Tail Risk and Long Memory in Financial Markets

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Duc Binh Benno Nguyen

Abstract

This thesis investigates the tail risk properties and long memory in financial markets and implications for asset pricing and hedging. Chapter 1 introduces the main concepts and delivers an overview of the subsequent chapters.

Chapter 2 examines the pricing of tail risk in international stock markets. We find that the tail risk of different countries is highly integrated. Introducing a new World Fear index, we find that local and global aggregate market returns are mainly driven by global tail risk rather than local tail risk. World fear is also priced in the cross-section of stock returns. Buying stocks with high sensitivities to World Fear while selling stocks with low sensitivities generates excess returns of up to 2.72% per month.

In Chapter 3 we shift to a different asset class and investigate tail risk in the commodity markets. We find that price jumps are rare and extreme events but occur less frequently than in stock markets. Nonetheless, jump correlations across commodities can be high depending on the commodity sectors. Energy, metal and grains commodities show high jump correlations while jumps of meats and softs commodities are barely correlated. Looking at cross-market correlations, we find that returns of commodities co-move with the stock market, while jumps can be diversified. Most commodities are strong hedges for U.S. Dollar returns but weak hedges for U.S. Dollar

jumps. Most commodities act as both return and jump hedges for Treasury notes.

Chapter 4 focuses on the probably most prominent commodity, gold, which is due to its source of value and its capacity as money and investment. We estimate a parsimonious model for the gold risk premium and uncover important time variations in the dynamics of the risk premium. We also estimate risk premia of the stock and bond markets, and investigate the role of gold as a hedge and safe haven asset from an ex-ante point of view. The results show that gold is not expected to serve as hedge and safe haven for the bond and stock markets, but it is so realized ex-post. Further, we find that gold is neither expected to be an inflation hedge nor is it realized.

In Chapters 5 and 6 we examine a different phenomenon and stylized fact in financial data, which has gained a lot of attention over the past decades, long memory. We start by linking the cross-sectional variation in long memory to differences in economic fundamentals. To do so, we examine long memory volatility in international stock markets. We show that long memory volatility is widespread in eighty-two countries and that the degree of memory can be related to macroeconomic variables such as inflation, unemployment rates, interest rates or stability of a country measured by jumps. The relationships hold both in the time-series and the cross-sectional dimension. We also find that developed countries possess longer memory in volatility than emerging and frontier countries. We do not only study long memory in volatility at an aggregate level but also at the firm level. More specifically, we examine long memory volatility in the cross-section of U.S. stock returns. We show that long memory volatility is widespread in the U.S. and that the degree of memory can be related to firm characteristics such as market capitalization, book-to-market ratio, prior performance and price jumps. Long memory volatility is negatively priced in the cross-section. Buying stocks with shorter memory and selling stocks with longer memory in volatility generates significant excess returns of 1.71% per annum. Consistent with theory, we find that the volatility of stocks with longer memory is more predictable than stocks with shorter memory. This makes the latter more uncertain, which is compensated for with higher average returns.

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

Keywords: Asset Pricing, Long Memory, Return Predictability, Tail Risk, Volatility

Zusammenfassung

Diese Arbeit beschäftigt sich mit den Eigenschaften von Randrisiken und langem Gedächtnis in Finanzmärkten und die Auswirkung auf die Bepreisung in Kapitalmärkten und Absicherungsgeschäfte durch Hedging. Kapitel 1 stellt die Hauptkonzepte vor und liefert einen Überblick über die nachfolgenden Kapitel.

Kapitel 2 untersucht die Preise von Randrisiko in internationalen Aktienmärkten. Die Resultate deuten darauf hin, dass das Randrisiko über verschiedene Länder stark integriert ist. Wir führen einen neuen World Fear Index ein und zeigen, dass sowohl lokale als auch globale aggregierte Marktrenditen hauptsächlich vom globalen anstatt vom lokalen Randrisiko getrieben sind. Außerdem ist World Fear in den internationalen Aktienmärkten gepreist. Durch das Kaufen von Aktien mit hoher Sensitivität zu World Fear und das Verkaufen von Aktien mit niedriger Sensitivität können Überschussrenditen von bis zu 2.72% pro Monat erzeugt werden.

In Kapitel 3 wechseln wir zu einer anderen Assetklasse und untersuchen Randrisiken in Rohstoffmärkten. Unsere Ergebnisse zeigen, dass Preissprünge seltene und extreme Ereignisse darstellen, aber weniger häufig auftreten als in Aktienmärkten. Dennoch kann die Sprungkorrelation zwischen Rohstoffen je nach Rohstoffsektor sehr hoch sein. Energie-, Metall- und Getreide-Rohstoffe zeigen hohe Sprungkorrelationen während Sprünge

von Fleisch- und Weichwaren-Rohstoffen kaum korreliert sind. In einer marktübergreifenden Analyse zeigen wir, dass Renditen von Rohstoffen zeitgleiche Bewegungen mit Renditen am Aktienmarkt aufweisen, während Sprünge diversifizierbar sind. Die meisten Rohstoffe sind starke Absicherungen für U.S. Dollar Renditen aber schwache Absicherungen für U.S. Dollar Sprünge. Gleichzeitig sichern die meisten Rohstoffe gegen Änderungen in Preisen und Sprüngen von Banknoten ab.

Kapitel 4 konzentriert sich auf den wahrscheinlich bedeutendsten Rohstoff, Gold. Dies ist ihrer Quelle der Wertschöpfung und Funktion als Geld und Investition zu verdanken. Wir schätzen ein einfaches Modell für die Goldrisikoprämie und enthüllen wichtige Zeitvariationen in der Dynamik der Risikoprämie. Außerdem schätzen wir auch die Risikoprämie in Aktien und Bondmärkten und untersuchen die Rolle von Gold als Absicherung und sicherer Anlagehafen aus einer ex-ante Perspektive. Die Ergebnisse deuten darauf hin, dass Gold nicht als Absicherung oder sicherer Hafen für Bond- und Aktienmarkt angenommen wird, sich ex-post aber als solche darstellt. Ferner, wird Gold weder als Absicherung für Inflation erwartet noch liefert Gold diese Absicherung ex-post.

In den Kapiteln 5 und 6 untersuchen wir ein weiteres Phänomen und stilistischen Fakt in Finanzdaten, welches über die letzten Jahrzehnte viel Aufmerksamkeit erregt hat: langes Gedächtnis. Als erstes stellen wir einen Zusammenhang zwischen der Variation des langen Gedächtnis im Querschnitt und Unterschieden in ökonomischen Fundamentaldaten her. Hierzu untersuchen wir langes Gedächtnis in Volatilität in internationalen Aktienmärkten. Langes Gedächtnis in Volatilität ist in zweiundachtzig Ländern weit verbreitet und das Maß des Gedächtnisses kann makroökonomischen Variablen wie Inflation, Arbeitslosenrate, Zinsrate oder Stabilität eines Landes gemessen an Sprüngen zugeordnet werden. Diese Beziehungen gelten sowohl in der Zeitreihen- als auch in der Querschnittsdimension. Weiterhin besitzen entwickelte Länder längeres Gedächtnis in Volatilität als Schwellen- und Entwicklungsländern. Wir untersuchen langes Gedächtnis in Volatilität nicht nur auf Aggregatebene sondern auch auf Unternehmensebene. Insbesondere untersuchen wir langes Gedächtnis in Volatilität im Querschnitt von U.S. amerikanischen Aktienrenditen. Die Ergebnisse indizieren, dass das lange Gedächtnis in der USA weit verbreitet ist und dass das Maß des Gedächtnisses unternehmensspezifischen Eigenschaften wie Marktkapitalisierung, Kurs-Buchwert-Verhältnis, vergangene Leistung und Preissprüngen zugeordnet werden kann. Langes Gedächtnis in Volatilität ist mit einer negativen Risikoprämie angehaftet. Durch das Kaufen von Aktien mit kurzem Gedächtnis in Volatilität und das Verkaufen von Aktien mit langem Gedächtnis in Volatilität kann eine statistisch signifikante Überschussrendite von 1.71% pro Jahr erzeugt werden. Konsistent mit der Theorie zeigen wir, dass die Volatilität von Aktien mit langem Gedächtnis besser vorhersagbar ist als von Aktien mit kurzem Gedächtnis. Dadurch sind letztere ungewisser und werden mit höherer durchschnittlicher Rendite kompensiert.

Abschließend präsentiert Kapitel 7 Schlussfolgerungen und liefert Anregungen für mögliche zukünftige Forschungsthemen.

Schlagwörter: Bestimmungsfaktoren der Aktienrenditen, Langes Gedächtnis, Vorhersage von Aktienrenditen, Randrisiko, Volatilität

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Chapter 1

Introduction

The importance of downside losses relative to potential upside gains goes back to at least the work of Roy (1952). More recently, the occurrence of long periods of financial distress such as the burst of the dot-com bubble, the Lehman default and the European debt crisis lead to further focus on research on disaster, crisis and tail risk. Studying tail risk properties of financial markets, on the one hand, is important to help us understand interdependencies, often referred to as spillover effects or contagion. On the other, a better understanding of tail risks allows for predictions of effects on the overall economy and potential asset pricing implications. Thus, it is useful for hedging purposes of investors, who are concerned about the performance under extreme market circumstances.

Chapter 2 relates to the recent developments in estimating tail risk. Tail risk can be estimated from option implied measures (Bollerslev et al., 2015; Cremers et al., 2015), based on historical high-frequency return data (Bollerslev & Todorov, 2011a,b) or using stock return data from a country's large cross-section (Kelly & Jiang, 2014). All methodologies mentioned face certain advantages and disadvantages. While the availability of options data may be limited for many countries or individual stocks, the estimation based on historical time series data is often infeasible due to the rare occurrence of extreme movements.

Chapter 2 contributes to the literature by providing international evidence of tail risk based on return data. We investigate tail risk in seven major economies, the co-movements across countries as well as asset implications for stock returns both in the time-series and the cross-sectional dimension. Further, we introduce a new measure World Fear, which captures global tail risk. Our World Fear index adds to the growing list of predictors for international returns including the dividend yield, short rates and the variance risk premium (Ang & Bekaert, 2007; Bollerslev et al., 2014).

Our key findings suggest that there is a positive and significant relationship between World Fear and future aggregate stock market returns around the globe. In line with the intertemporal CAPM (ICAPM) and the findings of Maio & Santa-Clara (2012), we find that World Fear has impact on the cross-section of stock returns for most countries. We document a positive and statistically significant risk premium associated with World Fear in international markets. We discuss a potential explanation and channel through which tail risk on the firm level may impact asset prices. By linking World Fear to the real economy we show that an increase in World Fear is followed by higher unemployment in subsequent months for all countries followed by a slow recovery.

Motivated by the conclusions drawn from the analysis of tail risk measures, we demonstrate the importance of tail risk and jump risk in further asset classes with a focus on commodities. Deaton & Laroque (1992) and Pindyck (2001), among others, document evidence of jumps and fat tails in commodity returns .

Chapter 3 investigates the benefits of the jump diversification in commodity, currency and bond markets in order to hedge against large price movements. This allows for enhanced risk control through diversification of extreme movements not only across countries but also across assets and asset classes. While the literature mainly focuses on the co-movement of commodity prices given by the excess co-movement hypothesis introduced by Pindyck & Rotemberg (1993), see for example Palaskas & Varangis (1991), Deb et al. (1996), and Malliaris & Urrutia (1996), the focus of Chapter 3 is the co-movement of extreme events. Jumps can be estimated non-parametrically from historical return data (Barndorff-Nielsen & Shephard, 2006; Tauchen & Zhou, 2011; Laurent et al., 2011) or be incorporated by continuous finance models for commodities (Hilliard & Reis, 1999; Deng, 2000; Manoliu & Tompaidis, 2002; Casassus & Collin-Dufresne, 2005).

We deliver a comprehensive study of jumps in commodity markets by investigating 29 different commodity futures including the comparison of jump intensity, size and dates across the commodities. Further, we analyze the co-movement of normal and extreme returns both within and across commodity sectors and across asset classes. Jumps are captured by the Barndorff-Nielsen & Shephard (2006) (BNS) jump test statistic which is calculated using historical return data.

Our empirical analysis indicates that jumps are rare and extreme events, which on average occur in less than 1% of the days with a size 1000 times higher than average returns. While some commodities such as energy commodities exhibit high jump correlations, others such as soft commodities are essentially uncorrelated. Nonetheless, jumps of commodities are generally not correlated with jumps in the stock and currency market and treasury notes. This is good news for investors who value good performance of their portfolios under extreme market stress. We additionally analyze co-movements of normal returns between commodities and other asset classes and emphasize that there are different conclusions drawn compared to the analysis of the co-movement of extreme events.

Chapter 4 brings into focus the hedging property of one particular commodity, gold. In both the media and the academic literature, gold is claimed to serve as a hedge and safe haven asset due to its sacred property. Several studies rely on realized returns and some dependence measure in order to empirically investigate the claim (Capie et al., 2005; Baur & McDermott, 2010; Reboredo, 2013; Ciner et al., 2013).

Chapter 4 sheds new light on gold as a hedge and safe haven asset. We analyze the ability of gold both from an ex-ante point of view, i.e. whether it is expected to serve as a hedge or safe haven, opposed to the ex-post point of view in the recent literature. For this purpose, we estimate a parsimonious forecasting model for the gold risk premium and show that it is well predictable. In a second step, we investigate the co-movements between the risk premia of gold and other relevant markets. Implications on hedging and safe haven properties are made based on the expected and unexpected relationship between gold and other assets.

Our results provide strong evidence of the predictive power of jump and variance risk premium for the gold risk premium both in-sample and out-of-sample and for short and long forecast horizons. Consistent with the literature, our equity risk premium model uses the dividend yield and the variance risk premium as predictors (Campbell & Shiller, 1988; Bollerslev et al., 2009, 2014). For the bond risk premium we rely on the framework of Cochrane & Piazzesi (2005) while time-series models are used for the expected inflation following Ang et al. (2007). We find that gold is generally not expected to be a hedge or safe haven for the stock and bond markets but it is realized as such ex-post. The same analysis with expected inflation reveals that gold does not serve as a hedge against inflation both ex-ante and ex-post. Our analysis reveals that one has to carefully differentiate between conclusions drawn from an ex-ante perspective and conclusions drawn from ex-post computations. However, for most useful applications and from an asset pricing perspective, it is much more important to understand, whether gold is also expected to be a hedge or safe haven asset.

Besides the presence of extreme returns often measured by the leptokurtic distribution of returns, volatility clustering and leverage effects, long memory is considered as another important stylized fact in financial data. Long memory processes exhibit high persistence, which are often characterized by hyperbolic decaying autocorrelation functions, as opposed to the exponential function of short memory processes such as autoregressive moving average (ARMA) processes.

Long memory of returns and volatility have been investigated for the U.S. stock market (Bollerslev & Mikkelsen, 1996; Ding & Granger, 1996; Breidt et al., 1998; Lobato & Savin, 1998) and for further international stock indices (Sadique & Silvapulle, 2001; Henry, 2002; Kasman et al., 2009)

Chapter 5 investigates long memory in stock market volatility for a large cross-section of countries. The degree of memory is linked to macroeconomic variables such as interest rates, unemployment rates, inflation and gross domestic product, in both the time-series and cross-sectional dimension. Further, the degree of memory is differentiated between frontier, emerging and developed countries.

Our empirical analysis shows that long memory volatility is prevalent in international stock markets with an average memory parameter of 0.27, which is statistically significant. While longer memory is associated to lower interest rates in the time-series dimension, longer memory is related to more developed countries in the cross-sectional dimension.

Motivated by the findings at the aggregate level, Chapter 6 analyzes the memory of volatility on the firm level in the cross-section of U.S. stocks. We relate the degree of memory of a stock to firm characteristics and examine asset pricing implications of long memory volatility. To the best of our knowledge, we are the first to analyze the asset pricing implications of long memory volatility. We show that long memory is prevalent in the volatility of individual stock returns. Long memory can be related to the size, past performance and jump intensity of a firm. Moreover, we provide time-series and cross-sectional evidence for a negative price of long memory volatility in the cross-section of stock returns. Our findings suggest that the volatility of stocks with longer memory is better predictable than stocks with short memory. The longer memory and more persistent volatility related to lower uncertainty results in the negative risk premium. The results of this chapter are in line with existing theoretical models, in which long memory is generated through heterogeneity in the market.

This thesis proceeds as follows. Chapter 2 studies tail risk in international major economies and introduces a new measure denoted as World Fear. Chapter 3 studies the role of jumps in commodity markets and how these are correlated within commodity markets and with further asset classes. Chapter 4 compares the role of gold as a hedge and safe haven from both an ex-ante and an ex-post perspective. Chapter 5 investigates the relationship between the long memory volatility in equity indices and macroeconomic variables while Chapter 6 examines whether long memory is priced in the cross-section of U.S. equity returns. Finally, Chapter 7 summarizes the main findings of this thesis and suggests several lines for future research.

For reasons of improved readability, especially of the separate parts constituting the complete thesis, each chapter is self-contained. This means, variables and acronyms are redefined in each chapter. Whenever possible, notations are consistent throughout the thesis in order to facilitate the reading.

Chapter 2

International Tail Risk and World Fear*

2.1 Introduction

The study of tail risk has been the focus of recent studies, especially since past years have been marked by times of financial distress like the burst of the dot-com bubble, the Lehman default, the great recession followed by the European debt crisis and the Chinese stock market crash.

In this chapter, we examine the pricing of tail risk in international equity markets. We begin by analyzing the tail risk of each country and analyze their co-movements. Motivated by the finding that tail risk co-moves across countries, we construct a global version of tail risk which we call World Fear (WF). We then investigate the asset implication of World Fear for international stock returns both in the time-series and the cross-section.

Our key findings can be summarized as follows. First, there is a positive

*This chapter is based on the Working Paper "International Tail Risk and World Fear" authored by Duc Binh Benno Nguyen, Marcel Prokopczuk and Chardin Wese Simen, 2017.

and significant relationship between World Fear and future aggregate market returns around the globe. A one-standard-deviation increase in World Fear predicts an increase of future excess returns by up to 8.46% at the one year horizon. The explanatory power in terms of R^2 is highest for the one year horizon with values between 3.57% and 18.10%. We also find that World Fear is a strong predictor of the cross-section of stock returns for most countries. Stocks that have a high exposure to World Fear significantly outperform stocks with low exposure by 1.06%, 1.28%, 2.72%, 0.97% and 1.00% per month in Canada, France, Germany, Italy and the U.K., respectively. Overall, we document a positive and statistically significant risk premium associated with World Fear for international markets. We present a potential explanation for the predictive power of World Fear. To achieve this goal, we explore the link between World Fear and the real economy. Our empirical results establish that an increase in World Fear is followed by higher unemployment in subsequent months for all countries followed by a slow recovery.

The modeling of tail risk can be generally separated into two strands of literature. The first is based on option implied measures. Using deep-out-of-the-money and short maturity options of the S&P 500 index, Bollerslev et al. (2015) decompose the variance risk premium into a premium for diffusive and a premium for large movements referred to as jump tail variation or fear. Cremers et al. (2015) use at-the-money S&P 500 straddles to capture jump and volatility risk portfolios. More precisely, they relate jump and volatility risk to the Black-Scholes greeks and create mimicking portfolios by ensuring that they are market-neutral, vega-neutral (vega-positive) and gamma-positive (gamma-neutral) for the jump (volatility) factor. The second stream relies on underlying return data. For instance, Bollerslev & Todorov (2011b) use high-frequency S&P 500 index returns in order to quantify the tail risk of the S&P 500. Kelly &

Jiang (2014) use the cross-section of stock returns in the U.S. to estimate the tail risk of the equity market.

While the data set for options is limited for international countries, papers using tail risk estimation based on return data mainly focus on the U.S. We contribute to the literature by providing international evidence of tail risk based on return data.[1]

Our work adds to the growing literature that analyzes the predictability of returns in an international context. For instance, Ang & Bekaert (2007) study the predictive power of traditional predictors such as dividend yields and short rates in international countries. Bollerslev et al. (2014) introduce the global variance risk premium and show that it outperforms the local variance risk premium in predicting aggregate local market returns. Relative to these studies, we introduce a new predictor, which we denote World Fear, and contribute to the literature on international return predictability of both the aggregate market and the cross-section of stock returns. The impact of World Fear is both economically and statistically significant.

The rest of the chapter is organized as follows. Section 2.2 describes our data set and methodology. Section 2.3 discusses the results related to local and global tail risk. Section 2.4 analyzes a possible economic mechanism. Section 2.5 presents robustness tests and Section 2.6 concludes. In the appendix to this chapter, which can be found in Section A, we present the results of additional analyses.

[1]When we started this project, we could not find any study that focused on tail risk in international markets. After completing the current version of our chapter, we have become aware of Wang (2015), which also examines international markets.

2.2 Data and Methodology

2.2.1 Data

Our primary data set contains stock returns of the G-7 countries: Canada, France, Germany, Italy, Japan, the U.K. and the U.S. This choice is motivated by the economic importance of these countries on the one hand, and data availability on the other. Equity price and market capitalization data are obtained from Datastream except for the U.S. data which are from the Center for Research in Security Prices (CRSP). We include the universe of stocks from the major exchanges for each country, which are defined as the exchanges in which the majority of the stocks are traded. Canada, France, Italy and the U.K. have a single major exchange while there are two for Germany (Frankfurt and Xetra) and Japan (Osaka and Tokyo), and three for the U.S. (AMEX, NYSE and NASDAQ).

The data span the period from January 2000 to December 2015, including a total of 4,023 trading days. Most companies are from the U.S. with a median of about 5,000 stocks over the whole sample period, followed by Japan with a median of around 3,500. Italy has the smallest number of equities with a median of just 274.[2] CRSP total returns (including dividends) are obtained directly from CRSP for the U.S. while local returns are calculated using total return indices for the remaining countries from Datastream. We conduct our analyses in U.S. dollar returns. We convert the returns into U.S. dollar returns using the corresponding exchange rates from Datastream.

Following existing studies such as Lesmond (2005) and Lee (2011), we

[2]Even though equity data goes back as far as 1980, we focus on the most recent years. This choice is motivated by data availability. The year 1980 starts with just under 8,000 stocks across all countries from which around 4,000 are U.S. equities. Starting in 2000, the sample size rises to above 15,000. Moreover, for our robustness checks, some predictor variables, e.g. the implied volatility indices, are available starting in 2000 only.

include all listed and delisted companies and exclude Depository Receipts (DRs), Real Estate Investment Trusts (REITs) and preferred stocks from Datastream. For the U.S. market, we only include stocks with share codes 10 and 11, following Kelly & Jiang (2014). As in Hou et al. (2011) and Lee (2011) , we exclude anomalous observations. More specifically, if the current or past return, r_t or r_{t-1}, are higher than 300% and $(1+r_t)(1+r_{t-1})-1 <$ 50% both r_t and r_{t-1} are set missing.[3] Moreover, we require a minimum number of return observations per trading day. If more than 90% of the stocks have zero returns on a day, the day is declared as non-trading and dropped (see, e.g., Amihud (2002), Lesmond (2005) and Lee (2011)). Lastly, we require a minimum price in order to exclude illiquid stocks. We follow Lee (2011) and set the lower limit at 0.01.

Table 2.1 summarizes descriptive statistics for the daily returns of the cross-section of the individual countries. We report means, standard deviations, selected quantiles, skewness and kurtosis.

The average cross-sectional median return is close to zero.[4] The cross-sectional distribution exhibits both high skewness and high kurtosis. In the subsequent analysis we rely on the decay of the tail rather than the higher moments to proxy for tail risk.

[3] The cutoff level of 300% employed in extant studies is somewhat arbitrary. As robustness check, we therefore also estimate JKTR using raw data without the 300% return cutoff. The correlations of JKTR based on raw and cleaned data are essentially 100% and the return predictability regressions deliver qualitatively and quantitatively similar results. We also experiment with cutoff values of 100% and 200% and lower limits of 0.05 and 0.10. The correlation coefficients with our main estimates vary between 98.96% and 100% and the return predictability regressions again deliver qualitatively and quantitatively similar results.

[4] Even though the mean returns are relatively high for Canada, France and Germany, the medians are both of lower magnitude and in line with the remaining countries. The average cross-sectional median return varies between -0.1% and -0.01%. Since the row Mean takes the average return both in the cross-section and the time series, it is sensitive to outlier returns. When removing the outliers (0.1% and 99.9% percentiles), we find values of 0.09%, 0.06% and 0.06% for Canada, France and Germany, respectively. As noted above, we also experimented with alternative cutoffs for our empirical analysis and show that our results are robust and hence not driven by the outliers.

Table 2.1: Summary Statistics of Returns for G-7 Countries

This table presents descriptive statistics for the daily returns in *U.S. dollar currency* of the G-7 countries for the period from January 2000 until December 2015. We report time-series averages of selected quantiles (5%, 25%, 50%, 75%, 95%), the mean, the standard deviation (SD), the skewness and the kurtosis of the cross-sectional return distribution.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
5%	−0.0576	−0.0362	−0.0513	−0.0303	−0.0371	−0.0381	−0.0499
25%	−0.0113	−0.0048	−0.0085	−0.0108	−0.0110	−0.0040	−0.0141
Mean	0.0015	0.0010	0.0036	0.0001	0.0005	0.0003	0.0007
Median	−0.0004	−0.0001	−0.0001	−0.0011	−0.0006	−0.0002	−0.0004
75%	0.0104	0.0042	0.0068	0.0090	0.0098	0.0026	0.0134
95%	0.0633	0.0403	0.0534	0.0333	0.0406	0.0378	0.0530
SD	0.0569	0.0477	0.1536	0.0238	0.0301	0.0415	0.0410
Skewness	3.5611	3.9073	8.6135	1.3311	2.6654	4.3906	3.8432
Kurtosis	82.6331	131.8120	268.8520	19.9402	77.2840	151.5709	137.9877

2.2.2 Estimation of Tail Risk

This section briefly describes the estimation procedure of the tail risk introduced by Kelly & Jiang (2014), from now on referred to as JKTR. The tail risk is measured by the tail parameter of the tail distribution. The distribution of equity index returns is assumed to obey a potentially time-varying power law and the tail parameter is estimated from the cross-section of returns. The tail probability distribution of an asset's return is given by:

$$P(r^*_{i,t+1} < R | r^*_{i,t+1} < u_t; \mathbb{F}_t) = \left(\frac{R}{u_t}\right)^{-a_i/\lambda_t} \tag{2.1}$$

where $r^*_{i,t}$ is the return of asset i on day t, $\mathbb{F}_t$ is the information set at time t and u_t is the tail threshold, where $R < u_t < 0$.[5] The JKTR is estimated by the power law estimator of Hill (1975) using the cross-section of daily

[5]We rely on simple returns for our estimation, i.e. $r^*_{i,t} = (P_{i,t}/P_{i,t-1}) - 1$, where $P_{i,t}$ is the total return price index of asset i on day t. We denote the returns with a superscript $(^*)$ since we work with excess returns later denoted as $r_{i,t}$.

return observations for all stocks at time t:

$$JKTR_t = \frac{1}{K_t}\sum_{i=1}^{K_t} log(r^*_{i,t}) - log(u_t) \tag{2.2}$$

where K_t is the total number of daily returns falling below the threshold u_t for period t. Facing the trade-off between a sufficiently low threshold and an appropriate number of observations below it, the threshold is fixed to the 5% quantile of the cross-sectional return distribution using a month of daily return data (Kelly & Jiang, 2014). The JKTR can be interpreted as a rate of decay in the left tail since a higher λ_t results into a fatter left tail.

