs for hedgers.

Several studies argue that equity risk factors may not be perfectly suited for pricing commodities (e.g., Daskalaki, Kostakis, & Skiadopoulos, 2014; Fernandez-Perez et al., 2018). It is likely that there are different types of fundamental risks driving stock and commodity markets. Yang (2013) introduces a 2-factor model along with an average return factor and documents the explanatory power for portfolios sorted according to

⁸Engelberg et al. (2018) find an annual 5-factor alpha of 9.6 % of a long-short portfolio based on their short-selling risk proxy. They also show that this pattern is even more pronounced at longer trading horizons.

the basis. Szymanowska et al. (2014) provide evidence that a factor model with an average return factor and a term structure factor notably explains the cross-section of commodity futures returns sorted according to several characteristics. Bakshi et al. (2017) state that a 3-factor model including a momentum factor describes the cross-section of commodity futures returns even more clearly. In addition, Fernandez-Perez et al. (2018) introduce a 4-factor commodity pricing model, augmented by a hedging pressure factor. As a consequence, we need to be careful to examine the abnormal returns of anomalies in commodity futures markets, with respect not only to equity but also to commodity factors models. Typically, our results are very similar across all factor models. It is thus unlikely that differences in systematic risk materially affect our main conclusions.

The remainder of this chapter proceeds as follows. Section 6.2 introduces the data, factor models and variables. Section 6.3 presents our main empirical results. Section 6.4 shows robustness results. Finally, Section 6.5 concludes.

6.2 Data & Methodology

6.2.1 Data

We retrieve futures and options data for 26 commodities from the Commodity Research Bureau (CRB). All time series are denoted in U.S. Dollar (USD). Our sample period spans the time from August 1959 until December 2015. Table 6.1 provides an overview of the commodities and the corresponding numbers of observations.

To avoid irregular pricing patterns in a futures contract maturities, we roll the futures returns following Szymanowska et al. (2014) and Bakshi

Table 6.1: Summary Statistics Monthly Commodity Excess Returns

This table summarizes key statistics about monthly commodity excess returns. We sample all data at the monthly frequency. “Average”, “Std Dev”, “Skewness”, and “Kurtosis” denote the (annualized) mean, (annualized) standard deviation, skewness, and kurtosis, respectively. The next two measures represent the 10 % and 90 % quantile, respectively. “Nobs”, and “First Obs.” are the number of observations and the first observation available, respectively.

Variable	Average	Std Dev	Skewness	Kurtosis	10%-Quantile	90%-Quantile	Nobs	First Obs.
Brent Oil	0.0585	0.2914	1.1902	8.7608	-0.9654	1.1599	677	31.08.1959
Cocoa	-0.0185	0.2411	1.1994	9.4976	-0.9239	0.8814	677	31.08.1959
Coffee	0.1086	0.3275	0.4497	6.2880	-1.2030	1.3326	317	31.08.1989
Corn	0.0350	0.3055	0.6782	4.3679	-1.1818	1.4283	677	31.08.1959
Cotton	0.0772	0.3304	0.3714	5.5903	-1.2602	1.3579	393	29.04.1983
Feeder Cattle	0.0208	0.2363	0.6376	6.2230	-0.8689	0.8964	677	31.08.1959
Gold	0.0598	0.2646	0.4369	4.8893	-0.9420	1.1731	236	29.02.1996
Heating Oil	0.0368	0.1648	-0.4698	5.4982	-0.6045	0.6743	528	31.01.1972
High Grade Copper	0.0108	0.1935	0.4844	6.2515	-0.6962	0.7600	491	28.02.1975
Lean Hogs	0.1048	0.2650	0.1758	5.1679	-0.8796	1.2052	677	31.08.1959
Live Cattle	0.0799	0.3193	0.8946	7.4362	-1.2109	1.2593	445	29.12.1978
Lumber	0.0532	0.3263	1.6490	11.499	-1.1737	1.3338	586	31.03.1967
Milk	0.0532	0.3723	1.1827	6.5348	-1.3093	1.5145	520	29.09.1972
Natural Gas	-0.0465	0.2713	0.0999	3.1760	-1.2144	1.1786	554	28.11.1969
Oats	0.0493	0.1623	-0.2492	5.4700	-0.5706	0.7009	612	29.01.1965
Oranges	0.0350	0.2513	0.1326	3.9913	-1.0414	1.0266	597	29.04.1966
Palladium	-0.0824	0.4850	0.6014	4.3127	-2.0478	1.8740	308	31.05.1990
Platinum	-0.0076	0.2910	2.3066	23.965	-1.0576	1.0048	677	31.08.1959
Rough Rice	0.1094	0.3475	0.3695	5.9824	-1.2187	1.4380	467	28.02.1977
Silver	0.0459	0.2733	0.4572	7.3223	-0.9768	1.0321	573	30.04.1968
Soybeans	-0.0442	0.2682	1.0327	7.8229	-1.1480	1.0291	352	30.09.1986
Soybean Meal	0.0545	0.2575	1.4853	13.217	-0.7885	1.0095	677	31.08.1959
Soybean Oil	0.0561	0.4235	1.1669	6.5380	-1.5383	1.6760	659	28.02.1961
Sugar	0.0333	0.3105	0.7161	8.9322	-1.1201	1.2662	630	31.07.1963
Wheat	0.0954	0.2917	2.0091	18.720	-0.9204	1.1888	677	31.08.1959
WTI Oil	-0.0127	0.2532	0.7644	6.8882	-0.9937	0.9848	677	31.08.1959

et al. (2017). We consider the nearest to maturity contract as the spot contract and roll over the contracts during the month that is two months prior to maturity. It is important to note that we sort the commodities and hold commodity futures with fixed maturity. That is, we regularly roll the commodity futures and our strategy earns only commodity futures spot, not

term premia (Szymanowska et al., 2014).

The CRB does not provide unique strike prices for commodity options. We therefore run an algorithm to determine the exact strike price.⁹ We also check for standard no-arbitrage conditions and discard observations not fulfilling these.¹⁰ We then compute the implied volatility following Barone-Adesi & Whaley (1987), accounting for the early exercise premium in American options. Finally, we impose a monotonicity condition so that call (put) option prices of the same maturity decrease (increase) with the strike price. Finally, to limit the effect of recording errors, we impose the condition that deletes all options with implied volatility greater than three times the median implied volatility.

We obtain the monthly time series of the S&P 500 total return index from the Center for Research in Security Prices (CRSP) database. In addition, we take the non-standardized S&P 500 index option data with different maturities from OptionMetrics. We take the factors for the Fama & French (1996) 3-factor model, the Carhart (1997) 4-factor model, as well as the Fama & French (2015) 5-factor model from Kenneth French's website. Finally, we collect data on the holdings of investors classified into different categories from the website of Commodity Futures Trading Commission (CFTC). As risk-free rate, we use the 1-month Treasury Bill rate provided by Kenneth French.

⁹The CRB fills the actual strike price with zeros to obtain a 4-digit number. Therefore, to find the exact strike price, we first divide the reported strike price by 1000, 100, 10, and 1, and then we minimize the distance between the early exercise payoff and the option price, i.e., we compute $\epsilon_{C,K_i} = |C - \max(S - K_i, 0)|$ and $\epsilon_{P,K_i} = |P - \max(K_i - S, 0)|$ in the case of calls and puts, respectively. C and P denote the call and put price, respectively. S and K_i are the stock and strike price, respectively. We then take the strike price with the smallest pricing error. Finally, repeating this procedure for every day, we compute the mode of the strike price per contract.

¹⁰No-arbitrage states for calls and puts that $\max(K - S_t, 0) \leq P_t \leq K$ and $\max(S_t - K, 0) \leq C_t \leq S_t$, respectively, where K is the option's strike price, and S_t , P_t , and C_t are the time- t stock, put, and call prices, respectively.

6.2.2 Factor Models

To test whether several characteristics are priced in the cross-section of commodity futures returns, we examine the abnormal performance of the strategies relative to both equity and commodity factor models. As equity factor models, we use the Capital Asset Pricing Model (CAPM), the Fama & French (1996) 3-factor model, comprising a market factor (MRP), a size factor (SMB), and a value factor (HML). We also use the Carhart (1997) 4-factor model, which augments the 3-factor model by a momentum factor (UMD). Finally, we take the Fama & French (2015) 5-factor model, incorporating the market, the size, the value, as well as a profitability (RMW) and an investment factor (CMA).

Under the law of one price and free portfolio formation, there exists a unique stochastic discount factor (SDF) that prices all assets (Cochrane, 2005a). Given that theorem, asset pricing models for stocks should also have explanatory power for the cross-section of commodity futures. However, this is true only when equity and commodity markets are integrated. Bessembinder (1992) studies commodity and currency futures, testing integration against a general futures pricing function. The author shows that equity and commodity markets are well but not perfectly integrated. More recently, Daskalaki et al. (2014) argue that equity and commodity markets are segmented rather than integrated in that different factors price equities and commodity futures.

Consequently, following Bakshi et al. (2017), we also use a 3-factor commodity model, labeled as the *BGR model*, comprising a long-only commodity factor (EW), a term structure factor (TS), and a commodity momentum factor (MOM). We also follow Fernandez-Perez et al. (2018) and augment that model by a hedging pressure factor (HP). The resulting 4-factor model is in the following labeled as the *FFFM model*. Section E.1

of the Appendix to this chapter describes the construction of the factors in more detail and Table 6.2 provides summary statistics of the factors.

6.2.3 Variables

Commodity Futures Excess Returns Following Gorton et al. (2012) and Bakshi et al. (2017), we compute the simple return on a fully collateralized futures position as

$$r_{t+1} = \frac{F_{t+1,T} - F_{t,T}}{F_{t,T}} + r_t^f, \quad (6.1)$$

where $F_{t+1,T}$ and $F_{t,T}$ are the futures prices on the nearby contract with expiration at T at the end of month $t + 1$ and t , respectively. r_t^f represents the interest on a fully collateralized futures position. We therefore define the corresponding excess return on a fully collateralized futures position as

$$er_{t+1} = r_{t+1} - r_t^f, \quad (6.2)$$

where er_{t+1} denotes the excess return.¹¹ We are cautious not to mix information from different futures contracts in the return computation in that we always compute the returns comparing prices from one contract at different points in time (Singleton, 2013).

Characteristics We analyze several characteristics that have been introduced and discussed in the literature. We study aggregate volatility (Ang, Hodrick, Xing, & Zhang, 2006b; Cremers, Halling, & Weinbaum, 2015) and aggregate jump risk (Cremers et al., 2015). We also examine co-skewness (Harvey & Siddique, 2000), co-kurtosis (Dittmar, 2002), and downside beta (Ang et al., 2006a). In addition, we consider historical moment measures

¹¹Since we base our analysis on the most conservative position by using fully collateralized futures positions, the mean return of our, e.g., 3–1 hedge portfolio is defined as the difference between the half of the mean return on portfolio 3 and half of the mean return on portfolio 1. The remaining half of the investment serves as collateral and earns the risk-free interest rate.

6.2. DATA & METHODOLOGY

Table 6.2: Summary Statistics Factors and Characteristics

This table summarizes key statistics about the factors and characteristics used in this chapter. We sample all data at the monthly frequency. “Average”, “Std Dev”, “Skewness”, and “Kurtosis” denote the (annualized) mean, (annualized) standard deviation, skewness, and kurtosis, respectively. The final two statistics represent the 10 % and 90 % quantiles, respectively.

Variable	Average	Std Dev	Skewness	Kurtosis	10%-Quantile	90%-Quantile
Factors						
<i>EW</i>	0.0442	0.4724	0.1652	6.4959	-0.4918	0.5501
<i>TS</i>	0.0491	0.2740	-0.2475	3.6795	-0.2822	0.3628
<i>MOM</i>	0.0744	0.3295	0.0636	4.4322	-0.3234	0.4777
<i>HP</i>	0.0523	0.3939	0.0400	4.8443	-0.4304	0.5112
<i>MRP</i>	0.0599	0.5333	-0.5227	4.9253	-0.5798	0.6526
<i>SMB</i>	0.0304	0.3653	0.3733	6.2292	-0.4048	0.4384
<i>HML</i>	0.0415	0.3371	0.0456	5.1604	-0.3396	0.4482
<i>UMD</i>	0.0849	0.5079	-1.3695	13.715	-0.4728	0.5954
<i>RMW</i>	0.0293	0.2680	-0.3037	15.645	-0.2316	0.2771
<i>CMA</i>	0.0360	0.2415	0.2907	4.6797	-0.2344	0.3352
Characteristics						
<i>AggVol^{VIX}</i>	0.0108	0.1449	0.1980	3.5456	-0.1513	0.1762
<i>AggVol</i>	0.0058	0.0781	-0.2629	3.9450	-0.0813	0.0919
<i>AggJump</i>	-0.0025	0.0335	0.2899	3.6987	-0.0391	0.0350
<i>CoSkew</i>	-1.0000	11.833	-0.0861	3.5506	-14.039	11.530
<i>CoKurt</i>	-34.290	935.10	-0.0346	3.7577	-1044.5	947.03
<i>DownBeta</i>	0.1087	0.3063	0.0020	3.4029	-0.2203	0.4577
<i>HistVar</i>	0.0774	0.0586	1.6070	6.0708	0.0286	0.1351
<i>HistSkew</i>	-0.0703	1.0402	-0.2005	5.1713	-1.0628	0.8221
<i>HistKurt</i>	8.6770	8.5927	2.1915	7.8006	3.4744	15.639
<i>IdioVol^{FF3}</i>	0.2520	0.0918	0.8388	3.9534	0.1593	0.3529
<i>IdioVol^{BGR}</i>	0.2082	0.0698	0.8640	3.8496	0.1377	0.2887
<i>ILLIQ</i>	0.0003	0.0006	2.1051	6.8580	0.0000	0.0010
<i>Mom^{char}</i>	0.0445	0.2889	0.2770	3.4417	-0.2658	0.3667
<i>3Y Reversal</i>	0.0481	0.1660	0.1474	3.2254	-0.1269	0.2392
<i>5Y Reversal</i>	0.0502	0.1300	0.2007	3.4487	-0.0862	0.1957
<i>RNVar</i>	0.0768	0.0580	1.2762	4.9523	0.0295	0.1324
<i>RNSkew</i>	0.0360	0.5871	-0.2511	3.1161	-0.6023	0.6245
<i>RNExKurt</i>	2.4557	2.9468	1.5136	5.2971	0.4208	5.3778
<i>MAX</i>	0.0454	0.0192	1.1780	4.8505	0.0271	0.0657
<i>Value</i>	0.9526	0.3349	-0.2655	9.7875	0.8708	1.0604
<i>VoV</i>	0.1457	0.0577	0.6413	3.0613	0.0908	0.2093

(Amaya, Christoffersen, Jacobs, & Vasquez, 2015), idiosyncratic volatility (Ang et al., 2006b; Ang, Hodrick, Xing, & Zhang, 2009), and illiquidity (Amihud, 2002). Finally, we examine past performance measures (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993), measures characterizing the risk-neutral distribution (Bakshi et al., 2003), a maximum return measure (Bali et al., 2011), as well as value (Asness et al., 2013), and volatility-of-volatility (Baltussen, Van Bakkum, & Van Der Grient, 2018). Table 6.2 provides an overview of the characteristics, and Section E.2 of the Appendix to this chapter describes the construction of the characteristics in further detail.

6.3 Main Empirical Results

6.3.1 The Rationality of Commodity Markets

Yu & Yuan (2011) and Stambaugh et al. (2012), among others, suggest that investor sentiment is directly related to the degree of market rationality. The authors argue that high-sentiment periods are associated with higher participation of noise traders in the market. Yu & Yuan (2011) assert that these noise traders contaminate the mean–variance trade-off, while Stambaugh et al. (2012) show that several market anomalies are stronger during high-sentiment periods.

To examine whether this channel also holds for commodity markets, we use the CFTC data on institutional investor holdings as well as the sentiment index of Baker & Wurgler (2006).¹² We regress the change in the percentage share of institutional investors in commodity markets (hedgers

¹²We use the sentiment index orthogonalized to macroeconomic variables. The data are available on Jeffrey Wurgler’s website.

6.3. MAIN EMPIRICAL RESULTS

and speculators) on the change in sentiment.¹³

In Table 6.3, we present the regression results. For 23 out of 26 individual commodities, we cannot reject the hypothesis that changes in the share of institutional investors in commodity markets are unrelated to changes in sentiment. Only for platinum do we find a significantly negative relation. For Brent oil and rough rice, we even detect a positive relation between sentiment and the share of institutional investors in the commodity market. Hence, there is no evidence to indicate that an increase in sentiment does induce noise traders to enter the market.

This simple analysis underlines the notion that the impact of noise traders is reduced substantially in commodity markets. Since noise traders are an important ingredient for creating and sustaining “irrational” prices, we are confident in our notion that commodity markets provide an excellent environment to study the economic sources of return anomalies.

6.3.2 Summary Statistics

Table 6.1 reports summary statistics on the different monthly commodity futures excess returns. Examining the performance of the commodities, we observe two-fold patterns. On the one hand, most commodity futures perform exceptionally well as an investment over the time period under investigation. Notable annualized mean excess returns are observable in the case of coffee (10.86 %), cotton (7.72 %), lean hogs (10.48 %), rough rice (10.94 %), and wheat (9.54 %). On the other hand, some commodities show a very poor performance, indicated by negative annualized mean returns, and so reflect recent developments in specific commodity markets.¹⁴

¹³To account for high autocorrelation and potential non-stationarity in the variables, we use the changes instead of the levels of the variables. Using the levels, we obtain qualitatively similar results.

¹⁴We may mention, among others, the development in the oil market due to the introduction of fracking in the U.S., driving down the trading price of WTI oil.

Table 6.3: Institutional Investors and Sentiment

*This table reports the results of regressions of the change in the share of reportable institutional investors according to the definition of the CFTC in the individual commodity markets on the innovation in sentiment. In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. "Adj. R²" denotes the adjusted R² of the regressions.*

	Soybean Oil	Corn	Brent Oil	Cocoa	WTI Oil	Cotton	Milk	Feeder Cattle	Gold	High Grade Copper	Heating Oil	Oranges	Coffee
<i>Constant</i>	0.0011* (0.0006)	0.0012** (0.0006)	0.0025 (0.0015)	0.0003 (0.0005)	0.0005 (0.0006)	0.0010 (0.0007)	0.0012 (0.0019)	0.0006 (0.0012)	0.0005 (0.0005)	0.0023** (0.0010)	0.0006 (0.0008)	0.0009 (0.0011)	0.0007 (0.0008)
<i>Slope</i>	0.0062 (0.0059)	0.0044 (0.0062)	0.0527** (0.0236)	0.0039 (0.0068)	0.0008 (0.0051)	0.0058 (0.0059)	0.0014 (0.0127)	-0.0029 (0.0093)	-0.0094 (0.0058)	0.0053 (0.0081)	0.0076 (0.0083)	0.0045 (0.0099)	-0.0074 (0.0075)
<i>Adj. R²</i>	-0.0004	-0.0001	0.0959	-0.0017	-0.0028	-0.0003	-0.0047	-0.0026	0.0017	-0.0021	-0.0005	-0.0022	-0.0004

	Lumber	Live Cattle	Lean Hog	Natural Gas	Oats	Palladium	Platinum	Rough Rice	Soybeans	Sugar	Silver	Soybean Meal	Wheat
<i>Constant</i>	0.0008 (0.0019)	0.0013* (0.0007)	0.0031** (0.0015)	0.0014* (0.0008)	0.0004 (0.0014)	0.0008 (0.0009)	0.0009 (0.0007)	0.0005 (0.0020)	0.0011* (0.0007)	0.0004 (0.0009)	0.0005 (0.0006)	0.0009 (0.0006)	0.0010* (0.0005)
<i>Slope</i>	0.0011 (0.0184)	-0.0087 (0.0067)	0.0130 (0.0094)	-0.0063 (0.0048)	0.0051 (0.0124)	-0.0076 (0.0096)	-0.0173** (0.0087)	0.0242* (0.0130)	0.0061 (0.0062)	0.0085 (0.0082)	-0.0063 (0.0074)	0.0060 (0.0065)	0.0066 (0.0068)
<i>Adj. R²</i>	-0.0042	0.0026	0.0041	-0.0009	-0.0040	-0.0016	0.0060	0.0082	0.0002	0.0003	-0.0005	-0.0005	0.0018

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Examples are cocoa (−1.85 %), natural gas (−4.65 %), palladium (−8.24 %), platinum (−0.76 %), soybeans (−4.42 %), and WTI oil (−1.27 %).¹⁵ Overall, the patterns of our summary statistics are similar to those of Gorton & Rouwenhorst (2006) and Bakshi et al. (2017).

Table 6.2 presents summary statistics on the factors and characteristics under study. We observe that *MOM* and *UMD* exhibit a similar magnitude in annualized average returns (7.44 % and 8.49 %, respectively), but have different standard deviations (32.95 % and 50.79 %, respectively). Thus, it seems that even though the risk premia appear similar on average, in equity markets the momentum strategy is more volatile than that in commodity markets.

We also observe that the idiosyncratic volatility under the BGR model is lower than that under the Fama & French (1996) 3-factor model, indicated by annualized average returns of 20.82 % and 25.20 %, respectively. The BGR model thus appears to explain, on average, a larger fraction of the variation in commodity returns compared to the 3-factor model. However, since the main purpose of factor models is to explain differences in average returns rather than the variation in returns, this preliminary evidence does not necessarily imply that the BGR model is better suited for explaining commodity returns than the 3-factor model.¹⁶

Table 6.4 reports the time series averages of cross-sectional correlations among the characteristics under investigation. We observe that *AggJump* and *AggVol* exhibit a correlation of −0.76. There thus seems to be a strong negative relation between the smooth volatility and jump risk sensitivities of commodities. Further, we notice high correlations between *Mom^{char}* and *3Y Reversal*, as well as *5Y Reversal* of 0.57 and 0.78, respectively, which

¹⁵Note that because we annualize the monthly returns, some 10 %-quantiles exhibit values smaller than −1.

¹⁶We discuss the suitability of the different factor models for commodity markets further, in Section 6.3.4.

is not surprising, because all these measures cover the past performance of commodities. The relatively high negative correlations between *Value* and *3YReversal* as well as *5YReversal* of -0.37 and -0.43 , respectively, are likewise not surprising given the definition of *Value* as a ratio of past to current futures prices.

The high correlations between *RNVar* and *HistVar* (0.78), *IdioVol^{FF3}* (0.77), and *IdioVol^{BGR}* (0.69), respectively, indicate that these characteristics have largely a similar information content. Likewise, the correlations between *HistVar* and *IdioVol^{FF3}* (0.97), and *IdioVol^{BGR}* (0.88) indicate that both factor models have difficulty in explaining the variation in returns for the same commodities. Interestingly, we find a high correlation between *MAX* and *HistVar* of 0.88, *MAX* and *IdioVol^{FF3}* of 0.89, and *MAX* and *IdioVol^{BGR}* of 0.84.¹⁷

We find substantial negative correlations between *DownBeta* and *AggJump* of -0.35 and *CoSkew* of -0.57 , respectively, indicating a somewhat similar information content in these variables. Finally, we observe a consistent negative correlation pattern between *HistSkew* and measures based on the historical performance (momentum and reversal), with values between -0.30 and -0.42 . Interestingly, even though *MAX* is sometimes interpreted as a measure of skewness, its correlation to *HistSkew* is only moderate, amounting to 0.39.

6.3.3 Portfolio Sorts

To test whether several characteristics are priced in the cross-section of commodity returns, at the end of each month, we sort the commodities into

¹⁷The high correlations between *MAX* and idiosyncratic volatility are consistent with those reported by Hou & Loh (2016), who find a correlation of 0.90 for equity markets.

Table 6.4: Correlation Matrix: Characteristics

This table reports time series averages of cross-sectional correlations of the sorting characteristics. Each month we first compute the pairwise correlations between the characteristics. Afterwards, we obtain the time series of these correlations.

	AggVolVIX	AggVol	AggJump	CoSkew	CoKurt	DownBeta	HistVar	HistSkew	HistKurt	IdioVol ^{FF3}	IdioVol ^{BGR}	ILLIQ	Mom ^{char}	3YReversal	5YReversal	RNVar	RNSkew	RNExKurt	Value
AggVolVIX	-0.13																		
AggVol	0.40	-0.76																	
AggJump	0.11	-0.41	0.52																
CoSkew	-0.13	0.09	-0.14	-0.04															
DownBeta	-0.05	0.26	-0.35	-0.57	0.27														
HistVar	-0.05	-0.10	0.04	-0.01	-0.04	0.06													
HistSkew	0.15	-0.10	0.09	0.17	-0.02	-0.10	0.08												
HistKurt	0.05	0.00	0.02	0.10	-0.02	-0.11	0.07	0.11											
IdioVol ^{FF3}	-0.06	-0.08	0.02	-0.02	-0.03	0.06	0.97	0.08	0.08										
IdioVol ^{BGR}	-0.03	-0.12	0.08	0.06	-0.02	-0.03	0.88	0.13	0.15	0.92									
ILLIQ	0.07	0.06	0.04	-0.09	0.01	0.05	-0.03	-0.16	-0.06	-0.02	-0.02								
Mom ^{char}	-0.03	0.16	-0.13	-0.18	-0.04	0.05	-0.01	-0.30	-0.12	0.00	-0.04	0.09							
3YReversal	-0.15	0.09	-0.09	-0.23	-0.05	0.10	0.05	-0.42	-0.15	0.05	-0.03	0.13	0.57						
5YReversal	-0.11	0.08	-0.07	-0.20	-0.04	0.14	0.08	-0.38	-0.16	0.07	-0.04	0.19	0.48						
RNVar	-0.05	-0.04	0.00	-0.09	-0.04	0.16	0.78	-0.01	-0.06	0.77	0.69	0.02	0.03	0.11	0.14				
RNSkew	0.11	-0.07	0.10	0.06	-0.01	-0.02	0.13	0.09	-0.14	0.19	0.16	0.15	-0.07	-0.07	-0.04	0.15			
RNExKurt	0.07	0.04	0.02	0.04	-0.01	-0.06	-0.12	-0.05	-0.05	-0.12	-0.17	0.26	0.00	0.00	-0.02	-0.04	-0.02		
MAX	0.02	-0.09	0.06	0.05	-0.03	0.02	0.88	0.39	0.25	0.89	0.84	-0.07	-0.11	-0.14	-0.09	0.66	0.16	-0.12	
Value	0.01	-0.02	-0.02	0.01	0.05	-0.01	0.01	0.10	0.08	0.03	0.07	-0.04	-0.27	-0.37	-0.43	-0.11	0.01	0.04	0.06
VoV	-0.04	0.00	-0.04	-0.03	-0.02	0.07	0.18	0.00	0.04	0.15	0.09	-0.02	0.02	0.03	0.02	0.20	-0.02	0.01	0.16
																			-0.08

3 portfolios according to the specific characteristic under study.¹⁸ Tables 6.5–6.11 summarize the results. Table 6.5 presents the results when sorting on aggregate volatility and aggregate jump risk sensitivities, Table 6.6 those for co-skewness, co-kurtosis, and downside beta, and Table 6.7 sorts on historical moment characteristics. In Table 6.8, we report the results for illiquidity and idiosyncratic volatility, in Table 6.9 those for momentum and reversal characteristics, in Table 6.10 those for risk-neutral moments, and in Table 6.11, we examine the *MAX*, value, and volatility-of-volatility measures.

In each table, portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the sorting characteristic. We refer to portfolio P3–P1 as the hedge portfolio and define it as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short in portfolio P1 and long in portfolio P3.^{19,20}

Aggregate Volatility Risk Sorting the commodities according to their sensitivities to aggregate volatility, following Ang et al. (2006b), we find an insignificant negative mean return of the hedge portfolio of -1.63% p.a. (Table 6.5). The factor alphas are of similar magnitude and none of them is significantly different from zero. Thus, it seems that, in contrast to equity returns, commodity futures returns are not affected by total stock volatility risk.

Our findings are in accordance with those reported in Ang et al. (2006b)

¹⁸We split the commodities into 3 portfolios to deal with a limited number of commodities available, particularly at the beginning of our sample period. We examine the robustness of our results to building 2, 4, and 5 portfolios in Section 6.4.1. These are very similar to those for 3 portfolios reported in this section.

¹⁹We impose the restriction that each month at least 6 commodities must be available.

²⁰For robustness, we follow Locke & Venkatesh (1997) and also impose monthly transaction costs of two times 0.033%. Although we take a conservative viewpoint and assume a complete turnover of the commodities, we find that the results are largely unaffected by transaction costs. The results including transaction costs are qualitatively similar and are available upon request.

Table 6.5: Portfolio Sorts: Aggregate Volatility and Jump Characteristics

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3-P1 is referred to as the hedge portfolio and is defined as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). "Mean return" denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	AggVol ^{VIX}			AggVol			AggJump			
	P1	P2	P3	P1	P2	P3	P1	P2	P3	P3 - P1
Mean return	0.0376 (0.0314)	0.0266 (0.0325)	0.0050 (0.0286)	-0.0163 (0.0140)	0.0336 (0.0410)	0.0321 (0.0440)	0.0507 (0.0453)	0.0158 (0.0440)	-0.0420 (0.0386)	-0.0463*** (0.0161)
CAPM alpha	0.0222 (0.0343)	0.0099 (0.0333)	-0.0059 (0.0295)	-0.0141 (0.0143)	0.0147 (0.0396)	0.0131 (0.0433)	0.0322 (0.0454)	-0.0035 (0.0424)	-0.0619* (0.0367)	-0.0471*** (0.0165)
3-factor alpha	0.0160 (0.0323)	0.0066 (0.0330)	-0.0081 (0.0290)	-0.0121 (0.0136)	0.0128 (0.0394)	0.0089 (0.0419)	0.0265 (0.0448)	-0.0057 (0.0414)	-0.0601 (0.0371)	-0.0433*** (0.0174)
4-factor alpha	0.0212 (0.0328)	0.0016 (0.0336)	-0.0052 (0.0295)	-0.0132 (0.0133)	0.0078 (0.0393)	0.0033 (0.0416)	0.0215 (0.0448)	-0.0074 (0.0407)	-0.0599 (0.0380)	-0.0407*** (0.0186)
5-factor alpha	0.0259 (0.0348)	0.0113 (0.0355)	0.0005 (0.0302)	-0.0127 (0.0142)	0.0114 (0.0426)	0.0019 (0.0460)	0.0222 (0.0493)	-0.0142 (0.0442)	-0.0630 (0.0421)	-0.0426*** (0.0193)
BGR alpha	-0.0226 (0.0183)	-0.0327* (0.0176)	-0.0556*** (0.0161)	-0.0165 (0.0138)	-0.0316* (0.0162)	-0.0392* (0.0215)	-0.0183 (0.0220)	-0.0525*** (0.0180)	-0.0926*** (0.0216)	-0.0371*** (0.0159)
FFFM alpha	-0.0204 (0.0179)	-0.0354*** (0.0174)	-0.0557*** (0.0162)	-0.0177 (0.0137)	-0.0313** (0.0158)	-0.0361* (0.0211)	-0.0130 (0.0222)	-0.0569*** (0.0186)	-0.0938*** (0.0214)	-0.0404*** (0.0158)

for the equity market regarding the direction of pricing, however, much smaller in magnitude and insignificant. Ang et al. (2006b) obtain a highly significant -1% per month. The authors argue that the price of aggregate volatility has to be negative because an increasing market volatility is associated with a worsening of investment opportunities. Thus, risk-averse investors want to hedge against changes in aggregate volatility (Campbell, 1993, 1996). High levels of aggregate volatility tend to go along with market downturns (French, Schwert, & Stambaugh, 1987; Campbell & Hentschel, 1992). Investors increase their demand for assets with high sensitivities to aggregate volatility, because such assets represent a natural hedge against market downturns (Bakshi & Kapadia, 2003). The rising demand leads to an increase in the assets' prices, which is associated with a reduction in expected returns.

However, when separating aggregate volatility and jump risk, following Cremers et al. (2015), we find a significant positive mean return of a long-short portfolio of 3.56% p.a. The alphas relative to all factor models are statistically significant. Thus, it seems that smooth aggregate volatility is priced in the cross-section of commodity returns. Our findings are in contrast to Cremers et al. (2015), who observe a negative contemporaneous relationship between stock returns and smooth aggregate volatility with a significant alpha of -2.7% p.a. of a 5-1 portfolio, relative to the Fama & French (1996) 3-factor model. They motivate the negative risk premium also with hedging opportunities against market risk. Assets that exhibit a positive correlation with market volatility risk provide a natural hedge and, thus, investors require lower expected returns.

There is one important potential reason why our results for commodity futures differ from theirs for equity returns. Commodity futures returns typically perform well in the early stages of recessions (Gorton & Rouwenhorst, 2006) when (continuous) aggregate volatility typically spikes

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most strongly. Thus, aggregate volatility risk may be well-hedgeable with all commodities. Even stronger reactions to innovations to continuous aggregate volatility may simply indicate higher variability of the commodity returns.

Aggregate Jump Risk Related to the previous part, we also sort according to the sensitivities to the jump part of aggregate volatility (Cremers et al., 2015). Going short (long) a portfolio with low (high) aggregate jump risk sensitivities generates a significant mean return of -4.63% p.a. (Table 6.5). We find significant alphas, relative to all factor models. Thus, jump risk appears to be significantly priced in the cross-section of commodity returns.

Our findings are consistent with those in Cremers et al. (2015) for equity returns, who find a significant contemporaneous alpha of -9.4% p.a., relative to the 3-factor model. The authors relate the negative pricing to investors who seek a hedge against crises, thus, they demand stocks that positively co-vary with aggregate jump risk, leading to lower expected returns. This intuition is consistent with our findings. Commodities that are more positively correlated with innovations in aggregate jump risk earn lower average returns. The smaller magnitude of the average returns we find is natural, since contemporaneously the anomalies will always be stronger than in the predictive setting used in our study as long as factor sensitivities are time-varying. Note also that the results across aggregate volatility and jump risk are consistent in total. Aggregate unseparated volatility risk is unpriced in commodity markets. When separating into continuous and jump parts, the continuous part is priced positively and the jump part is priced negatively.

Thus, aggregate jump risk appears to be a severe rationally motivated risk factor in the economy that is priced both in commodity and equity markets.

Co-Skewness Sorting the commodities according to their co-skewness, we obtain an insignificant mean return of the hedge portfolio of 1.70 % p.a. (Table 6.6). Generally, we find insignificant alphas relative to the factor models. Only for the BGR model do we detect a weakly positively significant alpha. It seems that, overall, co-skewness is not priced in the cross-section of commodity returns.

Our findings are in contrast to those in Harvey & Siddique (2000), who provide evidence for a significant negative relationship between co-skewness and stock returns. They also find that augmenting the Fama & French (1996) 3-factor model with co-skewness improves the model's accuracy. The authors motivate their findings (rationally) by investors' preference for a positively skewed portfolio (see also Kraus & Litzenberger, 1976). Investors require a higher expected return for holding negatively skewed assets. The fact that our results for commodity markets do not match these predictions, along with a weak performance of co-skewness as a control variable in cross-sectional regression tests on stocks (e.g., Bollerslev, Li, & Todorov, 2016; Hollstein & Prokopczuk, 2017), indicates that co-skewness is largely unpriced in asset markets.

Co-Kurtosis Next, we sort the commodities according to their co-kurtosis. The 3–1 long–short portfolio generates an insignificant average spread return of –1.50 % p.a. (Table 6.6). The alphas relative to all factor models are not statistically significant. Thus, it seems investors do not demand a risk premium for co-kurtosis in commodity markets.

These findings are in contrast to Dittmar (2002), who provides evidence for a significant relationship between co-kurtosis and stock returns, indicated by a significant monthly alpha of 1.15 %, relative to the 3-factor model. However, similar to co-skewness, co-kurtosis is typically not priced in cross-sectional asset pricing tests when employed as a control variable

Table 6.6: Portfolio Sorts: Co-Moments and Downside Beta Characteristics

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3-P1 is referred to as the hedge portfolio and is defined as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). "Mean return" denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	CoSkew			CoKurt			DownBeta					
	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1
Mean return	0.0307 (0.0267)	0.0345 (0.0220)	0.0647** (0.0270)	0.0170 (0.0138)	0.0592** (0.0237)	0.0449* (0.0248)	0.0292 (0.0274)	-0.0150 (0.0137)	0.0559** (0.0232)	0.0468** (0.0231)	0.0285 (0.0280)	-0.0137 (0.0136)
CAPM alpha	0.0229 (0.0278)	0.0258 (0.0225)	0.0551* (0.0288)	0.0161 (0.0142)	0.0493** (0.0249)	0.0377 (0.0262)	0.0198 (0.0282)	-0.0148 (0.0137)	0.0498** (0.0241)	0.0396* (0.0240)	0.0154 (0.0294)	-0.0172 (0.0138)
3-factor alpha	0.0185 (0.0272)	0.0196 (0.0225)	0.0459* (0.0278)	0.0137 (0.0136)	0.0436* (0.0245)	0.0318 (0.0262)	0.0122 (0.0279)	-0.0157 (0.0134)	0.0390 (0.0241)	0.0356 (0.0240)	0.0111 (0.0288)	-0.0139 (0.0135)
4-factor alpha	0.0220 (0.0292)	0.0183 (0.0240)	0.0424 (0.0290)	0.0102 (0.0144)	0.0397 (0.0266)	0.0299 (0.0262)	0.0166 (0.0233)	-0.0116 (0.0143)	0.0339 (0.0256)	0.0389 (0.0257)	0.0123 (0.0297)	-0.0108 (0.0142)
5-factor alpha	0.0287 (0.0303)	0.0246 (0.0249)	0.0590* (0.0309)	0.0151 (0.0150)	0.0575** (0.0266)	0.0412 (0.0309)	0.0166 (0.0294)	-0.0204 (0.0137)	0.0499* (0.0271)	0.0403 (0.0263)	0.0232 (0.0319)	-0.0133 (0.0153)
BGR alpha	-0.0477*** (0.0154)	-0.0256*** (0.0129)	-0.0018 (0.0171)	0.0229* (0.0133)	-0.0111 (0.0170)	-0.0208* (0.0126)	-0.0421** (0.0185)	-0.0155 (0.0152)	-0.0147 (0.0152)	-0.0153 (0.0129)	-0.0450** (0.0176)	-0.0152 (0.0138)
FFFM alpha	-0.0430** (0.0180)	-0.0375** (0.0174)	-0.0309 (0.0224)	0.0061 (0.0163)	-0.0175 (0.0168)	-0.0467*** (0.0162)	-0.0460** (0.0222)	-0.0142 (0.0155)	-0.0357** (0.0183)	-0.0327** (0.0165)	-0.0432** (0.0218)	-0.0038 (0.0160)

(e.g., Bollerslev et al., 2016; Hollstein & Prokopczuk, 2017). Thus, it seems that co-kurtosis is also not priced in asset markets in general.

Downside Beta Sorting the commodities according to their downside betas, we find an insignificant mean return of the hedge portfolio of -1.37% p.a. (Table 6.6). Relative to all the factor models, the alphas of the 3–1 portfolio are not statistically significant either. Thus, downside beta risk appears to be not priced in the cross-section of commodity returns.

Our results are in contrast to those in Ang et al. (2006a), who find that downside beta is positively priced in the cross-section of stock returns. Using contemporaneous portfolio sorts, they obtain a 5–1 return of 11.8% p.a. Examining the joint cross-section of different asset classes, Lettau, Maggiori, & Weber (2014) find that downside risk is positively priced with a 6–1 return of 9.66% p.a.

Ang et al. (2006a) theoretically justify their findings with a behavioral property of investors: disappointment-aversion. Disappointment-averse investors have a larger (marginal) dis-utility from losses relative to a certain benchmark than their positive (marginal) utility from a gain of the same size. Thus, their utility functions have a kink at the expected value. Given the substantially decreased likelihood of behavioral biases to showing up in the cross-section of commodity returns, our results are consistent with the disappointment-aversion explanation. A substantial segment of investors in the equity market fears disappointments, which leads to downside risk being priced in stock markets. In contrast, in commodity markets, it appears that this behavioral bias does not materialize.

Historical Variance Next, we turn the focus on historical return moments (Table 6.7). First, we sort the commodities according to their historical variances. We find that the hedge portfolio has an insignificant mean return

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of 0.50 % p.a. The alphas relative to all factor models are not statistically significant.

For the cross-section of stock returns, Amaya et al. (2015) obtain an insignificant (weekly) 10–1 hedge portfolio return of 0.11 %, sorting stocks according to realized volatility. The results thus indicate that historical variance is priced neither in stock nor in commodity futures markets.

Historical Skewness Second, we sort the commodities according to their historical skewness. We observe that low-skewness portfolios outperform high-skewness portfolios, resulting in a significant negative mean return of -3.50 % p.a. Only the BGR model is able to explain the skewness effect, however: none of the equity factor models is able to do so.

Fernandez-Perez et al. (2018) also provide evidence for a significant negative relationship between commodity futures returns and historical skewness. They use a reduced sample period of 1987–2014 and detect a significant annualized alpha estimate of -6.58 % relative to the FFFM model. Although we find that the skewness risk premium can be explained by the BGR model, our results are overall quite similar.

Our findings are consistent with those in Amaya et al. (2015), who detect an average weekly return spread of -0.19 % for the equity market.²¹ For (idiosyncratic) skewness, Barberis & Huang (2008) demonstrate that, due to investors having cumulative prospect theory (CPT) preferences, their probability weighting leads to positively skewed stocks being overpriced and, thus, earning low future returns. Mitton & Vorkink (2007) argue that the overpricing does not disappear because there are short-selling restrictions in equity markets.

²¹The authors show that historical skewness computed using intraday rather than daily data might contain different information. Although we use daily data, we obtain similar results.