2.3 International Tail Risk

2.3.1 Estimation Results

To get an initial impression about the characteristics of international tail risk, we investigate the time series of JKTR for each country separately.

Figure 2.1 plots monthly estimated tail risk time series for the seven countries for the period from January 2000 to December 2015. Recessions are indicated by shaded areas defined by the National Bureau of Economic Research (NBER) and the Organisation for Economic Co-operation and Development (OECD).[6] Table 2.2 reports summary statistics for tail risk for each country in Panel A, mean differences in Panel B and sample correlations in Panel C. The tail risk is time-varying and has its own dynamics for each country.

The JKTR of Canada, France, Germany, Italy, Japan, the U.K. and the U.S. are on average 0.47, 0.59, 0.58, 0.33, 0.39, 0.54 and 0.41 over the

[6]For the non-U.S. countries we rely on recession indicators from the OECD which are determined by the same methodology established by the NBER until 2008, and use a simplified version afterwards.

Figure 2.1: JKTR of G-7 Countries

This figure shows the monthly time series of the JKTR of the primary data set, the G-7 countries, for the period from January 2000 to December 2015. The shaded area indicates the recession defined by NBER and OECD for the U.S. and the remaining countries, respectively.

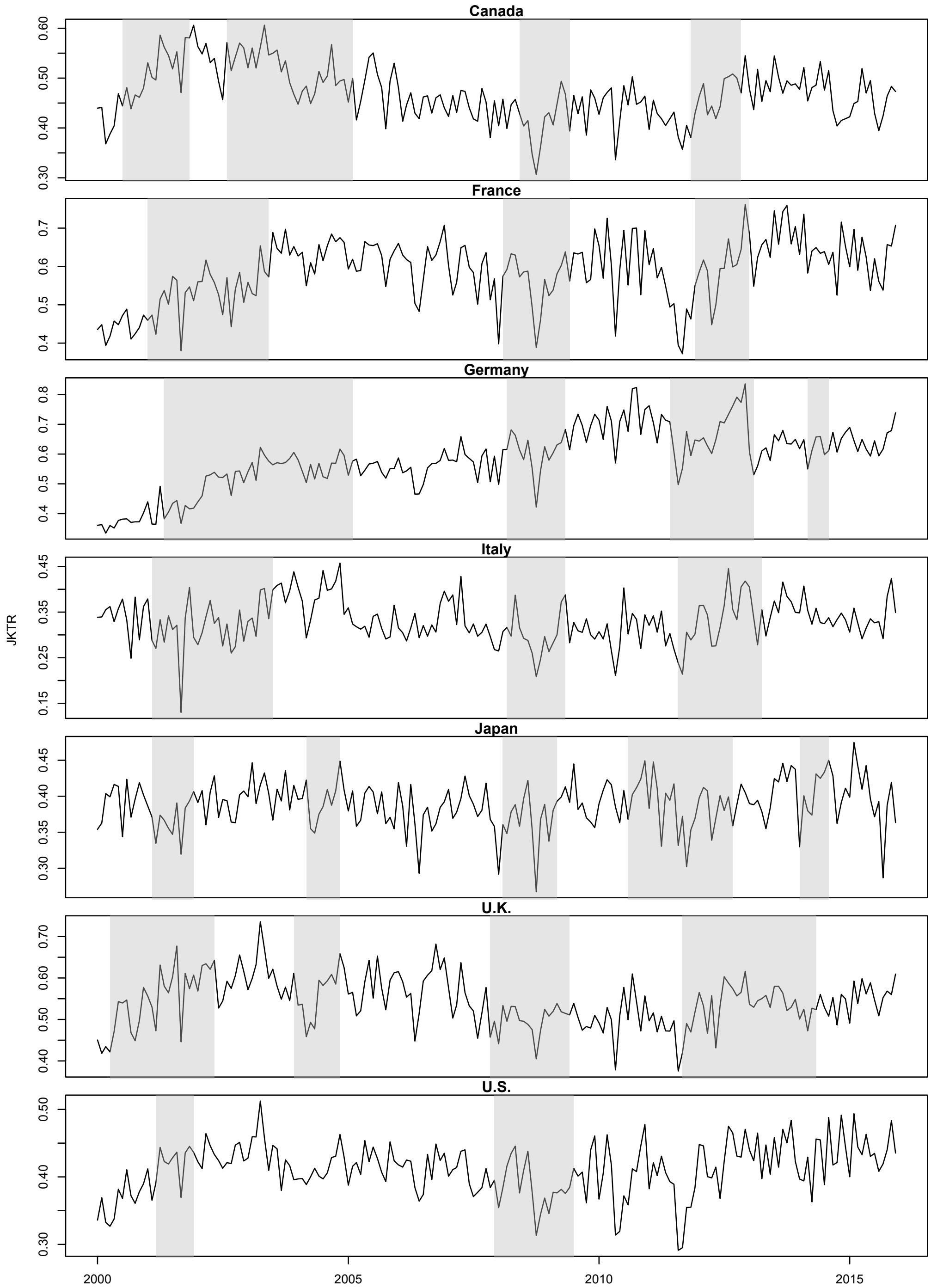


Table 2.2: Descriptive Statistics for JKTR of G-7 Countries and World Fear

This table presents descriptive statistics for the JKTR and World Fear in Panel A, mean differences between tail risks of two countries or World Fear in Panel B and correlations in Panel C. The investigated countries are Canada, France, Germany, Italy, Japan, the U.K. and the U.S. over the period from January 2000 until December 2015. Mean describes the time-series average of the JKTR, SD stands for the standard deviation, Min and Max are the minimum and maximum values of the JKTR and AR(1) stands for the first-order autocorrelation.

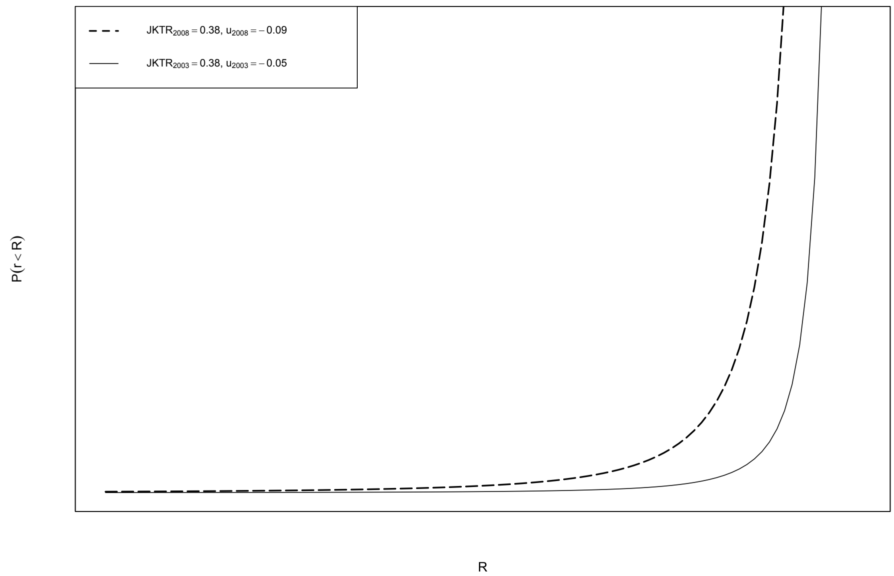
	Canada	France	Germany	Italy	Japan	U.K.	U.S.	WF
Panel A: Descriptive Statistics								
Mean	0.47	0.59	0.58	0.33	0.39	0.54	0.41	0.47
SD	0.05	0.08	0.10	0.05	0.03	0.06	0.04	0.04
Min	0.31	0.37	0.33	0.13	0.27	0.38	0.29	0.33
Max	0.61	0.76	0.84	0.46	0.47	0.74	0.51	0.58
AR(1)	0.66	0.58	0.83	0.43	0.26	0.54	0.50	0.55
Panel B: Mean Differences								
Canada								
France	−0.12							
Germany	−0.11	0.00						
Italy	0.14	0.25	0.25					
Japan	0.08	0.20	0.19	−0.06				
U.K.	−0.07	0.04	0.04	−0.21	−0.15			
U.S.	0.06	0.17	0.17	−0.08	−0.02	0.13		
WF	−0.00	0.11	0.11	−0.14	−0.08	0.07	−0.06	
Panel C: Correlations								
Canada								
France	0.33							
Germany	−0.10	0.65						
Italy	0.38	0.55	0.19					
Japan	0.31	0.44	0.25	0.38				
U.K.	0.70	0.52	0.09	0.44	0.30			
U.S.	0.58	0.61	0.32	0.40	0.43	0.63		
WF	0.56	0.90	0.64	0.64	0.56	0.71	0.77	

whole sample, respectively.[7] The tail risk of France is the highest with an

[7]For comparison, (standard) normal distributed returns show a JTKR value of 0.21. Returns following a t-distribution with $3, 5$ or 10 degrees of freedom exhibit JKTR values of 0.41, 0.32 and 0.26, respectively. The corresponding p-value or probability of a $3-\sigma$ event is 0.13% for the standard normal distribution. For the t-distributions with 3, 5 or 10 degrees of freedom the probabilities are 0.72%, 0.59% and 0.37%, respectively. The estimates are means obtained by applying the Hill estimator to random samples with the according distributions. We repeat the procedure 10,000 times for an exemplary country with 500 stocks and 20 daily return observations in a month.

Figure 2.2: Tail of Return Distribution

This figure shows tail probability distribution of the U.S. using decay parameter and thresholds of both a relatively calm period (2003) and during the financial crisis (2008).



average value of 0.59. Italy has the lowest tail risk followed by the Japan and the U.S. with marginally higher tail risk. We examine the relationship between the level of tail risk and its price as a risk factor in the cross-section in Section 2.3.5.

The tail risks for all countries except for Japan are moderately persistent with first-order autocorrelations of typically 50% and as high as 83% for Germany. While Kelly & Jiang (2014) show the predictive power of the U.S. tail risk for the stock market, we investigate the predictive power for the other countries in Section 2.3.4.

Kelly & Jiang (2014) find for the U.S. that the tail risk is countercyclical and stays flat during the financial crisis in 2007-2009. This may seem surprising. They argue that volatility is predictable over short horizons for that time and that the JKTR is a volatility-adjusted measure. The time-varying threshold u_t is viewed as a proxy for market volatility with a correlation of 60%. The effect of dramatic changes in volatility is absorbed by the time-varying threshold and hence the JKTR is unaffected. Figure 2.2 illustrates this feature of the JKTR.

The JKTR for the U.S. for example is very similar during both relatively calm (09/2003) and turbulent (09/2008) times. The obtained estimates are $JKTR_{2003} = JKTR_{2008} = 0.38$, indicating equally heavy tails. But the relatively low estimate during the financial crisis is due to the time-varying threshold and the resulting volatility adjustment. The tail distribution is plotted for the two identical JKTR estimates but different thresholds. By utilizing a lower threshold the tail becomes drastically fatter as it is the case during the financial crisis. The JKTR is hence a volatility-adjusted measure.[8]

Similar to the U.S., the tail risk of the remaining countries does not show clear peaks in the times of financial distress indicated by the OECD. The tail risk measures of France and Germany show the highest fluctuations, exhibiting low values at the beginning of the sample which are more than doubled by the end of the sample, while the tail risk measure of Italy is rather stable. These findings are also supported by the high (low) standard deviations. Looking at the reported correlations in more detail, we observe that the correlations are positive for the tail risk of all countries (except for the pair Canada–Germany). Canada and the U.K. show the highest correlation coefficient with a value of 0.70. The JTKR of the U.K. and the U.S. are also highly correlated, with a value of 0.63. With correlation

[8] In this chapter we focus on the asset implications of tail risk and World Fear rather than the relationship or differences concerning tail risk and volatility. Nonetheless, we control for two volatility factors in our asset pricing tests in Section 2.3.5 and thus show that the stocks' sensitivity to World Fear contains information about future excess returns beyond that of volatility.

coefficients as low as 0.09, the tail risk of Germany and the U.K. exhibit the lowest overall correlation with other countries. Overall, the markets show a positive contemporaneous relation. We investigate whether there is a lead-lag relationship between the tail risk of the countries in Section 2.3.2.

2.3.2 Granger Causality

After examining each country individually, we now turn to lead-lag relationships of international tail risk. In order to further quantify the interactions between international tail risks, we estimate vector autoregressive (VAR) models and perform a series of Granger causality tests (Granger, 1969).[9] In the following model:

$$\begin{pmatrix} JKTR_t^i \\ JKTR_t^j \end{pmatrix} = \begin{pmatrix} \alpha_{1,0} \\ \alpha_{2,0} \end{pmatrix} + \sum_{p=1}^{P} \begin{pmatrix} \beta_{1,p} & \gamma_{1,p} \\ \beta_{2,p} & \gamma_{2,p} \end{pmatrix} \begin{pmatrix} JKTR_{t-p}^i \\ JKTR_{t-p}^j \end{pmatrix} + \begin{pmatrix} \epsilon_{i,t} \\ \epsilon_{j,t} \end{pmatrix} \tag{2.3}$$

the null hypothesis that tail risk JKTR of country i does not Granger-cause the tail risk of country j is rejected if the coefficients of the lagged terms of country i in the equation of country j are not jointly equal to zero. The joint significance of the coefficients is tested using an F-test. The optimal lag order P is chosen according to the Bayesian Information Criterion (BIC).

The results can be summarized as follows.[10] In 21 out of the 42 bivariate relationships, the null is rejected, suggesting high interaction of the countries' tail risk rather than the tail risk of all countries being driven by the tail risk of one country. The tail risk of every country both Granger-causes the tail risk of another country and is Granger-caused by another country as well, even though the significance and the number of significant lead-lag relationships vary from country to country. The results

[9]To ascertain that the series are stationary, the Phillips-Perron test and the Augmented Dickey-Fuller test are performed. We test the null hypothesis that the time series has a unit-root against the alternative of stationarity. The null can be rejected for all countries using both tests.

[10]Detailed results are provided in the appendix (Tables A.1 and A.2) .

are similar to the ones from the correlation analysis in Section 2.3.1 where a positive and significant correlation is found between the tail risks of the countries. This makes sense economically, especially since the period has long phases of financial distress, i.e. the Lehman Default and the European debt crisis. The results can be confirmed by estimating a multivariate VAR model for all seven countries and running corresponding Granger causality tests.[11]

The overall implication of these findings is that there is high interdependence of tail risk in the G-7 countries with no explicit direction of causality.

2.3.3 World Fear

Due to the high level of integration of developed markets, which is shown by both our contemporaneous and lead-lag correlation analyses, the question arises whether the tail risk of one country is relevant for market and stock returns or whether global tail risk is more important. We estimate the *World Fear Index* as a proxy for global tail risk as the average of the individual tail risk estimates of each country:

$$WF_t = \frac{1}{7}\sum_{j=1}^{7} JKTR_t^j \tag{2.4}$$

where $JKTR_t^j$ is the tail risk of country j.[12]

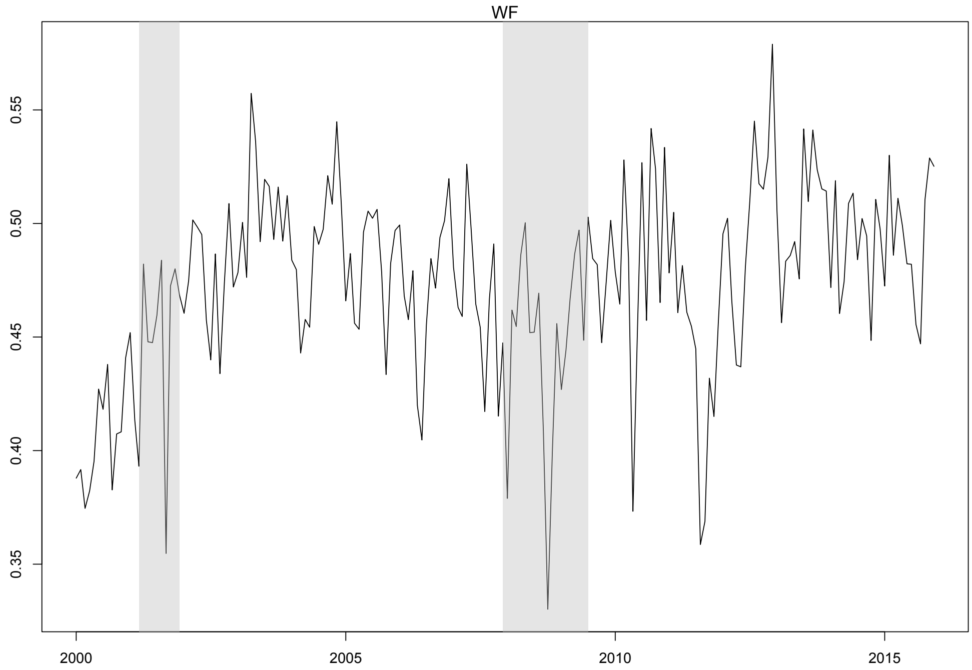
Figure 2.3 displays the time series and descriptive statistics are reported in the last column of Panel A in Table 2.2. World Fear has an average value of 0.47. The index has similar dynamics to the countries France, the U.K. and the U.S. The last row of Panel C in Table 2.2 presents the correlation

[11] These results are available upon request.

[12] We also considered World Fear defined as the market capitalization weighted average of the individual tail risk estimates following Bollerslev et al. (2014), which leads to qualitatively similar but somewhat weaker results.

Figure 2.3: World Fear (2000-2015)

This figure shows the monthly time series of World Fear, for the period from January 2000 to December 2015. The shaded area indicates the recession defined by NBER.



between the World Fear index and the tail risk of the individual countries. It is highly correlated to the JKTR of countries such as France, the U.K. and the U.S., with correlation coefficients as high as 90% and moderately correlated to the remaining countries, with values between 56% and 64%. We find that World Fear exhibits an $AR(1)$ coefficient of 0.55. Due to the high autocorrelation and the resemblance to local tail risk the question arises whether World Fear is a good predictor or an even better predictor than local tail risk for future returns both in the time-series and the cross-section for the different countries.[13]

[13] We provide further evidence of a common component in the tail risk of individual countries by regressing the JKTR on our World Fear index. Table A.3 in the appendix shows that World Fear has strong explanatory power for the JKTR across all countries. The slope coefficient is positive and statistically significant at the 1% level for all countries and the adj. R^2 varies between 31% and 81%. Our findings are in line with the high positive contemporaneous correlations.

2.3.4 Time-Series Return Predictability

Recent literature finds for the U.S. that high (low) tail risk is associated with relatively high (low) market returns in the future (see, e.g., Kelly & Jiang (2014), Bollerslev et al. (2014) and Bollerslev et al. (2015)). We test whether this finding holds outside of the U.S. The following regression model is estimated separately for each country:

$$r_{j,t+h} = a_{j,h} + b_{j,h} TR_t + \epsilon_{j,t+h} \tag{2.5}$$

where $r_{j,t+h}$ is the continuously compounded market excess return in country j over the horizon h and TR is either the local tail risk of country j, $JTKR_j$ or World Fear, WF. Monthly returns are in excess of the monthly return of the 1-month U.S. Treasury bill yield. In order to account for overlapping observations we use Hodrick (1992) standard errors with lags equal to the return horizon expressed in months. For the adjusted R^2 values, we conduct a bootstrap in order to obtain statistical significance following Welch & Goyal (2008). The following data generating process under the null is assumed:

$$r_{j,t+h} = a_{j,h} + u_{1,j,t+h} \tag{2.6}$$

$$TR_{t+1} = \alpha_j + \beta_j TR_t + u_{2,j,t+h} \tag{2.7}$$

We obtain pseudo time series for both the future excess returns and TR time series by drawing with replacement from the residuals simultaneously. We hence preserve the cross-correlation structure of the residuals in the predictive regressions and the autoregressive models. We then compute the in-sample adjusted R^2 for the pseudo sample. We repeat this process 5,000 times and obtain an empirical distribution and critical values for the adjusted R^2. We focus our discussion on the estimated slope coefficients, their statistical significance and the forecast accuracy of the regressions as measured by the adjusted R^2.

Table 2.3 reports the results for the JKTR. We find that local tail risk is generally not a statistically significant predictor of future aggregate market returns.

The degree of predictability starts out quite low, with R^2 values close to zero for all countries at the one month horizon. Only for France (Germany), it is statistically significant at the three month and six month (three month) horizon with adj. R^2 values up to 4.95% (3.58%), which are statistically significant as well.[14]

Replacing JTKR with WF dramatically increases the forecasting performance concerning both the statistical significance of the predictor and the explanatory power, which is consistent with the overall positive correlation and strong lead-lag interdependencies we find. The results are reported in Table 2.4. World Fear is a statistically significant predictor for future local market returns in six out of seven countries at the three month to one year horizons and for all countries at the two year horizon.[15]

At the one year horizon, the adj. R^2 vary between 3.57% and 18.10%. A one-standard-deviation increase (4.20%) in World Fear predicts an increase in futures market excess returns of 4.95%, 5.92%, 6.35%, 5.44%, 8.46%, 4.47%, 5.33% and 5.47% for Canada, France, Germany, Italy, Japan, the

[14]This result for the U.S. is in contrast to Kelly & Jiang (2014). However, their sample period differs from ours. If we consider the same period from 1963 to 2015, we obtain similar results as theirs. Details are provided in the appendix (Table A.4). Figure 2.5 of the appendix shows the time series of tail risk together with the market return over the next three years, similar to Figure 1 in Kelly & Jiang (2014). Our results suggest that tail risk is more integrated in recent years and the tail risk of other developed countries plays a more important role for the market returns of a country than local tail risk.

[15]Figure 2.6 in the appendix plots the realized aggregate market returns against the fitted values from our predictive regressions. Both time series are standardized to have mean zero and standard deviation of one. One can observe that the fitted values closely follows the realized ones. Inoue & Kilian (2005) argue that one-sided t-tests are asymptotically more powerful than tests of equal predictive accuracy or test of forecast encompassing. Due to our relatively small sample and the knowledge of the theoretical sign of the slope coefficient, we feel confident on applying the one-sided test, which would yield even stronger evidence of predictive power for World Fear, while results remain unchanged for the local tail risk. The asymptotic critical values are 1.28, 1.64 and 2.33 for the 10%, 5% and 1% significance level, respectively.

Table 2.3: Return Predictability Regressions

This table presents results for monthly return predictive regressions of value-weighted market index returns in *U.S. dollar currency* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor is the JKTR of the country [name in column]. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. We report bootstrapped p-values below the corresponding adjusted R^2.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Intercept	−0.0335	−0.0289	−0.0346	−0.0430	0.0155	−0.0203	−0.0141
	(0.0465)	(0.0346)	(0.0279)	(0.0353)	(0.0397)	(0.0342)	(0.0441)
$JKTR_{1Month}$	0.0834	0.0551	0.0683	0.1350	−0.0394	0.0439	0.0425
	(0.0959)	(0.0560)	(0.0456)	(0.1013)	(0.1011)	(0.0602)	(0.1040)
adj. R^2	0.0003	0.0004	0.0064	0.0053	−0.0045	−0.0023	−0.0040
	{0.3582}	{0.3532}	{0.1646}	{0.1618}	{0.7138}	{0.4392}	{0.7152}
Intercept	−0.0541	−0.1403	−0.1183	−0.1211	−0.0221	−0.0734	0.0283
	(0.1083)	(0.0867)	(0.0775)	(0.0867)	(0.0785)	(0.0836)	(0.1018)
$JKTR_{3Month}$	0.1534	0.2576*	0.2299*	0.3813	0.0596	0.1573	−0.0434
	(0.2192)	(0.1387)	(0.1277)	(0.2428)	(0.1982)	(0.1450)	(0.2390)
adj. R^2	0.0001	0.0342	0.0358	0.0206	−0.0049	0.0054	−0.0049
	{0.1558}	{0.0072}	{0.0018}	{0.1880}	{0.1652}	{0.0250}	{0.3294}
Intercept	−0.0446	−0.2437	−0.1723	−0.1535	−0.0855	−0.1523	0.0929
	(0.2044)	(0.1537)	(0.1463)	(0.1474)	(0.1300)	(0.1488)	(0.1649)
$JKTR_{6Month}$	0.1763	0.4554*	0.3566	0.5050	0.2311	0.3300	−0.1707
	(0.4099)	(0.2436)	(0.2431)	(0.4031)	(0.3200)	(0.2556)	(0.3840)
adj. R^2	−0.0022	0.0495	0.0391	0.0151	−0.0024	0.0143	−0.0027
	{0.4334}	{0.0014}	{0.0032}	{0.0540}	{0.4010}	{0.0576}	{0.4738}
Intercept	−0.1413	−0.3237	−0.2715	−0.1197	−0.2246	−0.2865	−0.0930
	(0.3870)	(0.2728)	(0.2986)	(0.2552)	(0.2286)	(0.2803)	(0.2396)
$JKTR_{1Year}$	0.4765	0.6423	0.6082	0.4527	0.6283	0.6387	0.3525
	(0.7691)	(0.4280)	(0.5013)	(0.6672)	(0.5539)	(0.4778)	(0.5496)
adj. R^2	0.0058	0.0467	0.0568	0.0032	0.0044	0.0294	−0.0006
	{0.1558}	{0.0072}	{0.0018}	{0.1880}	{0.1652}	{0.0250}	{0.3294}
Intercept	−0.4688	−0.2806	−0.2187	0.0008	−0.2518	−0.2482	−0.0625
	(0.6795)	(0.3245)	(0.4948)	(0.4169)	(0.3188)	(0.4599)	(0.3548)
$JKTR_{2Year}$	1.4462	0.7089	0.7224	0.2561	0.8180	0.7241	0.4647
	(1.3363)	(0.4920)	(0.8508)	(1.0254)	(0.7468)	(0.7767)	(0.7862)
adj. R^2	0.0408	0.0244	0.0371	−0.0046	0.0027	0.0152	−0.0024
	{0.0094}	{0.0172}	{0.0058}	{0.6166}	{0.2132}	{0.0586}	{0.4088}

U.K. and the U.S., respectively.[16]

[16] For comparison, Kelly & Jiang (2014) finds that a one-standard-deviation increase of tail risk leads to future excess returns of 4.5% for the U.S. and the period from 1963 until 2010.