Table 6.7: Portfolio Sorts: Historical Characteristics

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3-P1 is referred to as the hedge portfolio and is defined as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). "Mean return" denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	HistVar			HistSkew			HistKurt					
	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1
Mean return	0.0460** (0.0215)	0.0300 (0.0246)	0.0560* (0.0298)	0.0050 (0.0147)	0.0826*** (0.0227)	0.0353 (0.0310)	0.0127 (0.0228)	-0.0350*** (0.0124)	0.0144 (0.0279)	0.0496* (0.0257)	0.0656*** (0.0203)	0.0256** (0.0129)
CAPM alpha	0.0412* (0.0225)	0.0189 (0.0260)	0.0454 (0.0312)	0.0021 (0.0154)	0.0782*** (0.0243)	0.0245 (0.0327)	0.0015 (0.0224)	-0.0384*** (0.0121)	0.0017 (0.0295)	0.0399 (0.0265)	0.0616*** (0.0213)	0.0300** (0.0132)
3-factor alpha	0.0373* (0.0226)	0.0124 (0.0261)	0.0361 (0.0296)	-0.0006 (0.0146)	0.0718*** (0.0237)	0.0174 (0.0330)	-0.0045 (0.0223)	-0.0382*** (0.0125)	-0.0059 (0.0297)	0.0318 (0.0262)	0.0578*** (0.0204)	0.0318** (0.0133)
4-factor alpha	0.0358 (0.0234)	0.0171 (0.0270)	0.0323 (0.0313)	-0.0018 (0.0151)	0.0759*** (0.0240)	0.0104 (0.0340)	-0.0036 (0.0241)	-0.0397*** (0.0125)	-0.0168 (0.0296)	0.0375 (0.0290)	0.0627*** (0.0215)	0.0398*** (0.0131)
5-factor alpha	0.0417* (0.0252)	0.0272 (0.0294)	0.0443 (0.0316)	0.0013 (0.0154)	0.0849*** (0.0252)	0.0285 (0.0377)	-0.0011 (0.0242)	-0.0430*** (0.0131)	0.0066 (0.0334)	0.0442 (0.0286)	0.0611*** (0.0222)	0.0273* (0.0147)
BGR alpha	0.0031 (0.0139)	-0.0358** (0.0141)	-0.0415** (0.0176)	-0.0223 (0.0136)	-0.0053 (0.0131)	-0.0445** (0.0174)	-0.0254* (0.0130)	-0.0100 (0.0100)	-0.0709*** (0.0149)	-0.0240* (0.0143)	0.0193 (0.0143)	0.0451*** (0.0122)
FFFM alpha	-0.0229 (0.0165)	-0.0378** (0.0174)	-0.0523** (0.0211)	-0.0147 (0.0155)	-0.0102 (0.0143)	-0.0510** (0.0211)	-0.0512*** (0.0145)	-0.0205* (0.0107)	-0.0653*** (0.0171)	-0.0390** (0.0185)	-0.0103 (0.0164)	0.0275** (0.0131)

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At first glance, these results appear puzzling, since the pricing of skewness is behaviorally-based in theory. Thus, according to our main reasoning, we should not be able to find a skewness risk premium in commodity markets. Fernandez-Perez et al. (2018) deliver a possible solution. They argue that selective hedging under “rational” skewness preferences might well explain the results for commodity markets (Stulz, 1996; Gilbert, Jones, & Morris, 2006).

Historical Kurtosis Third, sorting the commodities according to their historical kurtosis, we observe a positive relationship with future returns, indicated by a significant mean return of the hedge portfolio of 2.56 % p.a. Neither equity models nor commodity models are able to explain this positive relationship, indicated by significant alphas relative to all factor models subject to our investigation. The BGR alpha even significantly exceeds the mean return of the hedge portfolio, amounting to 4.51 % p.a. Thus, historical kurtosis seems to be priced in the cross-section of commodity returns.

Examining the cross-section of stock returns, Amaya et al. (2015) find a significant average weekly return of 0.10 % for a long–short portfolio.²² Overall, the results for stock and commodity markets are consistent and kurtosis seems to be either a proxy for a “rational” risk, or part of the consideration for selective hedging strategies in commodity markets.

Idiosyncratic Volatility When sorting the commodities according to their idiosyncratic volatilities based on the Fama & French (1996) 3-factor model (BGR model), we find an insignificant mean spread return of 0.23 % p.a. (0.85 % p.a.), presented in Table 6.8. The alphas relative to all factor

²²However, their finding is not entirely robust throughout all their test specifications.

models are not statistically significant. It seems that in commodity markets, investors are not compensated for bearing idiosyncratic risk.²³

These results are in contrast to those in Ang et al. (2006b) for the equity market. The authors find a significant negative relationship between idiosyncratic volatility and stock returns, indicated by a significant monthly mean spread return (alpha) of -1.04% (-0.83%). The authors provide one possible explanation: assets with high sensitivity to idiosyncratic volatility are associated with a high sensitivity to aggregate volatility and, thus, tend to have lower expected returns. Ang et al. (2009) confirm their previous findings in an international setting and provide evidence that the negative relationship cannot be explained by market frictions, information flow, and option pricing theories.

Many studies deliver potential explanations for the idiosyncratic volatility puzzle. Merton (1987) extends the classic CAPM framework to include market frictions and shows that investors do not hold optimally diversified portfolios and, thus, might require compensation for bearing idiosyncratic risk. Thus, in this static mean–variance framework, higher idiosyncratic volatility should be associated with higher returns on average. Explicitly modeling commodity markets, Hirshleifer (1988) obtains similar predictions.

On the other hand, Miller (1977) argues that short-sale constraints can lead to an overvaluation of assets, because asset prices might then only reflect the view of the optimistic market participants. The result could be a negative relationship between expected stock returns and idiosyncratic

²³Our findings are consistent with those in Miffre, Fuertes, & Fernandez-Perez (2012), who find an insignificant monthly alpha of 0.12% relative to a modified commodity factor model.

Table 6.8: Portfolio Sorts: Idiosyncratic Volatility and Illiquidity Characteristics

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3-P1 is referred to as the hedge portfolio and is defined as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). "Mean return" denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	IdioVol ^{FF3}						IdioVol ^{BGR}						ILLIQ					
	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1		
Mean return	0.0450** (0.0215)	0.0298 (0.0248)	0.0496* (0.0293)	0.0023 (0.0146)	0.0358 (0.0234)	0.0386 (0.0254)	0.0529* (0.0275)	0.0085 (0.0135)	0.0141 (0.0318)	-0.0129 (0.0227)	-0.0007 (0.0343)	-0.0074 (0.0169)	0.0450** (0.0215)	0.0298 (0.0248)	0.0496* (0.0293)	0.0023 (0.0146)	0.0358 (0.0234)	
CAPM alpha	0.0383* (0.0225)	0.0189 (0.0263)	0.0388 (0.0309)	0.0003 (0.0154)	0.0296 (0.0248)	0.0270 (0.0263)	0.0435 (0.0288)	0.0069 (0.0140)	-0.0032 (0.0335)	-0.0259 (0.0239)	-0.0218 (0.0320)	-0.0093 (0.0169)	0.0383* (0.0225)	0.0189 (0.0263)	0.0388 (0.0309)	0.0003 (0.0154)	0.0296 (0.0248)	
3-factor alpha	0.0347 (0.0226)	0.0130 (0.0265)	0.0311 (0.0293)	-0.0018 (0.0147)	0.0235 (0.0250)	0.0207 (0.0270)	0.0394 (0.0274)	0.0080 (0.0138)	-0.0117 (0.0338)	-0.0303 (0.0244)	-0.0208 (0.0311)	-0.0046 (0.0173)	0.0347 (0.0226)	0.0130 (0.0265)	0.0311 (0.0293)	-0.0018 (0.0147)	0.0235 (0.0250)	
4-factor alpha	0.0344 (0.0234)	0.0156 (0.0274)	0.0294 (0.0312)	-0.0025 (0.0153)	0.0217 (0.0258)	0.0183 (0.0280)	0.0435 (0.0289)	0.0109 (0.0139)	-0.0085 (0.0339)	-0.0292 (0.0251)	-0.0120 (0.0320)	-0.0018 (0.0178)	0.0344 (0.0234)	0.0156 (0.0274)	0.0294 (0.0312)	-0.0025 (0.0153)	0.0217 (0.0258)	
5-factor alpha	0.0388 (0.0254)	0.0274 (0.0293)	0.0398 (0.0316)	0.0005 (0.0155)	0.0317 (0.0269)	0.0342 (0.0299)	0.0415 (0.0280)	0.0049 (0.0136)	-0.0019 (0.0344)	-0.0290 (0.0256)	-0.0121 (0.0322)	-0.0051 (0.0174)	0.0388 (0.0254)	0.0274 (0.0293)	0.0398 (0.0316)	0.0005 (0.0155)	0.0317 (0.0269)	
BGR alpha	0.0137 (0.0137)	-0.0354** (0.0144)	-0.0423** (0.0178)	-0.0222 (0.0138)	-0.0163 (0.0142)	-0.0349** (0.0141)	-0.0236 (0.0177)	-0.0036 (0.0135)	-0.0381* (0.0197)	-0.0474*** (0.0155)	-0.0364 (0.0249)	0.0009 (0.0179)	0.0137 (0.0137)	-0.0354** (0.0144)	-0.0423** (0.0178)	-0.0222 (0.0138)	-0.0163 (0.0142)	
FFFM alpha	-0.0229 (0.0162)	-0.0377** (0.0189)	-0.0532*** (0.0205)	-0.0151 (0.0156)	-0.0252 (0.0195)	-0.0379** (0.0164)	-0.0495** (0.0201)	-0.0121 (0.0166)	-0.0432** (0.0199)	-0.0363** (0.0170)	-0.0440** (0.0223)	-0.0004 (0.0162)	-0.0229 (0.0162)	-0.0377** (0.0189)	-0.0532*** (0.0205)	-0.0151 (0.0156)	-0.0252 (0.0195)	

risk.²⁴ Shleifer & Vishny (1997) argue that the overpricing cannot be arbitrated away, because shorting these stocks is particularly risky. Thus, idiosyncratic volatility limits arbitrage. Boehme et al. (2009) confirm these predictions. Lamont (2012) argues that firms can impede short sellers by strengthening the short-selling constraints on their own stocks, resulting in a further increase in overpricing. The increasing idiosyncratic volatility might be associated with an increase in the short-selling risk which, in turn, might further strengthen the existing limits to arbitrage. Stambaugh, Yu, & Yuan (2015) document that both arbitrage risk, incorporated in idiosyncratic volatility, and arbitrage asymmetry, lead to a more susceptible mispricing in the case of overpriced stocks.²⁵ Hence, the relation between idiosyncratic volatility and expected returns has to be negative for overpriced stocks, and positive for underpriced stocks.

Hou & Loh (2016) provide an overview and a comparable evaluation of possible explanations in the existing literature. The main explanations for the idiosyncratic volatility puzzle they detect are lottery-like preferences, explaining up to 25 %, and market friction proxies, explaining up to 24 % of the puzzle. They find that several other possible explanations are only able to explain a very small part (5–10 %).

Thus, the literature generally associates the negative pricing of idiosyncratic volatility with the behavioral biases of investors along with binding short-sale restrictions. Our findings are consistent with this notion. In commodity markets, where we expect substantially attenuated effects of

²⁴Lamont (2012) demonstrates what short-selling constraints are: investors might face challenges to borrow a stock or to overcome several legal or institutional restrictions which might be associated with substantial expenses. Moreover, they face the risk that the shorted asset might be coincidentally closed or that the stock loan has to be paid back before the contract period. The more binding the constraints are, the more likely it is that the respective stocks will be overpriced, which is associated with subsequent lower returns until a correction of the overvaluation takes place.

²⁵The authors define arbitrage asymmetry as the investors' preference to go long rather than short stocks.

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behavioral biases and have lower limits to arbitrage, we no longer detect an idiosyncratic volatility puzzle.

Illiquidity Forming a long–short portfolio, sorting according to the Amihud (2002) illiquidity measure, generates an insignificant mean return of -0.74% p.a. (Table 6.8). None of the factor model alphas on the hedge portfolio is statistically significant. Thus, there seems to be no illiquidity premium in commodity futures markets.

Our results are in contrast to Szymanowska et al. (2014), who find a significant negative relationship between Amivest liquidity (Amihud, Mendelson, & Lauterbach, 1997) and commodity futures returns, indicated by a significant mean return of a 4–1 portfolio of -9.40% p.a. for their sample period 1986–2010. Thus, the results for whether and how (il-)liquidity is priced in commodity futures markets seems to strongly depend on how liquidity is computed, the sample period, and the number of portfolios selected.²⁶

Our findings are also in contrast to those in Amihud (2002) for the equity market, who observes a significant positive relationship between illiquidity and stock returns. Using Fama & MacBeth (1973) cross-sectional regressions, the author finds a highly significant slope coefficient with a mean of 0.162. He builds on the theory of Amihud & Mendelson (1986), stating that investors likely demand compensation for holding illiquid assets. Our findings indicate that this illiquidity is not positively priced in commodity markets. A possible explanation for our findings is that the commodity futures markets we examine are all highly liquid, especially in relation to the markets for most individual stocks. Thus, investors may not require illiquidity premia or they are too small to be detected.

²⁶Marshall, Nguyen, & Visaltanachoti (2011) conclude that the Amihud (2002) measure, which we employ, measures liquidity in commodity futures markets best.

Momentum Going short a commodity portfolio with the worst past 1-year performance and simultaneously going long a commodity portfolio with the best past 1-year performance yields a highly significant mean return of 7.44 % p.a. (Table 6.9). We find that the alphas relative to all factor models are statistically significant.²⁷ Thus, our findings indicate that 1-year momentum is priced in the cross-section of commodity returns.

Consistent with our results, analyzing the cross-section of commodity futures returns, Erb & Harvey (2006) and Gorton et al. (2012) document a significant mean return of 10.80 % p.a. and 5.97 % p.a., respectively, of a long–short portfolio, using half of the commodities in the long (short) portfolio, with a holding period of one month and sorting the commodities according to the 12-months’ past performance. Similarly, Asness et al. (2013) provide evidence of a substantial mean return of 12.40 % p.a. of a non-collateralized 3–1 portfolio. Szymanowska et al. (2014) document a significant mean return of 9.00 % p.a. of a 4–1 portfolio.²⁸

Our findings are consistent with those in Jegadeesh & Titman (1993), who examine the cross-section of stock returns and show that a strategy based on 12-months’ past performance (and 3 months’ holding period) generates a significant monthly average return of 1.31 %. They motivate the success of that strategy with delayed price reactions based on idiosyncratic

²⁷In the case of the BGR and FFFM model, we skip the momentum factor. Otherwise, we would obtain the case of perfect multicollinearity.

²⁸Among other studies providing evidence for time series momentum of Moskowitz, Ooi, & Pedersen (2012) are Erb & Harvey (2006), who find a significant average return of 13.47 % (using the 12-months’ past performance and a 1-month holding period) for the Goldman Sachs Commodity Index (GSCI), and find a somewhat lower magnitude in more recent years. Moskowitz et al. (2012) find a significant alpha of 4.66 % p.a. (momentum average returns are obtained using the 12-months’ past performance and a 1-month holding period) relative to an extended 5-factor model.

Table 6.9: Portfolio Sorts: Reversal Characteristics

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3-P1 is referred to as the hedge portfolio and is defined as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). "Mean return" denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	Mean ^{char}						3Y Reversal						5Y Reversal					
	P1	P2	P3	P3 - P1	P1	P2	P1	P2	P3	P3 - P1	P1	P2	P1	P2	P3	P3 - P1		
Mean return	-0.0251 (0.0223)	0.0333 (0.0241)	0.1237*** (0.0278)	0.0744*** (0.0129)	0.0159 (0.0221)	0.0509** (0.0246)	0.0631** (0.0306)	0.0236* (0.0139)	0.0299 (0.0269)	0.0293 (0.0230)	0.0751** (0.0311)	0.0226 (0.0150)						
CAPM alpha	-0.0352 (0.0226)	0.0236 (0.0251)	0.1169*** (0.0296)	0.0760*** (0.0129)	0.0046 (0.0223)	0.0410 (0.0257)	0.0575* (0.0333)	0.0265* (0.0142)	0.0195 (0.0275)	0.0222 (0.0238)	0.0688** (0.0331)	0.0247* (0.0150)						
3-factor alpha	-0.0415* (0.0226)	0.0189 (0.0251)	0.1082*** (0.0292)	0.0748*** (0.0131)	-0.0005 (0.0224)	0.0350 (0.0263)	0.0493 (0.0320)	0.0249* (0.0144)	0.0155 (0.0274)	0.0146 (0.0235)	0.0588* (0.0328)	0.0216 (0.0154)						
4-factor alpha	-0.0299 (0.0231)	0.0182 (0.0276)	0.0964*** (0.0297)	0.0632*** (0.0132)	0.0051 (0.0235)	0.0364 (0.0277)	0.0396 (0.0322)	0.0173 (0.0148)	0.0197 (0.0289)	0.0175 (0.0247)	0.0501 (0.0329)	0.0152 (0.0157)						
5-factor alpha	-0.0301 (0.0249)	0.0230 (0.0272)	0.1202*** (0.0323)	0.0751*** (0.0140)	0.0042 (0.0237)	0.0438 (0.0281)	0.0617* (0.0339)	0.0287* (0.0147)	0.0196 (0.0289)	0.0203 (0.0254)	0.0769** (0.0339)	0.0287* (0.0153)						
BGR alpha	-0.0693*** (0.0136)	-0.0241 (0.0153)	0.0209 (0.0152)	0.0451*** (0.0121)	0.0024 (0.0139)	-0.0156 (0.0140)	-0.0651*** (0.0162)	-0.0337*** (0.0113)	0.0111 (0.0169)	-0.0388*** (0.0136)	-0.0509*** (0.0168)	-0.0310** (0.0134)						
FFFM alpha	-0.0642*** (0.0163)	-0.0500*** (0.0188)	0.0038 (0.0167)	0.0340*** (0.0128)	-0.0172 (0.0167)	-0.0281 (0.0184)	-0.0720*** (0.0185)	-0.0274** (0.0134)	-0.0246 (0.0189)	-0.0342** (0.0153)	-0.0537*** (0.0191)	-0.0145 (0.0152)						

firm information.²⁹

Many behavioral theories have tried to explain the momentum effect. Among others, Barberis et al. (1998) set up a model of how investors form beliefs that relates to conservatism (Edwards, 1968) and anchoring biases, and is consistent with the underreaction hypothesis.³⁰ Daniel et al. (1998) show that biased self-attribution of investment outcomes is associated with changes in investors' confidence about their own abilities, generating an underreaction to public information and a positive return autocorrelation in the short-term. Hong & Stein (1999) provide evidence for underreaction in the short-term due to a slow diffusion of new information. Grinblatt & Han (2005) and Frazzini (2006) relate the disposition effect to momentum. Frazzini (2006) argues that an underreaction to news creates the momentum effect by the disposition to sell winners too early and hold losers too long, which is also related to mental accounting, regret aversion, self-control, and tax considerations (Shefrin & Statman, 1985).

On the other hand, rational asset pricing theories have been developed to explain the momentum effect. Berk et al. (1999) form a model to link expected returns to firms' investment decisions that explains (short- and long-term) momentum. Johnson (2002) provides evidence that stochastic dividend growth rates help to explain the apparent underreaction. Ahn, Conrad, & Dittmar (2003) show that positive average returns of a momentum strategy can be explained, at least in part, by the risk investors applying this strategy take rather than by underreaction. Sagi & Seasholes

²⁹In their study, Jegadeesh & Titman (1993) rule out systematic risk, and a cross-sectional lead-lag relation between large and small stocks, as suggested by Lo & MacKinlay (1990b), as main drivers: they show that the momentum effect disappears after a holding period of 12 months. Jegadeesh & Titman (2001) confirm their previous results.

³⁰The underreaction hypothesis states that in the period after an announcement of good news, a firm's stock generates positive average returns. The underreaction is related to the short-term of 1 to 12 months: prices react slowly to news, generating a positive autocorrelation in the short-term.

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(2007) document that revenues, costs, and growth options affect a firm's positive return autocorrelation structure and drive momentum. Liu & Zhang (2008) provide evidence that momentum returns are mainly driven by macroeconomic risk, measured by the growth rate of industrial production.³¹

Our result that the momentum effect is also present in commodity markets indicates that one of the rational explanations, rather than the behavioral ones, drives the momentum effect across asset markets. This result is consistent, e.g., with evidence provided by Birru (2015), who shows that the disposition effect does not suffice to explain momentum for the equity market.

It is also interesting to note that the stock market momentum factor in the Carhart (1997) 4-factor model is not able to explain the returns of the commodity momentum strategy. On the one hand, Cochrane (2005b) argues that since in equity markets momentum can be explained by a momentum factor, it is not possible to form an arbitrage portfolio based on the momentum strategy: by following the strategy, one exposes oneself to systematic factor risk. On the other hand, given that equity momentum cannot explain commodity momentum, momentum investors can diversify their strategies and enhance their portfolio performance by also considering the commodity market.

3- and 5-Year Reversal A portfolio going short the commodities showing the worst 36-month (60-month) past performance and long the commodities with the best 36-month (60-month) past performance generates a positive mean return of 2.36 % p.a. (2.26 % p.a.), as presented in Table 6.9. This mean return is weakly significant for the 36-month period. We find that the

³¹Daniel & Moskowitz (2016) show that the momentum strategy infrequently faces substantial losses. This finding, in itself, is consistent with a risk-based explanation of momentum. On the other hand, the authors argue that this explanation is not entirely sufficient and leave the door open for behavioral alternatives.

4-factor model can explain both the 3-year and the 5-year reversal effect. Interestingly, the slightly positive excess return on 3- and 5-year reversal translates into a strongly statistically significant negative BGR alpha.

Our findings are inconsistent with those in De Bondt & Thaler (1985) for the equity market. The authors find that the cumulative return difference between the portfolio with the best performing stocks and the portfolio with the worst performing stocks is -25% after a holding period of 3 years. Fama & French (1996) find that the “low” portfolio outperforms the “high” portfolio by 0.6% per month. De Bondt & Thaler (1985) motivate their findings by an overreaction hypothesis according to which the prices of stocks suffering from extreme events over the formation period fall too strongly and subsequently outperform. There is also overreaction to good news, but De Bondt & Thaler (1985) find that bad news seem to be the main driver. The authors emphasize that most of the excess returns are realized in January.³²

Analyzing the cross-section of stocks, Fama & French (1996) and Carhart (1997) provide evidence that both the 3- and 4-factor model can explain both the 3- and 5-year reversal. Thus, these results suggest that both effects are eventually captured by systematic risk factors and therefore one could argue that they are not priced in the cross-section of stocks. We obtain broadly similar results for commodities.

Several behavioral models try to explain long-term reversals. The model of Barberis et al. (1998) relates to the representativeness heuristic, which leads to a distortion of probabilities regarding the occurrence of a specific event that is considered to be representative (Tversky & Kahneman, 1974).

³²In contrast, Jegadeesh & Titman (1993), among others, criticize the argumentation, since their portfolios might be affected by systematic risk and a size effect. Further, the fact that most returns are realized in January might contradict the overreaction hypothesis. Jegadeesh & Titman (1993) also argue that practitioners base their stock selection decisions on the performance of the past 3 to 12 months rather than 3 to 5 years.

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This leads to overreactions.³³ Bikhchandani, Hirshleifer, & Welch (1992) document that the phenomenon that investors follow the mass opinion rather than their own (herding behavior) is consistent with overreaction. Daniel et al. (1998) show that investors' overconfidence about private information is associated with an overreaction to private information, thus, generating a negative return autocorrelation in the long-term. In their theoretical model, Hong & Stein (1999) provide evidence for overreaction in the long-term, by trading on the positive feedback that goes along with buying stocks when prices rise and selling when prices fall (De Long, Shleifer, Summers, & Waldmann, 1990b). Analyzing the cross-section of stock returns, Baker & Wurgler (2006, 2007) show a negative relationship between current investor sentiment and subsequent average returns. On the other hand, Berk et al. (1999) also link expected returns in their rational asset pricing model to firms' investment decisions that can also help to explain momentum also in the long-term.

Thus, overall, consistent with the behavioral theories, the reversal effect is present in equity markets, at least in returns. Since we do not observe the same pattern in commodity markets, in fact, we rather detect evidence for very long-term momentum instead of reversal, consistent with the model predictions of Berk et al. (1999), it is likely that overreaction indeed creates these returns. On the other hand, the fact that empirical factor models seem to be able to explain the effect in both equity and commodity markets calls this interpretation and the existence of a reversal effect somewhat into question.

³³The overreaction hypothesis is consistent with long-term reversals and states that after a series of good (bad) news, investors become too optimistic (pessimistic), which is associated with an increasing (decreasing) stock price. Subsequent news do not coincide with the investors' expectations, leading to falling (increasing) prices, thus to lower (higher) average returns in the following periods and thus generating a negative autocorrelation up to 3 and 5 years, respectively.

Risk-Neutral Variance Sorting the commodities according to their risk-neutral variance estimates, we obtain an insignificant mean return of -1.54 % p.a. for the hedge portfolio (Table 6.10). The alphas are insignificant relative to all equity factor models. In contrast, both commodity models show highly significant alpha estimates. Thus, the two commodity factor models do an extremely poor job in explaining an anomaly that is not even present in average returns.

Our results are similar to those of Conrad, Dittmar, & Ghysels (2013), who also find a negative, but insignificant, average return for a 3–1 portfolio on stock returns. Risk-neutral total variance thus seems to be priced neither in the cross-section of equity nor in that of commodity returns.³⁴

Risk-Neutral Skewness Analogously to the previous paragraph, a portfolio going long the commodities with the highest and simultaneously going short the commodities with the lowest risk-neutral skewness generates an insignificant mean return of 0.03 % p.a. (Table 6.10). We find insignificant alphas relative to all factor models.

Our results differ from those of Conrad et al. (2013), who detect a significant 3–1 portfolio return of -0.8 % per month for equities. However, the results in the literature are not completely clear-cut. For risk-neutral skewness, e.g., Xing et al. (2010), Bali et al. (2017b), and Stilger et al. (2017) document a positive relation. Thus, given the ambiguity in the equity literature about the pricing of risk-neutral skewness, our results are broadly in line with those from the equity literature.

³⁴Our results are somewhat inconsistent with those in Bali et al. (2017b). Using Fama & MacBeth (1973) cross-sectional regressions, the authors provide evidence for a highly significant positive relationship between risk-neutral volatility and price target-based expected, as opposed to realized, stock returns.

Table 6.10: Portfolio Sorts: Risk-Neutral Moments

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3-P1 is referred to as the hedge portfolio and is defined as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). "Mean return" denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	RNV _{ar}			RNS _{hew}			RNE _{xKurt}					
	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1
Mean return	0.0087 (0.0281)	-0.0069 (0.0284)	-0.0222 (0.0345)	-0.0154 (0.0136)	-0.0083 (0.0265)	-0.0070 (0.0347)	-0.0076 (0.0324)	0.0003 (0.0154)	-0.0123 (0.0357)	-0.0034 (0.0276)	-0.0062 (0.0312)	0.0031 (0.0171)
CAPM alpha	-0.0030 (0.0281)	-0.0299 (0.0281)	-0.0394 (0.0359)	-0.0182 (0.0139)	-0.0204 (0.0304)	-0.0265 (0.0352)	-0.0278 (0.0302)	-0.0037 (0.0158)	-0.0264 (0.0393)	-0.0227 (0.0265)	-0.0251 (0.0305)	0.0007 (0.0182)
3-factor alpha	-0.0082 (0.0270)	-0.0316 (0.0284)	-0.0425 (0.0352)	-0.0171 (0.0137)	-0.0251 (0.0292)	-0.0314 (0.0342)	-0.0280 (0.0308)	-0.0014 (0.0159)	-0.0321 (0.0384)	-0.0248 (0.0263)	-0.0269 (0.0304)	0.0026 (0.0178)
4-factor alpha	-0.0134 (0.0278)	-0.0248 (0.0299)	-0.0409 (0.0358)	-0.0138 (0.0139)	-0.0224 (0.0300)	-0.0328 (0.0343)	-0.0247 (0.0308)	-0.0011 (0.0162)	-0.0340 (0.0400)	-0.0216 (0.0266)	-0.0241 (0.0302)	0.0049 (0.0183)
5-factor alpha	-0.0115 (0.0275)	-0.0360 (0.0309)	-0.0374 (0.0371)	-0.0129 (0.0142)	-0.0230 (0.0299)	-0.0279 (0.0367)	-0.0364 (0.0333)	-0.0067 (0.0164)	-0.0255 (0.0394)	-0.0304 (0.0287)	-0.0300 (0.0326)	-0.0023 (0.0179)
BGR alpha	-0.0161 (0.0206)	-0.0543*** (0.0181)	-0.0885*** (0.0167)	-0.0362*** (0.0131)	-0.0542** (0.0224)	-0.0598*** (0.0203)	-0.0452** (0.0201)	0.0045 (0.0159)	-0.0730*** (0.0247)	-0.0447*** (0.0171)	-0.0424** (0.0195)	0.0153 (0.0160)
FFFM alpha	-0.0156 (0.0201)	-0.0572*** (0.0179)	-0.0870*** (0.0163)	-0.0357*** (0.0129)	-0.0540** (0.0226)	-0.0594*** (0.0198)	-0.0471** (0.0205)	0.0034 (0.0163)	-0.0705*** (0.0240)	-0.0458*** (0.0168)	-0.0448** (0.0195)	0.0129 (0.0157)

Risk-Neutral Excess Kurtosis For risk-neutral excess kurtosis, we obtain an insignificant mean return for the 3–1 portfolio of 0.31 % p.a. (Table 6.10). We find insignificant alphas relative to all factor models.

Conrad et al. (2013) find a significant 3–1 portfolio return of 0.7 % per month for the equity market. Bali et al. (2017b) also obtain similar results using price target-based expected returns. Using Fama & MacBeth (1973) cross-sectional regressions, the authors find a highly significant positive relationship between excess kurtosis and these returns.

Thus, as opposed to equity markets, the level of risk-neutral kurtosis does not seem to be compensated for in commodity markets. It is therefore likely that the pricing of risk-neutral kurtosis in equity markets is created by individual investors who dislike assets with higher risk-neutral kurtosis and demand a risk premium. Such a risk premium cannot be found in commodity markets.

Maximum Daily Returns Going short a portfolio of commodities with the lowest average across the 5 largest daily returns during the previous 12 months and going long a portfolio of commodities with the highest 5 maximum daily returns over the previous 12 months generates an insignificant mean return of the hedge portfolio of -0.13 % p.a. (Table 6.11). We find insignificant alphas relative to all factor models.

Our findings are in contrast to those in Bali et al. (2011) for the equity market. The authors provide evidence for a significant negative relationship, indicated by a significant negative average monthly 10–1 return spread of -1.03 % and a significant monthly 4-factor alpha of -1.18 %. Bali, Brown, Murray, & Tang (2017a) report results of a similar magnitude. The authors argue with the investor preference for positively skewed assets along with overweighting of the probability of occurrence of these events according to CPT (Barberis & Huang, 2008) leads to overpricing of stocks with high

Table 6.11: Portfolio Sorts: MAX, Value, and VoV Characteristics

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3-P1 is referred to as the hedge portfolio and is defined as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). "Mean return" denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	MAX					Value					VoV					
	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1	P1	P2	P3	P3 - P1
Mean return	0.0538** (0.0216)	0.0264 (0.0234)	0.0512* (0.0282)	-0.0013 (0.0130)	0.0520 (0.0338)	0.0253 (0.0237)	0.0608** (0.0250)	0.0044 (0.0140)	0.0096 (0.0307)	0.0189 (0.0303)	-0.0448 (0.0299)	-0.0272** (0.0121)	0.0096 (0.0307)	0.0189 (0.0303)	-0.0448 (0.0299)	-0.0272** (0.0121)
CAPM alpha	0.0475** (0.0227)	0.0188 (0.0252)	0.0389 (0.0288)	-0.0043 (0.0132)	0.0456 (0.0354)	0.0183 (0.0244)	0.0517** (0.0261)	0.0031 (0.0139)	-0.0068 (0.0311)	0.0013 (0.0301)	-0.0637** (0.0294)	-0.0285** (0.0122)	-0.0068 (0.0311)	0.0013 (0.0301)	-0.0637** (0.0294)	-0.0285** (0.0122)
3-factor alpha	0.0435* (0.0229)	0.0092 (0.0255)	0.0335 (0.0274)	-0.0050 (0.0126)	0.0358 (0.0349)	0.0123 (0.0246)	0.0469* (0.0255)	0.0055 (0.0141)	-0.0091 (0.0310)	-0.0051 (0.0293)	-0.0651** (0.0294)	-0.0280** (0.0123)	-0.0091 (0.0310)	-0.0051 (0.0293)	-0.0651** (0.0294)	-0.0280** (0.0123)
4-factor alpha	0.0451* (0.0234)	0.0075 (0.0251)	0.0323 (0.0303)	-0.0064 (0.0130)	0.0231 (0.0355)	0.0152 (0.0258)	0.0562** (0.0269)	0.0165 (0.0149)	-0.0093 (0.0313)	-0.0056 (0.0297)	-0.0628** (0.0297)	-0.0268** (0.0127)	-0.0093 (0.0313)	-0.0056 (0.0297)	-0.0628** (0.0297)	-0.0268** (0.0127)
5-factor alpha	0.0507** (0.0258)	0.0246 (0.0280)	0.0390 (0.0302)	-0.0058 (0.0136)	0.0478 (0.0365)	0.0216 (0.0264)	0.0548** (0.0267)	0.0035 (0.0143)	-0.0085 (0.0326)	0.0020 (0.0302)	-0.0750** (0.0354)	-0.0333** (0.0130)	-0.0085 (0.0326)	0.0020 (0.0302)	-0.0750** (0.0354)	-0.0333** (0.0130)
BGR alpha	-0.0018 (0.0123)	-0.0453*** (0.0130)	-0.0286* (0.0159)	-0.0134 (0.0117)	-0.0683*** (0.0174)	-0.0397*** (0.0146)	0.0309** (0.0156)	0.0496*** (0.0121)	-0.0328* (0.0192)	-0.0284 (0.0206)	-0.0956** (0.0172)	-0.0314*** (0.0119)	-0.0328* (0.0192)	-0.0284 (0.0206)	-0.0956** (0.0172)	-0.0314*** (0.0119)
FFFM alpha	-0.0092 (0.0155)	-0.0646*** (0.0159)	-0.0383** (0.0184)	-0.0145 (0.0135)	-0.0715*** (0.0201)	-0.0279* (0.0168)	-0.0132 (0.0148)	0.0292** (0.0124)	-0.0328* (0.0190)	-0.0293 (0.0206)	-0.0970*** (0.0172)	-0.0321*** (0.0117)	-0.0328* (0.0190)	-0.0293 (0.0206)	-0.0970*** (0.0172)	-0.0321*** (0.0117)

MAX measures.

Our finding that MAX is not priced in the cross-section of commodity returns, as opposed to that of equity returns, indicates that this probability overweighting bias of investors indeed creates the MAX anomaly in the equity market.

Value Going long (short) a portfolio with the highest (lowest) magnitude in value generates an insignificant mean return of 0.44 % (Table 6.11). All equity factor models are able to explain the value effect, expressed by insignificant alpha estimates. On the contrary, we find significant alphas relative to both commodity factor models. It seems that equity rather than commodity factor models are able to explain the value effect in the cross-section of commodity returns.

Our results are inconsistent with those in Asness et al. (2013). Analyzing the cross-section of U.S. stocks and commodities, they find a significant annualized (non-collateralized) mean return of 3.7 % and 6.3 % for a 3–1 portfolio, respectively. Thus, the presence of a value effect in commodity markets seems to strongly depend on the time period and commodity return specification.³⁵ Because of the unclear results and the rather loose connection of the commodity value characteristic to that on equity markets, we do not regard it as sensible to draw further conclusions.

Volatility-of-Volatility Forming a long–short portfolio according to the volatility of option-implied volatility generates a weakly statistically significant negative mean return of –2.72 % p.a. (Table 6.11). The alphas relative to all factor models are larger in magnitude compared to the mean return and statistically significant. It seems that investors demand a premium for bearing volatility-of-volatility risk.

³⁵Instead of buying and holding one commodity future, Asness et al. (2013) cumulate daily returns obtained from the most liquid futures contract on that day.

6.3. MAIN EMPIRICAL RESULTS

Our results are consistent with those in Baltussen et al. (2018) for the equity market. Analyzing the cross-section of stock returns, they find a significant mean excess return of -0.85% per month for a 5–1 portfolio. None of the equity factor models is able to explain that effect, indicated by significant alphas of -0.94% , -0.79% , and -0.69% per month, relative to the CAPM, 3-factor, and 4-factor models. Even though the return premium has the “wrong” sign, the authors motivate their findings by the ambiguity preferences of investors.

The fact that the volatility-of-volatility premium also exists in commodity markets points toward a risk-based rather than to a behavioral explanation for the effect.

6.3.4 A Note on Commodity Factor Models

While our primary focus is on studying market anomalies, this chapter also provides implications for factor models in commodity markets. Bakshi et al. (2017) forcefully argue that the BGR model succeeds in pricing the cross-section of commodity returns. They test their model for sorts on term-structure slopes, momentum, as well as commodity sectors, and find that the model cannot be rejected.

Testing the model on return anomalies, we obtain a substantially different picture. For numerous anomalies in Tables 6.5–6.11, the model yields economically and statistically significant alphas. In numerous cases, the abnormal returns relative to the BGR model, which is designed in particular for commodity markets, are even larger in magnitude and more strongly significant than those for the equity models. This is the case, e.g., for co-skewness, historical kurtosis, 3-year and 5-year reversal, risk-neutral variance, and value. On the other hand, only in rare cases does the BGR model perform substantially better in explaining the anomalies than the

equity factor models (e.g., for historical skewness). The FFFM model yields better results, e.g., for co-skewness and 5-year reversal. However, it also rather under- than outperforms the equity factor models in terms of explaining the anomaly returns in general.

Studying the factor models at the individual commodity level, in untabulated results, we find that the BGR and FFFM models do better in explaining the time-variation in commodity futures returns, with average adjusted R²s of 22 % and 23 %, respectively. The equity factor models explain on average only about 1–2 % of the return variation. However, the equity factor models do a substantially better job in explaining average returns. In our dataset, 4 commodities have a significant alpha (at 10 %) relative to the CAPM, and 3 commodities relative to the 3-factor, 4-factor, and 5-factor models. On the other hand, 6 and 8 commodities have significant alphas relative to the BGR and FFFM models, respectively. This pattern is induced by the alpha point estimates rather than by differences in the standard errors. While there is only little difference in the latter, the average alphas are highest in magnitude for the commodity pricing models.³⁶

Thus, our findings point toward substantial integration of commodity and equity market *risk factors*. Previous findings reveal that the markets themselves are not fully integrated (Bessembinder, 1992; Daskalaki et al., 2014). Our findings indicate that differences across the markets may, to some extent, be driven by behavioral biases manifesting themselves particularly in equity prices.

³⁶For example, the average alpha for the 3-factor model amounts to 2.14 %, while that for the BGR model is –3.11 %. The average standard errors of the two models are 5.12 % and 4.31 %, respectively.

6.3.5 Cross-Sectional Regressions

In this section, we perform Fama & MacBeth (1973) cross-sectional regressions. Table E.1 of the Appendix to this chapter reports the average coefficient estimates. Each month, we regress the commodity futures returns on a constant and the lagged value of the characteristic.^{37,38} We compute robust Newey & West (1987) standard errors using 6 lags. The findings are generally consistent with our previous results. The anomalies that yield a significant 3–1 portfolio return also produce an average regression slope coefficient of the same sign and similar statistical significance. There is only one substantial difference: for *HistKurt*, we detect an insignificant slope estimate as opposed to a significantly positive 3–1 portfolio return. Small differences are observable for 3-year reversal, where for cross-sectional regressions, we find a slope estimate insignificantly different from zero. Finally, as opposed to portfolio sorts, we detect a weakly significant regression slope for risk-neutral variance.

Table E.2 of the Appendix to this chapter reports the average coefficient estimates using monthly Fama & MacBeth (1973) cross-sectional regressions, controlling for the average 12-months' roll yield and the average 12-months' past performance; the characteristics which serve as main ingredients for the BGR model in addition to the average factor. The results are essentially similar to those without control variables. We only detect two noteworthy differences. First, again consistent with the portfolio sorts, risk-neutral volatility does not carry a significant price of risk. Second, volatility-of-volatility does not generate a positive risk premium when controlling for the roll yield and momentum. Thus, in commodity markets,

³⁷We use uni- rather than multivariate cross-sectional regressions because the commodity cross-section is rather small, leaving only few degrees of freedom for the estimation.

³⁸We impose the restriction that at least 10 commodities must be available.

volatility-of-volatility appears to be associated to these characteristics in the cross-section. An alternative explanation could be that the relation of volatility-of-volatility and future returns is non-monotonic, i.e., the medium portfolio generates a higher return on average compared to P1. Although the 3–1 spread is strongly significant, this pattern may prevent us from finding a clear relation in cross-sectional regressions.

6.4 Robustness

6.4.1 Portfolio Splits and Subsamples

We test the robustness of our results in two dimensions. On the one hand, we form different numbers of portfolios. We additionally consider the case of 2, 4, and 5 portfolios. We then examine the returns of the 2–1, 4–1, and 5–1 hedge portfolio, respectively. Furthermore, to build subsamples, we use two distinct breakpoints. First, we examine an early time range from the beginning of our sample period until February 1986. The second subsample period starts in March 1986, the time Szymanowska et al. (2014) start their period under study, and ends in November 2000. The final subsample period starts in December 2000 with the passing of the Commodity Futures Modernization Act (CFMA), which can be regarded as a post-financialization period. The CFMA substantially eases speculation in commodity markets (Boons, De Roon, & Szymanowska, 2012) and with and after its introduction, Tang & Xiong (2012) and Cheng & Xiong (2014) document a substantial increase in commodity trading activity.