Table 2.4: Return Predictability – World Fear

This table presents results for monthly return predictive regressions of value-weighted market index returns in *U.S. dollar currency* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor is World Fear WF. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. We report bootstrapped p-values below the corresponding adjusted R^2.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	Global
Intercept	−0.0682	−0.0462	−0.0758	−0.0783	−0.1140**	−0.0583	−0.0642	−0.0731*
	(0.0581)	(0.0548)	(0.0629)	(0.0589)	(0.0402)	(0.0439)	(0.0459)	(0.0441)
WF_{1Month}	0.1563	0.1049	0.1711	0.1690	0.2415**	0.1307	0.1431	0.1614*
	(0.1191)	(0.1126)	(0.1286)	(0.1221)	(0.0823)	(0.0898)	(0.0940)	(0.0901)
adj. R^2	0.0064	−0.0001	0.0068	0.0070	0.0418	0.0074	0.0125	0.0165
	{0.1844}	{0.3604}	{0.1744}	{0.1544}	{0.0020}	{0.1238}	{0.0842}	{0.0484}
Intercept	−0.1320	−0.2026	−0.2667*	−0.2678**	−0.3551**	−0.1682*	−0.1863*	−0.2114**
	(0.1239)	(0.1321)	(0.1532)	(0.1338)	(0.1161)	(0.0971)	(0.1055)	(0.1004)
WF_{3Month}	0.3177	0.4503*	0.5969*	0.5768**	0.7540**	0.3814*	0.4168*	0.4695**
	(0.2495)	(0.2687)	(0.3106)	(0.2747)	(0.2379)	(0.1976)	(0.2134)	(0.2031)
adj. R^2	0.0085	0.0254	0.0401	0.0389	0.1197	0.0243	0.0393	0.0458
	{0.0702}	{0.0374}	{0.0084}	{0.0046}	{0.0000}	{0.0206}	{0.0068}	{0.0016}
Intercept	−0.1464	−0.3936*	−0.3775	−0.3915*	−0.5524**	−0.2484	−0.2759	−0.3126*
	(0.2256)	(0.2275)	(0.2518)	(0.2239)	(0.1929)	(0.1631)	(0.1847)	(0.1763)
WF_{6Month}	0.3909	0.8802*	0.8721*	0.8562*	1.1788**	0.5822*	0.6323*	0.7104**
	(0.4520)	(0.4584)	(0.5068)	(0.4555)	(0.3950)	(0.3298)	(0.3709)	(0.3536)
adj. R^2	0.0040	0.0467	0.0382	0.0385	0.1323	0.0232	0.0392	0.0431
	{0.1766}	{0.0028}	{0.0090}	{0.0028}	{0.0000}	{0.0136}	{0.0048}	{0.0030}
Intercept	−0.4728	−0.6148	−0.6333	−0.5810	−0.9304**	−0.4424	−0.5470*	−0.5616*
	(0.4007)	(0.3918)	(0.4102)	(0.3858)	(0.2894)	(0.2814)	(0.2886)	(0.2922)
WF_{1Year}	1.1783	1.4106*	1.5128*	1.2950*	2.0134***	1.0644*	1.2690**	1.3029**
	(0.7976)	(0.7817)	(0.8140)	(0.7745)	(0.5927)	(0.5601)	(0.5714)	(0.5765)
adj. R^2	0.0357	0.0586	0.0572	0.0477	0.1810	0.0397	0.0746	0.0696
	{0.0094}	{0.0042}	{0.0040}	{0.0072}	{0.0000}	{0.0098}	{0.0004}	{0.0012}
Intercept	−0.4872	−0.7790*	−0.7084	−0.7181	−0.9859**	−0.5848	−0.6424*	−0.6696*
	(0.4346)	(0.4484)	(0.4954)	(0.4426)	(0.3552)	(0.3583)	(0.3359)	(0.3422)
WF_{2Year}	1.4868*	1.9320**	1.9238**	1.7079**	2.2345**	1.5517**	1.6367**	1.7044**
	(0.8469)	(0.8398)	(0.9319)	(0.8384)	(0.7151)	(0.6765)	(0.6246)	(0.6373)
adj. R^2	0.0236	0.0530	0.0434	0.0394	0.1209	0.0389	0.0527	0.0550
	{0.0204}	{0.0012}	{0.0048}	{0.0038}	{0.0000}	{0.0080}	{0.0022}	{0.0020}

The adj. R^2 values are generally higher when relying on WF instead of $JKTR$ and they are all statistically significant for horizons longer than one month.[17] And for France and Germany, we find that $JKTR$ has higher explanatory power than global tail risk for short horizons up to six months. Economically, this means that France and Germany (and their tail risk) are less sensitive to foreign developed countries in general and the aggregate market returns of these countries mainly depend on their own tail risk. This makes sense since a relatively large part of our sample covers the European debt crisis and France and Germany as the economically strongest members of the European Union are more affected by the Euro-zone rather than crisis periods in other countries. Nonetheless, the market returns of developed countries in general are strongly predicted by World Fear.

We also find that World Fear as a proxy for global tail risk is a strong predictor for future global market returns (last column in Table 2.4). The slope coefficient is statistically significant for all horizons and the adj. R^2 range from 1.65% at the one month horizon to 6.96% at the one year horizon, which are all statistically significant as well.

Having investigated the in-sample predictability, we now turn to an out-of-sample exercise. As argued by Welch & Goyal (2008), it is not sufficient to only investigate in-sample tests since most of the predictors are unable to consistently forecast the equity premium out-of-sample. Most of their examined models underperform the recursive mean model out-of-sample. Similar to them we use the historical mean as a benchmark for our models. The historical mean is given by:

$$\bar{r}_{t+h} = \frac{1}{t}\sum_{j=1}^{t} r_j \tag{2.8}$$

using return observations until t. Following Campbell & Thompson (2008), we evaluate our models using the out-of-sample R^2 which measures the differences in mean squared prediction errors (MSPE) for the predictive

[17] There an exception: For Canada, the adj. R^2 is not statistically significant at the six month horizon.

model and the historical mean model, and is given by:

$$R^2_{OOS} = 1 - \frac{\sum_{t=s}^{T}(r_{t+1} - \hat{r}_{t+1})^2}{\sum_{t=s}^{T}(r_{t+1} - \bar{r}_{t+1})^2} \tag{2.9}$$

where $\hat{r}_{t+1}$ stands for the out-of-sample forecast obtained from model (2.5) using the data until t, s is the break point splitting the whole sample for the out-of-sample analysis. Positive values for R^2_{OOS} indicate that the predictor outperforms the historical mean model in terms of the MSPE. We further test whether World Fear significantly outperforms the historical mean using the Clark & West (2007) augmented test, i.e. testing the null of $R^2_{OOS} \leq 0$. Under the null hypothesis, the MSPE-adjusted test statistic of Clark & West (2007) follows a standard normal distribution. Defining

$$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - \left[(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2\right] \tag{2.10}$$

and regressing f_{t+1} on a constant, i.e. $f_{t+1} = \alpha + \epsilon_{t+1}$, the MSPE-adjusted test statistic is equal to the t-statistic of the constant. Following Rapach & Wohar (2006), Welch & Goyal (2008), Clark & McCracken (2012) and Rapach et al. (2013), we rely on bootstrapped p-values instead of the asymptotic distribution. The procedure is the same as for the bootstrapped critical values for the in-sample adjusted R^2. By using this approach we guard against biases that could arise because of our relatively small sample, the high serial autocorrelation of our World Fear index and the overlapping observations for long horizons.

Table 2.5 reports the results for the same period as the in-sample analysis using 120 observations for the initial estimation.

We focus on World Fear, which has shown the strongest overall predictive power. World Fear has good out-of-sample forecasting performance for the majority of the countries considered. At all horizons except for the one year horizon, at least five out of the seven countries exhibit positive R^2_{OOS} values. At the three month horizon and two year horizons, World

Table 2.5: Return Predictability Regressions – Out-of-Sample R^2

This table presents results for monthly out-of-sample return forecasts. Out-of-sample R^2 from predictive regressions of value-weighted market index excess returns in *U.S. dollar currency* over a one month, three months, six months, one year and two year horizons are reported. The investigated countries are Canada, France, Germany, Italy, Japan, the U.K. and the U.S. over the period from January 2000 until December 2015. To obtain statistical significance we conduct a Clark & West (2007) MSPE test. The null hypothesis is the recursive mean model outperforming the predictive model, i.e. $R_{OOS} \leq 0$. We rely on bootstrapped critical values instead of the asymptotic distribution. In each month t (beginning at $t = 120$), we estimate rolling univariate forecasting regressions of monthly market returns on the lagged World Fear index WF. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	Global
1 Month	−0.0016	0.0041*	0.0100*	0.0109**	0.0071*	0.0123**	0.0185**	0.0151**
	(0.1398)	(0.0936)	(0.0674)	(0.0492)	(0.0744)	(0.0416)	(0.0276)	(0.0242)
3 Month	0.0013*	0.0243**	0.0232**	0.0247**	0.0294*	0.0217**	0.0305**	0.0151***
	(0.0926)	(0.0290)	(0.0258)	(0.0170)	(0.0672)	(0.0204)	(0.0112)	(0.0080)
6 Month	−0.0006	0.0108*	0.0014	−0.0033	0.0420**	0.0077*	0.0050*	0.0151*
	(0.1234)	(0.0818)	(0.1206)	(0.1834)	(0.0206)	(0.0578)	(0.0952)	(0.0612)
1 Year	−0.0142	−0.0156	−0.0227	−0.0234	0.0658**	0.0002	−0.0041	0.0151
	(0.4176)	(0.4396)	(0.6270)	(0.6188)	(0.0218)	(0.1474)	(0.2280)	(0.2032)
2 Year	0.0168**	0.0284**	0.0281**	0.0176**	0.0199*	0.0260**	0.0085*	0.0151**
	(0.0308)	(0.0200)	(0.0172)	(0.0356)	(0.0630)	(0.0162)	(0.0700)	(0.0456)

Fear significantly beats the historical mean in all countries.[18] Similar to our in-sample analysis, World Fear is also able to predict future global market returns out-of-sample for all horizons. The test statistic shows statistical significance for all horizons except for the one year horizon. Overall, the results suggest that World Fear has predictive power for market returns of

[18]Figure 2.7 in the appendix plots the performance of our out-of-sample predictive regressions. Following Welch & Goyal (2008) we plot the difference between the cumulative squared prediction errors of the historical mean model and our prediction model using World Fear. An increase (a decrease) in the line indicates that our model outperforms (underperforms) the historical mean model. One can observe that our model shows rather weak performance in the beginning but outperforms the benchmark especially during the financial crisis, indicated by the shaded area, where a sharp increase is present for all plots. The performance of both models are similar in the ending, where the lines are rather flat.

the G-7 countries both in-sample and out-of-sample.

2.3.5 World Fear and the Cross-Section of Stock Returns

In the framework of the ICAPM, relevant risk factors should predict future investment opportunities and price the cross-section of returns. We now test the latter condition. If investors are averse to World Fear, and World Fear is priced, we expect a positive risk premium. Stocks with low loadings on World Fear measure can be used as hedges and hence should have higher prices and lower expected returns. As in Kelly & Jiang (2014) we estimate the sensitivities to the tails for the individual stocks using the same predictive regression model as in Equation (2.5) but replace the market excess returns with the excess stock return of individual stocks. The stock returns are all measured in U.S. dollars.

Each month, the tail risk loadings are estimated for each stock in regressions using the most recent 60 observations. The stocks are then sorted into equally weighted portfolios based on the estimated loadings whereby firms with the lowest coefficient are in the first decile portfolio and firms with the highest coefficients are in the tenth decile portfolio. Excess returns of the portfolios are tracked over the subsequent month. The analysis is out-of-sample in the sense that there is no overlap between the data used for the beta estimation and the data used to compute the excess return of the portfolio. High minus low portfolio returns are then regressed on risk factors in order to test whether these returns merely reflect passive exposure to standard factors. We rely on the state of the art Fama & French (1993) three-factor model (FF3) :

$$r_{i,t} = \alpha_i + \beta_{Mkt} Mkt_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \epsilon_{i,t} \tag{2.11}$$

where MKT stands for the market excess return, and SMB and HML stand for Small Minus Big and High Minus Low, respectively. These factors measure historical excess returns of small caps over big caps and of value stocks over growth stocks. We construct country specific factors for non–U.S. countries following the method described on Kenneth R. French's website and use the available ones for the U.S.[19]

Lastly, in order to quantify the risk premium associated with tail risks, cross-sectional Fama–MacBeth regressions are conducted using the estimated betas.[20]

$$r_{i,t+1} = \gamma + \gamma_{JKTR}\beta_{JKTR,i,t} + \epsilon_{i,t} \tag{2.12}$$

$$r_{i,t+1} = \gamma + \gamma_{JKTR}\beta_{JKTR,i,t} + \gamma_{Control}Control_{i,t} + \epsilon_{i,t} \tag{2.13}$$

We control for further firm characteristics, which are the sensitivity to the market return, the logarithmic size ($Size$), the book-to-market ratio (BTM), the momentum (measured as the return from the past twelve months excluding the most recent month) (Mom) and the illiquidity (Liq) following Amihud (2002). These variables have been shown to be priced in the cross-section of stock returns (Jegadeesh & Titman, 1993; Amihud, 2002; Fama & French, 2008; Jiang & Yao, 2013). Since World Fear captures the global downside risk, we examine the interaction between our index and further downside measures by including the downside beta of Ang et al. (2006a) and coskewness of Harvey & Siddique (2000) as control variables. We also include the idiosyncratic volatility effect of (Ang et al., 2006b) and the aggregate volatility effect of (Ang et al., 2006a). For the computation of

[19] Website: http://mba.tuck.dartmouth.edu/pages/facult/ken.french. We find that the size premium is close to zero and statistically insignificant for the majority of countries. The value premia on the under hand are all positive and statistically significant at the 1% level. These findings are consistent with the results of Fama & French (2016).

[20] For our cross-sectional analysis, we winsorize the variables at 1st and 99th percentile to restrict the effect of outliers (Fama & French, 2008; Baltussen et al., 2017). Also, we use Shanken (1992) corrected standard errors in order to take into account measurement error in beta.

downside beta ($DownsideBeta$), coskewness ($Coskewness$), idiosyncratic volatility ($iVol$) and aggregatve volatility ($Aggr.Vol$), we rely on monthly observations over the past 60 months, similar to the estimation of our World Fear betas (Kelly & Jiang, 2014). The vector $\gamma_{Control}$ presents the risk premia associated with the additional control variables. Table 2.6 reports the results for the portfolio sorts, simple Fama–MacBeth regressions and multiple Fama–MacBeth regressions in Panels A, B and C, respectively.

Sorting returns by the exposure to WF and buying the decile portfolio with high loadings and selling the decile portfolio with low loadings yields a positive and statistically significant spread excess return for five countries: Canada, France, Germany, Italy, the U.K. with values of 1.06%, 1.28%, 2.72%, 0.97% and 1.00% per month, respectively.[21] The risk-adjusted returns are very similar to the raw returns, suggesting that the returns cannot be explained by the Fama & French (1993) risk factors.

Turning next to the cross-sectional regressions, we find positive risk premia for the same five countries: Canada, France, Germany, Italy and the U.K., which are statistically significant at the 5% level. The risk premia for the sensitivity to World Fear remain statistically significant when controlling for the sensitivity to the excess market return, market capitalization, book-to-market ratio, momentum and illiquidity, downside risk and volatility measures. The t-statistics for World Fear in the multiple regressions for Canada, France, Germany and Italy all exceed the rigorous threshold of 3 as recommended by Harvey et al. (2016) and hence give statistical evidence for the proposed asset pricing factor.

The results confirm that market participants seem to be crash averse and avoid stocks which are highly sensitive towards World Fear in the

[21] Figure 2.8 in the appendix displays the average returns of the decile portfolios for the seven countries. The returns are generally increasing from the first to the tenth decile portfolio for the countries except for Japan and the U.S. for which we do not find a significant spread.

Table 2.6: Portfolio Sorts and Fama–MacBeth Regressions – World Fear

This table presents results from portfolio sorts based on WF. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. Quintile portfolios are formed based on WF betas for each country. Betas are calculated in predictive regressions using the most recent 60 returns measured in *U.S. Dollars*. We then track 1 month out-of-sample equally weighted holding period returns. We report the average returns of the high minus low portfolio in the first row of Panel A. *FF3* report alphas from the Fama & French (1993) 3 factor model. In Panel B, Intercept and γ_{WF} are means of the coefficients from the cross-sectional regressions of individual stock returns on an intercept and the World Fear loadings. Panel C additionally includes the market loading, $log(Size)$, book-to-market ratios (BTM), prior returns (Mom), illiquidity (Liq), aggregate Volatility ($Aggr.Vol$), coskewness ($Coskewness$), downside beta ($DownsideBeta$) and idiosyncratic volatility ($iVol$) of individual stocks in the cross-sectional regressions. The according mean coefficients γ_{Market}, γ_{Size}, γ_{BTM}, γ_{Mom}, γ_{Liq}, $\gamma_{Aggr.Vol}$, $\gamma_{Coskewness}$, $\gamma_{DownsideBeta}$ and γ_{iVol} are reported. For the cross-sectional regressions, we apply the Shanken (1992) correction. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A: Portfolio Sorts							
Average return	0.0106*	0.0128***	0.0272***	0.0097*	−0.0007	0.0100*	0.0009
	(0.0057)	(0.0048)	(0.0066)	(0.0050)	(0.0046)	(0.0055)	(0.0042)
FF3	0.0118**	0.0106**	0.0298***	0.0116**	0.0028	0.0112*	−0.0027
	(0.0054)	(0.0045)	(0.0067)	(0.0050)	(0.0037)	(0.0059)	(0.0037)
Panel B: Simple Fama–MacBeth Regressions							
(Intercept)	0.0061	0.0030	0.0043	−0.0048	0.0053	−0.0019	0.0055
	(0.0062)	(0.0046)	(0.0049)	(0.0059)	(0.0037)	(0.0051)	(0.0040)
γ_{WF}	0.0004**	0.0015***	0.0000***	0.0016**	0.0001	0.0009**	0.0003
	(0.0002)	(0.0004)	(0.0000)	(0.0006)	(0.0004)	(0.0004)	(0.0004)
Panel C: Multiple Fama–MacBeth Regressions							
(Intercept)	−0.0073	0.0011	0.0065	0.0015	−0.0000	−0.0031	0.0064
	(0.0055)	(0.0061)	(0.0059)	(0.0061)	(0.0044)	(0.0053)	(0.0062)
γ_{WF}	0.0015***	0.0034***	0.0022***	0.0027***	0.0011*	0.0011*	0.0005
	(0.0004)	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0006)	(0.0006)
γ_{Market}	−0.0077**	−0.0025	−0.0066*	−0.0014	0.0022	0.0006	0.0029
	(0.0031)	(0.0036)	(0.0036)	(0.0045)	(0.0020)	(0.0022)	(0.0019)
γ_{Size}	0.0006	0.0001	−0.0003	−0.0001	−0.0001	0.0012**	0.0001
	(0.0005)	(0.0006)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0004)
γ_{BTM}	0.0124***	0.0065***	0.0025**	0.0045***	0.0060***	0.0078***	−0.0019*
	(0.0013)	(0.0015)	(0.0011)	(0.0011)	(0.0008)	(0.0009)	(0.0010)
γ_{Mom}	0.0037	0.0044	0.0092*	0.0031	−0.0027	0.0060	−0.0035
	(0.0047)	(0.0044)	(0.0047)	(0.0067)	(0.0032)	(0.0045)	(0.0031)
γ_{Liq}	0.0001	−0.0013	−0.0004	−0.0013	0.0002	0.0001	−0.2129
	(0.0001)	(0.0012)	(0.0003)	(0.0035)	(0.0004)	(0.0002)	(0.1539)
$\gamma_{Aggr.Vol}$	0.0661	−0.4776***	−0.0011	−0.4340	−0.0658	−0.0901	0.0139
	(0.1142)	(0.1547)	(0.1895)	(0.2728)	(0.1856)	(0.1250)	(0.0957)
$\gamma_{Coskewness}$	−0.0001	0.0010	0.0014*	0.0015*	0.0002	−0.0003	−0.0001
	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0002)	(0.0004)	(0.0002)
$\gamma_{DownsideBeta}$	−0.0001	−0.0012	0.0102***	−0.0006	0.0009	−0.0037*	−0.0016
	(0.0017)	(0.0026)	(0.0036)	(0.0034)	(0.0012)	(0.0019)	(0.0011)
γ_{iVol}	0.0137	−0.0404	−0.0438*	−0.0809***	−0.0323*	−0.0586***	−0.0254
	(0.0182)	(0.0256)	(0.0245)	(0.0278)	(0.0187)	(0.0143)	(0.0169)

majority of countries. Stocks with higher tail risk earn higher average future and risk-adjusted returns. World Fear is able to predict future aggregate market returns and explain the cross-section of stock returns for most countries.

2.4 Economic Mechanism

In this section, we investigate one economic mechanism which could drive the reported return predictability of the JKTR. If asset pricing effects are channeled by uncertainty shocks, JKTR must have a direct impact on aggregate real economic outcomes. Following Kelly & Jiang (2014) we study the effect of tail risk on the real economy proxied by the unemployment for the G-7 countries. Unemployment rates for the G-7 countries are obtained from Datastream. We focus on the World Fear index and its effect on unemployment over the next year.[22]

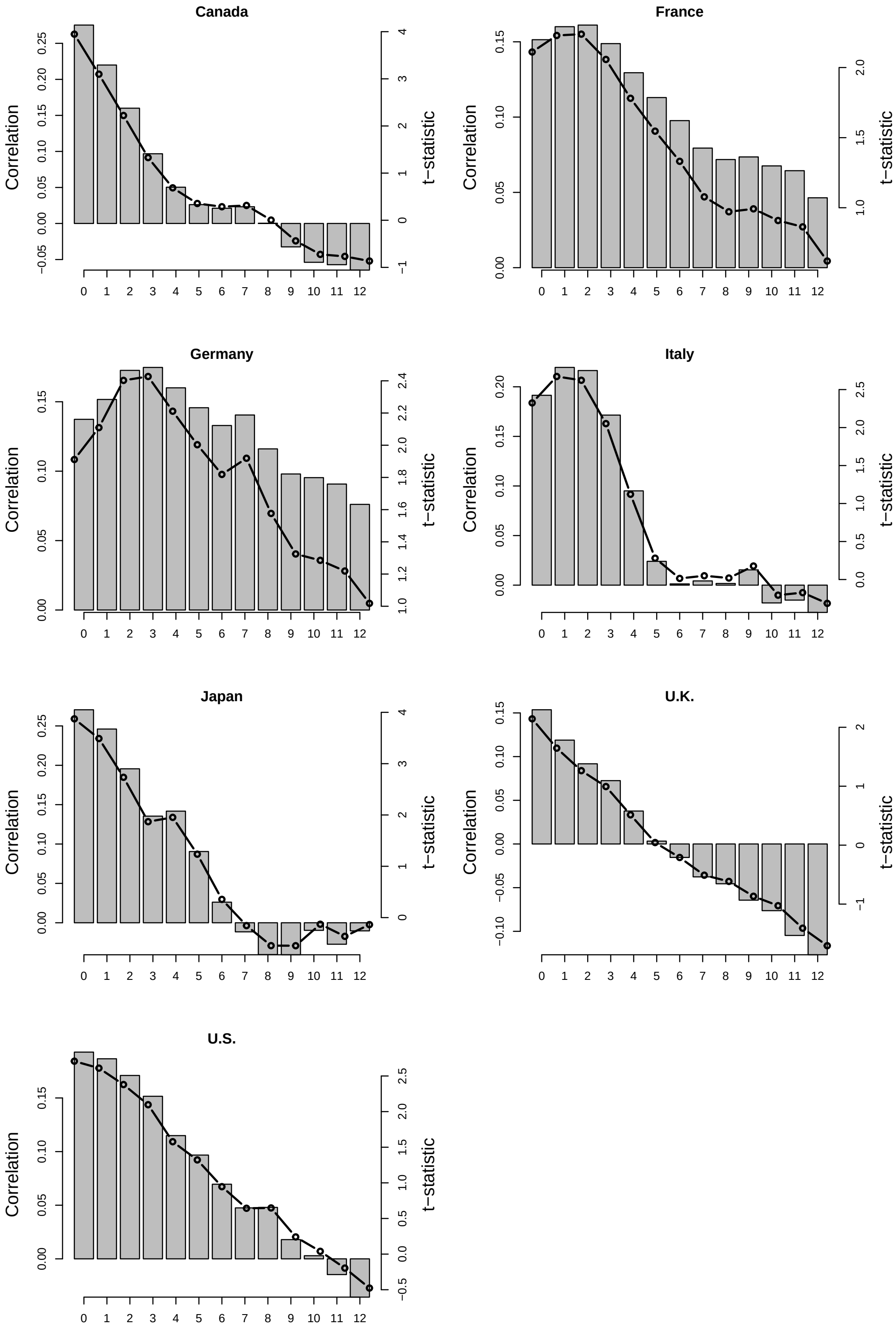
Figure 2.4 shows the cross-correlations between World Fear in month t, and unemployment of the G-7 countries in month $t + 0$ to $t + 12$.

It shows that there is a positive and significant contemporaneous correlation for most countries, which remains both positive and statistically significant over the subsequent months but slowly disappears when the horizon reaches twelve months. For Canada, Japan, the U.K. and the U.S., there is an immediate increase in unemployment followed by an increase in tail risk with correlation coefficients of 0.22, 0.25, 0.12 and 0.19 at the one month horizon, respectively, which are all statistically significant. The cross-correlations (and t-statistics) then slowly fall for the four countries and reach values close to zero at the twelve month horizon. Only for the U.K. the correlation is negative (-0.13). For France, Germany and Italy, the

[22] We focus on World Fear because it is shown to be the overall strongest predictor for local market returns. The unemployment rate is detrended using the Hodrick-Prescott filter.

Figure 2.4: Correlogram: World Fear and Unemployment

This figure plots the percentage correlation (bars corresponding to the left axis) between the estimated World Fear at month t with unemployment rates in month $t + i$ for $i = 0, ..., 12$ and t-statistics (line plot corresponding to right axis).



cross-correlation is positive and increases over the first four months and then drops for longer horizons. The highest correlation is reached at the three, four and two month horizons with values of 0.16, 0.17 and 0.22 for France, Germany and Italy, respectively, which are again all statistically significant.

Economically, an increase in World Fear is followed by an immediate increase in unemployment and hence a contraction in economic activity within the subsequent year, followed by a slow recovery. We are hence able to extend the results from previous literature for the U.S. to further major countries using our introduced World Fear index.

2.5 Robustness

2.5.1 Return Predictability

In order to further assess the robustness of the tail risk's return predictability, we repeat the simple regressions in local returns and run multiple regressions including alternative predictors. All tables are reported in the appendix to this chapter, and discussed in the following.

U.S. Dollar vs. Local Currencies

The analysis in the predictability Section 2.3.4 focuses on market returns expressed in U.S. dollar. However, it might be worth repeating this analysis from the perspective of a local investor. To be more specific, we rely on local returns rather than U.S. returns and explore the extent to which they can be predicted by World Fear. The monthly returns of non-U.S. countries are in excess of local three month interest rates obtained from Datastream.[23] These results are presented in Table A.5 of the appendix. The World Fear

[23]We use the Canadian Dollar, Euro, Japanese Yen and Sterling 3-Month Deposit rates for Canada, the European countries, Japan and the U.K., respectively.

index is statistically significant and positive for six out of seven countries at the three month and one year horizon and for all seven countries at the two year horizon. The magnitudes of the explanatory power in terms of adj. R^2 are similar to our main results. The robustness tests hence support our main findings in Section 2.3.4.

Controlling for other Predictors

For the additional predictors, we include option implied measures, macroeconomic variables and asset-related variables.

We include the dividend-price ratio, given as the difference between the log of 12-month trailing dividends and the log of prices (see, for example, Cochrane (2008), Welch & Goyal (2008) and Cochrane (2011)). The inflation rate is defined as changes in the consumer price index and we further include the volatility indices for each country (see, for example, Bollerslev et al. (2009) and Drechsler & Yaron (2011)).[24] All data are obtained from Datastream.

The control variables show in general low correlations with the tail risk. Only the implied volatilities exhibit moderate correlations with the tail risk with absolute values of 39% to 54%, see Table A.6 of the appendix.[25] For the sake of brevity, we focus on the one year horizon and additionally report Wald tests for the joint significance of our predictors.[26] Results for the regressions can be found in Table A.7 of the appendix and can be

[24] For Italy, dividend yield data is available starting in 2009 only. We hence exclude the regressions including the dividend-price ratio for Italy from the robustness tests. Further, there is no data available for the volatility index before 2010. We hence use the Euro Stoxx 50 Volatility as a proxy. For Canada, we combine the data of the MVX and the VICX using the data from MVX for the period from December 2002 to September 2009 and data from the VICX from October 2009 until December 2015.

[25] The findings are consistent with Kelly & Jiang (2014) who find significant correlations of their tail risk measure with option implied measures and a negative relationship with the option implied volatility.

[26] Results for alternative horizons are qualitatively similar and available on upon request.

summarized as follows: when including the volatility indices, the World Fear index remains significantly positive at the one year horizon. WF still helps in predicting future market returns in the same six countries as before and the adj. R^2 reach higher values of 7.72% to 22.24%. Additionally including the inflation of the individual countries leaves the World Fear index positive and statistically significant and the adj. R^2 can generally be further increased. Lastly, when adding the dividend-price ratio, World Fear remains a statistically significant predictor for three of the six countries. Even though the t-statistics are reduced somewhat compared to the simple and multiple regressions for France and the U.K., when controlling for the dividend-price ratio, the Wald tests for their joint significance are highly significant with test statistics above 10. Hence, the dividend yield is not able to fully span the predictive power of World Fear. In general, the Wald tests support the joint significance of the predictor variables for all countries.

Finite Sample Bias

In our predictive regressions in Section 2.3.4 we rely on Hodrick (1992) standard errors for the slope coefficients and bootstrapped p-values for the adj. R^2. While Hodrick (1992) standard errors take into account the impact of data overlap, they do not address the issue of persistence in the World Fear index. In order to take into account the finite sample bias and the potential Stambaugh (1999) bias, we apply the same bootstrap method for our OLS slope coefficients in the predictive regressions. As shown by Ang & Bekaert (2007) and Kelly & Jiang (2014), Hodrick (1992) standard errors are the most conservative when taking into account overlapping observations and the bootstrap standard errors of Welch & Goyal (2008) produce even stronger statistical significance for the slope coefficients. In unreported results, we also find that the p-values of all coefficients based on Hodrick

(1992) standard errors are higher than the corresponding bootstrapped p-values. Only for France and the one month horizon the bootstrapped p-value is higher but the coefficient is statistically insignificant according to both p-values.

Alternative Thresholds

In our main analysis we define the tail of the cross-sectional distribution of a monthly pool of daily returns as the 5% quantile, which is fixed across the sample period and across countries. We now consider alternative thresholds to show that our results are robust against the chosen estimation procedure. This is especially relevant since the number of firms varies for the different countries with a median number of firms between 274 and 5000.

Table A.8 of the appendix presents the return predictability regressions of aggregate market returns for the one year horizon using our introduced World Fear index.[27] The threshold is fixed as the 6% and 7% quantile of the cross-sectional distribution.[28] We find that World Fear remains a statistically significant predictor of future market returns for the majority of countries just as in our main analysis and is further able to predict global market returns. The adj. R^2 show similar magnitudes to our main results and are all statistically significant as well.

Table A.9 reports the results for the Fama–MacBeth regressions using the World Fear index, which are based on the alternative thresholds. The results are qualitatively and quantitatively similar to our main analysis. Hence, our findings for both the time-series and cross-sectional predictive power of World Fear are robust to the estimation procedure.

[27] Results are qualitatively similar for alternative horizons.

[28] Due to the relatively small sample size of Italy, we choose to increase the threshold and include more observations rather than the opposite.

2.5.2 Portfolio Sorts and the Cross-Section of Stock Returns

In this section, we investigate whether the relation between World Fear betas and returns is robust to our factor choices. In Section 2.3.5 we use local Fama & French (1993) factors for the individual countries. Griffin (2002) argues that country-specific three-factor models have more explanatory power for average stock returns than international or world versions but their data sample only covers the period from January 1981 to December 1995. Fama & French (2012) compare local and global models and suggest rather using local models in order to explain regional portfolio returns.

Nonetheless, we repeat the sorts as in Section 2.3.5 but control for global Fama & French (1993) risk factors instead of local factors using the data provided by the Kenneth R. French data library.[29] We find FF3 alphas of 1.06%, 1.11%, 3.30%, 1.04% and 1.13% for Canada, France, Germany, Italy and the U.K., respectively, which are all statistically significant. The findings are qualitatively similar to our main findings.

2.5.3 Foreign Tail Risk

In Section 2.3.2 we analyze the interaction between the different countries, comparing each country's tail risk. It is also of particular interest how the individual tail risk and aggregate tail risk of the other countries interact. We therefore decompose the World Fear into one country's own tail risk and the aggregate tail risk of the remaining countries, which we denote as foreign tail risk $Foreign$. We then compare the ability of predicting market and stock returns of local tail risk $JKTR$ and our World Fear index with foreign tail risk $Foreign$.

[29] Website: Http://mba.tuck.dartmouth.edu/pages/facult/ken.french.

In this section, we investigate the predictive power of $Foreign$ for aggregate market returns and its pricing in the stock markets. The results for the predictive regressions are reported in Table A.10.[30] Foreign tail risk is a stronger predictor than local tail risk in terms of explanatory power for most countries. The adj. R^2 can generally be increased for the remaining countries and horizons. The slope coefficient is also statistically significant for most countries. At the six month, one year and two year horizons, foreign tail risk is statistically significant for five out of seven countries, respectively. At the one year horizon, the adj. R^2 vary between 0.35% and 19.39% for those countries, which are all statistically significant. The explanatory power is highest for Japan for all horizons, indicating that especially Japan is sensitive to the tail risk of other countries. Even though the explanatory power is higher for some countries when relying on foreign tail risk, our World Fear index has a stronger overall predictive power across the countries.

We also repeat the cross-sectional analysis but estimate the sensitivity of individual stocks to foreign tail risk rather than World Fear. The results are reported in Table A.12 of the appendix. We find that sorting by $Foreign$ loadings yields positive and statistically significant (at the 5% level or lower) spreads for Germany, Italy and the U.K. As argued above, foreign tail risk has more predictive power for some countries, which leads to the stronger statistical significance of the spreads but has a less overall predictive power across countries. These findings are consistent with our results from the aggregate market return predictions. The results for the Fama–MacBeth regressions are similar to the ones using WF.

[30]Table A.11 of the appendix presents the explanatory power of the regressions relying on $JKTR$, WF or $Foreign$ in the terms of explanatory power (adj. R^2) and allows for a more convenient comparison.

2.6 Conclusion

The aim of the present chapter is to analyze tail risk internationally. We investigate the interaction between the tail risk of different developed countries and combine them to capture global tail risk. We show that the local tail risk is highly integrated across developed countries. While local tail risk does not help to predict future market returns, foreign tail risk and World Fear do. The return predictability is economically and statistically strong, both in-sample and out-of-sample when using World Fear. Further, sorting stocks by World Fear exposure generates positive excess returns for the majority of countries. The results are similar for both foreign and global tail risk. Our results are found to be robust after testing various variations of the examined models.

Overall, we conclude that global tail risk is a useful predictor of market returns while local tail risk generally does not predict future returns. An increase of World Fear has an impact on future aggregate economic activity such as unemployment which presents potential channels through which World Fear influences asset prices.

A Appendix

A.1 Additional Figures

Figure 2.5: JKTR and Subsequent Market Returns for the U.S. (1963-2015)

This figure shows the monthly time series of the JKTR for the U.S. for the period from 1963 to 2015. Also plotted in each month is the realized market return over the three years following the current month. The shaded areas present recessions defined by NBER. Both series are scaled to have mean zero and variance one.

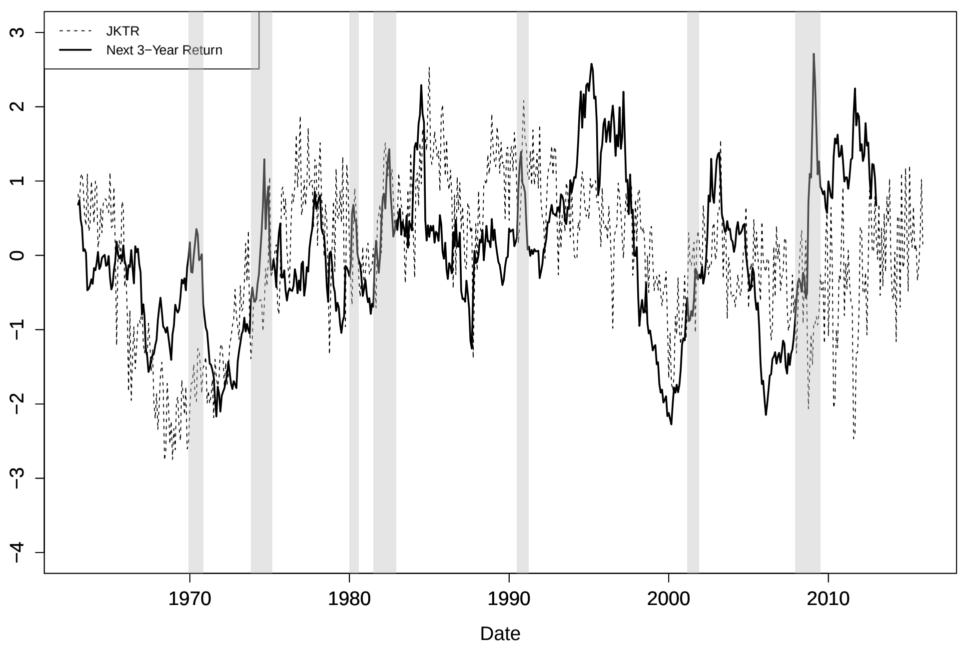


Figure 2.6: Expected Market Returns vs. Realized Market Returns

This figure plots the market returns over the next twelves months (dotted line) and the expected market returns over the same period (solid line). Expected market returns are the fitted values from the predictive regressions. The shaded areas present recessions defined by NBER.

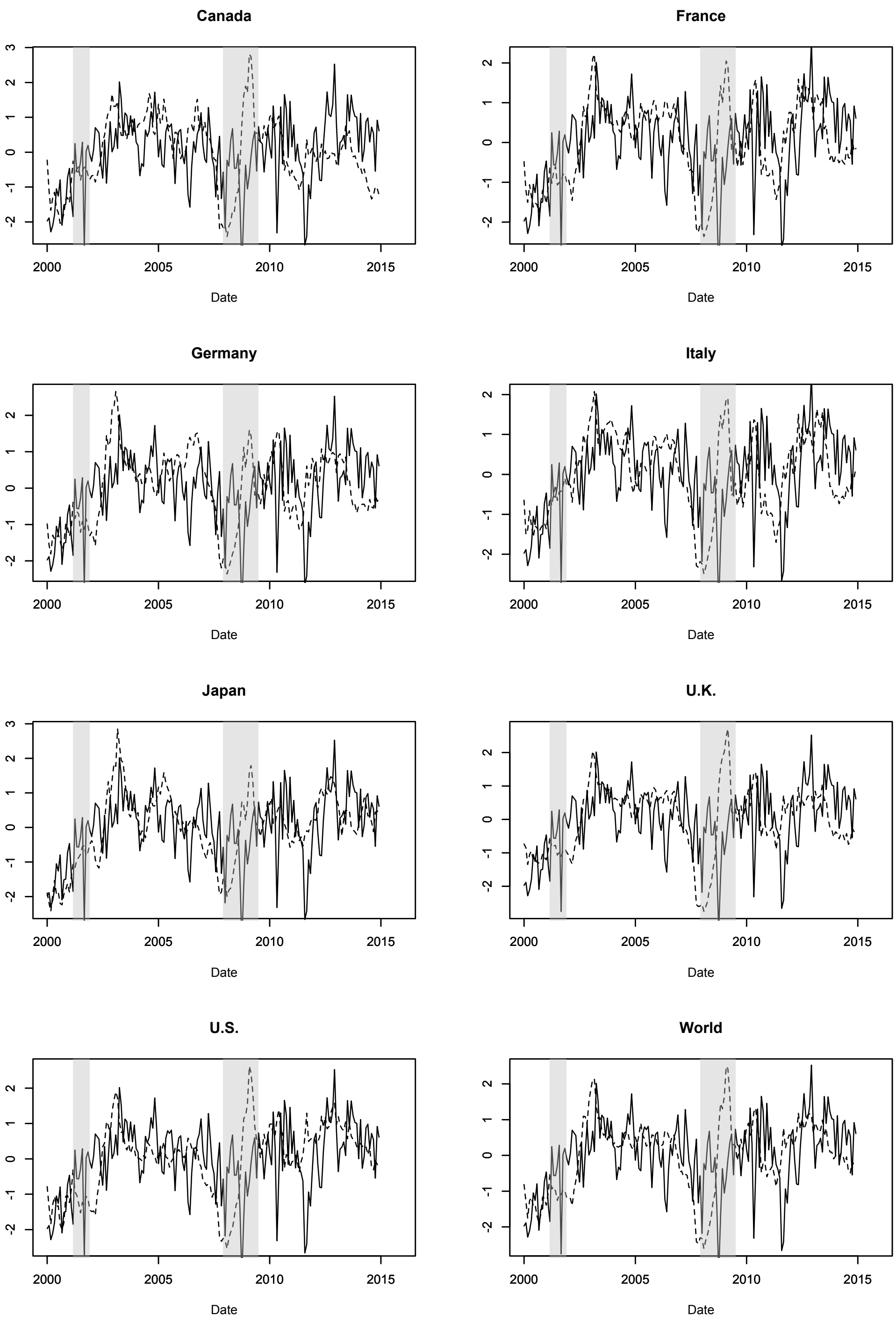


Figure 2.7: Performance of Predictors – Out-of-Sample

This figure shows the out-of-sample performance of predictive regressions for the three month horizon. We plot the cumulative squared prediction errors of the historical mean model minus the cumulative squared prediction error of our prediction model using WF. An increase (a decrease) in the line indicates that our model outperforms (underperforms) the historical mean model. The shaded areas present recessions defined by NBER.

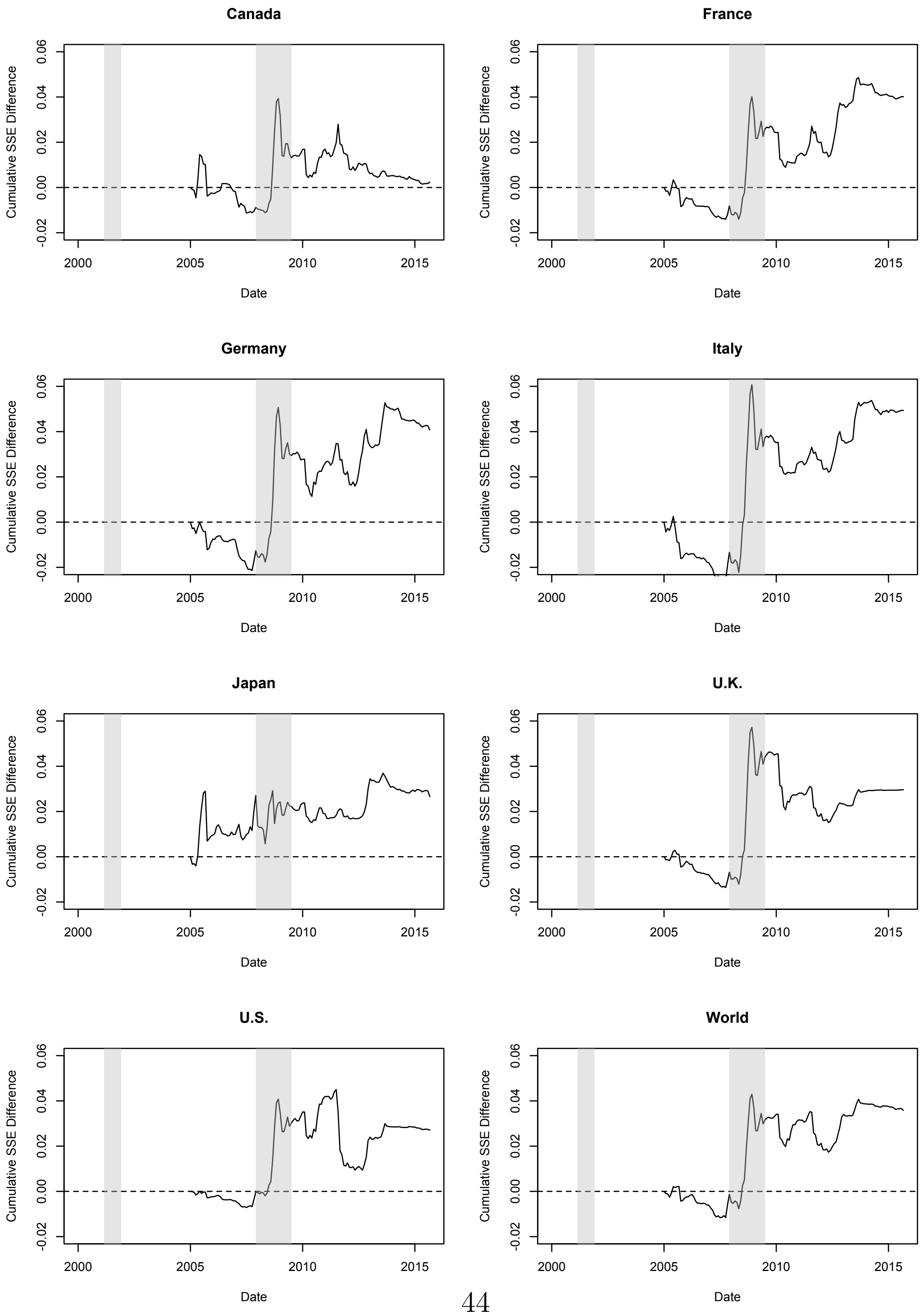
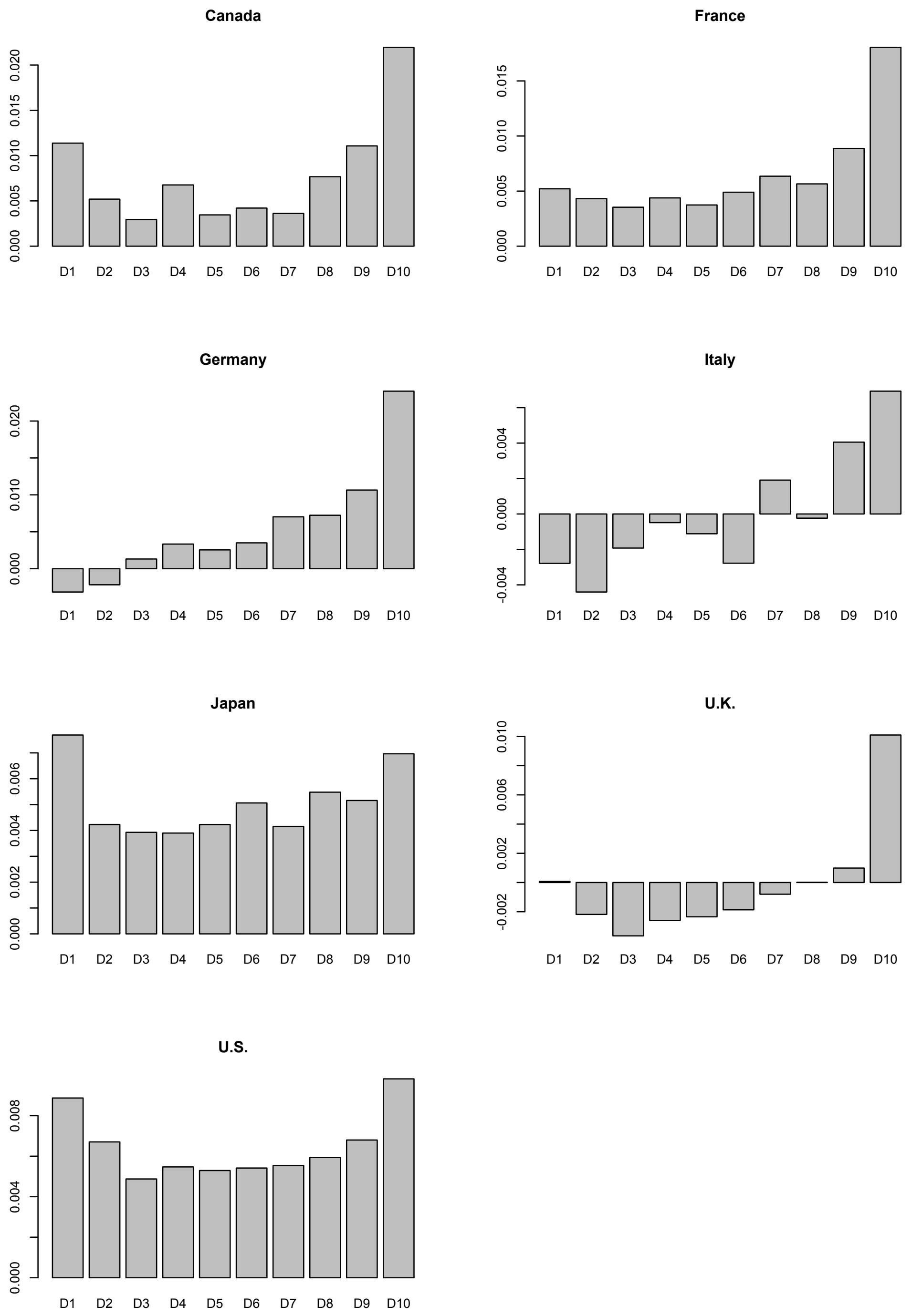


Figure 2.8: Average Return of Decile Portfolios

This figure shows average return of decile portfolios. Each month, the World Fear loadings are estimated for each stock in regressions using the most recent 60 observations. Stocks are sorted into equally weighted portfolios based on the estimated loadings whereby firms with the lowest coefficient are in the first decile portfolio and firms with the highest coefficients are in the tenth decile portfolio.



A.2 Additional Tables

Table A.1: Granger Causality

This table presents the results for Granger causality tests between the JKTR. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. We test the null hypothesis that the JKTR of one individual country is not Granger-caused by the JKTR of the remaining countries. We report the F-statistic with the corresponding p-values below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
1 Month	2.8730***	2.0862*	3.5633***	1.1326	2.2581**	3.2466***	1.8821*
	0.0087	0.0522	0.0017	0.3409	0.0358	0.0036	0.0806
3 Month	1.2240	1.7376**	1.8430**	0.7861	0.8719	1.6875**	0.9474
	0.2330	0.0282	0.0170	0.7186	0.6137	0.0356	0.5200
6 Month	0.9144	1.1466	1.1095	0.8401	0.8828	1.0288	0.6753
	0.6151	0.2560	0.3036	0.7360	0.6679	0.4234	0.9285
1 Year	0.5977	0.7839	0.8342	0.8551	0.8924	0.7858	0.7954
	0.9964	0.9023	0.8315	0.7955	0.7228	0.9000	0.8881

Table A.2: Granger Causality – Bivariate

This table presents results for Granger causality tests between the JKTR of two individual countries. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. We test the null hypothesis that the JKTR of one individual country does not Granger-cause the JKTR of another country. We report the lag order chosen by the Bayesian Information Criterion (BIC), the F-statistic and the corresponding p-values. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Lag	F-statistic	p-value
Canada → France	3	0.1997	0.8966
France → Canada	3	3.7589**	0.0111
Canada → Germany	1	10.5611***	0.0013
Germany → Canada	1	10.1047***	0.0016
Canada → Italy	2	1.0075	0.3661
Italy → Canada	2	1.9082	0.1498
Canada → Japan	1	3.0531*	0.0814
Japan → Canada	1	6.6604**	0.0102
Canada → U.K.	1	3.2235*	0.0734
U.K. → Canada	1	0.5604	0.4546
Canada → U.S.	1	2.6836	0.1022
U.S. → Canada	1	0.9627	0.3271
France → Germany	3	3.7109**	0.0118
Germany → France	3	1.6399	0.1798
France → Italy	2	2.2752	0.1042
Italy → France	2	0.2593	0.7718
France → Japan	1	8.4291***	0.0039
Japan → France	1	6.0887**	0.0140
France → U.K.	3	2.9467**	0.0329
U.K. → France	3	0.6926	0.5570
France → U.S.	2	0.5589	0.5723
U.S. → France	2	2.3000	0.1017
Germany → Italy	1	0.0312	0.8599
Italy → Germany	1	10.6340***	0.0012
Germany → Japan	1	3.8502*	0.0505
Japan → Germany	1	7.8163***	0.0054
Germany → U.K.	1	6.8772***	0.0091
U.K. → Germany	1	11.4396***	0.0008
Germany → U.S.	3	0.1829	0.9080
U.S. → Germany	3	2.4459*	0.0636
Italy → Japan	1	7.3125***	0.0072
Japan → Italy	1	0.8912	0.3457
Italy → U.K.	1	0.6702	0.4135
U.K. → Italy	1	1.7429	0.1876
Italy → U.S.	1	0.5526	0.4577
U.S. → Italy	1	0.1029	0.7486
Japan → U.K.	1	7.2711***	0.0073
U.K. → Japan	1	1.9872	0.1595
Japan → U.S.	1	1.1260	0.2893
U.S. → Japan	1	4.4459**	0.0356
U.K. → U.S.	1	7.8834***	0.0052
U.S. → U.K.	1	0.5805	0.4466

Table A.3: JTKR vs. World Fear

This table reports results from the following regression: $JKTR_{i,t} = a_i + b_i WF_t + \epsilon_{i,t}$ where $JKTR_{i,t}$ is the tail risk of country i at time t, WF_t is World Fear at time t and $\epsilon_{i,t}$ is the error term. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Intercept	0.1278***	−0.2582***	−0.1665**	−0.0231	0.1822***	0.0589*	0.0790***
	(0.0368)	(0.0297)	(0.0653)	(0.0306)	(0.0221)	(0.0355)	(0.0201)
WF	0.7228***	1.7826***	1.5833***	0.7476***	0.4368***	1.0233***	0.7036***
	(0.0774)	(0.0626)	(0.1375)	(0.0645)	(0.0466)	(0.0747)	(0.0423)
adj. R^2	0.3109	0.8090	0.4078	0.4113	0.3128	0.4945	0.5907

Table A.4: Return Predictability U.S. (1963-2015)

This table presents results for monthly return predictive regressions of CRSP value-weighted market index returns over horizons from one month to five years. The period starts in 1963 following Kelly & Jiang (2014) but is extended until 2015 in Panel A. Panel B reports results for the same period as Kelly & Jiang (2014) while Panel C investigates the period from 1963 to 1979. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	1 Month	1 Year	2 Year	3 Year	5 Year
Panel C: 1963-2015					
(Intercept)	-0.0259^{*}	-0.2242	-0.4157	-0.7320^{*}	-1.3684^{**}
	(0.0144)	(0.1479)	(0.2939)	(0.4311)	(0.6800)
JKTR	0.0816^{**}	0.7955^{**}	1.5392^{**}	2.5963^{**}	4.8275^{**}
	(0.0326)	(0.3366)	(0.6696)	(0.9831)	(1.5473)
adj. R^2	0.0088	0.0649	0.1105	0.1850	0.2262
Panel B: 1963-2010					
(Intercept)	-0.0304^{**}	-0.2722^{*}	-0.5494^{*}	-0.9769^{**}	-1.6229^{**}
	(0.0145)	(0.1578)	(0.3105)	(0.4605)	(0.7323)
JTKR	0.0921^{**}	0.8967^{**}	1.8132^{**}	3.1107^{**}	5.3930^{**}
	(0.0329)	(0.3581)	(0.7064)	(1.0487)	(1.6532)
adj. R^2	0.0115	0.0797	0.1524	0.2580	0.2895
Panel C: 1963-1979					
(Intercept)	-0.0187	-0.0716	-0.2098	-0.3796	-0.7782
	(0.0177)	(0.2080)	(0.3941)	(0.5692)	(0.8154)
JKTR	0.0640	0.3801	0.9099	1.4917	2.8872^{*}
	(0.0420)	(0.4942)	(0.9108)	(1.2949)	(1.7418)
adj. R^2	0.0041	0.0193	0.0611	0.1703	0.2892