Table E.3 of the Appendix to this chapter summarizes the results. Analyzing the full sample period, we observe that the different portfolio splits do not affect our overall conclusions in general. Whether we sort into

6.4. ROBUSTNESS

2, 3, 4, or 5 portfolios usually affect the results only marginally, while there are no clear patterns. Some effects get marginally stronger when building fewer, others when forming more portfolios. An exception is *RNVar*, where we find a highly significant mean return of -5.65% p.a. for the 5–1 hedge portfolio and significant alphas relative to the factor models. It seems that in this case a finer classification of the commodities is associated with a strengthening of the effect. Further, in the case of *HistKurt*, *3Y Reversal*, and *5Y Reversal* splitting commodities into 4 or 5 portfolios typically leads to insignificant mean returns and alpha estimates relative to the factor models.

Analyzing the subsamples, generally, we also obtain similar results as for the full sample. For aggregate volatility and aggregate jump risk, we obtain similar but statistically weaker results, indicating that reduced power due to a smaller sample size might be an issue. For co-skewness, we obtain significantly positive average mean returns for the first subsample period, but nothing for the more recent periods. For co-kurtosis and downside beta, the results are essentially similar across subperiods. For historical variance, we detect a positive effect in returns in the second subsample period and a rather negative one in the most recent subsample. These ambiguous results make it hard to interpret the effect. The return premium for historical skewness is stronger from the second subsample period on, while the premium on historical kurtosis seems to vanish in the post-financialization period.

For idiosyncratic volatility, the results are largely consistent across subsamples. In the most recent post-financialization period, there is some indication of a negative idiosyncratic volatility premium, but only when building at least 4 portfolios. Thus, financialization appears to change the properties of commodity markets to some extent. For illiquidity, there seems to be overall no premium. For momentum, we find a strong return premium

in the first two subperiods, but interestingly a clearly weaker premium during the post-financialization period. Reversal appears to be overall unpriced in the cross-section of commodity futures returns. For risk-neutral variance, skewness, and excess kurtosis, we obtain overall similar results across the subperiods.

For MAX, interestingly, we find a clear pattern. Before the financialization period, there is no or at most a weak positive return premium. However, post-financialization, there is a strong and significant negative effect across all specifications. For example, we detect a mean return of -4.1% p.a. for the 3–1 portfolio. For value, we find no return premium throughout. Finally, for volatility-of-volatility, we detect weak results for the second subperiod and also overall slightly weaker results in the post-financialization period compared to the entire period. This pattern might be created by lower power of the statistical tests due to a reduced sample size.

Thus, overall our results are largely independent of how many portfolios we build and consistent across different time periods of our sample. There are some interesting patterns, though, especially for the post-financialization period, where especially MAX and, to some extent, also idiosyncratic volatility and risk-neutral variance, seem to be negatively priced. On the other hand, the momentum effect seems to be much attenuated in the post-financialization period.

6.4.2 Annual Horizon

Lastly, we examine the robustness of our results to a longer holding period. We hold the portfolios for 12 months instead of 1 month. Tables E.4–E.10 of the Appendix to this chapter report the results. Overall, the results are consistent with our previous findings. However, typically these are somewhat weaker. Interestingly, for the 12-months' holding period, we

6.5. CONCLUSION

find that the return on the momentum strategy is clearly smaller and the factor alphas are typically not statistically significant.

6.5 Conclusion

In this study, we examine whether equity return anomalies are also priced in commodity markets. In our view, commodity markets provide an ideal testing ground to analyze whether anomalies are risk-based or induced by behavioral biases: commodity markets are largely populated by institutional investors and there are only small limits to arbitrage. We find that behavioral explanations are most likely for downside beta, idiosyncratic volatility, and MAX. On the other hand, it is highly likely that “rational” explanations prevail for jump risk, momentum, and volatility-of-volatility.

E Appendix

In this section, we provide additional material for Chapter 6: “The Economic Sources of Return Anomalies: Evidence from Commodity Futures Markets”.

E.1 Factors

Commodity Long-only Factor (Bakshi et al., 2017, “*EW*”) is the excess return of an equally-weighted monthly rebalanced portfolio that goes long all available commodity futures.

Commodity Term Structure Factor (Bakshi et al., 2017, “*TS*”) is the excess return of a long–short monthly rebalanced fully-collateralized portfolio sorted by the average past 12-months’ roll yield. The roll yield for each commodity is defined as the daily difference in the log prices of the first-nearby (referred to as “spot” in Section 6.2.1) and second-nearest futures contract.

Commodity Momentum Factor (Bakshi et al., 2017, “*MOM*”) is the excess return of a long–short monthly rebalanced fully-collateralized portfolio sorted by the average 12-months’ past performance.

Commodity Hedging Pressure Factor (Basu & Miffre, 2013, “*HP*”) is the excess return of a monthly rebalanced fully-collateralized portfolio that buys (sells) the commodities with the lowest (highest) hedgers’ hedging pressure and highest (lowest) speculators’ hedging pressure. In doing so, we first split the average hedging pressure of hedgers over the past 12 months into two equal parts. We then sort according to the average 12-months’

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past hedging pressure of speculators and buy (sell) the 30 % of the lowest (highest) hedging pressure of hedgers for which speculators have the highest (lowest) hedging pressure.

Equity Market Factor (Fama & French, 1996, “*MRP*”) is the excess return on the market, using value-weighted returns from all firms in CRSP.

Equity Size Factor (Fama & French, 1996, “*SMB*”) is the return difference between a portfolio of small and large stocks (“Small minus Big”).

Equity Value Factor (Fama & French, 1996, “*HML*”) is the return difference between a portfolio of high and low book-to-market stocks (“High minus Low”).

Equity Momentum Factor (Carhart, 1997, “*UMD*”) is the return difference between a portfolio of stocks sorted by the past performance from month $t = -12$ to $t = -2$ (“Up minus Down”).

Equity Profitability Factor (Fama & French, 2015, “*RMW*”) is the return difference between a portfolio of robust and weak profitability stocks (“Robust minus Weak”).

Equity Investment Factor (Fama & French, 2015, “*CMA*”) is the return difference between a portfolio of conservative and aggressive investment stocks (“Conservative minus Aggressive”).

E.2 Characteristics

Aggregate Volatility (VIX) (Ang et al., 2006b, “*AggVol^{VIX}*”) is the coefficient $\beta_{i,t}^{\Delta VIX}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^M(r_{M,d} - r_{f,d}) + \beta_{i,t}^{\Delta VIX} \Delta VIX_d + \epsilon_{i,d}$, where $r_{i,d}$ is the daily excess return on commodity i over the period $d = 1, \dots, D$, where D is the number of daily return observations, using daily data during the previous 12 months, and t indicates rebalancing days (month-ends). $r_{M,d} - r_{f,d}$ is the stock market excess return, and ΔVIX is the daily innovation (simple first difference) in the Volatility Index (*VIX*), which is provided by the Chicago Board Options Exchange (CBOE).

Aggregate Volatility (Cremers et al., 2015, “*AggVol*”) is the coefficient $\beta_{i,t}^{VOL}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^M(r_{M,d} - r_{f,d}) + \beta_{i,t}^{VOL} VOL_d + \epsilon_{i,d}$, where *VOL* is the volatility factor of Cremers et al. (2015), using daily data during the previous 12 months. All other variables are as previously defined.

Aggregate Jump (Cremers et al., 2015, “*AggJump*”) is the coefficient $\beta_{i,t}^{JUMP}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^M(r_{M,d} - r_{f,d}) + \beta_{i,t}^{JUMP} JUMP_d + \epsilon_{i,d}$, where *JUMP* is the jump factor of Cremers et al. (2015), using daily data during the previous 12 months. All other variables are as previously defined.

Co-Skewness (Harvey & Siddique, 2000, “*CoSkew*”) and **Co-Kurtosis** (Dittmar, 2002, “*CoKurt*”) are the coefficients $\beta_{i,t}^{CS}$ and $\beta_{i,t}^{CK}$ in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^M(r_{M,d} - r_{f,d}) + \beta_{i,t}^{CS}(r_{M,d} - r_{f,d})^2 + \beta_{i,t}^{CK}(r_{M,d} - r_{f,d})^3 + \epsilon_{i,d}$, including the stock market risk premium, the squared and the cubed stock market risk premia, using daily data during the previous 12 months. All variables are as previously defined.

Downside Beta (Ang et al., 2006a, “*DownBeta*”) is the coefficient $\beta_{i,t}^{Down}$

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in the regression $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{Down}(r_{M,d} - r_{f,d}) + \epsilon_{i,d}$. All variables are as previously defined. The regression is estimated using daily commodity excess returns only when the market excess return is below the average daily market excess return during the previous 12 months.

Historical Variance (Amaya et al., 2015; Fernandez-Perez et al., 2018, “*HistVar*”) is the monthly variance, defined as $Var_{i,t}^{hist} = \sigma_{i,t}^2 = \frac{1}{D-1} \sum_{d=1}^D (r_{i,d} - \mu_{i,t})^2$, with $\mu_{i,t} = \frac{1}{D} \sum_{d=1}^D r_{i,d}$, using daily data during the previous 12 months. All other variables are as previously defined.

Historical Skewness (Amaya et al., 2015; Fernandez-Perez et al., 2018, “*HistSkew*”) is the monthly skewness, defined as $Skew_{i,t}^{hist} = [\frac{1}{D} \sum_{d=1}^D (r_{i,d} - \mu_{i,t})^3] / \sigma_{i,t}^3$, with $\mu_{i,t} = \frac{1}{D} \sum_{d=1}^D r_{i,d}$, and $\sigma_{i,t} = \sqrt{\sigma_{i,t}^2}$, using daily data during the previous 12 months. All other variables are as previously defined.

Historical Kurtosis (Amaya et al., 2015; Fernandez-Perez et al., 2018, “*HistKurt*”) is the monthly kurtosis, defined as $Kurt_{i,t}^{hist} = [\frac{1}{D} \sum_{d=1}^D (r_{i,d} - \mu_{i,t})^4] / \sigma_{i,t}^4$, using daily data during the previous 12 months. All other variables are as previously defined.

Idiosyncratic Volatility (FF3) (Ang et al., 2006b; Ang et al., 2009, “*IdioVol^{FF3}*”) is the standard deviation of the residuals $\epsilon_{i,d}$ using the Fama & French (1993) 3-factor model $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^M(r_{M,d} - r_{f,d}) + \beta_{i,t}^{SMB}SMB_d + \beta_{i,t}^{HML}HML_d + \epsilon_{i,d}$, where *SMB* and *HML* are the size and value factors of Fama & French (1996), using daily data during the previous 12 months. All other variables are as previously defined.

Idiosyncratic Volatility (BGR) (Ang et al., 2006b; Ang et al., 2009, “*IdioVol^{BGR}*”) is the standard deviation of the residuals $\epsilon_{i,d}$ using the BGR model of Bakshi et al. (2017) $r_{i,d} = \alpha_{i,t} + \beta_{i,t}^{EW}EW_d + \beta_{i,t}^{TST}TST_d +$

$\beta_{i,t}^{MOM} MOM_d + \epsilon_{i,d}$, where EW , TS , and MOM are the long-only, term structure, and momentum factors of Bakshi et al. (2017), using daily data during the previous 12 months. All other variables are as previously defined.

Illiquidity (Amihud, 2002; Fernandez-Perez et al., 2018, “*ILLIQ*”) is the ratio of the daily absolute commodity futures excess return to the daily dollar trading volume, averaged over the recent 12 months.

Momentum (Jegadeesh & Titman, 1993; Fernandez-Perez et al., 2018, “*Mom^{char}*”) is the average commodity futures excess return over the past 12 months.

3-year Reversal (De Bondt & Thaler, 1985, “*3Y Reversal*”) is the average commodity futures excess return over the past 36 months.

5-year Reversal (De Bondt & Thaler, 1985, “*5Y Reversal*”) is the average commodity futures excess return over the past 60 months.

Risk-Neutral Variance (Bakshi et al., 2003, “*RNVar*”), **Risk-Neutral Skewness** (Bakshi et al., 2003, “*RNSkew*”), and **Risk-Neutral Excess Kurtosis** (Bakshi et al., 2003, “*RNExKurt*”) are defined as

$$RNVar_{i,t} = \frac{e^{r\tau}V - \mu^2}{\tau}, \quad (\text{E.1})$$

$$RNSkew_{i,t} = \frac{e^{r\tau}W - 3\mu e^{r\tau}V + 2\mu^3}{[e^{r\tau}V - \mu^2]^{3/2}}, \quad (\text{E.2})$$

$$RNExKurt_{i,t} = \frac{e^{r\tau}X - 4\mu e^{r\tau}W + 6e^{r\tau}\mu^2V - 3\mu^4}{[e^{r\tau}V - \mu^2]^2} - 3, \quad (\text{E.3})$$

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where V , W , X , and μ are computed as

$$V = \int_{K=0}^S \frac{2(1 + \log[\frac{S}{K}])}{K^2} P(K) dK + \int_{K=S}^{\infty} \frac{2(1 - \log[\frac{K}{S}])}{K^2} C(K) dK, \quad (\text{E.4})$$

$$W = \int_{K=S}^{\infty} \frac{6 \log[\frac{K}{S}] - 3(\log[\frac{K}{S}])^2}{K^2} C(K) dK - \int_{K=0}^S \frac{6 \log[\frac{S}{K}] + 3(\log[\frac{S}{K}])^2}{K^2} P(K) dK, \quad (\text{E.5})$$

$$X = \int_{K=S}^{\infty} \frac{12(\log[\frac{K}{S}])^2 + 4(\log[\frac{K}{S}])^3}{K^2} C(K) dK + \int_{K=0}^S \frac{12(\log[\frac{S}{K}])^2 + 4(\log[\frac{S}{K}])^3}{K^2} P(K) dK, \quad (\text{E.6})$$

$$\mu = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V - \frac{e^{r\tau}}{6} W - \frac{e^{r\tau}}{24} X. \quad (\text{E.7})$$

r is the continuously compounded (annualized) interest rate for the period from t to $t + \tau$, where τ indicates the time to maturity of each option. We express τ as a fraction of a year.³⁹ Further, K and S denote the strike and spot prices, respectively, where $C(K)$ and $P(K)$ represent the call and put prices at strike price K , respectively.⁴⁰ In the next step, we compute the corresponding option prices, using the Black & Scholes (1973) option pricing model. Finally, we use a trapezoidal algorithm to approximate the integrals V , W , and X and thus we obtain the (annualized) risk-neutral measures with corresponding maturity. For our analysis, we linearly interpolate

³⁹We follow the literature and use the Ivy curve from OptionMetrics to proxy for the interest rate.

⁴⁰We focus on out-of-the-money (OTM) option prices. To obtain a wide range of option prices, we follow Chang et al. (2012) and compute a grid of 1,000 equidistant interpolated moneyness levels, i.e., K/S , ranging from 0.3% to 300%. Subsequently, for each available moneyness level, we interpolate the implied volatility using a spline interpolation method. For moneyness levels outside of the moneyness range observed in the market, we simply use a nearest neighborhood algorithm to extrapolate the implied volatilities (Jiang & Tian, 2005). In practice, this means that if a moneyness level is lower (higher) than the lowest (highest) moneyness level available in the market, we simply use the implied volatility corresponding to the lowest (highest) level of moneyness available in the market.

the measures to obtain risk-neutral measures with maturity 91 days (3 months).⁴¹

MAX Measure (Bali et al., 2011, “*MAX*”) is the average of the five largest daily commodity futures excess returns during the past 12 months.

Value (Asness et al., 2013; Fernandez-Perez et al., 2018, “*Value*”) is the ratio of the log of the average daily futures prices from 4.5 to 5.5 years ago to the current log futures price, using the first-nearby commodity futures contract.

Volatility-of-Volatility (Baltussen et al., 2018, “*VoV*”) is computed as

$$VoV_{i,t} = \frac{\sqrt{\frac{1}{252} \sum_{d=t-251}^t (\sigma_{i,d}^{iv} - \bar{\sigma}_{i,t}^{iv})^2}}{\bar{\sigma}_{i,t}^{iv}}, \quad (\text{E.8})$$

where $\sigma_{i,d}^{iv}$ is the daily implied volatility of commodity i , and $\bar{\sigma}_{i,t}^{iv}$ denotes the average implied volatility over the past 12 months. We use $\sqrt{RNVar_{i,d}}$ as measure of $\sigma_{i,d}^{iv}$.

⁴¹A horizon of 12 months would be more desirable to exclude any seasonal patterns in commodity volatilities. However, there is only limited data available on commodity options above 6 months to maturity.

Table E.1: Simple Cross-Sectional Regression: Characteristics

This table reports the average coefficient estimates from monthly Fama & MacBeth (1973) cross-sectional regressions. Each month, we regress the commodity futures returns on a constant and the lagged value of the characteristic [name in column]. We impose the restriction that each month at least 10 commodities must be available. In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. “Adj. R²” denotes the average adjusted R² of the regressions.

	<i>AggVolVIX</i>	<i>AggVol</i>	<i>AggJump</i>	<i>CoSkew</i>	<i>CoKurt</i>	<i>DownBeta</i>	<i>HistVar</i>	<i>HistSkew</i>	<i>HistKurt</i>	<i>IdioVolF3</i>	<i>IdioVolBGR</i>
<i>Constant</i>	0.0217 (0.0259)	0.0122 (0.0388)	0.0086 (0.0401)	0.0498** (0.0227)	0.0495** (0.0219)	0.0480** (0.0215)	0.0384 (0.0276)	0.0435* (0.0227)	0.0562* (0.0306)	0.0345 (0.0448)	0.0317 (0.0509)
<i>Char</i>	-0.1854 (0.1769)	0.7318*** (0.2464)	-1.2615** (0.5710)	-0.0015 (0.0034)	0.0001 (0.0001)	0.0005 (0.0534)	0.0825 (0.2724)	-0.0559*** (0.0189)	-0.0015 (0.0030)	0.0268 (0.7154)	-0.0458 (0.9111)
<i>Adj. R²</i>	0.0285	0.0313	0.0284	0.0430	0.0512	0.0504	0.0727	0.0150	0.0156	0.0585	0.0438
	<i>ILLIQ</i>	<i>Mom^{char}</i>	<i>3Y Reversal</i>	<i>5Y Reversal</i>	<i>RNV^{ar}</i>	<i>RNSkew</i>	<i>RNExKurt</i>	<i>MAX</i>	<i>Value</i>	<i>Vol</i>	
<i>Constant</i>	0.0044 (0.0240)	0.0303 (0.0194)	0.0404* (0.0230)	0.0361 (0.0252)	0.0482 (0.0324)	-0.0041 (0.0271)	-0.0147 (0.0318)	0.0558 (0.0415)	-0.0675 (0.1319)	0.0464 (0.0403)	
<i>Char</i>	8.7910 (26.0703)	0.2439*** (0.0446)	0.0255 (0.0881)	0.1314 (0.1092)	-0.5399* (0.3118)	0.0100 (0.0229)	0.0010 (0.0072)	-0.2089 (0.8439)	0.1204 (0.1334)	-0.3895** (0.1965)	
<i>Adj. R²</i>	0.0321	0.0648	0.0561	0.0456	0.0753	0.0149	-0.0082	0.0562	0.0421	0.0164	

Table E.2: Multiple Cross-Sectional Regression: Characteristics

This table reports the average coefficient estimates from monthly Fama & MacBeth (1973) cross-sectional regressions. Each month, we regress the commodity futures returns on a constant, the lagged value of the characteristic [name in column], the lagged average 12-months roll yield, and the lagged average 12-months' past performance. We impose the restriction that each month at least 10 commodities must be available. In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively. "Adj. R²" denotes the average adjusted R² of the regressions.