Table A.5: Return Predictability Regressions – Local Market Returns

This table presents results for monthly return predictive regressions of value-weighted market index returns in *local currencies* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor is World Fear. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	Global
Intercept	−0.0705*	−0.0263	−0.0488	−0.0496	−0.1286**	−0.0090	−0.0705*	−0.0731*
	(0.0371)	(0.0400)	(0.0476)	(0.0473)	(0.0406)	(0.0312)	(0.0371)	(0.0441)
WF_{1Month}	0.1565**	0.0605	0.1090	0.1061	0.2770**	0.0232	0.1565**	0.1614*
	(0.0757)	(0.0823)	(0.0982)	(0.0980)	(0.0848)	(0.0642)	(0.0757)	(0.0901)
adj. R^2	0.0219	−0.0028	0.0011	0.0012	0.0480	−0.0047	0.0219	0.0165
	{0.0352}	{0.5244}	{0.3336}	{0.2912}	{0.0020}	{0.7428}	{0.0388}	{0.0484}
Intercept	−0.1214	−0.1650*	−0.2149**	−0.1977**	−0.3811***	−0.0769	−0.1214	−0.2114**
	(0.0824)	(0.0879)	(0.1073)	(0.0982)	(0.1028)	(0.0729)	(0.0824)	(0.1004)
WF_{3Month}	0.2803*	0.3638**	0.4716**	0.4200**	0.8254***	0.1755	0.2803*	0.4695**
	(0.1658)	(0.1783)	(0.2179)	(0.2018)	(0.2144)	(0.1491)	(0.1658)	(0.2031)
adj. R^2	0.0168	0.0227	0.0313	0.0287	0.1080	0.0053	0.0168	0.0458
	{0.0310}	{0.0656}	{0.0192}	{0.0226}	{0.0000}	{0.1494}	{0.0422}	{0.0016}
Intercept	−0.1429	−0.3449**	−0.3309*	−0.3364*	−0.5606**	−0.1389	−0.1429	−0.3126*
	(0.1502)	(0.1692)	(0.1925)	(0.1895)	(0.1789)	(0.1326)	(0.1502)	(0.1763)
WF_{6Month}	0.3512	0.7602**	0.7377*	0.7180*	1.2295**	0.3209	0.3512	0.7104**
	(0.3006)	(0.3413)	(0.3907)	(0.3861)	(0.3732)	(0.2693)	(0.3006)	(0.3536)
adj. R^2	0.0099	0.0474	0.0351	0.0381	0.0969	0.0097	0.0099	0.0431
	{0.0984}	{0.0088}	{0.0164}	{0.0074}	{0.0000}	{0.0880}	{0.1012}	{0.0030}
Intercept	−0.4599*	−0.6299**	−0.6454**	−0.6414*	−1.0495***	−0.2871	−0.4599*	−0.5616*
	(0.2644)	(0.3014)	(0.3212)	(0.3300)	(0.2850)	(0.2321)	(0.2644)	(0.2922)
WF_{1Year}	1.0779**	1.4067**	1.4590**	1.3757**	2.3297***	0.6707	1.0779**	1.3029**
	(0.5241)	(0.5997)	(0.6400)	(0.6653)	(0.5883)	(0.4618)	(0.5241)	(0.5765)
adj. R^2	0.0655	0.0718	0.0669	0.0683	0.1545	0.0234	0.0655	0.0696
	{0.0010}	{0.0022}	{0.0016}	{0.0014}	{0.0000}	{0.0346}	{0.0022}	{0.0012}
Intercept	−0.5610**	−1.0187**	−1.0369**	−1.0910**	−1.2951***	−0.4167	−0.5610**	−0.6696*
	(0.2735)	(0.3896)	(0.4462)	(0.3956)	(0.3432)	(0.3100)	(0.2735)	(0.3422)
WF_{2Year}	1.4460**	2.3433**	2.4230**	2.3856**	3.0019***	1.0381*	1.4460**	1.7044**
	(0.5260)	(0.7280)	(0.8420)	(0.7487)	(0.6870)	(0.5722)	(0.5260)	(0.6373)
adj. R^2	0.0553	0.0863	0.0849	0.0869	0.1076	0.0265	0.0553	0.0550
	{0.0022}	{0.0000}	{0.0006}	{0.0000}	{0.0000}	{0.0300}	{0.0016}	{0.0020}

Table A.6: Correlation of Control Variables

This table presents sample correlations between World Fear and the country specific control variables for the period from January 2000 until December 2015. The control variables are the implied volatility IV, the inflation $Inflation$ and the dividend-price ratio $log(D/P)$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
IV	−0.5352	−0.4197	−0.3857	−0.4081	−0.4346	−0.5085	−0.5203
Inflation	−0.0214	−0.0446	0.0898	−0.0895	0.1853	0.0741	0.0320
log(D/P)	0.2129	0.1900	0.1126		0.1463	0.2303	0.2135

Table A.7: Return Predictability Regressions – Control Variables

This table presents robustness checks for return predictive regressions of value-weighted market index returns in *Dollar currencies* for the one year horizon. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The control variables are the implied volatility IV, the inflation $Inflation$ and the dividend-price ratio $log(D/P)$. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. The Wald row reports the Wald test statistic for the joint significance of the tail risk and the control variable.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Intercept	−0.6848	−1.2227**	−1.3307**	−1.2710**	−1.2853***	−0.9481**	−1.1753***
	(0.5245)	(0.5119)	(0.5540)	(0.4960)	(0.3456)	(0.3530)	(0.3501)
WF	1.2925	2.2238**	2.4407**	2.2151**	2.4796***	1.8009**	2.1929***
	(0.9775)	(0.9086)	(0.9724)	(0.8854)	(0.6245)	(0.6207)	(0.6298)
IV	0.0108**	0.0096*	0.0107*	0.0103**	0.0052	0.0078	0.0092**
	(0.0047)	(0.0054)	(0.0056)	(0.0051)	(0.0040)	(0.0051)	(0.0043)
adj. R^2	0.0772	0.1554	0.1889	0.1812	0.2224	0.0999	0.1908
Wald	5.6101	6.3545	6.6916	7.0476	15.7972	8.4224	12.4457
Intercept	−0.6578	−1.1575**	−1.3267**	−1.1655**	−1.3157***	−0.9467**	−1.0788**
	(0.5173)	(0.5128)	(0.5530)	(0.4831)	(0.3469)	(0.3529)	(0.3400)
WF	1.2591	2.1617**	2.4555**	2.0901**	2.5625***	1.8205**	2.0857***
	(0.9685)	(0.9101)	(0.9764)	(0.8678)	(0.6340)	(0.6237)	(0.6171)
IV	0.0104**	0.0093*	0.0105*	0.0098*	0.0049	0.0076	0.0079*
	(0.0047)	(0.0054)	(0.0056)	(0.0052)	(0.0041)	(0.0051)	(0.0044)
Inflation	−3.1697	−23.2123*	−4.9216	−21.6222*	−10.8589	−4.5471	−9.7053**
	(2.8307)	(12.4961)	(3.1089)	(12.5540)	(7.0593)	(4.6159)	(4.8193)
adj. R^2	0.0732	0.1812	0.1881	0.2065	0.2341	0.1009	0.2101
Wald	6.8105	9.8944	7.1857	8.5866	16.8375	8.9156	13.8955
Intercept	−2.8098**	0.5776	−0.3319	0.4479	−0.4126	1.5047	1.3131
	(1.3290)	(1.1981)	(1.2046)	(1.3607)	(0.6138)	(1.0620)	(1.0547)
WF	1.6765	1.2534	2.0481*	0.8441	2.1228**	0.7214	1.1241*
	(1.0134)	(1.0135)	(1.0919)	(0.9153)	(0.6535)	(0.7376)	(0.6143)
IV	0.0198**	0.0039	0.0079	0.0029	0.0021	0.0013	0.0031
	(0.0065)	(0.0062)	(0.0064)	(0.0081)	(0.0042)	(0.0046)	(0.0044)
Inflation	−4.4572	−18.9839	−4.1975	−12.8134	−11.8963*	−6.9369	−6.4796
	(2.9815)	(12.4498)	(3.1846)	(7.7342)	(6.9385)	(4.1969)	(5.0998)
log(D/P)	−0.4840*	0.3477	0.2037	0.2633	0.1443	0.5253**	0.4618**
	(0.2690)	(0.2315)	(0.2081)	(0.3462)	(0.0915)	(0.2317)	(0.2204)
adj. R^2	0.2228	0.2893	0.2360	0.0252	0.3147	0.2614	0.4199
Wald	11.0415	10.6539	8.6090	6.9029	18.3215	15.3518	14.9004

Table A.8: Return Predictability Regressions – Alternative Thresholds

This table presents robustness checks for return predictive regressions of value-weighted market index returns in *Dollar currencies* for the one year horizon. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor variables are the World Fear indices $WF_{0.06}$ and $WF_{0.07}$, which are based on a threshold of 6% and 7%, respectively. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.	Global.
Intercept	−0.5288	−0.6217	−0.6480	−0.6222	−0.9420**	−0.4598	−0.5229*	−0.5674*
	(0.4100)	(0.4002)	(0.4207)	(0.4022)	(0.2963)	(0.2989)	(0.2932)	(0.3014)
$WF_{0.06}$	1.2480	1.3715*	1.4855*	1.3301*	1.9611***	1.0596*	1.1719**	1.2656**
	(0.7851)	(0.7671)	(0.8059)	(0.7736)	(0.5855)	(0.5714)	(0.5589)	(0.5722)
adj. R^2	0.0426	0.0574	0.0573	0.0528	0.1784	0.0411	0.0654	0.0681
	{0.0066}	{0.0058}	{0.0044}	{0.0056}	{0.0000}	{0.0106}	{0.0024}	{0.0004}
Intercept	−0.5281	−0.5810	−0.6084	−0.6161	−0.9052**	−0.4397	−0.4764	−0.5357*
	(0.4123)	(0.4034)	(0.4260)	(0.4128)	(0.2983)	(0.3110)	(0.2944)	(0.3063)
$WF_{0.07}$	1.2004	1.2407*	1.3527*	1.2688*	1.8159**	0.9808*	1.0371*	1.1563**
	(0.7595)	(0.7437)	(0.7878)	(0.7624)	(0.5684)	(0.5721)	(0.5407)	(0.5600)
adj. R^2	0.0420	0.0495	0.0501	0.0511	0.1627	0.0371	0.0538	0.0600
	{0.0064}	{0.0082}	{0.0072}	{0.0070}	{0.0000}	{0.0144}	{0.0050}	{0.0018}

Table A.9: Fama–MacBeth Regressions – Alternative Thresholds

This table reports results for Fama–MacBeth Regressions based on World Fear loadings and alternative thresholds of 6% and 7%. Intercept and γ_{WF} are means of the coefficients from the cross-sectional regressions of individual stock returns on an intercept and the tail risk loadings. We apply the Shanken (1992) correction. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A: Threshold 6%							
Intercept	0.0060	0.0030	0.0043	−0.0050	0.0053	−0.0018	0.0055
	(0.0061)	(0.0045)	(0.0049)	(0.0058)	(0.0037)	(0.0050)	(0.0039)
γ_{WF}	0.0004**	0.0014***	0.0000**	0.0016**	0.0001	0.0008**	0.0003
	(0.0002)	(0.0004)	(0.0000)	(0.0007)	(0.0004)	(0.0004)	(0.0004)
Panel B: Threshold 7%							
Intercept	0.0061	0.0030	0.0043	−0.0051	0.0053	−0.0016	0.0055
	(0.0061)	(0.0045)	(0.0049)	(0.0058)	(0.0037)	(0.0050)	(0.0039)
γ_{WF}	0.0004**	0.0015***	0.0000**	0.0016**	0.0002	0.0008**	0.0003
	(0.0002)	(0.0004)	(0.0000)	(0.0007)	(0.0004)	(0.0004)	(0.0004)

Table A.10: Return Predictability – Foreign Tail Risk

This table presents results for monthly return predictive regressions of value-weighted market index returns in *U.S. dollar currency* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictor is the foreign tail risk $Foreign$ of the country [name in column]. Robust Hodrick (1992) standard errors are reported in parentheses using lags equal to the prediction horizon expressed in months. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. We report bootstrapped p-values below the corresponding adjusted R^2.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Intercept	−0.0613	−0.0471	−0.0594	−0.0731	−0.1152**	−0.0583	−0.0666
	(0.0532)	(0.0594)	(0.0662)	(0.0585)	(0.0389)	(0.0416)	(0.0440)
$Foreign_{1Month}$	0.1415	0.1111	0.1419	0.1506	0.2371**	0.1341	0.1450
	(0.1086)	(0.1277)	(0.1412)	(0.1157)	(0.0773)	(0.0874)	(0.0881)
adj. R^2	0.0054	−0.0007	0.0023	0.0055	0.0494	0.0083	0.0150
	{0.2044}	{0.3908}	{0.2878}	{0.1858}	{0.0008}	{0.1174}	{0.0606}
Intercept	−0.1199	−0.1980	−0.2127	−0.2578**	−0.3515**	−0.1637*	−0.2030**
	(0.1151)	(0.1420)	(0.1632)	(0.1304)	(0.1122)	(0.0915)	(0.1016)
$Foreign_{3Month}$	0.2917	0.4586	0.5018	0.5289**	0.7250**	0.3813**	0.4426**
	(0.2315)	(0.3023)	(0.3449)	(0.2560)	(0.2229)	(0.1917)	(0.2008)
adj. R^2	0.0078	0.0194	0.0242	0.0360	0.1339	0.0249	0.0506
	{0.0808}	{0.0562}	{0.0284}	{0.0066}	{0.0000}	{0.0200}	{0.0034}
Intercept	−0.1330	−0.4031*	−0.2891	−0.3826*	−0.5409**	−0.2272	−0.3079*
	(0.2118)	(0.2436)	(0.2778)	(0.2180)	(0.1850)	(0.1571)	(0.1789)
$Foreign_{6Month}$	0.3625	0.9370*	0.7119	0.7973*	1.1216**	0.5509*	0.6851*
	(0.4249)	(0.5139)	(0.5844)	(0.4245)	(0.3677)	(0.3280)	(0.3506)
adj. R^2	0.0036	0.0405	0.0213	0.0369	0.1450	0.0207	0.0528
	{0.1894}	{0.0056}	{0.0370}	{0.0028}	{0.0000}	{0.0190}	{0.0006}
Intercept	−0.4405	−0.6635	−0.4839	−0.6009	−0.8988**	−0.3976	−0.5677**
	(0.3721)	(0.4176)	(0.4478)	(0.3839)	(0.2726)	(0.2686)	(0.2830)
$Foreign_{1Year}$	1.1093	1.5758*	1.2427	1.2734*	1.8907***	0.9941*	1.2848**
	(0.7424)	(0.8728)	(0.9277)	(0.7413)	(0.5415)	(0.5534)	(0.5472)
adj. R^2	0.0354	0.0567	0.0333	0.0514	0.1939	0.0347	0.0860
	{0.0100}	{0.0044}	{0.0178}	{0.0066}	{0.0000}	{0.0134}	{0.0002}
Intercept	−0.3497	−0.9124*	−0.5389	−0.7805*	−0.9446**	−0.5583	−0.6691**
	(0.3724)	(0.5060)	(0.6300)	(0.4070)	(0.3312)	(0.3435)	(0.3323)
$Foreign_{2Year}$	1.1946	2.3044**	1.6232	1.7529**	2.0852**	1.5350**	1.6572**
	(0.7406)	(0.9998)	(1.2650)	(0.7486)	(0.6459)	(0.6769)	(0.6055)
adj. R^2	0.0153	0.0596	0.0265	0.0468	0.1284	0.0383	0.0611
	{0.0450}	{0.0012}	{0.0192}	{0.0020}	{0.0000}	{0.0088}	{0.0010}

Table A.11: Return Predictability – Adj. R^2

This table presents results for monthly return predictive regressions of value-weighted market index returns in *U.S. dollar currency* over horizons from one month to two years. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. The predictors are JKT, WF and $Foreign$. We report the adjusted R^2.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
$JKTR_{1Month}$	0.0003	0.0004	0.0064	0.0053	−0.0045	−0.0023	−0.0040
WF_{1Month}	0.0064	−0.0001	0.0068	0.0070	0.0418	0.0074	0.0125
$Foreign_{1Month}$	0.0054	−0.0007	0.0023	0.0055	0.0494	0.0083	0.0150
$JKTR_{3Month}$	0.0001	0.0342	0.0358	0.0206	−0.0049	0.0054	−0.0049
WF_{3Month}	0.0085	0.0254	0.0401	0.0389	0.1197	0.0243	0.0393
$Foreign_{3Month}$	0.0078	0.0194	0.0242	0.0360	0.1339	0.0249	0.0506
$JKTR_{6Month}$	−0.0022	0.0495	0.0391	0.0151	−0.0024	0.0143	−0.0027
WF_{6Month}	0.0040	0.0467	0.0382	0.0385	0.1323	0.0232	0.0392
$Foreign_{6Month}$	0.0036	0.0405	0.0213	0.0369	0.1450	0.0207	0.0528
$JKTR_{1Year}$	0.0058	0.0467	0.0568	0.0032	0.0044	0.0294	−0.0006
WF_{1Year}	0.0357	0.0586	0.0572	0.0477	0.1810	0.0397	0.0746
$Foreign_{1Year}$	0.0354	0.0567	0.0333	0.0514	0.1939	0.0347	0.0860
$JKTR_{2Year}$	0.0408	0.0244	0.0371	−0.0046	0.0027	0.0152	−0.0024
WF_{2Year}	0.0236	0.0530	0.0434	0.0394	0.1209	0.0389	0.0527
$Foreign_{2Year}$	0.0153	0.0596	0.0265	0.0468	0.1284	0.0383	0.0611

Table A.12: Portfolio Sorts and Fama–MacBeth Regressions – Foreign Tail Risk

This table presents results from portfolio sorts based on *Foreign*. The investigated countries are the G-7 countries over the period from January 2000 until December 2015. Decile portfolios are formed based on *Foreign* betas for each country. Betas are calculated in predictive regressions using the most recent 60 returns measured in *U.S. Dollars*. We then track 1 month out-of-sample equally weighted holding period returns. We report the average returns of the high minus low portfolio in the first row of Panel A. *FF3* report alphas from the Fama & French (1993) 3 factor model. In Panel B, Intercept and $\gamma_{Foreign}$ are means of the coefficients from the cross-sectional regressions of individual stock returns on an intercept and the foreign tail risk loadings. Panel C additionally includes the market loading, $log(Size)$, book-to-market ratios (BTM), prior returns (Mom), illiquidity (Liq), aggregate Volatility ($Aggr.Vol$), coskewness ($Coskewness$), downside beta ($DownsideBeta$) and idiosyncratic volatility ($iVol$) of individual stocks in the cross-sectional regressions. The according mean coefficients γ_{Market}, γ_{Size}, γ_{BTM}, γ_{Mom}, γ_{Liq}, $\gamma_{Aggr.Vol}$, $\gamma_{Coskewness}$, $\gamma_{DownsideBeta}$ and γ_{iVol} are reported. For the cross-sectional regressions, we apply the Shanken (1992) correction. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	U.K.	U.S.
Panel A: Portfolio Sorts							
Average return	0.0089	0.0036	0.0292***	0.0147***	−0.0015	0.0139**	0.0017
	(0.0059)	(0.0050)	(0.0070)	(0.0048)	(0.0046)	(0.0057)	(0.0043)
FF3	0.0102*	0.0013	0.0320***	0.0163***	0.0021	0.0157**	−0.0021
	(0.0058)	(0.0047)	(0.0074)	(0.0049)	(0.0038)	(0.0062)	(0.0036)
Panel B: Simple Fama–MacBeth Regressions							
(Intercept)	0.0061	0.0033	0.0043	−0.0051	0.0054	−0.0028	0.0051
	(0.0061)	(0.0045)	(0.0049)	(0.0059)	(0.0037)	(0.0051)	(0.0039)
$\gamma_{Foreign}$	0.0004**	0.0013***	0.0000***	0.0020***	−0.0000	0.0012***	0.0004
	(0.0002)	(0.0003)	(0.0000)	(0.0007)	(0.0004)	(0.0004)	(0.0004)
Panel C: Multiple Fama–MacBeth Regressions							
(Intercept)	−0.0074	−0.0008	0.0062	0.0017	−0.0001	−0.0025	0.0073
	(0.0054)	(0.0060)	(0.0060)	(0.0060)	(0.0044)	(0.0054)	(0.0062)
$\gamma_{Foreign}$	0.0013***	0.0022***	0.0022***	0.0034***	0.0010	0.0020***	0.0007
	(0.0004)	(0.0007)	(0.0007)	(0.0009)	(0.0007)	(0.0006)	(0.0007)
γ_{Market}	−0.0078**	−0.0047	−0.0053	−0.0023	0.0022	−0.0001	0.0024
	(0.0031)	(0.0036)	(0.0036)	(0.0045)	(0.0020)	(0.0021)	(0.0019)
γ_{Size}	0.0005	0.0003	−0.0003	−0.0001	−0.0001	0.0011**	0.0000
	(0.0005)	(0.0006)	(0.0005)	(0.0007)	(0.0005)	(0.0005)	(0.0004)
γ_{BTM}	0.0125***	0.0061***	0.0024**	0.0046***	0.0060***	0.0077***	−0.0018*
	(0.0013)	(0.0015)	(0.0011)	(0.0011)	(0.0008)	(0.0009)	(0.0010)
γ_{Mom}	0.0039	0.0042	0.0089*	0.0048	−0.0026	0.0058	−0.0035
	(0.0046)	(0.0044)	(0.0048)	(0.0066)	(0.0032)	(0.0045)	(0.0031)
γ_{Liq}	0.0001	−0.0017	−0.0004	−0.0000	0.0001	0.0001	−0.2271
	(0.0001)	(0.0012)	(0.0003)	(0.0036)	(0.0004)	(0.0002)	(0.1542)
$\gamma_{Aggr.Vol}$	0.0589	−0.2738*	−0.0170	−0.4710*	−0.0328	−0.1476	−0.0204
	(0.1139)	(0.1552)	(0.1876)	(0.2725)	(0.1852)	(0.1203)	(0.0949)
$\gamma_{Coskewness}$	−0.0000	0.0007	0.0013	0.0016*	0.0002	−0.0002	−0.0001
	(0.0005)	(0.0006)	(0.0008)	(0.0008)	(0.0002)	(0.0004)	(0.0002)
$\gamma_{DownsideBeta}$	0.0001	0.0010	0.0092**	−0.0004	0.0009	−0.0037**	−0.0018*
	(0.0017)	(0.0025)	(0.0036)	(0.0034)	(0.0012)	(0.0019)	(0.0011)
γ_{iVol}	0.0163	−0.0274	−0.0452*	−0.0807***	−0.0326*	−0.0605***	−0.0295*
	(0.0180)	(0.0255)	(0.0245)	(0.0276)	(0.0187)	(0.0144)	(0.0168)

Chapter 3

Jumps in Commodity Markets*

3.1 Introduction

This chapter discusses the importance of the jump diversification of commodity markets in order to hedge against price movements, and contributes to the literature by focusing on extreme returns rather than returns alone. The consideration of jumps is of great importance when relying on cross-sectional and cross-market diversification for risk control. From a portfolio perspective, it is relevant whether jumps are highly correlated in the cross-section and across markets or not, since high correlation would make diversification meaningless. The knowledge about specific commodities which show high/low jump correlation thus allows for a better portfolio allocation in times of market stress.

The contribution of this chapter is twofold. First, we extend the studies on correlated jumps to the commodity market by investigating 29 different commodity futures. Second, we relate our results to other markets in order to draw conclusions on the potential of hedging jumps across markets. We

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investigate the correlation of jumps across commodities by computing the correlation coefficients of the jump measure. Jumps are measured by the Barndorff-Nielsen & Shephard (2006) (BNS) jump test statistic which is calculated for each commodity and calender month using daily futures return data. This chapter differs from the literature which relies mainly on parametric models and co-jumps and/or their probabilities while we investigate the presence of jumps non-parametrically and present evidence of jump correlations. Further, the literature considers mainly the co-movement of commodity prices given by the excess co-movement hypothesis introduced by Pindyck & Rotemberg (1993). Generally, there is no empirical evidence of excess co-movement being found between various commodities using either cointegration techniques or multivariate GARCH models (Palaskas & Varangis, 1991; Deb et al., 1996; Malliaris & Urrutia, 1996). In Chapter 3, we are interested in the co-movement of extreme events, rather than returns, but we investigate both to draw a complete picture.

We apply the jump detection test of Barndorff-Nielsen & Shephard (2006) and correlation analysis to the daily futures return of 29 commodities over a period from January 1959 to December 2015. We show that some commodities' returns have more jumps than others with the percentage of jump months being as high as 20.5% for butter and as low as 0.1% for soybean meal. Jumps are very extreme and rare events where the jump size on average is more than 1000 times higher than the average raw returns but at the same time make up less than 1% of the average raw returns. Nonetheless, jumps in commodity markets occur much less frequently than in the stock market, as found by Pukthuanthong & Roll (2015). In a second step, we relate jumps of commodities to jumps in the U.S. stock market and the currency market. Most commodities show relatively high co-movement with stock market returns while jumps are generally diversifiable. For the currency market, we find that almost all commodities are strong hedges for

U.S. Dollar returns and weak hedges for U.S. Dollar jumps. We find that most commodities serve as weak hedges for Treasury notes concerning both returns and jumps.

This chapter draws from three strands of literature. The first concentrates on jumps in the stock market and their potential cause by news events and their future effects on the equity risk premium. Rietz (1988) and Barro (2006) model tail risk and rare disasters in order to explain different puzzles of asset returns for the U.S. and 20 OECD countries, respectively. Lee & Mykland (2008) find evidence for a relationship between jumps and news events in the U.S. equity market while the index jumps are associated with overall market news. Jiang & Yao (2013) investigate the cross-section of U.S. stock returns and find that small stocks, value stocks, illiquid stocks and past losers have higher jump returns than large stocks, growth stocks liquid stocks and past winners. The jumps are then related to future market returns. Pukthuanthong & Roll (2015) investigate 82 different countries and their stock indices over more than four decades. They find that jumps are far less correlated than returns in terms of both magnitude and significance. Jumps are found to be generally uncorrelated and diversifiable.

Second, this chapter is related to the commodity literature, especially studies investigating the dynamics and jumps in commodity markets. Chatrath & Song (1999) find a negative relationship between the frequency of price jumps in the cash markets of agricultural commodities and both the number of speculative contracts and the number of speculators. Different commodities have different stochastic properties and hence should not be considered as a unified asset class, as shown by Brooks & Prokopczuk (2013). They find that both returns and jumps are correlated within segments/sectors while generally independent across segments. Further, returns between commodities and the stock market are found to be low as well. For the co-movement of jumps they find mixed results between commodities and equities. Diewald et al. (2015) study jumps in the prices of energy futures and find that tail events exhibit seasonality. Their proposed model with seasonal jump intensity outperforms models with a constant jump intensity. The authors focus on the parametric modeling of jumps and (co-)jump intensities while we are interested in the detection of jumps and their correlation across commodity markets. Lombardi & Ravazzolo (2016) examines the correlation between equity and commodity returns. Employing a time-varying Bayesian DCC model they conclude that the benefits from the inclusion of commodities into portfolios come alongside higher volatilities. Ohashi & Okimoto (2016) investigate the co-movement of commodity prices for the period from 1983 to 2011, and show evidence for an increasing trend.

Lastly, the inclusion of jumps for the price modeling of commodities has gained some attention in the recent literature. Evidence of jumps and fat tails in commodity returns are documented by Deaton & Laroque (1992) and Pindyck (2001), among others. The continuous finance models for commodities by Brennan & Schwartz (1985), Gibson & Schwartz (1990), Schwartz (1997) and Schwartz & Smith (2000) has been since extended to take into account jumps (Hilliard & Reis, 1999; Deng, 2000; Manoliu & Tompaidis, 2002; Casassus & Collin-Dufresne, 2005). A few papers have focused on the detection and role of jumps non-parametrically in the sense that jumps are directly extracted from returns. Sévi (2015) examines the jumps in crude oil high-frequency prices and uses the methodology of Tauchen & Zhou (2011). Chevallier & Ielpo (2014) investigate the role of jumps at a daily frequency for 20 commodities and rely on the Laurent et al. (2011) methodology. They find that jumps in commodity markets are more frequent than in other asset classes, while there is a high discrepancy within the commodity markets concerning number, size and sign of the jumps. Prokopczuk et al. (2016) provide evidence of jumps in four energy markets and show that the modeling of jumps does not provide any significant improvement of the forecast accuracy.

The rest of the chapter is organized as follows. Section 3.2 describes our data sets and the essential methodology for our empirical analysis. Section 3.3 analyzes the jumps in commodity markets and investigates the impact of jumps on the returns. Section 3.4 correlates jumps across markets and permits some conclusions on hedging. Section 3.5 concludes.

3.2 Data and Methodology

3.2.1 Methodology

For our jump detection, we follow Pukthuanthong & Roll (2015) and rely on the Barndorff-Nielsen & Shephard (2006) (BNS) jump test.[1] The following jump-diffusion process is assumed for the logarithmic price p_t:

$$dp_t = \mu_t dt + \sigma_t dW_t + \eta_t dN_t \tag{3.1}$$

where dp_t is the change in the log price, μ_t is the drift which is a locally bounded and predictable process of finite variance and dt is an increment of time. σ_t denotes the instantaneous volatility, which is a càdlàg process, while W_t is a standard Brownian motion. The jump size is described by the random variable η_t and N_t is a Poisson jump process with intensity λ_t. The term dN_t equals 1 if there is a jump during the increment dt, which occurs with probability $P(dN_t) = \lambda_t dt$, and 0 otherwise. The test relies on the decomposition of the quadratic variation QV_t of the process described

[1] Alternative jump tests are compared by the authors, which were developed by Jiang & Oomen (2008), Lee & Mykland (2008) and Jacod & Todorov (2009). Their simulations show that their proposed test is preferable compared to the others using different jump sizes and frequencies.

above into a continuous and discontinuous component, i.e.

$$QV_t = \underbrace{\int_{t-1}^{t} \sigma_s^2 ds}_{\text{continuous}} + \underbrace{\sum_{t-1 \leq \pi_i \leq t} \eta_{\pi_i}^2}_{\text{discontinuous}} \tag{3.2}$$

where π_i refer to the times of corresponding jumps (with $i = 1, 2, ..., N_t$). The quadratic variation and its components are estimated at a monthly frequency from daily return data where the return in month t on day k is defined as:

$$r_{t,k} = p_{t,k} - p_{t,k-1} \tag{3.3}$$

Typically, a month consists of $K_t = 21$ business days, i.e. $k = 1, ..., K_t$. The squared variation is defined as the average of the sum of squared daily returns:

$$S_t = \frac{1}{K_t} \sum_{k=1}^{K_t} r_{t,k}^2 \tag{3.4}$$

For high sampling frequencies, the squared variation is a consistent estimator for the quadratic variation. The continuous component of the quadratic variation is estimated by the bipower variation:

$$B_t = \frac{1}{K_t - 1} \sum_{k=2}^{K_t} |r_{t,k}||r_{t,k-1}| \tag{3.5}$$

The BNS jump statistic relies on the continuous component described by the difference of S_t and B_t, and is given by:

$$BNS_t = \frac{(\pi/2)B_t - S_t}{\sqrt{((\pi^2/4) + \pi - 5)(\pi/2)^2 Q_t}} \tag{3.6}$$

$$Q_t = \frac{1}{K_t - 3} \sum_{k=4}^{K_t} |r_{t,k}||r_{t,k-1}||r_{t,k-2}||r_{t,k-3}| \tag{3.7}$$

where Q_t describes the quarticity of the jump-diffusion process. For months with smooth returns the squared variation is relatively small while jumps are magnified by the square leading to smaller values of the test statistic. The null hypothesis of no jumps is asymptotically unit normal and typically rejected for small values of BNS_t.

For our empirical analysis we follow Pukthuanthong & Roll (2015) and compute the monthly time series of $BNS_{i,t}$ for every asset i under consideration. We then compute Pearson correlation coefficients for pairwise time series of $BNS_{i,t}$.

3.2.2 Data

We obtain commodity futures data set from the Commodity Research Bureau (CRB) for commodities traded at the four major North American Exchanges (NYMEX, NYBOT, CBOT and CME). We include the same commodities following Gorton & Rouwenhorst (2006) and Gorton et al. (2013). We exclude *Propane* and *Pork Bellies* since these were delisted in 2009 and 2011, respectively. We also exclude the commodity futures traded on the London Metals Exchange (LME), resulting into 29 commodities. We divide these into five sectors: Energy, metals, grains, meats and softs. An overview of the commodities is reported in Table 3.1 including the start of available observations and exchanges. The earliest date with available daily observation starts in 1959 and varies across commodities.

Unlike stock returns, commodity futures prices have expiration dates. For the computation of a continuous return series we follow Diewald et al. (2015) and differentiate between normal returns and roll-over returns. More specifically, we compute the futures returns as follows:

$$r_{t+1}^{normal} = log\frac{F_{t+1}^{(1)}}{F_t^{(1)}}, \qquad\qquad r_{t+1}^{roll} = log\frac{F_{t+1}^{(1)}}{F_t^{(2)}} \tag{3.8}$$

where r_{t+1}^{roll} denotes the futures return at time $t+1$ on a business day immediately after the expiration day and r_{t+1}^{normal} denotes the futures return

Table 3.1: Overview of Selected Commodities

This table presents an overview of the commodities we investigate in this chapter. We report the sector, the commodity, the symbol, the exchange and the period, for which data is available. Source: http://www.crbtrader.com/marketdata/. For Copper, we use *Old Copper (CU)* for the period until December 1988 and *High Grade Copper (HG)* starting in January 1989. For Hogs, we use *Live Hogs (LG)* for the period until December 1996 and *Lean Hogs (LH)* starting in February 1997.

Sector	Commodity	Symbol	Exchange	Sample Period
Energy	Heating Oil	HO	NYMEX/COMEX	1978/11 - 2015/12
	Crude Oil	CL	NYMEX/COMEX	1983/03 - 2015/12
	Unleaded Gas	HU	NYMEX/COMEX	1984/12 - 2006/12
				2013/09 - 2015/12
	Natural Gas	NG	NYMEX/COMEX	1990/04 - 2015/12
	Coal	QL	NYMEX/COMEX	2001/07 - 2015/12
	Blendstock Gas	RB	NYMEX/COMEX	1984/12 - 2015/12
Metals	Copper	HG	NYMEX/COMEX	1959/07 - 2015/12
	Silver	SI	NYMEX/COMEX	1963/06 - 2015/12
	Platinum	PL	NYMEX/COMEX	1968/03 - 2015/12
	Gold	GC	NYMEX/COMEX	1974/12 - 2015/12
	Palladium	PA	NYMEX/COMEX	1977/01 - 2015/12
Grains	Wheat	W-	CBOT	1959/07 - 2015/12
	Corn	C-	CBOT	1959/07 - 2015/12
	Soybeans	S-	CBOT	1959/07 - 2015/12
	Soybean Oil	BO	CBOT	1959/07 - 2015/12
	Soybean Meal	SM	CBOT	1959/07 - 2015/12
	Oats	O-	CBOT	1959/07 - 2015/12
	Rough Rice	RR	CBOT	1986/08 - 2015/12
Meats	Live Cattle	LC	CME	1964/11 - 2015/12
	Lean Hogs	LH	CME	1966/02 - 2015/12
	Feeder Cattle	FC	CME	1971/11 - 2015/12
	Milk	DE	CME	1996/01 - 2015/12
	Butter	BA	CME	2005/09 - 2015/12
Softs	Cotton	CT	ICE	1959/07 - 2015/12
	Cocao	CC	ICE	1959/07 - 2015/12
	Sugar	SB	ICE	1961/01 - 2015/12
	Orange Juice	JO	ICE	1967/02 - 2015/12
	Lumber	LB	CME	1969/01 - 2015/12
	Coffee	KC	ICE	1972/08 - 2015/12

on any other business day.

$F_t^{(1)}$ and $F_t^{(2)}$ refer to the first nearby contract and the second nearby

Table 3.2: Summary Statistics of Daily Returns

This table presents the summary statistics of daily returns (in percent). We report the number of daily observations N, time-series averages, medians, standard deviations, skewness and kurtosis of the returns and the maximum and the minimum returns.

		N	Mean	Median	Std. dev.	Skewness	Kurtosis	Maximum	Minimum
Energy	Heating Oil	9319	0.01	0.03	2.25	−1.42	19.48	13.99	−39.09
	Crude Oil	8221	0.00	0.03	2.38	−0.79	15.16	16.41	−40.05
	Unleaded Gas	6127	0.01	0.05	2.66	1.56	70.64	63.29	−37.12
	Natural Gas	6460	0.01	0.00	3.58	0.17	14.71	44.70	−46.75
	Coal	3630	0.00	0.00	1.52	−0.11	10.43	12.61	−11.08
	Blendstock Gas	7798	0.01	0.06	2.53	−0.56	18.42	35.33	−37.12
Metals	Copper	14159	0.01	0.02	1.79	−1.11	16.87	17.07	−33.53
	Silver	13167	0.02	0.00	1.93	−0.48	13.54	28.69	−24.57
	Platinum	11996	0.01	0.04	1.80	−2.30	95.25	31.55	−57.04
	Gold	10301	0.02	0.00	1.24	−0.11	6.95	9.74	−9.91
	Palladium	9787	0.02	0.04	2.08	−0.27	5.89	15.25	−18.87
Grains	Wheat	14232	0.01	0.00	1.74	−1.37	28.56	23.30	−31.41
	Corn	14232	0.01	0.00	1.58	−1.08	56.78	35.47	−36.49
	Soybeans	14232	0.01	0.05	1.57	−0.82	14.76	20.32	−23.41
	Soybean Oil	14229	0.01	0.00	1.73	−0.37	9.40	17.65	−21.76
	Soybean Meal	14230	0.01	0.00	1.95	−0.39	12.57	22.87	−20.55
	Oats	14235	0.01	0.00	2.02	−0.98	13.24	19.79	−25.46
	Rough Rice	7402	0.01	0.00	1.74	0.43	32.76	32.38	−24.45
Meats	Live Cattle	12873	0.01	0.04	1.18	−0.63	11.03	13.30	−10.38
	Lean Hogs	12558	0.00	0.04	2.10	−0.55	29.40	28.56	−27.79
	Feeder Cattle	11113	0.01	0.00	1.04	−0.22	9.76	10.30	−12.49
	Milk	5025	0.00	0.00	1.92	−2.99	97.51	27.93	−35.13
	Butter	2591	0.01	0.00	1.63	−3.81	107.92	17.32	−31.40
Softs	Cotton	14155	0.00	0.00	1.75	−7.25	302.12	16.69	−78.41
	Cocao	14120	0.01	0.00	1.95	−0.20	4.89	16.61	−21.78
	Sugar	13733	0.01	0.00	2.78	0.43	11.50	35.36	−29.42
	Orange Juice	12248	0.01	0.03	2.11	−0.09	35.33	39.67	−39.97
	Lumber	11658	0.01	0.00	2.11	0.55	9.80	19.71	−20.44
	Coffee	10856	0.01	0.00	2.37	−0.06	9.66	23.77	−24.42

contract at time t, respectively.[2] This method ensures that every return could have been realized, i.e. is based on one contract only. We rely on daily futures returns in order to estimate monthly BNS statistics.[3]

Table 3.2 shows the summary statistics of daily returns for the 29 commodities. The daily mean return lies between 0.00% and 0.01% for all commodities while skewness and kurtosis vary a lot across commodities.

[2]We also consider alternative rolling dates such as the end of the first or second month prior to the delivery month in order to avoid irregular price behavior (Szymanowska et al., 2014). This is important since we are interested in jumps in particular which may appear more frequently in illiquid close-to-maturity futures contracts. Our main conclusions on the hedging and safe haven performance of commodities for various asset classes remain unchanged. The corresponding tables are available upon request.

[3]The returns present excess returns or futures risk premiums (Gorton & Rouwenhorst, 2006; Gorton et al., 2013; Bhardwaj et al., 2015).

Most commodity returns are left skewed while kurtosis is as low as 4.89 for Cocao and as high as 302.12 for Cotton. The generally large kurtosis, and the large minimum and maximum indicate the presence of extreme events which we examine below.

3.3 Commodity Jumps

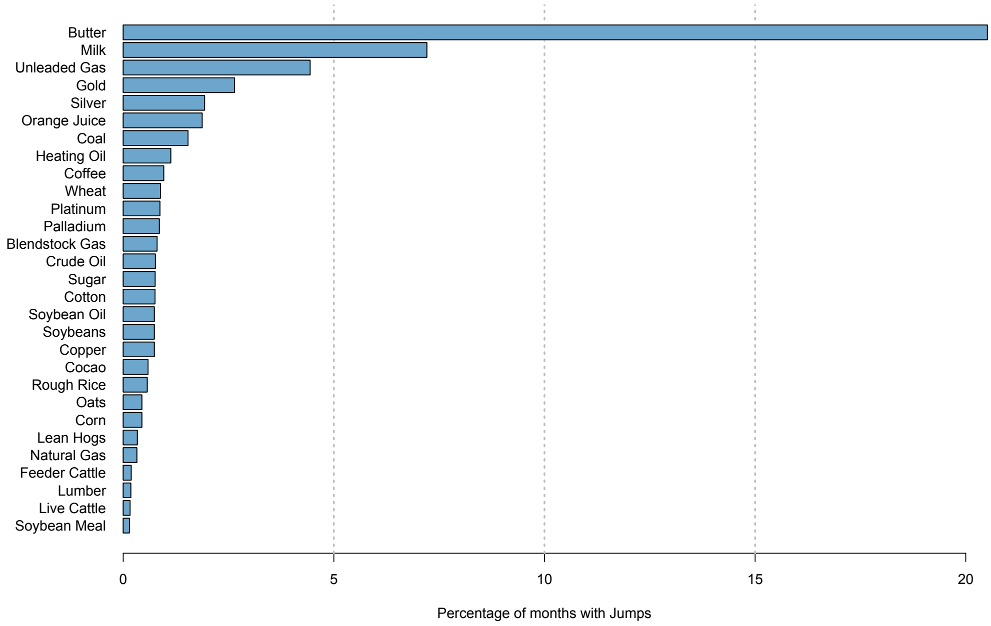
3.3.1 Individual Jumps

We first analyze jumps in individual commodity markets. Figure 3.1 illustrates the percentage of significant jumps (at the 5% significance level) for the individual commodities. The commodities butter and milk exhibit by far the most jumps, where 20.5% and 7.2% of the months include jumps. Both futures were introduced rather recently. The precious metals and infamous safe haven asset(s) gold (and silver) show relatively many jumps with a percentage of 2.6% (1.9%). Soybean meal and live cattle have the least jumps with a proportion of only 0.1% and 0.2%, respectively. These findings are also reflected in the summary statistics reported in Table 3.3, Panel A. Butter and milk exhibit the highest absolute average BNS statistic with values of –2.67 and –0.62, respectively. Unleaded gas, silver and gold have slightly lower averages with values between –0.36 and –0.34.

Panel B of Table 3.3 reports the summary statistics for the BNS jump statistic for all commodities in the first row, and different sectors in rows two to six. The mean varies between –0.71 and –0.08 which is much lower than the one computed by Pukthuanthong & Roll (2015) for international stock returns (–6.799). The meats sector shows the lowest average BNS statistic while the softs sector shows the largest. Again, the magnitude is much smaller than in international stock returns. For comparison, Pukthuanthong & Roll (2015) find that for 12 of the 82 investigated countries more than

Figure 3.1: Percentage of significant Jump Months

This figure presents the percentage of months that contain jumps which are significant at the 5% level. Jumps are measured by the test statistic of Barndorff-Nielsen & Shephard (2006) for the 29 commodities using daily observations within each calender month.



30% of the months include jumps. The skewness is negative for all sectors and the kurtosis shows remarkably large values for all sectors as well. While the average BNS statistics indicate that jumps are much less frequent than in international stock returns, the higher moments show evidence of extreme downside movements of the BNS statistic. This is supported by the maximum values, which are all lower than 0.50, and the minimum values dramatically lower than the 5% significance value of –1.96.[4]

[4]Our results somewhat differ from those of Chevallier & Ielpo (2014), who find that commodities generally show more jumps than the stock market. But the authors rely on a different jump test and consider the detection of realized jump days while we are interested in whether a certain month includes jumps following Pukthuanthong & Roll (2015). Also their investigation period is much shorter, including the period from 1995 until 2012, compared to our sample from 1959 until 2015.

Table 3.3: Summary Statistics of the Jump Measure

This table presents the summary statistics of the jumps measured by the test statistic of Barndorff-Nielsen & Shephard (2006). We report the number of monthly observations N, time-series averages, medians, standard deviations, the average t-statistic t, the mean absolute deviation MAD, the skewness and kurtosis and the maximum and minimum values for individual commodities across months in Panel A. Panel B reports the corresponding statistics for all commodities or sectors.

	N	Mean	Median	Std. dev.	t	MAD	Skewness	Kurtosis	Maximum	Minimum
Panel A: Individual Commodities										
Heating Oil	443.00	−0.13	−0.02	0.45	−6.03	0.28	−3.87	28.22	0.44	−4.43
Crude Oil	393.00	−0.15	−0.04	0.43	−6.98	0.30	−2.22	10.17	0.35	−2.71
Unleaded Gas	293.00	−0.34	−0.10	0.81	−7.09	0.48	−4.27	30.00	0.37	−6.84
Natural Gas	309.00	−0.14	−0.04	0.38	−6.38	0.28	−1.56	6.46	0.40	−2.13
Coal	130.00	−0.29	0.00	1.57	−2.08	0.53	−9.44	99.77	0.41	−16.96
Blendstock Gas	373.00	−0.12	−0.01	0.39	−6.07	0.28	−2.26	11.45	0.37	−2.72
Copper	678.00	−0.15	−0.03	0.45	−8.81	0.31	−2.46	12.36	0.42	−3.40
Silver	621.00	−0.36	−0.10	2.01	−4.47	0.55	−15.45	273.62	0.45	−39.53
Platinum	574.00	−0.15	−0.04	0.45	−7.76	0.30	−2.91	17.37	0.40	−3.97
Gold	492.00	−0.34	−0.18	0.66	−11.31	0.42	−4.31	38.07	0.33	−7.60
Palladium	467.00	−0.13	−0.01	0.47	−5.98	0.30	−3.63	27.45	0.40	−4.85
Wheat	678.00	−0.07	0.02	0.53	−3.63	0.26	−10.97	194.50	0.41	−10.07
Corn	678.00	−0.05	0.04	0.37	−3.61	0.26	−2.77	17.27	0.44	−3.43
Soybeans	678.00	−0.11	−0.00	0.42	−7.06	0.28	−3.26	22.35	0.40	−4.04
Soybean Oil	678.00	−0.09	0.00	0.38	−6.09	0.26	−2.56	12.96	0.46	−2.61
Soybean Meal	678.00	−0.11	−0.01	0.37	−7.84	0.26	−2.38	14.52	0.40	−3.48
Oats	678.00	−0.05	0.04	0.41	−3.46	0.25	−5.35	60.32	0.43	−5.63
Rough Rice	351.00	−0.06	0.03	0.36	−3.32	0.26	−2.20	10.75	0.41	−2.25
Live Cattle	613.00	−0.07	0.01	0.34	−5.02	0.25	−2.09	12.96	0.45	−3.04
Lean Hogs	598.00	−0.09	0.01	0.35	−6.04	0.26	−1.95	9.00	0.40	−2.35
Feeder Cattle	529.00	−0.09	0.00	0.38	−5.71	0.28	−1.74	7.31	0.45	−2.37
Milk	222.00	−0.62	−0.04	2.26	−4.11	0.99	−5.92	43.49	0.42	−20.01
Butter	78.00	−2.67	−0.14	8.72	−2.70	4.09	−5.07	31.51	0.39	−62.01
Cotton	662.00	−0.15	−0.05	0.46	−8.62	0.32	−2.33	11.25	0.40	−3.37
Cocao	678.00	−0.09	0.02	0.46	−5.24	0.28	−5.63	65.92	0.42	−6.59
Sugar	660.00	−0.13	−0.01	0.50	−6.86	0.31	−4.85	46.98	0.47	−6.35
Orange Juice	587.00	−0.26	−0.09	0.73	−8.49	0.40	−6.32	64.43	0.39	−9.53
Lumber	555.00	−0.04	0.09	1.08	−0.82	0.28	−20.63	463.63	0.43	−24.35
Coffee	520.00	−0.18	−0.05	0.48	−8.74	0.32	−2.99	18.88	0.40	−4.46
Panel B: Sectors										
All	513.59	−0.25	−0.02	0.92	−5.87	0.47	−4.86	54.07	0.47	−62.01
Energy	323.50	−0.19	−0.03	0.67	−5.77	0.36	−3.91	27.68	0.44	−16.96
Metals	566.40	−0.22	−0.07	0.81	−7.67	0.37	−5.74	70.52	0.45	−39.53
Grains	631.29	−0.08	0.02	0.41	−5.00	0.26	−4.20	44.38	0.46	−10.07
Meats	408.00	−0.71	−0.03	2.41	−4.71	1.17	−3.32	17.59	0.45	−62.01
Softs	628.40	−0.14	−0.01	0.65	−6.01	0.32	−7.95	127.44	0.47	−24.35

Table 3.4 compares the average return and jump size for the 29 commodities. We report the average return of positive and negative jump returns and the proportion to the total observations per commodity.

The table shows that jumps are rare and extreme events. Butter futures experience most jumps where 0.62% of the daily returns are jumps. Also, both positive and negative jumps have on average much higher magnitudes than the raw returns. Across all commodities (positive and negative) jumps

Table 3.4: Summary Statistics of Daily Returns and Jumps

This table presents the summary statistics of daily returns. We report the number of daily observations N, the average daily return Mean (in percent), the average positive (negative) jump returns *Pos. Jumps* (*Neg. Jumps*) and their proportion (in percent).

		N	Mean	Pos. Jumps	$N_{Pos.}/N$	Neg. Jumps	$N_{Neg.}/N$
Energy	Heating Oil	9319	0.03			−0.06	0.05
	Crude Oil	8221	0.01			−0.09	0.04
	Unleaded Gas	6127	0.02	0.09	0.11	−0.11	0.10
	Natural Gas	6460	−0.07	0.09	0.02		
	Coal	3630	−0.02	0.04	0.06		
	Blendstock Gas	7798	0.05	0.06	0.03	−0.07	0.01
Metals	Copper	14159	0.03	0.05	0.03	−0.03	0.01
	Silver	13167	0.01	0.05	0.05	−0.04	0.05
	Platinum	11996	0.01	0.08	0.02	−0.04	0.03
	Gold	10301	0.01	0.03	0.06	−0.04	0.08
	Palladium	9787	0.02	0.07	0.04		
Grains	Wheat	14232	−0.01	0.14	0.01	−0.05	0.03
	Corn	14232	−0.01			−0.06	0.02
	Soybeans	14232	0.02	0.04	0.03	−0.04	0.01
	Soybean Oil	14229	0.02	0.08	0.01	−0.05	0.03
	Soybean Meal	14230	0.05	0.04	0.01	−0.05	0.01
	Oats	14235	0.01	0.09	0.01	−0.14	0.01
	Rough Rice	7402	−0.01	0.07	0.04		
Meats	Live Cattle	12873	0.04	0.04	0.01		
	Lean Hogs	12552	0.04	0.27	0.01	−0.16	0.02
	Feeder Cattle	11113	0.02			−0.02	0.01
	Milk	5024	0.02	0.03	0.24	−0.05	0.14
	Butter	2591	−0.02	0.06	0.39	−0.04	0.23
Softs	Cotton	14155	−0.01	0.02	0.01	−0.05	0.03
	Cocao	14120	0.00	0.09	0.01	−0.10	0.02
	Sugar	13733	−0.04	0.06	0.01	−0.14	0.03
	Orange Juice	12248	0.02	0.17	0.07	−0.06	0.02
	Lumber	11658	−0.04	0.15	0.01	−0.94	0.01
	Coffee	10856	0.00	0.05	0.03	−0.08	0.03

are more than 1000 times higher than the raw returns.

3.3.2 Jumps and Liquidity

Jiang et al. (2011) show that liquidity shocks and jumps are related in the U.S. Treasury-bond market. They find that liquidity shocks have predictive power for jumps while macroeconomic announcements have limited predictive power. Jiang & Yao (2013) show that illiquid stocks exhibit higher jump returns than liquid stocks and that jumps are one main driver of the cross-sectional return predictability. Motivated by the findings in the recent literature which shows a clear relationship between jumps and liquidity in the stock and bond markets, we investigate whether this is true for the commodity markets as well. Following Amihud (2002), we measure the illiquidity of a commodity as the average ratio of absolute returns and dollar volume:

$$Illiquidity_t = \frac{|r_t|}{volume_t} \tag{3.9}$$

Marshall et al. (2012) compare various measures of liquidity based on both high-frequency and low-frequency data for 24 commodities and show that the Amihud measure has the best performance in the sense that it shows the largest correlation with liquidity benchmarks. We compute the monthly illiquidity as the average over that month following Marshall et al. (2012) and Marshall et al. (2013).

For each commodity we obtain the daily dollar volume, $volume_t$, of the closest to maturity contract by multiplying the volume with the price, which are both obtained from CRB. We conduct our analysis for the period from January 2001 until December 2015. Our choice of the subsample is restricted by the volume data availability from CRB. We test the relationship between jumps and liquidity by estimating the following cross-sectional regression in each month:

$$BNS_{i,t} = \alpha_t + \beta_t Illiquidity_{i,t} + \epsilon_t \tag{3.10}$$

where α_t and β_t are the intercept and slope coefficients in month t and ϵ_t is the error term. The time-series average of the coefficients and the t-statistics in square brackets are estimated as follows:

$$\bar{\alpha}_t = \underset{[-16.2991]}{-0.1995}, \qquad \bar{\beta}_t = \underset{[-1.7824]}{-0.0268} \tag{3.11}$$

Hence, there is some evidence for a negative relationship between the illiquidity and the jumps of a commodity (statistically significant at the 10%

level). Higher illiquidity leads to a lower BNS jump test statistic, i.e. a higher jump intensity. We therefore provide evidence that the negative relationship between illiquidity and jumps documented by Jiang et al. (2011) and Jiang & Yao (2013) for the stock and bond market is also present in commodity futures markets.

3.3.3 Jump Correlations

The results so far show that jumps are more relevant in certain commodity sectors than others, even though being in general less frequent than in equity markets. We next investigate the correlation of jumps across commodities. For each of the 406 commodity pairs, we calculate both individual BNS statistics for each month and correlate them across all months. Table 3.5 reports the results. The mean correlation coefficient of 0.03 for the jumps across all pairs is relatively low and much lower than the mean correlation of raw returns as reported in the second row. Further, only 11.82% of the commodity pairs show significantly correlated jumps compared to the 50.49% of significantly correlated returns. One should note that since we define co-jumps as jumps occurring in the same months, our results are an upper limit for the question whether jumps occur on the same day.