	AggVol _{VIX}	AggVol	AggJump	CostSkew	CostKurt	DownBeta	HistVar	HistSkew	HistKurt	IdioVol _{FE3}	IdioVol _{BGR}
Constant	0.0253 (0.0261)	0.0236 (0.0391)	0.0170 (0.0417)	0.0016 (0.0379)	0.0066 (0.0363)	0.0050 (0.0349)	0.0239 (0.0359)	0.0106 (0.0392)	0.0438 (0.0489)	0.0407 (0.0521)	0.0601 (0.0581)
Char	-0.1355 (0.1386)	0.5537** (0.2400)	-1.1126* (0.6455)	-0.0098 (0.0072)	0.0000 (0.0002)	0.0439 (0.0731)	-0.3460 (0.3807)	-0.0374* (0.0209)	-0.0050 (0.0041)	-0.7933 (0.9928)	-1.0873 (1.1040)
Roll yield	0.8515 (0.7862)	0.7959 (0.8336)	0.4282 (0.9136)	0.2422 (0.8240)	0.3647 (0.9164)	0.2880 (0.9053)	0.0582 (0.9586)	-0.1914 (0.9456)	0.2906 (0.8773)	0.0957 (0.9683)	0.3961 (0.9203)
Past perf.	0.2043*** (0.0628)	0.1874** (0.0774)	0.2162*** (0.0759)	0.1808** (0.0779)	0.2487*** (0.0757)	0.2226*** (0.0793)	0.2598*** (0.0804)	0.2209*** (0.0742)	0.2450*** (0.0733)	0.2573*** (0.0766)	0.2295*** (0.0758)
Adj. R ²	0.1104	0.1062	0.1062	0.1064	0.1115	0.1089	0.1298	0.0867	0.0873	0.1173	0.1071

ILLIO	Mom ^{char}	3Y Reversal	5Y Reversal	RNV _{var}	RNSkew	RNExKurt	MAX	Value	Vol
Constant	0.0001 (0.0382)	0.0175 (0.0391)	0.0245 (0.0402)	0.0118 (0.0350)	0.0227 (0.0369)	-0.0079 (0.0420)	0.0566 (0.0453)	0.0198 (0.1222)	0.0375 (0.0549)
Char	36.2426 (29.2430)	0.2291*** (0.0741)	-0.0490 (0.1479)	0.1487 (0.1562)	0.0382 (0.0282)	0.0095 (0.0084)	-1.2613 (0.9814)	-0.0054 (0.1115)	-0.3301 (0.2890)
Roll yield	0.4913 (0.8954)	0.5960 (0.8687)	0.7741 (1.0848)	0.6665 (0.9235)	1.1865 (0.9124)	0.8811 (0.9257)	-0.1214 (1.0479)	0.6914 (0.8449)	0.2362 (0.8632)
Past perf.	0.1994** (0.0783)	- (0.0795)	0.2425*** (0.0795)	0.1810** (0.0821)	0.2955*** (0.0756)	0.2035** (0.0805)	0.2476*** (0.0800)	0.2176*** (0.0817)	0.2034*** (0.0774)
Adj. R ²	0.0858	0.0786	0.1171	0.1152	0.0850	0.0652	0.1122	0.0928	0.0789

Table E.3: Robustness Single Sorts

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 2, 3, 4, or 5 portfolios, respectively, according to the characteristic indicated in the first row. Portfolio P1 (P2, P3, P4, and P5, respectively) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolios P2-P1, P3-P1, P4-P1, and P5-P1 are referred to as the hedge portfolios and are defined as the excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P2, P3, P4, and P5, respectively). Moreover, we impose the constraint that for each subperiod at least 5 years of observations must be available. "Mean return" denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the Fama & French (2015) 5-factor model, and the BGR model suggested by Bakshi et al. (2017). In parentheses we present robust Newey & West (1987) standard errors using 6 lags. *, **, *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

Portfolio	AggVol ^{VIX}					AggVol					AggJump					
	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1
Mean return	-0.0129 (0.0110)	-0.0163 (0.0140)	-0.0194 (0.0158)	-0.0282 (0.0179)	0.0253** (0.0125)	0.0356** (0.0154)	0.0554** (0.0216)	0.0651** (0.0257)	-0.0391*** (0.0132)	-0.0463*** (0.0161)	-0.0639*** (0.0215)	-0.0705*** (0.0235)				
5-factor alpha	-0.0119 (0.0110)	-0.0127 (0.0142)	-0.0218 (0.0148)	-0.0295* (0.0169)	0.0241* (0.0132)	0.0336** (0.0169)	0.0512** (0.0238)	0.0599** (0.0271)	-0.0363** (0.0167)	-0.0426** (0.0193)	-0.0600** (0.0250)	-0.0680** (0.0276)				
BGR alpha	-0.0140 (0.0112)	-0.0165 (0.0138)	-0.0229 (0.0151)	-0.0336* (0.0176)	0.0163 (0.0120)	0.0255* (0.0154)	0.0362* (0.0217)	0.0438* (0.0246)	-0.0344** (0.0136)	-0.0371** (0.0159)	-0.0558** (0.0229)	-0.0622** (0.0256)				
Mean return	Sample Period: 08.1939-02.1986															
5-factor alpha	Sample Period: 03.1986-11.2000															
BGR alpha	Sample Period: 12.2000-12.2015															
Mean return	-0.0014 (0.0176)	-0.0068 (0.0230)	-0.0142 (0.0232)	-0.0076 (0.0261)	0.0137 (0.0139)	0.0227 (0.0172)	0.0354 (0.0245)	0.0500* (0.0280)	-0.0235 (0.0145)	-0.0326* (0.0179)	-0.0407* (0.0218)	-0.0430* (0.0240)				
5-factor alpha	-0.0098 (0.0174)	-0.0118 (0.0224)	-0.0236 (0.0202)	-0.0172 (0.0247)	0.0073 (0.0141)	0.0135 (0.0176)	0.0263 (0.0255)	0.0392 (0.0293)	-0.0104 (0.0155)	-0.0167 (0.0184)	-0.0243 (0.0224)	-0.0280 (0.0251)				
BGR alpha	-0.0113 (0.0157)	-0.0164 (0.0205)	-0.0340 (0.0216)	-0.0309 (0.0248)	0.0056 (0.0136)	0.0127 (0.0164)	0.0156 (0.0237)	0.0268 (0.0276)	-0.0139 (0.0129)	-0.0175 (0.0158)	-0.0236 (0.0210)	-0.0258 (0.0235)				

Table E.3: Robustness Single Sorts (continued)

Portfolio	CoSkew					CoKurt					DownBeta					
	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1
Mean return	0.0039 (0.0104)	0.0170 (0.0138)	0.0170 (0.0165)	0.0102 (0.0200)	-0.0069 (0.0107)	-0.0150 (0.0137)	-0.0168 (0.0155)	-0.0126 (0.0192)	-0.0084 (0.0104)	-0.0137 (0.0136)	-0.0044 (0.0179)	-0.0165 (0.0197)	-0.0170 (0.0178)	-0.0383* (0.0228)	-0.0287 (0.0330)	-0.0735** (0.0354)
5-factor alpha	0.0031 (0.0112)	0.0151 (0.0150)	0.0133 (0.0178)	0.0102 (0.0230)	-0.0095 (0.0112)	-0.0204 (0.0137)	-0.0130 (0.0161)	-0.0225 (0.0198)	-0.0124 (0.0119)	-0.0133 (0.0153)	-0.0036 (0.0193)	-0.0205 (0.0223)	-0.0167 (0.0215)	-0.0278 (0.0270)	-0.0109 (0.0364)	-0.0592 (0.0451)
BGR alpha	0.0096 (0.0105)	0.0229* (0.0133)	0.0262* (0.0155)	0.0242 (0.0198)	-0.0055 (0.0115)	-0.0155 (0.0152)	-0.0171 (0.0168)	-0.0136 (0.0200)	-0.0102 (0.0103)	-0.0152 (0.0138)	-0.0087 (0.0176)	-0.0175 (0.0197)	-0.0128 (0.0187)	-0.0304 (0.0242)	-0.0226 (0.0332)	-0.0624* (0.0353)
Sample Period: 08.1959-02.1986																
Mean return	0.0259* (0.0156)	0.0555*** (0.0209)	0.0594** (0.0256)	0.0510 (0.0355)	-0.0131 (0.0190)	-0.0209 (0.0246)	-0.0502* (0.0259)	-0.0358 (0.0361)	-0.0170 (0.0178)	-0.0383* (0.0228)	-0.0287 (0.0330)	-0.0735** (0.0354)	-0.0170 (0.0178)	-0.0383* (0.0228)	-0.0287 (0.0330)	-0.0735** (0.0354)
5-factor alpha	0.0219 (0.0188)	0.0438* (0.0247)	0.0413 (0.0311)	0.0485 (0.0523)	-0.0276 (0.0209)	-0.0427 (0.0275)	-0.0529* (0.0314)	-0.0896* (0.0458)	-0.0167 (0.0215)	-0.0278 (0.0270)	-0.0109 (0.0364)	-0.0592 (0.0451)	-0.0167 (0.0215)	-0.0278 (0.0270)	-0.0109 (0.0364)	-0.0592 (0.0451)
BGR alpha	0.0251 (0.0168)	0.0480** (0.0217)	0.0512** (0.0258)	0.0494 (0.0387)	-0.0095 (0.0206)	-0.0189 (0.0275)	-0.0429 (0.0290)	-0.0247 (0.0394)	-0.0128 (0.0187)	-0.0304 (0.0242)	-0.0226 (0.0332)	-0.0624* (0.0353)	-0.0128 (0.0187)	-0.0304 (0.0242)	-0.0226 (0.0332)	-0.0624* (0.0353)
Sample Period: 03.1986-11.2000																
Mean return	-0.0129 (0.0204)	-0.0129 (0.0261)	-0.0019 (0.0306)	-0.0018 (0.0327)	0.0080 (0.0197)	0.0008 (0.0253)	0.0234 (0.0321)	0.0197 (0.0371)	0.0009 (0.0176)	0.0190 (0.0235)	0.0337 (0.0272)	0.0402 (0.0312)	0.0009 (0.0176)	0.0190 (0.0235)	0.0337 (0.0272)	0.0402 (0.0312)
5-factor alpha	-0.0129 (0.0195)	-0.0146 (0.0244)	-0.0035 (0.0303)	-0.0060 (0.0330)	0.0027 (0.0205)	-0.0023 (0.0260)	0.0203 (0.0326)	0.0191 (0.0359)	0.0059 (0.0205)	0.0244 (0.0276)	0.0415 (0.0329)	0.0481 (0.0373)	0.0059 (0.0205)	0.0244 (0.0276)	0.0415 (0.0329)	0.0481 (0.0373)
BGR alpha	0.0018 (0.0194)	0.0154 (0.0229)	0.0318 (0.0259)	0.0373 (0.0267)	0.0159 (0.0203)	0.0144 (0.0260)	0.0299 (0.0332)	0.0237 (0.0370)	0.0050 (0.0173)	0.0251 (0.0242)	0.0392 (0.0259)	0.0523* (0.0310)	0.0050 (0.0173)	0.0251 (0.0242)	0.0392 (0.0259)	0.0523* (0.0310)
Sample Period: 12.2000-12.2015																
Mean return	-0.0169 (0.0182)	-0.0192 (0.0234)	-0.0253 (0.0284)	-0.0230 (0.0338)	-0.0109 (0.0116)	-0.0203 (0.0137)	-0.0083 (0.0190)	-0.0184 (0.0239)	-0.0028 (0.0159)	-0.0040 (0.0200)	-0.0067 (0.0263)	-0.0088 (0.0298)	-0.0028 (0.0159)	-0.0040 (0.0200)	-0.0067 (0.0263)	-0.0088 (0.0298)
5-factor alpha	-0.0213 (0.0188)	-0.0204 (0.0260)	-0.0263 (0.0308)	-0.0187 (0.0363)	-0.0096 (0.0120)	-0.0253* (0.0141)	-0.0114 (0.0202)	-0.0226 (0.0240)	-0.0077 (0.0167)	-0.0096 (0.0207)	-0.0158 (0.0267)	-0.0199 (0.0308)	-0.0077 (0.0167)	-0.0096 (0.0207)	-0.0158 (0.0267)	-0.0199 (0.0308)
BGR alpha	-0.0052 (0.0158)	-0.0042 (0.0207)	-0.0080 (0.0255)	-0.0047 (0.0313)	-0.0159 (0.0125)	-0.0316** (0.0149)	-0.0215 (0.0188)	-0.0330 (0.0240)	-0.0194 (0.0154)	-0.0274 (0.0190)	-0.0328 (0.0219)	-0.0353 (0.0253)	-0.0194 (0.0154)	-0.0274 (0.0190)	-0.0328 (0.0219)	-0.0353 (0.0253)

Table E.3: Robustness Single Sorts (continued)

Portfolio	<i>HistVar</i>					<i>HistSnew</i>					<i>HistKurt</i>				
	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P6 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P6 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P6 - P1
Mean return	0.0045	0.0050	-0.0013	0.0071	-0.0288***	-0.0350***	-0.0513***	-0.0524***	0.0174	0.0256**	0.0099	0.0113	0.0113	0.0113	0.0113
5-factor alpha	0.0022	0.0013	-0.0046	-0.0021	-0.0359***	-0.0430***	-0.0552***	-0.0594***	0.0208*	0.0273*	0.0133	0.0157	0.0157	0.0157	0.0157
BGR alpha	-0.0158	-0.0223	-0.0296*	-0.0193	-0.0093	-0.0131	-0.0163	-0.0177	0.0125	0.0147	0.0177	0.0182	0.0182	0.0182	0.0182
	(0.0102)	(0.0136)	(0.0168)	(0.0172)	(0.0074)	(0.0100)	(0.0115)	(0.0128)	(0.0099)	(0.0122)	(0.0137)	(0.0144)	(0.0144)	(0.0144)	(0.0144)
Full Sample Period															
Sample Period: 08.1959-02.1986															
Mean return	0.0036	0.0063	-0.0037	0.0177	-0.0174	-0.0146	-0.0279	0.0039	0.0253	0.0400*	0.0341	0.0580**	0.0580**	0.0580**	0.0580**
5-factor alpha	0.0096	0.0104	0.0089	0.0488	-0.0193	-0.0143	-0.0118	0.0293	0.0307	0.0393	0.0417	0.0853**	0.0853**	0.0853**	0.0853**
BGR alpha	-0.0232	-0.0314	-0.0415	-0.0203	-0.0020	0.0018	0.0064	0.0148	0.0437***	0.0636***	0.0630***	0.0891***	0.0891***	0.0891***	0.0891***
	(0.0169)	(0.0224)	(0.0297)	(0.0306)	(0.0119)	(0.0180)	(0.0206)	(0.0209)	(0.0166)	(0.0218)	(0.0242)	(0.0238)	(0.0238)	(0.0238)	(0.0238)
Sample Period: 03.1986-11.2000															
Mean return	0.0312*	0.0404*	0.0421*	0.0481*	-0.0462***	-0.0579***	-0.0731***	-0.0980***	0.0272	0.0404**	0.0260	0.0237	0.0237	0.0237	0.0237
5-factor alpha	0.0260	0.0405*	0.0342	0.0417	-0.0415**	-0.0495**	-0.0631***	-0.0815***	0.0284	0.0449**	0.0279	0.0302	0.0302	0.0302	0.0302
BGR alpha	0.0037	0.0078	0.0066	0.0179	-0.0247*	-0.0184	-0.0276*	-0.0463**	0.0438***	0.0564***	0.0420**	0.0399*	0.0399*	0.0399*	0.0399*
	(0.0147)	(0.0205)	(0.0265)	(0.0270)	(0.0149)	(0.0163)	(0.0146)	(0.0182)	(0.0166)	(0.0177)	(0.0180)	(0.0208)	(0.0208)	(0.0208)	(0.0208)
Sample Period: 12.2000-12.2015															
Mean return	-0.0202	-0.0318	-0.0403	-0.0447*	-0.0313**	-0.0472***	-0.0634***	-0.0699**	-0.0057	-0.0131	-0.0407	-0.0525*	-0.0525*	-0.0525*	-0.0525*
5-factor alpha	0.0151	0.0197	0.0244	0.0251	-0.0380***	-0.0498***	-0.0668***	-0.0746**	0.0147	0.0188	0.0275	0.0280	0.0280	0.0280	0.0280
BGR alpha	-0.0207	-0.0346*	-0.0424	-0.0506*	-0.0141	-0.0160	-0.0244	-0.0301	-0.0001	-0.0072	-0.0249	-0.0370	-0.0370	-0.0370	-0.0370
	(0.0155)	(0.0206)	(0.0261)	(0.0263)	(0.0141)	(0.0160)	(0.0244)	(0.0301)	(0.0149)	(0.0187)	(0.0299)	(0.0313)	(0.0313)	(0.0313)	(0.0313)
	-0.0289*	-0.0440**	-0.0562**	-0.0620**	-0.0142	-0.0223	-0.0319	-0.0340	0.0040	0.0003	-0.0177	-0.0288	-0.0288	-0.0288	-0.0288
	(0.0152)	(0.0194)	(0.0232)	(0.0243)	(0.0125)	(0.0150)	(0.0205)	(0.0245)	(0.0140)	(0.0159)	(0.0226)	(0.0220)	(0.0220)	(0.0220)	(0.0220)

Table E.3: Robustness Single Sorts (continued)

Portfolio	<i>IdioVol^{FF3}</i>					<i>IdioVol^{BGR}</i>					<i>ILLIQ</i>					
	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1
	Full Sample Period															
Mean return	0.0034 (0.0114)	0.0023 (0.0146)	0.0013 (0.0173)	0.0084 (0.0179)	0.0075 (0.0094)	0.0085 (0.0135)	0.0047 (0.0168)	0.0027 (0.0179)	-0.0182 (0.0129)	-0.0074 (0.0169)	0.0039 (0.0184)	0.0030 (0.0225)	0.0025 (0.0128)	0.0018 (0.0144)	0.0009 (0.0114)	0.0032 (0.0213)
5-factor alpha	0.0027 (0.0116)	0.0005 (0.0155)	-0.0007 (0.0182)	-0.0005 (0.0182)	0.0099 (0.0099)	0.0101 (0.0136)	0.0025 (0.0169)	-0.0052 (0.0177)	-0.0144 (0.0131)	-0.0051 (0.0174)	0.0055 (0.0185)	0.0128 (0.0226)	0.0018 (0.0144)	0.0009 (0.0114)	0.0032 (0.0213)	
BGR alpha	-0.0169 (0.0104)	-0.0222 (0.0138)	-0.0231 (0.0171)	-0.0147 (0.0173)	-0.0034 (0.0098)	-0.0036 (0.0135)	-0.0077 (0.0163)	-0.0136 (0.0172)	-0.0114 (0.0129)	-0.0009 (0.0179)	0.0090 (0.0193)	0.0032 (0.0213)				
Sample Period: 08.1959-02.1986																
Mean return	0.0025 (0.0201)	0.0039 (0.0260)	0.0007 (0.0327)	0.0183 (0.0369)	0.0094 (0.0152)	0.0235 (0.0234)	0.0281 (0.0312)	0.0351 (0.0365)	-0.0557 (0.0452)	-0.0446 (0.0697)	0.0066 (0.0687)	-0.1529*** (0.0450)				
5-factor alpha	0.0096 (0.0192)	0.0063 (0.0272)	0.0155 (0.0312)	0.0469 (0.0374)	0.0195 (0.0171)	0.0283 (0.0238)	0.0411 (0.0289)	0.0585 (0.0365)	-0.0245 (0.0588)	-0.0096 (0.0793)	0.0055 (0.0754)	-0.1099* (0.0408)				
BGR alpha	-0.0246 (0.0170)	-0.0304 (0.0227)	-0.0331 (0.0301)	-0.0153 (0.0308)	-0.0032 (0.0151)	0.0054 (0.0217)	0.0097 (0.0285)	0.0117 (0.0324)	-0.0144 (0.0363)	0.0204 (0.0472)	0.0569 (0.0545)	0.0782 (0.0488)				
Sample Period: 03.1986-11.2000																
Mean return	0.0286 (0.0178)	0.0368* (0.0208)	0.0403 (0.0247)	0.0484* (0.0253)	0.0372** (0.0145)	0.0274 (0.0184)	0.0267 (0.0206)	0.0338 (0.0228)	-0.0239 (0.0191)	-0.0189 (0.0221)	-0.0229 (0.0263)	-0.0196 (0.0381)				
5-factor alpha	0.0253 (0.0201)	0.0360 (0.0228)	0.0306 (0.0280)	0.0411 (0.0280)	0.0347** (0.0138)	0.0237 (0.0186)	0.0173 (0.0216)	0.0230 (0.0237)	-0.0198 (0.0190)	-0.0185 (0.0230)	-0.0235 (0.0259)	-0.0097 (0.0389)				
BGR alpha	0.0019 (0.0163)	0.0040 (0.0196)	0.0103 (0.0266)	0.0193 (0.0271)	0.0143 (0.0155)	0.0112 (0.0179)	0.0103 (0.0207)	0.0106 (0.0224)	-0.0137 (0.0196)	-0.0154 (0.0242)	-0.0226 (0.0263)	-0.0018 (0.0338)				
Sample Period: 12.2000-12.2015																
Mean return	-0.0196 (0.0152)	-0.0339 (0.0207)	-0.0358 (0.0248)	-0.0414 (0.0253)	-0.0243 (0.0162)	-0.0339 (0.0217)	-0.0497* (0.0254)	-0.0607** (0.0270)	0.0000 (0.0169)	0.0164 (0.0220)	0.0293 (0.0256)	0.0259 (0.0286)				
5-factor alpha	-0.0207 (0.0159)	-0.0315 (0.0223)	-0.0340 (0.0262)	-0.0466* (0.0264)	-0.0175 (0.0165)	-0.0299 (0.0217)	-0.0474* (0.0271)	-0.0572** (0.0286)	0.0027 (0.0172)	0.0223 (0.0221)	0.0350 (0.0259)	0.0319 (0.0278)				
BGR alpha	-0.0281* (0.0153)	-0.0417** (0.0204)	-0.0486* (0.0249)	-0.0546** (0.0251)	-0.0253 (0.0176)	-0.0355 (0.0242)	-0.0529** (0.0261)	-0.0684** (0.0274)	0.0008 (0.0162)	0.0196 (0.0219)	0.0318 (0.0251)	0.0271 (0.0276)				