The relatively weak co-movement of jumps across commodities is also shown by the most influential calender months. A month is defined as influential for which the de-meaned product of returns is the absolute largest over all available months. Table 3.6 reports the percentage of commodity pairs for which a certain month was the most influential in terms of jumps (Panel A) and returns (Panel B).

For the returns, there are three grossly dominant months (July 1973, March 1980 and October 2008), where the Financial Crisis in October 2008 is the most influential (22.22% of the pairs). For the jumps, no month is

Table 3.5: Correlation of Jump Measure and Returns across Commodities

This table presents the summary statistics of the correlation of jumps measured by the test statistic of Barndorff-Nielsen & Shephard (2006) in the first row and of returns in the second row. There are 29 commodities and 406 pairs. The statistics below are computed across all 406 pairs. We report time-series averages, medians, standard deviations, the average t-statistic t, the average mean absolute deviation MAD, the skewness and kurtosis and the maximum and minimum values across all commodities and months. The last column reports the percentage of all correlation coefficients for which the t-statistic is higher than 2.0.

	Mean	Median	Std. dev.	t	MAD	Skewness	Kurtosis	Maximum	Minimum	$t > 2$
Jumps	0.03	0.02	0.09	0.66	0.06	2.91	15.38	0.76	−0.20	11.82%
Returns	0.13	0.10	0.16	3.13	0.11	1.97	5.16	0.89	−0.19	50.49%

even influential for 10% of the pairs. Further, the most influential months for returns do not appear in the list of influential months for jumps. Figure 3.2 provides a graphical illustration of the influential months. The large peaks for both jumps and returns occur at different points in time. So far, the results suggest that jumps not only happen infrequently but also at different times across commodity markets. Table 3.7 presents exceptions, which are the commodity pairs that show highly correlated jump months.

We list all pairs for which the t-statistic for the BNS statistic is at least 3.0. As immediately evident, the energy sector shows high co-movement of jumps, filling five of the first six rows. Other pairs with significant jump correlations are inter alia soybean commodities (soybeans, soybean meal and soybean oil) and precious metals (gold, platinum and silver). This motivates us to repeat the previous exercise for individual sectors since related commodities (commodities of the same sector) seem to show higher jump correlations than unrelated commodities.

Table 3.8 reports the average correlation coefficient of two sectors and the related percentage of significant coefficients in square brackets below.

The correlation of jumps within certain individual sectors and their

Table 3.6: Influential Months for Correlation of Returns and Jumps

This table presents the most influential months for the jump and return correlations in Panel A and B, respectively. The jumps are measured by the test statistic of Barndorff-Nielsen & Shephard (2006). The single calender month which contributes the most to the correlation of jump measures between a pair of commodities is defined as "influential". We only include months with at least 100 available pairs and which are most influential to at least 2% of the observations.

Panel A: Jumps

Year–Month	Most influential %
1969–11	2.50
1982–04	8.10
1983–02	2.38
1984–12	3.99
1991–06	2.15
1994–04	4.31
1996–03	4.27
1998–10	2.56
1999–12	2.85
2000–01	2.85
2000–04	2.28
2001–09	2.12
2003–09	2.85
2005–02	2.85
2012–05	4.50
2014–06	3.45
2014–11	4.68
2015–07	7.88

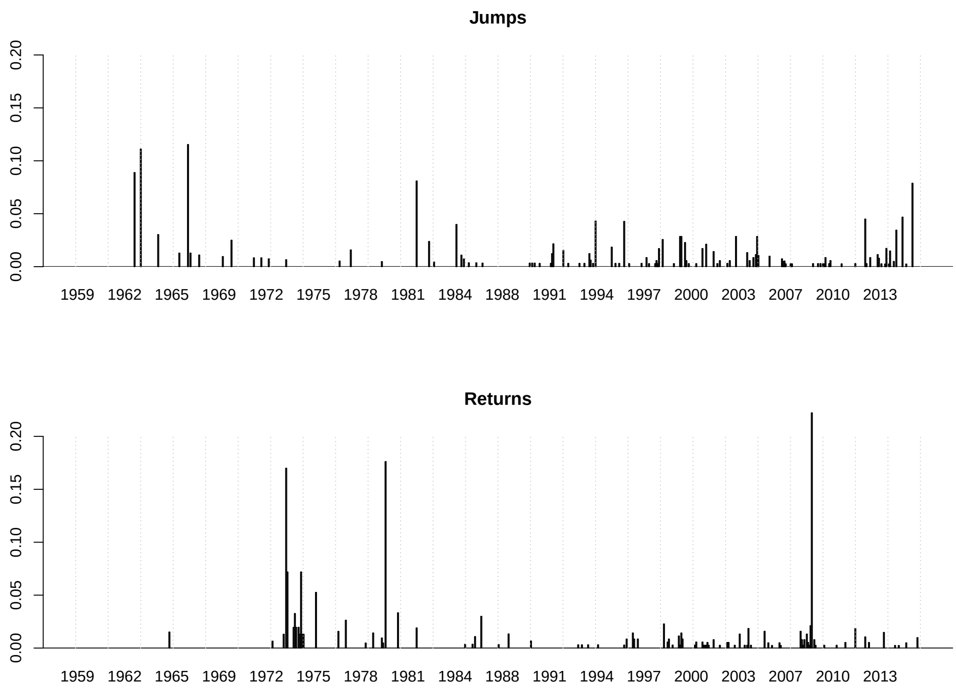
Panel B: Returns

Year–Month	Most influential %
1973–07	16.99
1973–08	7.19
1974–02	3.27
1974–07	7.19
1975–07	5.26
1980–03	17.62
1981–01	3.33
2008–10	22.22

statistical significance are much higher than the average across all commodities (0.03). The energy, metals and grains sector show relatively high correlations between 0.11 and 0.19 with 33.33% to remarkably 53.33% of the pairs showing significant correlations while meats and softs commodities show no jump co-movements within the sectors. Intuitively, the correlation of jumps across sectors are rather low, with values between –0.01 and 0.03. Return correlations are again much higher for both pairs

Figure 3.2: Influential Months

This figure presents the most influential months on the horizontal axis and the percentage of commodity pairs for which it is most influential on the vertical axis. We report the most influential months for jumps (top panel) and returns (bottom panel).



within and across sectors. All pairs within the metals and grains sector show significant return correlations with means of 0.62 and 0.44, respectively. The highest return correlations are found between the energy and metals sectors.

Overall, diversification of extreme movements in a commodity-based portfolio is thus most effective when using commodities of the meats and softs sector or commodities of different sectors, while diversification is less effective within energy, metals or grains sectors.

Table 3.7: Pairs of Commodities with Largest Jump Correlation

This table presents the commodity pairs with the highest jump correlation. Jumps are measured by the test statistic of Barndorff-Nielsen & Shephard (2006). The pairs of commodities listed here exhibit jump measure correlations with t-statistics higher than 3.0. The last column reports the related correlation coefficient.

		t-statistic	Correlation
Heating Oil	Coal	13.16	0.76
Heating Oil	Crude Oil	13.10	0.55
Soybeans	Soybean Meal	12.65	0.44
Unleaded Gas	Blendstock Gas	11.79	0.57
Crude Oil	Blendstock Gas	7.80	0.38
Heating Oil	Blendstock Gas	6.96	0.34
Soybeans	Soybean Oil	6.93	0.26
Crude Oil	Coal	6.83	0.52
Silver	Gold	6.56	0.28
Crude Oil	Unleaded Gas	5.64	0.31
Soybean Oil	Soybean Meal	5.28	0.20
Live Cattle	Feeder Cattle	4.78	0.20
Corn	Soybeans	3.99	0.15
Heating Oil	Unleaded Gas	3.84	0.22
Natural Gas	Copper	3.68	0.21
Soybeans	Feeder Cattle	3.64	0.16
Heating Oil	Cotton	3.55	0.17
Platinum	Gold	3.55	0.16
Wheat	Soybean Meal	3.54	0.13
Soybean Meal	Feeder Cattle	3.42	0.15

3.3.4 Impact of Jumps on Returns

Since the correlation of raw returns is found to be high while the correlation of jumps shows low to no correlation, returns without jumps should show even larger correlations. We therefore purge the raw returns of jumps and investigate those. Similar to the procedure for detecting jumps, we first compute the BNS statistic for each commodity and month. If there is no significant jump at the 10% significance level the monthly return is calculated from the month of daily returns. If there is a significant jump

Table 3.8: Correlation of Jump Measure across Commodity Sectors

This table presents the summary statistics of the correlation of jumps measured by the test statistic of Barndorff-Nielsen & Shephard (2006) in Panel A, of raw returns in Panel B and of returns purged by jumps in Panel C. There are 29 commodities divided into 5 sectors. The statistics below are computed within and across sectors. We report the average time-series correlation coefficient and the percentage of all correlation coefficients for which the t-statistic is higher than 2.0 in square brackets below.

	Energy	Metals	Grains	Meats	Softs
Panel A: Jumps					
Energy	0.19	0.00	0.02	−0.01	−0.01
	[40.00%]	[10.00%]	[10.00%]	[0.00%]	[5.00%]
Metals		0.12	0.01	0.01	0.01
		[33.33%]	[0.00%]	[0.00%]	[0.00%]
Grains			0.11	0.02	0.01
			[53.33%]	[16.67%]	[4.17%]
Meats				0.11	0.03
				[0.00%]	[0.00%]
Softs					0.02
					[0.00%]
Panel B: Returns					
Energy	0.43	0.14	0.08	−0.00	0.05
	[90.00%]	[60.00%]	[30.00%]	[10.00%]	[20.00%]
Metals		0.62	0.13	0.00	0.12
		[100.00%]	[83.33%]	[18.75%]	[70.00%]
Grains			0.44	0.04	0.12
			[100.00%]	[20.83%]	[66.67%]
Meats				0.13	0.03
				[33.33%]	[5.00%]
Softs					0.08
					[50.00%]
Panel C: Purged Returns					
Energy	0.43	0.15	0.08	0.00	0.05
	[90.00%]	[65.00%]	[33.33%]	[5.00%]	[20.00%]
Metals		0.62	0.13	−0.01	0.12
		[100.00%]	[79.17%]	[18.75%]	[70.00%]
Grains			0.44	0.04	0.11
			[100.00%]	[20.83%]	[66.67%]
Meats				0.16	0.03
				[33.33%]	[10.00%]
Softs					0.08
					[50.00%]

Table 3.9: Correlation of Returns Purged of Jumps across Commodities

This table presents the summary statistics of the correlation of jump-purged returns. Jumps are measured by the test statistic of Barndorff-Nielsen & Shephard (2006). There are 29 commodities and 406 pairs. The statistics below are computed across all 406 pairs. We report time-series averages, standard deviations, medians, the average t-statistic t, the average mean absolute deviation MAD, the skewness and kurtosis and the maximum and minimum values across all commodities and months. The last column reports the percentage of all correlation coefficients for which the t-statistic is higher than 2.0.

	Mean	Median	Std. dev.	t	MAD	Skewness	Kurtosis	Maximum	Minimum	$t > 2$
Jumps	0.03	0.02	0.09	0.66	0.06	2.91	15.38	0.76	−0.20	11.82%
Returns	0.13	0.10	0.16	3.13	0.11	1.97	5.16	0.89	−0.19	50.49%
Purged Returns	0.13	0.10	0.16	3.15	0.11	1.92	4.99	0.89	−0.20	50.25%

we repeatedly remove the highest absolute return and recalculate the BNS statistic until it is no longer significant. The remaining returns are then used to calculate the monthly return.

Table 3.9 reports the summary statistics of the jump-purged returns in comparison with raw returns and jumps. The difference of average correlations between raw and purged returns is essentially zero while the percentage of significant correlation coefficients barely decreases from 50.49% to 50.25%. The same is true when looking at correlations within and across market segments. Panel C in Table 3.8 shows the average time-series correlation coefficient and the percentage of significant correlations for purged returns. The results are very similar to the ones for the returns (including jumps). This supports our previous findings that jumps happen rarely and not at the same time across commodities and thus barely influence the return correlations.

3.4 Jump Correlations across Asset Classes

In Section 3.3 we examined the correlation of jumps across various commodities and commodity sectors. In the next step, we investigate the relationship to further markets, which can give an insight into diversifying jumps across markets. This is particularly interesting since some commodities are rumored to be good hedges/safe havens for stock, exchange rate or bond markets. Our analysis allows us to name commodities which are actually good and bad hedges with respect to large price fluctuations. We consider the overall commodity market proxied by the Goldman Sachs Commodity Index, the stock market proxied by the S&P 500 E-Mini futures and S&P 500 futures and the U.S. exchange rate market proxied by the U.S. Dollar Index futures. Further, we investigate the bond market and include futures on Treasury notes of various maturities. The results are reported in Table 3.10 in Panel A, B, C and D for the commodity, stock and exchange markets, respectively. Results for the bonds' futures are reported in Table 3.11. The relevant CRB symbols are *GI, ES, SP*, *DX*, *TU, FV* and *TY*. All contracts are traded on CME except for the Dollar Index futures, which is traded on the Intercontinental Exchange (ICE). All futures data are obtained from CRB. We differentiate between strong and weak hedges following Baur & McDermott (2010). If one asset is uncorrelated with another asset, we refer to it as a weak hedge. If it is negatively correlated with another asset, we refer to it as a strong hedge. We are interested in both the "normal" and jump hedge performance of the commodities and base our conclusions on return and jump correlations, respectively.

3.4.1 Commodities and The Goldman Sachs Index

The Goldman Sachs Commodity Index (GSCI) was introduced in 1991 and forms a weighted average of 24 different commodity futures. Nearly all of the constituents are covered by the 29 futures considered in our analysis where crude oil and heating oil have the highest weights of 23.04% and 20.43%, respectively.[5] Hence, it is intuitive that the energy sector including crude oil and heating oil has the highest correlations with the GSCI. Panel A of Table 3.10 shows that this is true for both jumps and returns where the correlations vary between 0.02 and 0.54 and 0.38 and 0.88, respectively. The coefficient is statistically significant for 5 out of the 6 energy commodities when looking at jumps and all when looking at returns. The return correlation of metals and the GSCI are lower but still considerably high, varying between 0.28 and 0.45 and being all statistically significant. The return correlation of meats commodities is the lowest. Turning next to the jump correlations, only the precious metals (and energy commodities) show (statistically significant) correlation coefficients higher than 0.10. The remaining commodities show low and insignificant jump correlation. Jumps for many meats and softs commodities are even negatively correlated to GSCI jumps.

All in all, the returns of most commodities show high and significant return correlations while only energy and precious metals show moderate to high jump correlations with the index.

3.4.2 Commodities and the Stock Market

Commodities have been the target for diversifying stock portfolios since they are seemingly uncorrelated with the stock market (Gorton & Rouwenhorst, 2006). But several studies provide evidence of increasing return correlation,

[5] Source Thomson Reuters Tick History (updated January 2016).

Table 3.10: Jump Correlation with Other Asset Classes

This table presents the jump and returns correlation of commodities with selected indices. We include the Goldman Sachs Commodity Index (*Goldman*), S&P 500 E-mini futures (*E-Mini*), S&P 500 futures (*S&P*) and Dollar futures (*Dollar*) in Panel A, B, C and D, respectively. Jumps are measured by the test statistic of Barndorff-Nielsen & Shephard (2006). T-statistics are reported in square brackets. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

		Panel A: Goldman				*Panel B: E-Mini*				*Panel C: S&P*				*Panel D: Dollar*			
		Jumps		*Returns*		*Jumps*		*Returns*		*Jumps*		*Returns*		*Jumps*		*Returns*	
Energy	Heating Oil	0.40***	[7.26]	0.87***	[29.88]	−0.11	[−1.58]	0.18***	[2.72]	−0.04	[−0.86]	0.08	[1.56]	0.00	[0.05]	−0.19***	[−3.61]
	Crude Oil	0.54***	[10.75]	0.88***	[30.76]	−0.01	[−0.21]	0.19***	[2.81]	−0.01	[−0.25]	0.06	[1.17]	0.02	[0.36]	−0.18***	[−3.46]
	Unleaded Gas	0.30***	[4.43]	0.66***	[12.53]	−0.06	[−0.69]	−0.01	[−0.13]	−0.02	[−0.27]	−0.05	[−0.79]	−0.06	[−1.01]	−0.03	[−0.56]
	Natural Gas	0.02	[0.39]	0.50***	[9.65]	0.04	[0.55]	−0.01	[−0.17]	0.03	[0.44]	0.01	[0.26]	−0.02	[−0.28]	−0.17***	[−2.93]
	Coal	0.37***	[4.49]	0.38***	[5.34]	0.00	[−0.04]	0.10	[1.38]	0.00	[−0.04]	0.10	[1.36]	−0.08	[−0.88]	−0.21***	[−2.83]
	Blendstock Gas	0.39***	[7.14]	0.81***	[23.15]	−0.11	[−1.56]	0.24***	[3.58]	−0.04	[−0.69]	0.12**	[2.34]	0.01	[0.10]	−0.15***	[−2.87]
Metals	Copper	−0.02	[−0.33]	0.45***	[8.48]	−0.08	[−1.19]	0.44***	[7.28]	−0.03	[−0.69]	0.26***	[5.31]	−0.05	[−0.99]	−0.27***	[−5.37]
	Silver	0.10	[1.61]	0.28***	[4.94]	−0.05	[−0.71]	0.23***	[3.48]	−0.04	[−0.82]	0.15***	[3.04]	0.00	[−0.01]	−0.21***	[−4.04]
	Platinum	0.13**	[2.18]	0.40***	[7.34]	−0.03	[−0.38]	0.24***	[3.63]	0.00	[0.07]	0.20***	[4.17]	0.00	[0.07]	−0.29***	[−5.80]
	Gold	0.26***	[4.45]	0.28***	[4.94]	0.02	[0.33]	0.06	[0.84]	0.00	[−0.03]	−0.02	[−0.47]	0.06	[1.06]	−0.34***	[−6.93]
	Palladium	0.12**	[2.01]	0.30***	[5.22]	0.00	[−0.01]	0.23***	[3.51]	−0.01	[−0.23]	0.21***	[4.29]	0.02	[0.46]	−0.12**	[−2.26]
Grains	Wheat	0.01	[0.13]	0.29***	[5.12]	0.02	[0.27]	0.20***	[3.06]	0.04	[0.83]	0.15***	[3.13]	−0.08	[−1.44]	−0.19***	[−3.59]
	Corn	−0.06	[−1.02]	0.31***	[5.53]	0.01	[0.21]	0.26***	[3.99]	0.01	[0.22]	0.16***	[3.27]	−0.04	[−0.84]	−0.11**	[−2.13]
	Soybeans	0.03	[0.51]	0.27***	[4.68]	0.02	[0.33]	0.25***	[3.83]	0.03	[0.62]	0.13***	[2.63]	0.06	[1.14]	−0.12**	[−2.35]
	Soybean Oil	0.09	[1.58]	0.28***	[4.87]	−0.01	[−0.09]	0.29***	[4.55]	0.01	[0.19]	0.15***	[2.98]	−0.01	[−0.28]	−0.13***	[−2.58]
	Soybean Meal	0.06	[1.05]	0.18***	[3.09]	−0.02	[−0.33]	0.19***	[2.88]	0.01	[0.24]	0.09*	[1.80]	0.02	[0.37]	−0.10*	[−1.87]
	Oats	0.01	[0.14]	0.27***	[4.71]	−0.01	[−0.19]	0.11	[1.60]	−0.01	[−0.30]	0.10*	[1.93]	−0.07	[−1.32]	−0.08	[−1.50]
	Rough Rice	−0.01	[−0.18]	0.08	[1.28]	0.00	[0.04]	0.18***	[2.75]	0.00	[0.03]	0.12**	[2.25]	0.02	[0.37]	−0.11**	[−1.99]
Meats	Live Cattle	0.12*	[1.94]	0.11*	[1.80]	−0.02	[−0.36]	0.09	[1.32]	−0.05	[−0.96]	0.10**	[1.99]	0.08	[1.52]	−0.02	[−0.30]
	Lean Hogs	−0.01	[−0.22]	0.11*	[1.93]	0.16**	[2.44]	−0.04	[−0.59]	0.10**	[2.02]	0.01	[0.27]	−0.03	[−0.54]	−0.04	[−0.68]
	Feeder Cattle	−0.04	[−0.63]	0.08	[1.32]	−0.10	[−1.45]	0.05	[0.72]	−0.03	[−0.58]	0.07	[1.38]	0.00	[0.04]	−0.01	[−0.28]
	Milk	−0.06	[−0.89]	−0.04	[−0.63]	−0.01	[−0.16]	0.06	[0.95]	−0.02	[−0.26]	0.01	[0.20]	0.16**	[2.43]	−0.03	[−0.46]
	Butter	−0.13	[−1.14]	0.04	[0.39]	−0.05	[−0.41]	0.11	[1.27]	−0.05	[−0.41]	0.12	[1.28]	0.08	[0.70]	−0.02	[−0.18]
Softs	Cotton	0.03	[0.57]	0.23***	[3.98]	−0.02	[−0.22]	0.25***	[3.83]	−0.01	[−0.10]	0.19***	[3.92]	−0.02	[−0.38]	−0.17***	[−3.32]
	Cocao	−0.07	[−1.23]	0.16***	[2.72]	0.02	[0.27]	0.07	[1.00]	0.04	[0.79]	0.05	[0.99]	0.00	[0.05]	−0.22***	[−4.22]
	Sugar	0.09	[1.50]	0.16***	[2.77]	0.01	[0.13]	0.09	[1.38]	0.00	[0.02]	0.04	[0.86]	−0.03	[−0.52]	−0.11**	[−2.12]
	Orange Juice	−0.01	[−0.13]	0.12**	[2.10]	0.09	[1.36]	0.21***	[3.22]	0.06	[1.17]	0.12**	[2.44]	0.00	[0.08]	−0.04	[−0.83]
	Lumber	−0.08	[−1.38]	0.10	[1.62]	−0.07	[−0.99]	0.27***	[4.09]	−0.07	[−1.49]	0.16***	[3.28]	−0.04	[−0.70]	0.01	[0.13]
	Coffee	−0.03	[−0.45]	0.11*	[1.86]	0.05	[0.78]	0.20***	[3.03]	0.05	[1.04]	0.07	[1.48]	0.09*	[1.72]	−0.02	[−0.40]

especially after the financialization of commodity markets (Tang & Xiong, 2012; Ohashi & Okimoto, 2016). Further, investors seek hedging or safe haven assets, especially since recent years have been marked by times of financial distress like the burst of the dot-com bubble, the Lehman default, the great recession followed by the European debt crisis and the Chinese stock market crash.

We look at the jump correlations between commodity and stock markets which indicate the hedging properties in times of market tumult. The S&P 500 index is the natural benchmark/proxy for the stock market but we also include the S&P 500 E-Mini futures since the liquidity is much higher for the latter: the results for both are qualitatively similar so we focus our discussion on the latter. Intuitively, both return and jump correlations of commodities with the stock market are significantly lower than with the GSCI. Only Lean Hogs show a positive (0.16) and statistically significant jump correlation with the S&P while the jumps of remaining commodities are uncorrelated or even negatively correlated (but statistically insignificant). Energy, metals and meats commodities in particular show negative jump correlations.

For the returns, the results are mixed. Lean Hogs show the lowest return correlation with the S&P with a coefficient of –0.04. For other commodities the coefficient is as high as 0.44 (Copper). Also, more than half of the commodities show a positive and statistically significant correlation with the returns of the stock market. The findings in the literature are mixed. Silvennoinen & Thorp (2013) argue that the correlation was rather low starting in the 1990s and increased significantly after major crises while Chong & Miffre (2010) find decreasing co-movement over time.

Even though the returns of commodities somewhat co-move with the stock market returns, jumps of both markets are generally uncorrelated or negatively correlated, which is good news for investors. Extreme commodity and stock market movements can hence be diversified by adding (weak) hedge assets from the market. This is consistent with Silvennoinen & Thorp (2013), who investigate 24 individual commodities and show that commodity–stock correlations are low during market turbulences.

3.4.3 Commodities and Dollar Investment

Next, we consider the currency market in the U.S. relying on the U.S. Dollar Index futures. The U.S. Dollar Index was introduced in 1973 and represents the value of U.S. Dollars by taking into account the exchange rate with six other currencies: Euro, Japanese yen, British pound, Canadian dollar, Swedish krona and Swiss franc.[6] Commodities and the dollar seem to be natural hedges for each other since they are negatively correlated. This makes sense because the Dollar price is the benchmark for most commodities and commodities are traded globally. Akram (2009) finds that lower commodity prices are followed by a fall of the Dollar value. Reboredo et al. (2014) focus their study on the commodity crude oil but also find a negative dependence to the Dollar.

Panel D in Table 3.10 confirms this intuition, which is consistent with the literature and shows that 28 of the 29 commodities possess negative return correlations with the U.S. Dollar Index from which 19 are statistically significant. The coefficients vary from –0.34 for Gold to 0.01 for Lumber. Jumps, on the other hand, show relatively low and mixed correlation coefficients. About half show negative correlations while none of the coefficients is higher than 0.09 in absolute terms and only two are statistically significant (Coffee and Milk). Commodities are overall strong hedges for the returns of the U.S. Dollar Index and at the same time weak hedges for jumps as well.

[6] For the time before 1999, the Belgian, Dutch, French, German and Italian currencies were used instead of the Euro.

3.4.4 Commodities and Bonds

Lastly, we investigate the relationship with fixed income securities. More specifically, we consider futures on Treasury notes with two, five and ten years' maturity. The results presented in Table 3.11 are generally similar for all Treasury notes. We find that the returns of most commodities are either uncorrelated or negatively correlated with Treasury note returns of all maturities. There are two exceptions: natural gas and gold returns are positively correlated with the returns of the Treasury notes which is statistically significant. Six, eight and seven of the commodities are strong hedges for the two, five and ten years' Treasury notes, respectively, while the remaining ones are weak hedges.

The results for the jump correlations are mixed. While five and two of the commodities show positive and statistically significant jump correlation with the two and five years' Treasury notes, all commodities are either weak or strong jump hedges for the ten years' Treasury note.

Hence, most commodities are suitable return and jump hedges for Treasury notes even though there are exceptions.

Our results concerning the return correlations are in accordance with the literature. Gorton & Rouwenhorst (2006) show that commodity futures returns and bond returns are generally negatively correlated. One of the exceptions we find is gold. Baur & Lucey (2010) show that gold serves as a safe haven for bonds in the U.S. but not as a hedge.