Table E.3: Robustness Single Sorts (continued)

Portfolio	Mom^{char}					$3Y Reversal$					$5Y Reversal$					
	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1
Mean return	0.0556*** (0.0099)	0.0744*** (0.0129)	0.0848*** (0.0163)	0.0982*** (0.0179)	0.0123 (0.0102)	0.0236* (0.0139)	0.0222 (0.0184)	-0.0086 (0.0204)	0.0173 (0.0115)	0.0226 (0.0150)	0.0109 (0.0174)	0.0242 (0.0218)	0.0142 (0.0214)	0.0205 (0.0275)	-0.0113 (0.0339)	0.0379 (0.0539)
5-factor alpha	0.0559*** (0.0108)	0.0751*** (0.0140)	0.0840*** (0.0172)	0.0911*** (0.0205)	0.0148 (0.0108)	0.0287* (0.0147)	0.0222 (0.0196)	-0.0135 (0.0232)	0.0223* (0.0117)	0.0287* (0.0153)	0.0137 (0.0181)	0.0267 (0.0220)	0.0197 (0.0218)	0.0236 (0.0284)	-0.0155 (0.0365)	0.0311 (0.0527)
BGR alpha	0.0341*** (0.0090)	0.0451*** (0.0121)	0.0499*** (0.0156)	0.0646*** (0.0168)	-0.0272*** (0.0092)	-0.0337*** (0.0113)	-0.0479*** (0.0146)	-0.0744*** (0.0178)	-0.0243** (0.0102)	-0.0310** (0.0134)	-0.0487*** (0.0162)	-0.0445** (0.0195)				
Sample Period: 08.1959-02.1986																
Mean return	0.0694*** (0.0168)	0.0843*** (0.0214)	0.1018*** (0.0304)	0.1206*** (0.0352)	0.0184 (0.0172)	0.0300 (0.0252)	0.0340 (0.0365)	-0.0211 (0.0426)	0.0142 (0.0214)	0.0205 (0.0275)	-0.0113 (0.0339)	0.0379 (0.0539)				
5-factor alpha	0.0739*** (0.0183)	0.0910*** (0.0232)	0.1075*** (0.0311)	0.1174*** (0.0443)	0.0163 (0.0175)	0.0237 (0.0262)	0.0153 (0.0387)	-0.0765 (0.0494)	0.0197 (0.0218)	0.0236 (0.0284)	-0.0155 (0.0365)	0.0311 (0.0527)				
BGR alpha	0.0451*** (0.0156)	0.0509*** (0.0215)	0.0620*** (0.0305)	0.0859*** (0.0340)	-0.0250* (0.0150)	-0.0362* (0.0189)	-0.0536** (0.0261)	-0.0993*** (0.0370)	-0.0368** (0.0184)	-0.0478** (0.0225)	-0.0832*** (0.0291)	-0.0449 (0.0414)				
Sample Period: 03.1986-11.2000																
Mean return	0.0573*** (0.0164)	0.0912*** (0.0240)	0.0987*** (0.0285)	0.1098*** (0.0322)	-0.0069 (0.0171)	0.0043 (0.0213)	0.0017 (0.0255)	-0.0220 (0.0288)	0.0240 (0.0174)	0.0300 (0.0249)	0.0262 (0.0278)	0.0192 (0.0337)				
5-factor alpha	0.0548*** (0.0166)	0.0876*** (0.0237)	0.0887*** (0.0259)	0.0969*** (0.0307)	-0.0106 (0.0184)	0.0079 (0.0225)	-0.0005 (0.0271)	-0.0248 (0.0289)	0.0180 (0.0182)	0.0242 (0.0271)	0.0227 (0.0285)	0.0109 (0.0409)				
BGR alpha	0.0340** (0.0133)	0.0579*** (0.0181)	0.0544** (0.0214)	0.0622*** (0.0232)	-0.0464*** (0.0166)	-0.0548*** (0.0192)	-0.0633*** (0.0203)	-0.0882*** (0.0238)	-0.0121 (0.0149)	-0.0140 (0.0243)	-0.0270 (0.0291)	-0.0425 (0.0352)				
Sample Period: 12.2000-12.2015																
Mean return	0.0304* (0.0156)	0.0412** (0.0192)	0.0468** (0.0212)	0.0619** (0.0247)	0.0214 (0.0166)	0.0325* (0.0195)	0.0269 (0.0267)	0.0167 (0.0315)	0.0151 (0.0179)	0.0182 (0.0209)	0.0219 (0.0250)	0.0174 (0.0258)				
5-factor alpha	0.0265 (0.0174)	0.0356* (0.0214)	0.0370 (0.0250)	0.0502* (0.0287)	0.0180 (0.0176)	0.0281 (0.0204)	0.0184 (0.0342)	0.0057 (0.0342)	0.0078 (0.0195)	0.0104 (0.0220)	0.0120 (0.0251)	0.0067 (0.0251)				
BGR alpha	0.0143 (0.0138)	0.0208 (0.0169)	0.0255 (0.0230)	0.0392 (0.0261)	-0.0097 (0.0152)	-0.0071 (0.0172)	-0.0197 (0.0228)	-0.0342 (0.0272)	-0.0153 (0.0153)	-0.0198 (0.0174)	-0.0274 (0.0207)	-0.0361* (0.0212)				

Table E.3: Robustness Single Sorts (continued)

Portfolio	RNV_{ar}					$RNSkew$					$RNExKurt$				
	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P5 - P1	P2 - P1	P3 - P1	P4 - P1	P5 - P1	P5 - P1
Mean return	-0.0163 (0.0113)	-0.0154 (0.0136)	-0.0201 (0.0187)	-0.0565** (0.0229)	-0.0064 (0.0143)	0.0003 (0.0154)	0.0067 (0.0167)	-0.0193 (0.0226)	-0.0004 (0.0142)	0.0031 (0.0171)	0.0122 (0.0185)	0.0179 (0.0276)			
5-factor alpha	-0.0145 (0.0123)	-0.0129 (0.0142)	-0.0213 (0.0197)	-0.0615** (0.0247)	-0.0164 (0.0154)	-0.0067 (0.0164)	-0.0017 (0.0181)	-0.0180 (0.0252)	-0.0052 (0.0146)	-0.0023 (0.0179)	0.0118 (0.0201)	0.0188 (0.0294)			
BGR alpha	-0.0315*** (0.0111)	-0.0362*** (0.0131)	-0.0462*** (0.0176)	-0.0841*** (0.0208)	-0.0054 (0.0138)	0.0045 (0.0159)	0.0096 (0.0164)	-0.0141 (0.0220)	0.0092 (0.0142)	0.0153 (0.0160)	0.0261 (0.0169)	0.0296 (0.0255)			
Full Sample Period															
Sample Period: 08.1959-02.1986															
Mean return															
5-factor alpha															
BGR alpha															
Sample Period: 03.1986-11.2000															
Mean return	-0.0146 (0.0140)	-0.0133 (0.0180)	0.0099 (0.0230)	0.0036 (0.0274)	-0.0281 (0.0196)	-0.0239 (0.0224)	-0.0046 (0.0245)	-0.0884*** (0.0314)	-0.0307 (0.0207)	-0.0366 (0.0263)	-0.0246 (0.0265)	-0.0627 (0.0509)			
5-factor alpha	-0.0082 (0.0165)	-0.0048 (0.0196)	0.0045 (0.0250)	0.0192 (0.0309)	-0.0367* (0.0211)	-0.0285 (0.0212)	-0.0148 (0.0264)	-0.0936*** (0.0297)	-0.0375* (0.0207)	-0.0407* (0.0242)	-0.0145 (0.0252)	-0.0459 (0.0465)			
BGR alpha	-0.0265** (0.0134)	-0.0209 (0.0166)	-0.0077 (0.0226)	0.0017 (0.0372)	-0.0229 (0.0181)	-0.0142 (0.0192)	-0.0006 (0.0186)	-0.0603* (0.0303)	-0.0165 (0.0207)	-0.0090 (0.0231)	0.0127 (0.0238)	-0.0179 (0.0385)			
Sample Period: 12.2000-12.2015															
Mean return	-0.0176 (0.0168)	-0.0171 (0.0198)	-0.0424 (0.0265)	-0.0778*** (0.0281)	0.0104 (0.0191)	0.0192 (0.0200)	0.0151 (0.0222)	0.0052 (0.0264)	0.0231 (0.0178)	0.0340 (0.0210)	0.0397 (0.0245)	0.0464 (0.0318)			
5-factor alpha	-0.0195 (0.0182)	-0.0219 (0.0210)	-0.0473* (0.0277)	-0.0912*** (0.0297)	0.0035 (0.0210)	0.0165 (0.0220)	0.0092 (0.0242)	0.0047 (0.0299)	0.0199 (0.0184)	0.0270 (0.0231)	0.0357 (0.0273)	0.0395 (0.0337)			
BGR alpha	-0.0348** (0.0166)	-0.0438** (0.0188)	-0.0718*** (0.0237)	-0.1093*** (0.0227)	0.0117 (0.0180)	0.0237 (0.0208)	0.0205 (0.0229)	0.0093 (0.0258)	0.0288 (0.0185)	0.0371* (0.0212)	0.0408* (0.0242)	0.0485 (0.0317)			

Table E.3: Robustness Single Sorts (continued)

Portfolio	MAX										Value										Vol																
	P2 - P1		P3 - P1		P4 - P1		P5 - P1		P2 - P1		P3 - P1		P4 - P1		P5 - P1		P2 - P1		P3 - P1		P4 - P1		P5 - P1														
Mean return	-0.0034 (0.0101)	-0.0013 (0.0130)	0.0051 (0.0157)	0.0005 (0.0175)	0.0038 (0.0107)	0.0044 (0.0140)	0.0151 (0.0167)	-0.0100 (0.0207)	-0.0197* (0.0109)	-0.0272** (0.0121)	-0.0252* (0.0137)	-0.0305* (0.0167)	5-factor alpha	-0.0091 (0.0108)	-0.0058 (0.0136)	0.0038 (0.0169)	-0.0053 (0.0185)	0.0040 (0.0109)	0.0035 (0.0143)	0.0173 (0.0175)	-0.0085 (0.0219)	-0.0333** (0.0130)	-0.0273* (0.0149)	-0.0389** (0.0181)	BGR alpha	-0.0138 (0.0089)	-0.0134 (0.0117)	-0.0053 (0.0150)	-0.0118 (0.0158)	0.0348** (0.0092)	0.0496** (0.0121)	0.0665** (0.0145)	0.0553*** (0.0167)	-0.0222** (0.0102)	-0.0314*** (0.0119)	-0.0313* (0.0141)	-0.0362** (0.0168)
Sample Period: 08.1959-02.1986																																					
Mean return	0.0020 (0.0179)	0.0078 (0.0232)	0.0170 (0.0290)	0.0068 (0.0346)	0.0147 (0.0206)	0.0162 (0.0271)	0.0383 (0.0320)	-0.0308 (0.0533)	5-factor alpha	0.0093 (0.0174)	0.0169 (0.0236)	0.0373 (0.0281)	0.0300 (0.0372)	0.0074 (0.0204)	0.0055 (0.0285)	0.0416 (0.0353)	-0.0422 (0.0511)	BGR alpha	-0.0165 (0.0146)	-0.0131 (0.0194)	0.0005 (0.0260)	-0.0093 (0.0259)	0.0555*** (0.0158)	0.0756*** (0.0217)	0.1065*** (0.0254)	0.0543 (0.0330)											
Sample Period: 03.1986-11.2000																																					
Mean return	0.0126 (0.0162)	0.0236 (0.0204)	0.0473** (0.0229)	0.0513** (0.0253)	-0.0024 (0.0149)	-0.0114 (0.0179)	-0.0139 (0.0243)	-0.0078 (0.0269)	-0.0020 (0.0138)	-0.0200 (0.0177)	-0.0236 (0.0194)	-0.0357 (0.0268)	5-factor alpha	0.0162 (0.0189)	0.0267 (0.0228)	0.0486* (0.0282)	0.0539* (0.0296)	0.0097 (0.0154)	0.0015 (0.0170)	0.0021 (0.0233)	0.0070 (0.0269)	-0.0178 (0.0212)	-0.0205 (0.0226)	-0.0352 (0.0366)	BGR alpha	0.0037 (0.0134)	0.0078 (0.0195)	0.0255 (0.0244)	0.0257 (0.0273)	0.0163 (0.0133)	0.0220 (0.0172)	0.0204 (0.0232)	0.0412 (0.0281)	-0.0065 (0.0142)	-0.0282 (0.0189)	-0.0376* (0.0218)	-0.0495 (0.0315)
Sample Period: 12.2000-12.2015																																					
Mean return	-0.0283** (0.0132)	-0.0411*** (0.0157)	-0.0532*** (0.0199)	-0.0563** (0.0243)	-0.0053 (0.0156)	0.0034 (0.0219)	0.0173 (0.0276)	0.0047 (0.0268)	-0.0331** (0.0159)	-0.0327* (0.0167)	-0.0265 (0.0194)	-0.0281 (0.0207)	5-factor alpha	-0.0312** (0.0140)	-0.0438*** (0.0166)	-0.0534** (0.0228)	-0.0586** (0.0257)	0.0017 (0.0159)	0.0077 (0.0225)	0.0241 (0.0287)	0.0125 (0.0277)	-0.0458*** (0.0169)	-0.0383** (0.0201)	-0.0261 (0.0218)	-0.0365* (0.0218)	BGR alpha	-0.0310** (0.0127)	-0.0426*** (0.0155)	-0.0530** (0.0206)	-0.0601** (0.0238)	0.0172 (0.0137)	0.0345** (0.0173)	0.0569** (0.0229)	0.0469** (0.0232)	-0.0377** (0.0137)	-0.0312* (0.0183)	-0.0337* (0.0197)

Table E.4: Portfolio Sorts: Aggregate Volatility and Jump Characteristics – Annual Horizon

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3–P1 is referred to as the hedge portfolio and is defined as the annual excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). “Mean return” denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 12 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	AggVol ^{VIX}			AggVol			AggJump					
	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1
Mean return	0.0310 (0.0274)	0.0463 (0.0301)	0.0181 (0.0342)	-0.0064 (0.0107)	-0.0033 (0.0521)	0.0153 (0.0413)	0.0558 (0.0529)	0.0295** (0.0134)	0.0592 (0.0527)	0.0233 (0.0392)	-0.0137 (0.0631)	-0.0364** (0.0151)
CAPM alpha	0.0079 (0.0338)	0.0286 (0.0383)	-0.0026 (0.0377)	-0.0053 (0.0116)	-0.0256 (0.0545)	-0.0042 (0.0399)	0.0300 (0.0605)	0.0278** (0.0135)	0.0312 (0.0514)	0.0016 (0.0410)	-0.0319 (0.0530)	-0.0315** (0.0141)
3-factor alpha	-0.0018 (0.0355)	0.0249 (0.0507)	-0.0098 (0.0461)	-0.0040 (0.0105)	-0.0424 (0.0633)	-0.0175 (0.0530)	0.0150 (0.0637)	0.0287** (0.0141)	0.0153 (0.0538)	-0.0135 (0.0542)	-0.0462 (0.0681)	-0.0307* (0.0159)
4-factor alpha	-0.0116 (0.0370)	0.0130 (0.0541)	-0.0184 (0.0492)	-0.0034 (0.0115)	-0.0628 (0.0550)	-0.0226 (0.0555)	-0.0042 (0.0537)	0.0293** (0.0147)	-0.0091 (0.0449)	-0.0218 (0.0530)	-0.0586 (0.0610)	-0.0247 (0.0152)
5-factor alpha	-0.0089 (0.0427)	0.0242 (0.0569)	0.0119 (0.0513)	0.0104 (0.0187)	-0.0392 (0.0710)	-0.0313 (0.0555)	0.0111 (0.0649)	0.0252 (0.0166)	0.0124 (0.0559)	-0.0259 (0.0653)	-0.0453 (0.0701)	-0.0288* (0.0150)
BGR alpha	-0.0232 (0.0198)	-0.0274** (0.0137)	-0.0487*** (0.0170)	-0.0127 (0.0121)	-0.0742*** (0.0269)	-0.0542*** (0.0108)	-0.0254 (0.0248)	0.0244 (0.0167)	-0.0287 (0.0242)	-0.0459*** (0.0143)	-0.0781*** (0.0179)	-0.0247* (0.0141)
FFFM alpha	-0.0209 (0.0179)	-0.0278** (0.0124)	-0.0483*** (0.0169)	-0.0137 (0.0118)	-0.0607*** (0.0202)	-0.0535*** (0.0123)	-0.0215 (0.0280)	0.0196 (0.0167)	-0.0218 (0.0236)	-0.0507*** (0.0156)	-0.0628*** (0.0151)	-0.0205 (0.0132)

Table E.5: Portfolio Sorts: Co-Moments and Downside Beta Characteristics – Annual Horizon

*This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3–P1 is referred to as the hedge portfolio and is defined as the annual excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). “Mean return” denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 12 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.*

	CoSkew			CoKurt			DownBeta					
	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1
Mean return	0.0575 (0.0378)	0.0632** (0.0263)	0.0677** (0.0309)	0.0051 (0.0144)	0.0718** (0.0363)	0.0556** (0.0223)	0.0615* (0.0337)	-0.0051 (0.0118)	0.0676** (0.0293)	0.0645*** (0.0246)	0.0556 (0.0348)	-0.0060 (0.0107)
CAPM alpha	0.0507 (0.0536)	0.0651* (0.0376)	0.0762* (0.0457)	0.0128 (0.0188)	0.0828 (0.0547)	0.0543* (0.0290)	0.0542 (0.0441)	-0.0143 (0.0125)	0.0716 (0.0471)	0.0683** (0.0338)	0.0507 (0.0440)	-0.0104 (0.0118)
3-factor alpha	0.0464 (0.0570)	0.0514 (0.0342)	0.0603 (0.0404)	0.0069 (0.0148)	0.0776 (0.0487)	0.0462 (0.0318)	0.0335 (0.0399)	-0.0221* (0.0120)	0.0579 (0.0419)	0.0614* (0.0351)	0.0380 (0.0450)	-0.0100 (0.0118)
4-factor alpha	0.0172 (0.0445)	0.0300 (0.0295)	0.0283 (0.0343)	0.0056 (0.0137)	0.0435 (0.0391)	0.0292 (0.0289)	0.0018 (0.0324)	-0.0209* (0.0119)	0.0281 (0.0368)	0.0405 (0.0317)	0.0065 (0.0378)	-0.0108 (0.0145)
5-factor alpha	0.0752 (0.0813)	0.0780* (0.0464)	0.0809 (0.0560)	0.0028 (0.0194)	0.1001 (0.0687)	0.0665 (0.0445)	0.0660 (0.0544)	-0.0170 (0.0131)	0.0819 (0.0498)	0.0869* (0.0445)	0.0628 (0.0705)	-0.0096 (0.0153)
BGR alpha	-0.0504*** (0.0131)	-0.0377*** (0.0123)	-0.0178 (0.0193)	0.0163 (0.0135)	-0.0377* (0.0198)	-0.0208** (0.0088)	-0.0467*** (0.0145)	-0.0045 (0.0131)	-0.0234 (0.0154)	-0.0232* (0.0129)	-0.0586*** (0.0143)	-0.0176 (0.0115)
FFFM alpha	-0.0390** (0.0183)	-0.0300** (0.0119)	-0.0285 (0.0210)	0.0052 (0.0139)	-0.0369** (0.0152)	-0.0228* (0.0123)	-0.0361* (0.0198)	0.0004 (0.0113)	-0.0359* (0.0217)	-0.0116 (0.0129)	-0.0477*** (0.0167)	-0.0059 (0.0114)

Table E.6: Portfolio Sorts: Historical Characteristics – Annual Horizon

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3–P1 is referred to as the hedge portfolio and is defined as the annual excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). “Mean return” denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 12 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	HistVar			HistSkew			HistKurt					
	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1
Mean return	0.0761 (0.0521)	0.0370 (0.0290)	0.0774 (0.0494)	0.0007 (0.0243)	0.0821*** (0.0292)	0.0578 (0.0420)	0.0504 (0.0384)	-0.0159 (0.0112)	0.0236 (0.0425)	0.0812** (0.0381)	0.0829*** (0.0271)	0.0296*** (0.0113)
CAPM alpha	0.0737 (0.0745)	0.0413 (0.0379)	0.0781 (0.0652)	0.0022 (0.0308)	0.0835** (0.0367)	0.0680 (0.0733)	0.0415 (0.0606)	-0.0210* (0.0125)	0.0269 (0.0566)	0.0881* (0.0522)	0.0758** (0.0357)	0.0245* (0.0127)
3-factor alpha	0.0630 (0.0712)	0.0344 (0.0409)	0.0609 (0.0573)	-0.0010 (0.0268)	0.0711* (0.0381)	0.0586 (0.0597)	0.0290 (0.0525)	-0.0210* (0.0111)	0.0150 (0.0620)	0.0713* (0.0432)	0.0707* (0.0423)	0.0278* (0.0145)
4-factor alpha	0.0455 (0.0572)	0.0198 (0.0374)	0.0110 (0.0456)	-0.0173 (0.0250)	0.0584* (0.0342)	0.0255 (0.0490)	-0.0080 (0.0378)	-0.0332*** (0.0086)	0.0212 (0.0483)	0.0465 (0.0366)	0.0487 (0.0380)	0.0350*** (0.0129)
5-factor alpha	0.0972 (0.0791)	0.0614 (0.0503)	0.0749 (0.0732)	-0.0111 (0.0271)	0.0913* (0.0480)	0.0844 (0.0748)	0.0573 (0.0651)	-0.0170 (0.0137)	0.0448 (0.0752)	0.0868* (0.0517)	0.1014* (0.0565)	0.0283 (0.0184)
BGR alpha	-0.0005 (0.0193)	-0.0523*** (0.0192)	-0.0508** (0.0222)	-0.0251 (0.0192)	-0.0282** (0.0114)	-0.0580*** (0.0167)	-0.0179 (0.0151)	0.0051 (0.0098)	-0.0824*** (0.0146)	-0.0491** (0.0204)	0.0229 (0.0144)	0.0527*** (0.0092)
FFFM alpha	-0.0167 (0.0150)	-0.0162 (0.0162)	-0.0638*** (0.0245)	-0.0235 (0.0152)	-0.0367*** (0.0128)	-0.0289** (0.0138)	-0.0316 (0.0223)	0.0026 (0.0109)	-0.0649*** (0.0185)	-0.0377** (0.0158)	0.0017 (0.0233)	0.0333*** (0.0113)

Table E.7: Portfolio Sorts: Idiosyncratic Volatility and Illiquidity Characteristics – Annual Horizon

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3–P1 is referred to as the hedge portfolio and is defined as the annual excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). “Mean return” denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 12 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	IdioVol ^{FF3}					IdioVol ^{BGR}					ILLIQ					
	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1
Mean return	0.0746 (0.0503)	0.0393 (0.0302)	0.0750 (0.0495)	0.0002 (0.0240)	0.0661 (0.0470)	0.0552 (0.0361)	0.0738 (0.0624)	0.0039 (0.0275)	0.0378 (0.0482)	-0.0089 (0.0257)	0.0219 (0.0484)	-0.0080 (0.0200)	0.0378 (0.0482)	-0.0089 (0.0257)	0.0219 (0.0484)	-0.0080 (0.0200)
CAPM alpha	0.0729 (0.0738)	0.0427 (0.0398)	0.0759 (0.0651)	0.0015 (0.0307)	0.0681 (0.0659)	0.0482 (0.0454)	0.0818 (0.1016)	0.0069 (0.0435)	0.0174 (0.0536)	-0.0314 (0.0293)	-0.0198 (0.0391)	-0.0186 (0.0195)	0.0174 (0.0536)	-0.0314 (0.0293)	-0.0198 (0.0391)	-0.0186 (0.0195)
3-factor alpha	0.0618 (0.0691)	0.0359 (0.0426)	0.0592 (0.0574)	-0.0013 (0.0268)	0.0615 (0.0623)	0.0400 (0.0495)	0.0639 (0.0731)	0.0012 (0.0338)	0.0101 (0.0776)	-0.0364 (0.0467)	-0.0194 (0.0406)	-0.0147 (0.0225)	0.0101 (0.0776)	-0.0364 (0.0467)	-0.0194 (0.0406)	-0.0147 (0.0225)
4-factor alpha	0.0438 (0.0552)	0.0194 (0.0385)	0.0116 (0.0475)	-0.0161 (0.0255)	0.0423 (0.0516)	0.0228 (0.0425)	0.0182 (0.0595)	-0.0121 (0.0321)	0.0062 (0.0847)	-0.0412 (0.0537)	-0.0154 (0.0443)	-0.0108 (0.0242)	0.0062 (0.0847)	-0.0412 (0.0537)	-0.0154 (0.0443)	-0.0108 (0.0242)
5-factor alpha	0.0972 (0.0779)	0.0619 (0.0534)	0.0739 (0.0737)	-0.0117 (0.0271)	0.0879 (0.0758)	0.0654 (0.0574)	0.0802 (0.0644)	-0.0038 (0.0228)	0.0133 (0.0720)	-0.0400 (0.0488)	-0.0438 (0.0388)	-0.0286 (0.0222)	0.0133 (0.0720)	-0.0400 (0.0488)	-0.0438 (0.0388)	-0.0286 (0.0222)
BGR alpha	-0.0015 (0.0186)	-0.0510** (0.0199)	-0.0523** (0.0222)	-0.0254 (0.0188)	-0.0063 (0.0191)	-0.0340** (0.0149)	-0.0644** (0.0281)	-0.0291 (0.0213)	-0.0358 (0.0274)	-0.0445*** (0.0153)	-0.0184 (0.0305)	0.0087 (0.0201)	-0.0358 (0.0274)	-0.0445*** (0.0153)	-0.0184 (0.0305)	0.0087 (0.0201)
FFFM alpha	-0.0182 (0.0148)	-0.0132 (0.0180)	-0.0639*** (0.0239)	-0.0228 (0.0150)	-0.0068 (0.0172)	-0.0147 (0.0159)	-0.0734*** (0.0265)	-0.0333*** (0.0151)	-0.0439 (0.0315)	-0.0436** (0.0182)	-0.0532* (0.0273)	-0.0046 (0.0233)	-0.0439 (0.0315)	-0.0436** (0.0182)	-0.0532* (0.0273)	-0.0046 (0.0233)

Table E.8: Portfolio Sorts: Reversal Characteristics – Annual Horizon

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3–P1 is referred to as the hedge portfolio and is defined as the annual excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). “Mean return” denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 12 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	Mom ^{char}											
	3Y Reversal						5Y Reversal					
	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1
Mean return	0.0523* (0.0293)	0.0637** (0.0309)	0.0726* (0.0405)	0.0102 (0.0122)	0.0526 (0.0377)	0.0618* (0.0334)	0.0724 (0.0584)	0.0099 (0.0180)	0.0569 (0.0640)	0.0529 (0.0449)	0.0862 (0.0624)	0.0146 (0.0308)
CAPM alpha	0.0418 (0.0400)	0.0742* (0.0445)	0.0755 (0.0503)	0.0169 (0.0129)	0.0521 (0.0569)	0.0584 (0.0479)	0.0903 (0.0858)	0.0191 (0.0239)	0.0616 (0.0878)	0.0482 (0.0606)	0.1039 (0.0921)	0.0212 (0.0397)
3-factor alpha	0.0305 (0.0392)	0.0667* (0.0401)	0.0603 (0.0489)	0.0149 (0.0118)	0.0444 (0.0580)	0.0478 (0.0474)	0.0788 (0.0715)	0.0172 (0.0233)	0.0539 (0.0803)	0.0399 (0.0558)	0.0901 (0.0763)	0.0181 (0.0375)
4-factor alpha	0.0143 (0.0309)	0.0438 (0.0352)	0.0176 (0.0418)	0.0016 (0.0108)	0.0231 (0.0498)	0.0233 (0.0368)	0.0456 (0.0615)	0.0112 (0.0240)	0.0275 (0.0603)	0.0190 (0.0377)	0.0496 (0.0627)	0.0110 (0.0289)
5-factor alpha	0.0568 (0.0591)	0.0866* (0.0509)	0.0894 (0.0585)	0.0163 (0.0164)	0.0615 (0.0669)	0.0658 (0.0593)	0.1087 (0.0738)	0.0236 (0.0198)	0.0753 (0.0902)	0.0673 (0.0768)	0.1166* (0.0603)	0.0206 (0.0340)
BGR alpha	-0.0083 (0.0152)	-0.0355** (0.0149)	-0.0388** (0.0183)	-0.0153 (0.0124)	0.0047 (0.0164)	-0.0367** (0.0145)	-0.0852*** (0.0214)	-0.0450*** (0.0139)	-0.0030 (0.0210)	-0.0384** (0.0174)	-0.0924*** (0.0265)	-0.0447** (0.0180)
FFFM alpha	-0.0050 (0.0188)	-0.0329** (0.0132)	-0.0489*** (0.0123)	-0.0219** (0.0094)	0.0005 (0.0247)	-0.0380** (0.0148)	-0.0656*** (0.0188)	-0.0331** (0.0166)	-0.0051 (0.0237)	-0.0226 (0.0166)	-0.0787*** (0.0250)	-0.0368* (0.0191)

Table E.9: Portfolio Sorts: Risk-Neutral Moments – Annual Horizon

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3–P1 is referred to as the hedge portfolio and is defined as the annual excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). “Mean return” denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 12 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	RNV _{var}			RNS _{skew}			RNE _{kurt}					
	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1
Mean return	0.0098 (0.0292)	0.0121 (0.0329)	-0.0039 (0.0308)	-0.0068 (0.0104)	0.0142 (0.0273)	0.0028 (0.0281)	0.0018 (0.0382)	-0.0062 (0.0131)	0.0211 (0.0320)	-0.0016 (0.0251)	-0.0020 (0.0318)	-0.0116 (0.0143)
CAPM alpha	-0.0113 (0.0307)	-0.0188 (0.0295)	-0.0180 (0.0468)	-0.0034 (0.0117)	-0.0010 (0.0407)	-0.0265 (0.0307)	-0.0187 (0.0464)	-0.0088 (0.0187)	0.0000 (0.0424)	-0.0253 (0.0264)	-0.0220 (0.0357)	-0.0110 (0.0173)
3-factor alpha	-0.0165 (0.0414)	-0.0268 (0.0371)	-0.0206 (0.0509)	-0.0020 (0.0122)	-0.0087 (0.0459)	-0.0314 (0.0341)	-0.0223 (0.0561)	-0.0068 (0.0181)	-0.0020 (0.0518)	-0.0324 (0.0316)	-0.0288 (0.0378)	-0.0134 (0.0164)
4-factor alpha	-0.0327 (0.0440)	-0.0272 (0.0411)	-0.0315 (0.0522)	0.0006 (0.0154)	-0.0144 (0.0513)	-0.0404 (0.0401)	-0.0336 (0.0497)	-0.0096 (0.0174)	-0.0174 (0.0552)	-0.0380 (0.0321)	-0.0354 (0.0359)	-0.0090 (0.0153)
5-factor alpha	-0.0207 (0.0457)	-0.0513 (0.0447)	-0.0319 (0.0507)	-0.0056 (0.0128)	-0.0197 (0.0551)	-0.0300 (0.0392)	-0.0524 (0.0621)	-0.0164 (0.0241)	0.0088 (0.0572)	-0.0344 (0.0397)	-0.0756 (0.0397)	-0.0422** (0.0178)
BGR alpha	-0.0172 (0.0172)	-0.0254* (0.0137)	-0.0614*** (0.0168)	-0.0203** (0.0093)	-0.0332 (0.0227)	-0.0461** (0.0194)	-0.0271* (0.0155)	0.0030 (0.0116)	-0.0499** (0.0224)	-0.0401*** (0.0110)	-0.0186 (0.0206)	0.0157 (0.0164)
FFFM alpha	-0.0144 (0.0146)	-0.0255* (0.0144)	-0.0607*** (0.0151)	-0.0231** (0.0090)	-0.0253 (0.0198)	-0.0468** (0.0199)	-0.0273* (0.0147)	-0.0010 (0.0105)	-0.0409** (0.0188)	-0.0429*** (0.0110)	-0.0177 (0.0191)	0.0116 (0.0156)

Table E.10: Portfolio Sorts: MAX, Value, and VoV Characteristics – Annual Horizon

This table reports the results of portfolio sorts according to several characteristics. At the end of each month, we sort the commodities into 3 portfolios according to the characteristic indicated in the first row. Portfolio P1 (P3) contains the commodities with the lowest (highest) magnitude of the characteristic. Portfolio P3–P1 is referred to as the hedge portfolio and is defined as the annual excess return of a monthly rebalanced fully-collateralized portfolio that simultaneously goes short (long) portfolio P1 (P3). “Mean return” denotes the annualized average excess return on the respective portfolio. We report the (annualized) alpha estimates based on the CAPM, the Fama & French (1993) 3-factor model, the Carhart (1997) 4-factor model, the Fama & French (2015) 5-factor model, the BGR model suggested by Bakshi et al. (2017), and the FFFM model suggested by Fernandez-Perez et al. (2018). In parentheses we present robust Newey & West (1987) standard errors using 12 lags. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % level, respectively.

	MAX					Value					VoV					
	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1	P1	P2	P3	P3 – P1
Mean return	0.0666 (0.0469)	0.0451 (0.0318)	0.0773 (0.0573)	0.0054 (0.0263)	0.0654 (0.0615)	0.0560 (0.0411)	0.0777* (0.0403)	0.0061 (0.0175)	0.0247 (0.0421)	0.0186 (0.0285)	-0.0190 (0.0319)	-0.0218* (0.0127)	0.0247 (0.0421)	0.0186 (0.0285)	-0.0190 (0.0319)	-0.0218* (0.0127)
CAPM alpha	0.0651 (0.0618)	0.0463 (0.0410)	0.0802 (0.0955)	0.0076 (0.0425)	0.0803 (0.0938)	0.0590 (0.0583)	0.0869 (0.0605)	0.0003 (0.0245)	0.0022 (0.0515)	-0.0006 (0.0313)	-0.0446 (0.0297)	-0.0234* (0.0129)	0.0022 (0.0515)	-0.0006 (0.0313)	-0.0446 (0.0297)	-0.0234* (0.0129)
3-factor alpha	0.0593 (0.0613)	0.0307 (0.0421)	0.0680 (0.0753)	0.0043 (0.0347)	0.0694 (0.0750)	0.0480 (0.0491)	0.0733 (0.0555)	0.0020 (0.0219)	-0.0036 (0.0609)	-0.0055 (0.0387)	-0.0526 (0.0333)	-0.0245* (0.0129)	-0.0036 (0.0609)	-0.0055 (0.0387)	-0.0526 (0.0333)	-0.0245* (0.0129)
4-factor alpha	0.0517 (0.0556)	0.0086 (0.0354)	0.0160 (0.0536)	-0.0178 (0.0281)	0.0190 (0.0602)	0.0281 (0.0353)	0.0562 (0.0450)	0.0186 (0.0181)	-0.0197 (0.0600)	-0.0117 (0.0391)	-0.0564* (0.0341)	-0.0184 (0.0163)	-0.0197 (0.0600)	-0.0117 (0.0391)	-0.0564* (0.0341)	-0.0184 (0.0163)
5-factor alpha	0.0874 (0.0729)	0.0644 (0.0518)	0.0787 (0.0674)	-0.0043 (0.0280)	0.0932 (0.0712)	0.0744 (0.0663)	1.003 (0.0641)	0.0035 (0.0186)	-0.0335 (0.0631)	-0.0094 (0.0440)	-0.0602 (0.0405)	-0.0133 (0.0162)	-0.0335 (0.0631)	-0.0094 (0.0440)	-0.0602 (0.0405)	-0.0133 (0.0162)
BGR alpha	-0.0073 (0.0197)	-0.0551*** (0.0115)	-0.0416 (0.0258)	-0.0172 (0.0189)	-0.1040*** (0.0244)	-0.0315* (0.0179)	0.0013 (0.0159)	0.0527*** (0.0139)	-0.0123 (0.0298)	-0.0360*** (0.0128)	-0.0532*** (0.0133)	-0.0204 (0.0134)	-0.0123 (0.0298)	-0.0360*** (0.0128)	-0.0532*** (0.0133)	-0.0204 (0.0134)
FFFM alpha	-0.0100 (0.0173)	-0.0461*** (0.0147)	-0.0428 (0.0260)	-0.0164 (0.0124)	-0.0824*** (0.0220)	-0.0095 (0.0164)	-0.0161 (0.0192)	0.0332*** (0.0127)	-0.0095 (0.0250)	-0.0332** (0.0132)	-0.0524*** (0.0139)	-0.0214* (0.0124)	-0.0095 (0.0250)	-0.0332** (0.0132)	-0.0524*** (0.0139)	-0.0214* (0.0124)

Chapter 7

Conclusion and Further Research

7.1 Summary and Conclusion

This thesis studies the predictability of stock and commodity returns. It also examines the sources of return anomalies in financial markets. Overall, we find evidence for a notable degree of return predictability in both stock and commodity markets. Moreover, by analyzing commodity futures markets, we are able to show that specific capital market anomalies are behaviorally caused, whereas others have a risk-based explanation.

In Chapter 2, we show that return predictability is a phenomenon that exists world-wide. Using price ratios, interest-related variables, and economic indicators, respectively, investors can realize substantial utility gains. We also demonstrate that investors can use simple techniques as forecast combinations to exploit information contained in various variables.

We then examine the predictive power of forward looking variables.

7.1. SUMMARY AND CONCLUSION

In Chapter 3, we provide evidence for return and variance predictability using option-implied information. Using the correlation risk premium and the variance risk premium, investors are able to predict the future return and the variance of the S&P 500, and thus gain sizable economic profits.

Based on the findings in Chapters 2 and 3, investors are able to improve their portfolio choices and to set up profitable timing strategies. In the most developed countries, they can use not only historical measures but also forward looking information for portfolio selection.

We extend the analysis to commodity spot markets to identify economic linkages between macroeconomic variables and commodity excess returns and volatilities. Overall, Chapter 4 provides evidence for return and volatility predictability in commodity spot markets. That means that producers may predict to some extent future price developments of physical commodities and use that information for future purchases and sales, respectively. They also can use the predicted information for hedging purposes. On the other hand, consumers may also exploit the information for future purchases.

In Chapter 5, we provide evidence that metal futures returns are significantly predictable based on historical measures. So, investors can also set up profitable trading strategies in commodity markets and obtain sizable utility gains up to 2.18 % p.a. in the case of gold. In doing so, investors are well advised when using gold in particular for their tactical asset allocations, especially since gold might be considered as hedge possibility and as safe heaven.

Finally, in Chapter 6 we use commodity futures markets to identify the sources of capital market anomalies. We find that downside beta, idiosyncratic volatility, and MAX are likely behaviorally caused, whereas jump risk, momentum, and volatility-of-volatility can be explained as risk-based. Our findings can help us to understand what are the driving

factors of stock prices. Further implications may be to understand the under- and overreaction of (retail) investors in crises.

7.2 Suggestions for Further Research

Interesting topics for future research may arise in particular by analyzing the predictability of commodity returns using components of option-implied measures that reflect specific attitudes of investors. New insights can also be gained by examining the impact of commodity markets on equity markets. Finally, making use of recent developments in the literature, we can use newly developed indicators that claim to reflect, e.g., stages of the economy.

First, a well known fact in the existing literature is that asset return variance is time-varying and that investors insure themselves against variance risk by paying an additional premium, i.e., the variance risk premium (e.g., Bakshi & Kapadia, 2003; Carr & Wu, 2008). The percentage shares of the diffusion and the jump component of the total variance risk premium vary over time, and thus, may affect the predictability of returns at different horizons. Moreover, the jump component in particular may reflect investors' fear of market crashes (Li & Zinna, 2017). Making use of recent developments in the literature on option-implied measures, one could use the level and the slope of the term structure of the total variance risk premium and of its components to examine the predictive power for commodity returns. One could also gain insights about business cycle dependent predictability: in particular, focusing on the jump component, one could make inferences about the degree of investors' fear over time.

Second, recent studies analyze the connection of commodity markets with equity markets. Among others, Jacobsen, Marshall, & Visaltanachoti

7.2. SUGGESTIONS FOR FURTHER RESEARCH

(2018) show that changes in industrial metal prices predict stock returns. In particular, they provide evidence that a price increase in industrial metals is considered to be good (bad) news for equity markets in recessions (expansions).

One could extend the analysis in various dimensions. In the first step, it is not obvious why only industrial metals should systematically affect equity markets. In doing so, one could examine the impact and the predictive power of agricultural, energy, and non-industrial metal commodities on stock returns. Here, the central role of WTI oil for the world market has to be mentioned, to name only one example. Moreover, one could analyze the impacts using individual commodities rather than a commodity index and only few metals, respectively. In the second step, one could analyze the link between both commodity futures and spot prices on equity markets. Accordingly, one would gain insights about any economic linkages between stock returns and physical commodities. One could also extend the analysis using a much longer sample period.

Third, the predictability literature has so far mostly focused on classical historical variables, among many others, such as the dividend–price ratio, the term spread, and the default yield spread. The analysis of predictability is limited due to the fact that each of these variables exhibit only a small predictive fraction per se. One could make use of recent developments concerning new indicators that claim to reflect a comprehensive fraction of the economy. Among others, the OECD has published composite leading indicators that claim to detect business cycle turning points six to nine months in advance. Given this, one would expect predictive power for stock and commodity returns. In addition, one would expect to gain new insights about business cycle stage dependent predictability. Further indicators that could have predictive power for returns, among others, are the S&P/Case–Shiller Home Price Index, reflecting the house price

development in the U.S., and the Economic Policy Uncertainty Index, capturing the economic uncertainty of policy in a respective country. To exploit the information incorporated in individual indicators, one could make use of combination approaches to aggregate the information and obtain more reliable forecasts.

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