3.5 Conclusion

To have a diversified cross-market portfolio allocation, it is important to know to which extent the jumps of commodities, stocks and other assets are correlated. If they are uncorrelated across markets one can protect oneself

Table 3.11: Jump Correlation with Bond Futures

This table presents the jump and returns correlation of commodities with selected bond futures. We include the 2 (TU), 5 (FV) and 10 (TY) years treasury notes in Panel A, B, and C, respectively. Jumps are measured by the test statistic of Barndorff-Nielsen & Shephard (2006). T-statistics are reported in square brackets. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

		Panel A: 2 Years' T-Note				*Panel B: 5 Years' T-Note*				*Panel C: 10 Years' T-Note*			
		Jumps		*Returns*		*Jumps*		*Returns*		*Jumps*		*Returns*	
Energy	Heating Oil	0.01	[0.22]	−0.10*	[−1.73]	−0.05	[−0.93]	−0.11**	[−2.05]	−0.06	[−1.22]	−0.11**	[−2.23]
	Crude Oil	0.13**	[2.26]	−0.09	[−1.48]	0.04	[0.74]	−0.13**	[−2.37]	−0.05	[−1.01]	−0.17***	[−3.46]
	Unleaded Gas	0.46***	[7.78]	−0.04	[−0.63]	0.07	[1.03]	−0.08	[−1.20]	−0.00	[−0.04]	−0.13**	[−2.16]
	Natural Gas	−0.05	[−0.83]	0.12**	[2.16]	−0.04	[−0.77]	0.14**	[2.46]	−0.01	[−0.14]	0.10*	[1.84]
	Coal	−0.07	[−0.75]	0.04	[0.49]	−0.03	[−0.29]	−0.00	[−0.01]	−0.01	[−0.09]	0.02	[0.22]
	Blendstock Gas	0.09*	[1.65]	−0.08	[−1.45]	−0.01	[−0.11]	−0.12**	[−2.27]	0.01	[0.13]	−0.15***	[−2.95]
Metals	Copper	−0.02	[−0.37]	−0.12**	[−2.11]	0.07	[1.26]	−0.13**	[−2.45]	0.01	[0.23]	−0.09*	[−1.90]
	Silver	−0.06	[−1.09]	−0.02	[−0.37]	0.00	[0.09]	−0.00	[−0.07]	−0.05	[−0.93]	−0.05	[−1.01]
	Platinum	0.05	[0.84]	−0.04	[−0.76]	0.05	[0.87]	−0.02	[−0.43]	0.00	[0.01]	−0.02	[−0.36]
	Gold	0.01	[0.26]	0.14**	[2.48]	−0.01	[−0.26]	0.16***	[3.00]	−0.02	[−0.36]	0.10*	[1.91]
	Palladium	0.01	[0.23]	−0.09	[−1.54]	−0.03	[−0.59]	−0.06	[−1.15]	−0.00	[−0.03]	−0.07	[−1.32]
Grains	Wheat	0.02	[0.31]	0.08	[1.41]	0.01	[0.20]	0.09	[1.59]	0.01	[0.24]	0.04	[0.76]
	Corn	−0.01	[−0.10]	−0.04	[−0.69]	−0.01	[−0.13]	0.02	[0.31]	−0.05	[−1.01]	−0.04	[−0.77]
	Soybeans	0.05	[0.85]	0.01	[0.25]	0.10*	[1.88]	−0.00	[−0.01]	−0.06	[−1.14]	−0.06	[−1.30]
	Soybean Oil	0.14**	[2.53]	−0.02	[−0.32]	−0.05	[−0.99]	−0.03	[−0.48]	−0.10*	[−1.95]	−0.05	[−1.02]
	Soybean Meal	0.01	[0.12]	0.01	[0.17]	0.13**	[2.30]	−0.01	[−0.20]	−0.04	[−0.83]	−0.04	[−0.71]
	Oats	0.01	[0.23]	0.04	[0.70]	0.04	[0.76]	0.02	[0.30]	0.02	[0.36]	−0.02	[−0.38]
	Rough Rice	0.11*	[1.93]	0.01	[0.09]	0.04	[0.64]	0.04	[0.78]	0.07	[1.27]	0.05	[0.84]
Meats	Live Cattle	−0.08	[−1.35]	−0.11**	[−1.99]	−0.05	[−0.93]	−0.12**	[−2.25]	−0.08*	[−1.69]	−0.07	[−1.38]
	Lean Hogs	−0.08	[−1.31]	0.06	[0.97]	0.01	[0.23]	0.06	[1.13]	0.06	[1.15]	0.06	[1.25]
	Feeder Cattle	0.03	[0.52]	−0.10*	[−1.72]	0.02	[0.30]	−0.10*	[−1.84]	0.02	[0.46]	−0.04	[−0.88]
	Milk	−0.07	[−0.99]	−0.08	[−1.22]	−0.06	[−0.96]	−0.03	[−0.52]	−0.03	[−0.47]	−0.04	[−0.56]
	Butter	−0.15	[−1.33]	−0.09	[−0.96]	0.10	[0.87]	−0.02	[−0.19]	−0.00	[−0.04]	−0.03	[−0.32]
Softs	Cotton	−0.02	[−0.41]	−0.05	[−0.91]	−0.11**	[−1.97]	−0.04	[−0.75]	−0.05	[−0.92]	−0.08*	[−1.67]
	Cocao	0.05	[0.87]	0.07	[1.30]	0.02	[0.36]	0.04	[0.68]	0.07	[1.45]	−0.02	[−0.32]
	Sugar	0.02	[0.40]	−0.02	[−0.27]	0.00	[0.00]	0.01	[0.25]	−0.08	[−1.53]	0.01	[0.20]
	Orange Juice	−0.03	[−0.43]	0.01	[0.09]	−0.07	[−1.18]	−0.00	[−0.06]	−0.00	[−0.10]	−0.04	[−0.74]
	Lumber	−0.07	[−1.27]	−0.10*	[−1.81]	−0.04	[−0.71]	−0.12**	[−2.15]	−0.05	[−0.92]	−0.02	[−0.37]
	Coffee	−0.03	[−0.57]	−0.15***	[−2.71]	0.01	[0.11]	−0.18***	[−3.36]	0.02	[0.49]	−0.08*	[−1.69]

against sharp price movements through diversification.

We investigate the jump correlation within the commodity market and the U.S. stock, currency and bond markets. We do so by correlating the monthly estimates of the BNS test statistic. While jumps occur much less frequently than in stock markets, some commodities exhibit relatively many jumps, e.g. butter and milk. While returns show moderate and statistically significant correlations, jump correlations differ a lot across commodities. Energy, metal and grains commodities in particular show high jump co-movements while jumps of meats and softs commodities are uncorrelated. The same is true for the returns, where energy, metals and grains commodities exhibit much higher return correlations of 0.43 to 0.62, compared to 0.08 to 0.13 of the remaining two sectors.

The hedging abilities of commodities also varies. Correlation coefficients for commodity returns and stock market returns vary from –0.04 to 0.44, while jumps are uncorrelated or negatively correlated. Commodity returns and U.S. Dollar returns are (except for Lumber) negatively correlated while jumps are uncorrelated or negatively correlated. Commodities are generally hedging assets against Treasury note returns and jumps, even though there are several exceptions. In summary, most commodities are strong hedges for Dollar and bond returns while only some are able to hedge for S&P 500 returns. At the same time jumps in the stock, currency and bond markets are generally diversifiable by adding commodities to the basket.

Chapter 4

The Risk Premium of Gold*

4.1 Introduction

In this chapter, we first show that the excess return of gold is time-varying and predictable both in-sample and out-of-sample using a parsimonious forecasting model. In a second step, we examine the co-movements between the risk premia of gold and other important markets. We investigate the hedging and safe haven properties of gold by examining their expected and unexpected relationship. We find for the stock and bond markets that gold is generally not expected to be a hedge, but it is realized as such ex-post. Also, gold is not expected to act as a safe haven asset, but it does. The same analysis with expected inflation reveals that gold does not serve as a hedge against inflation both ex-ante and ex-post.

Gold is often considered as a store of value. The media often claim that gold is a hedge and safe haven asset and the recent literature has empirically tested this claim (Capie et al., 2005; Baur & McDermott, 2010; Ciner et al., 2013; Reboredo, 2013). Typically, these studies use realized returns and

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compute covariances or other dependence measures. As such, they focus on an ex-post setting and only answer the question whether gold and other assets co-moved ex-post. However, for most useful applications and from an asset-pricing perspective, it is much more important to understand, whether gold is also expected to be a hedge or safe haven asset.

We contribute to the literature in at least two ways. First, we provide evidence of time-varying excess returns in the gold market and show that the gold risk premium is predictable. Second, we analyze the question of whether gold is a hedge or safe haven asset from an ex-ante point of view, i.e. whether such properties can be expected.

We differentiate between hedges and safe havens as suggested by Baur & McDermott (2010). Gold is a hedge for another asset if it is uncorrelated or negatively correlated in general, while it serves as as safe haven asset for another asset when it is uncorrelated or negatively correlated in times of market stress.

Our empirical analysis shows that the jump tail premium and the variance risk premium are strong predictors for the gold risk premium, with high explanatory power both in-sample and out-of-sample and for all horizons investigated, varying from one month to two years. The adjusted R^2 and out-of-sample R^2 reach values of 13.39% and 12.44% at the one-year horizon, respectively. We then investigate the expected relationship of gold and equity relying on linear regression models. Our equity risk premium model relies on the two most predominant predictors: the dividend yield and the variance risk premium. We find that the expectation of gold as a hedge and safe haven ex-ante differs from its actual role ex-post not only by magnitude but also by sign depending on the horizons. The results are similar for bonds. Relying on the framework of Cochrane & Piazzesi (2005) for the bond risk premium, we find that gold is not expected to serve as a hedge and safe haven, but it does serve as both ex-post. The relationship between gold and inflation is different. Gold is not expected to be an inflation hedge, which is also realized ex-post.

Gold markets have been analyzed in several existing studies. Capie et al. (2005) investigate whether gold acts as an exchange rate hedge for Sterling–Dollar and Yen–Dollar exchange rates. The Dollar notation refers to the currency of the U.S. They find a negative relationship over more than thirty years (January 1971 to February 2004) of investigation. Their results are based on autoregressive lagged regressions including changes in the gold log-price and exchange rates. Baur & McDermott (2010) test whether gold is a safe haven against the stocks of major emerging and developing countries using daily data for the period from 1979 to 2009. Gold returns are regressed on stock returns whereby they differentiate between "normal" returns and extreme returns defined by empirical quantiles of the return distribution. They find that gold acts both as a hedge and a safe haven for major European stock markets and the U.S. but not for Australia, Canada, Japan and large emerging markets. Reboredo (2013) shows that gold can act as a hedge against U.S. dollar movements and as a safe haven in periods of financial distress using weekly data in the period from January 2000 until September 2012. He uses different copulas in order to model the dependence structure. Ciner et al. (2013) examine dynamic conditional correlation (DCC) GARCH models for crude oil, gold, currency, bond and stock markets using daily data from the U.S. and the U.K. Gold performs as a safe haven for exchange rates and bonds while crude oil acts as a safe haven only for bonds. For further literature on gold we refer to a very comprehensive survey by O'Connor et al. (2015).

The rest of the chapter is organized as follows. Section 4.2 presents our data set. Section 4.3 presents our risk premium model for gold and Sections 4.4 and 4.5 compare the hedge and safe haven performance of gold for the stock and bond markets, respectively. Gold's role as an inflation hedge is investigated in Section 4.6. Section 4.7 reports robustness tests and Section 4.8 concludes. In the appendix to this chapter, which can be found in Section B, we present the results of additional analyses.

4.2 Data & Prediction Variables

4.2.1 Data

The data used for our subsequent analyses come from various sources. Our primary data set consists of end-of-the-day futures for gold traded on the New York Mercantile Exchange/New York Commodities Exchange (NYMEX/COMEX). These are obtained from the Commodity Research Bureau (CRB). End-of-the-day futures for the S&P 500 index traded on the Chicago Mercantile Exchange (CME) are also obtained from the CRB. Futures contracts have expiration dates and hence cannot be tracked continuously. At each point of time we consider the two nearest contracts. For the computation of the returns, we follow Diewald et al. (2015) and differentiate between normal returns and roll-over returns. More specifically, we compute gold futures returns as follows:

$$r_{t+1}^{normal} = log\frac{F_{t+1}^{(1)}}{F_t^{(1)}}, \qquad r_{t+1}^{roll} = log\frac{F_{t+1}^{(1)}}{F_t^{(2)}} \tag{4.1}$$

where r_{t+1}^{roll} denotes the return at time $t+1$ on a business day immediately after the expiration day and r_{t+1}^{normal} denotes the return on any other business day. $F_t^{(1)}$ and $F_t^{(2)}$ refer to the first nearby contract and the second nearby contract at time t, respectively.[1] This approach ensures that all returns are

[1]We also consider alternative rolling dates such as the end of the first or second month prior to delivery month in order to avoid irregular price behavior and obtain qualitatively similar results (Szymanowska et al., 2014). The relevant tables are available upon request.

"real" returns, i.e. they are based on two consecutive prices of the same contract.[2]

Options data for gold are obtained from CRB and contain information on the strike price, maturity and settlement price. The options on futures contracts are traded on NYMEX/COMEX. Implied volatilities are calculated using binomial trees. We also use options data for the S&P 500 index. These consist of closing bid and ask quotes, strike prices, maturities and implied volatilities of options traded on the Chicago Board of Options Exchange (CBOE) and are obtained from Optionmetrics.

Our analysis covers the period from January 1996 until February 2015 leading to a total of 4825 trading days.[3] Our gold data set comprises American options. For short maturity, deep out-of-the-money (OTM) options, the difference between European and American options is negligible, so we rely on the original prices.[4]

4.2.2 Predictor Variables

Macroeconomic Variables

Macroeconomic variables such as employment rates, federal funds rates, industrial production, inflation or treasury bill rates are potential predictors of stock market movements (Geske & Roll, 1983; Thorbecke, 1997; Rapach et al., 2005; Chen, 2009). They affect future consumption and investment

[2]Following Gorton & Rouwenhorst (2006), Gorton et al. (2013) and Bhardwaj et al. (2015), the return of the futures price r_t is defined as an excess return without subtracting any proxy for the risk-free rate. For our predictive regressions, we also consider futures returns in excess of the one-month treasury bill, which is obtained from Kenneth R. French's data library, leading to qualitatively similar results.

[3]The earliest available date for the gold options is 1989, but we start our analysis at a slightly later point since the data in Optionmetrics starts only in 1996.

[4]Bakshi et al. (2003) argue that the early-exercise premium of OTM options can be ignored and hence the usage of American options barely changes the results. Further, Barone-Adesi & Whaley (1987) argue that the early-exercise premium is negligible for OTM options with a time-to-maturity less than 100 days. We conduct robustness tests supporting our choice of using the original options data.

opportunities and consequently also stock returns, as outlined by the consumption capital asset-pricing model (CCAPM). Changes in interest rates are related to discounted cashflows on the one hand and represent monetary policy on the other, which both impact stock prices and returns. The macroeconomic variables have been shown to be related to gold returns as well. Sherman (1983), Fortune (1988), Jaffe (1989), Mahdavi & Zhou (1997), Ghosh et al. (2004) and Blose (2010), among others, investigate the relationship between gold prices and inflation. The impact of macroeconomic news announcements on gold prices has been analyzed by Christie-David et al. (2000) and Cai et al. (2001), especially news on the inflation and employment rate. We further include the oil price and the U.S. Dollar index as macroeconomic predictor variables for the gold premium (Capie et al., 2005; Levin et al., 2006; Tully & Lucey, 2007; Pukthuanthong & Roll, 2011; Baur, 2013; Reboredo, 2013):

- **Dollar:** The U.S. Dollar index is a real trade weighted index obtained from the Federal Reserve Bank of St. Louis (FRED) and presents a weighted average of the foreign exchange value against the currencies of major U.S. trading partners. For details, we refer to the FRED website: https://fred.stlouisfed.org/series/TWEXBPA. Our predictor variable is defined as changes in the U.S. Dollar index.

- **Employment, Federal funds rate and industrial production:** (Empl., FFR, IP) are employment rates, federal funds rates and industrial production obtained from FRED and the Board of Governors of the Federal Reserve System (FED). All time series are filtered by the Hodrick–Prescott filter ($\lambda = 129,600$) following Bloom (2009).

- **Inflation:** This is defined as the change in the Consumer Price Index

(CPI) and obtained from the Bureau of Labor Statistics.

- **Oil price changes:** (OIL) We include monthly changes in the nominal price of oil (West Texas Intermediate) obtained from FRED.

- **Treasury bill rates:** (Tbill) are the three-month treasury bill rates obtained from FRED.

Equity Market Related Variables

The dividend yield and earnings price ratio measure the stock price relative to fundamentals and are the most popular equity premium predictors (Rozeff, 1984; Campbell & Shiller, 1988; Fama & French, 1988; Hodrick, 1992; Kothari & Shanken, 1997; Lamont, 1998; Lewellen, 2004). Since gold, unlike stocks, is typically traded on the futures market or physically, it does not pay any dividends. Hence, instead of considering the dividend yield or earnings price ratio, we include the basis of gold futures contracts. We consider three different definitions of the basis:

- **Dividend yield and earnings price ratio**: The dividend yield, which is defined as the difference between the log of dividends and the log of past prices $log(D/P)$ and the earnings price ratio, which is defined as the difference between the log of earnings and the log of prices $log(E/P)$, measure the stock price relative to fundamentals and are the most popular equity premium predictors (Rozeff, 1984; Campbell & Shiller, 1988; Fama & French, 1988; Hodrick, 1992; Kothari & Shanken, 1997; Lamont, 1998; Lewellen, 2004).

- **Basis:** Fama & French (1987) define the monthly basis B_t^{FF} as the normalized difference between the cash and futures price $B_t^{FF} = \frac{F_{t,T}-S(t)}{S(t)}$ for one-, three-, six- and twelve-month maturities.

Gorton & Rouwenhorst (2006) and Bhardwaj et al. (2015) calculate the basis as the normalized difference between the first and second nearest futures contract, which presents the slope of the futures curve: $B_t^{GR} = \frac{F_{t,1}-F_{t,2}}{F_{t,1}} \frac{365}{t_2-t_1}$, where $F_{t,1}$ and $F_{t,2}$ are the two contracts closest to maturity with the relevant time to maturities t_1 and t_2.

Yang (2013) defines the monthly basis B_t^Y as the normalized log difference between the one-month and twelve-month contract: $B_t^Y = \frac{log(F_{t,T_1})-log(F_{t,T_{12}})}{T_{12}-T_1}$ where F_{t,T_1} and $F_{t,T_{12}}$ are the one-month and twelve-month futures prices, respectively.

Uncertainty and Tail Risk

Another source of fluctuations in gold and stock prices and risk premia are changes in economic uncertainty (Bansal & Yaron, 2004; Bekaert et al., 2009). Various methods have been introduced in order to capture uncertainty. Stock market volatility can be viewed as a measure of economic uncertainty, which has been represented by either the stock market variance (French et al., 1987) or the implied volatility (Bloom, 2009). There is a growing literature investigating the predictive power of the (equity) risk premium using the difference between the two, the variance risk premium, which proxies the aggregate degree of risk aversion in the market (Bollerslev et al., 2009, 2014; Bekaert & Hoerova, 2014). Lastly, recent studies address the ability of rare disaster events to explain the (equity) risk premium (Gabaix, 2012; Wachter, 2013). We rely on the jump risk premium following Bollerslev & Todorov (2011b) and Bollerslev et al. (2015), which has been shown to amount for a large fraction (two–thirds) of the equity premium:

- **Left and right jump tail premia:** (LJP, RJP) The calculation of the jump tail premia closely follows the approach of Bollerslev & Todorov (2011a) and Bollerslev et al. (2015). The jump risk premium is defined as:

$$JP_t(k) = \frac{1}{\tau}\left[\mathbb{E}_t^{\mathbb{P}}\left(\int_t^{t+\tau}\int_{|x|>k} x\nu_s^{\mathbb{P}}(dx)ds\right) - \mathbb{E}_t^{\mathbb{Q}}\left(\int_t^{t+\tau}\int_{|x|>k} x\nu_s^{\mathbb{Q}}(dx)ds\right)\right] \tag{4.2}$$

We denote the left and right risk-neutral components of the jump tail premia as LJP^Q and RJP^Q, which are given by:

$$LJP^{\mathbb{Q}} = \int_t^{t+\tau}\int_{x<k} x\nu_s^Q(dx)ds \tag{4.3}$$

$$RJP^{\mathbb{Q}} = \int_t^{t+\tau}\int_{x>k} x\nu_s^Q(dx)ds \tag{4.4}$$

where the jump intensity process $\nu_s^{\mathbb{Q}}(dx)$ is a function of a level shift parameter $\phi_t^{\pm}$ and a tail decay parameter $\alpha_t^{\pm}$, which allow for time-varying and asymmetric dynamics for the left and the right tail:

$$\nu_t^{\mathbb{Q}}(dx) = \left[\phi_t^- e^{-\alpha_t^-|x|}1_{x<0} + \phi_t^+ e^{-\alpha_t^+|x|}1_{x>0}\right] dx. \tag{4.5}$$

The left and right tail measures are estimated in a two-step procedure where the tails are extrapolated from the short maturity and deep OTM options. Applying extreme value theory leads to the following approximations, see Bollerslev & Todorov (2014):

$$\frac{e^{r_{t,\tau}}O_{t,\tau}(k)}{F_{t,\tau}} \approx \frac{\tau\phi_t^{\pm}e^{k(1\mp\alpha_t^{\pm})}}{\alpha_t^{\pm}(\alpha_t^{\pm}\mp 1)} \tag{4.6}$$

$$1 \pm \alpha^{\pm} \approx \frac{log(O_{t,\tau}(k_{t,i})) - log(O_{t,\tau}(k_{t,i-1}))}{k_{t,i} - k_{t,i-1}} \tag{4.7}$$

where $O_{t,\tau}(k)$ denotes the price of an option with maturity τ and log-moneyness k at time t. $F_{t,\tau}$ is the corresponding futures price and $r_{t,\tau}$ is the risk-free rate over the same horizon. The two parameters completely describe the jump intensity process resulting in the first moment of the jump intensity, i.e. for the time interval from t to $t+\tau$:

$$RJP^{\mathbb{Q}}_{[t,t+\tau]} = \tau\phi_t^+ e^{-a_t^+k_t}\frac{[a_t^+k_t + 1]}{(a_t^+)^2} \tag{4.8}$$

$$LJP^{\mathbb{Q}}_{[t,t+\tau]} = \tau\phi_t^- e^{-a_t^-k_t}\frac{[-(a_t^-k_t + 1)]}{(a_t^-)^2} \tag{4.9}$$

In unreported results, we show that the physical components of the jump tail premia are dwarfed by their risk-neutral counterparts and hence focus on the risk-neutral components as a proxy for the jump tail premia.

- **Model-free implied volatility:** (MFIV) For the S&P 500 we proxy the model-free implied volatility by the VIX obtained from Optionmetrics. For gold we rely on the methodology proposed by Bakshi et al. (2003). The annualized model-free implied variance can be described as:

$$MFIV = \frac{1}{\tau}\int_{F_{t,\tau}}^{\infty} \frac{2(1 - ln(\frac{K}{F_{t,\tau}}))}{K^2} C(t,\tau,K)dK + \int_{0}^{F_{t,\tau}} \frac{2(1 + ln(\frac{K}{F_{t,\tau}}))}{K^2} P(t,\tau,K)dK \tag{4.10}$$

  where $F_{t,\tau}$ is the price of a futures contract at time t with time to maturity τ. $C(t,\tau,K)$ and $P(t,\tau,K)$ denote the European call and put option prices at time t with strike K and time to maturity τ.

- **Stock variance:** (Stock Var.) We include the monthly stock variance which is given by the sum of squared returns in that month (Bollerslev et al., 2009). The same procedure is applied to gold returns in order to obtain gold realized variances.

- **Variance risk premium:** The monthly variance risk premium is defined as the difference between the implied volatility the realized variance (Bollerslev et al., 2009).

4.3 Gold Risk Premium Prediction Model

4.3.1 Risk Premium Prediction

Our first objective is to analyze whether the gold excess return is time-varying and whether it is predictable. To find the best model, we include a variable only if it is a statistically significant regressor and it is able to increase the explanatory power when added to the model. The variables we consider include financial, macroeconomic and option implied measures and are described in Section 4.2.2. In summary, we use the following 18 predictor variables: gold basis, dividend yield, trade weighted U.S. dollar index, earnings price ratio, employment rates, federal funds rate, implied volatility of gold, industrial production, inflation, left and right jump risk premium (gold and stock market), oil price changes, stock market variance, treasury bill rates and variance risk premium (gold and stock market). We estimate the following regression model for the gold futures return:

$$r_{t+h} = a_h + b_h X_t + \epsilon_{t+h} \tag{4.11}$$

where r_{t+h} is the continuously compounded excess futures return over the horizon h, X_t presents one or more of the introduced predictor variables at time t and ϵ is the error term. In order to account for the overlapping observations we use Newey & West (1987) standard errors with lags equal to the return horizon expressed in months. In addition, we compute the more conservative Hodrick (1992) standard errors. We focus our discussion on the estimated slope coefficients and their statistical significance and the forecast accuracy of the regressions as measured by the corresponding adjusted R^2.

Table 4.1 summarizes the significance of the individual explanatory variables in simple regressions from the one-month horizon to the two-year horizon. Even though the $VRP^{S\&P}$ seems to show relatively good

Table 4.1: Comparison of Predictors for the Gold Risk Premium

This table compares the significance of the introduced predictors. We regress gold futures excess returns on the explanatory variables in simple regressions for horizons from one month to two years. The check marks indicate whether the explanatory variable is statistically significant (at the 5% level).

	1-month	3-month	6-month	9-month	12-month	24-month
Basis						
Dollar						
Empl.						
FFR						
Inflation	✓					
IP						
log(D/P)						
log(E/P)						
LJP (Gold)		✓	✓	✓	✓	
LJP (S&P)						
LTR						
MFIV (Gold)						✓
Oil						
RJP (Gold)						
RJP (S&P)						
Stock Var.						✓
Tbill						
VRP (Gold)		✓	✓		✓	
VRP (S&P)		✓				✓

forecasting performance in simple regressions for gold futures excess returns, the variable is insignificant in multiple regressions and hence is excluded from the model.

Investigating all predictor variables we find that the best model for the gold risk premium includes the left jump risk premium (LJP) of gold and the gold variance risk premium (VRP) as explanatory variables. The final model is:

$$r_{t+h}^{Gold} = a_h + b_{1,h} LJP_t^{Gold} + b_{2,h} VRP_t^{Gold} + \epsilon_{t+h} \tag{4.12}$$

Panel A of Table 4.2 presents the results from the multiple regressions for the horizons from one month to two years.

Table 4.2: Predictive Regressions: Gold

This table presents the results for monthly predictive regressions for the period from 1996 until 2015 in Panel A. The investigated predictors are the LJP and the VRP of gold. The LJP is calculated on the basis of $k = 5\sigma_{ATM,t}$, where $\sigma_{ATM,t}$ stands for the at-the-money (ATM) volatility. The dependent variables are the gold futures excess returns. Robust Newey & West (1987) standard errors are reported in parentheses below using lags equal to the return horizon expressed in months. We also report Hodrick (1992) standard errors in square brackets for the slope coefficients. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$ according to the Newey & West (1987) standard errors. The last row reports Wald test statistics for the joint significance of the predictor variables using Newey & West (1987) standard errors in parentheses and Hodrick (1992) standard errors in square brackets. Panel B presents results for monthly out-of-sample predictive regressions for horizons from one month to two years for gold. The investigated predictors are the LJP and the VRP of gold. The LJP is calculated on the basis of $k = 5\sigma_{ATM,t}$, where $\sigma_{ATM,t}$ stands for the ATM volatility. The dependent variables are the gold futures excess returns. We rely on expanding rolling windows and include five years of data for the initial regression. To obtain statistical significance we conduct a Clark & West (2007) MSPE test. The null hypothesis is the recursive mean model outperforming the predictive model, i.e. $R_{OOS} \leq 0$. The p-values are reported in braces below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	1-month	3-month	6-month	9-month	12-month	24-month
Panel A: In-Sample						
Intercept	0.0050	0.0206*	0.0479*	0.0749**	0.0988**	0.2068**
	(0.0038)	(0.0113)	(0.0257)	(0.0349)	(0.0414)	(0.0894)
LJP	0.7278**	1.9513**	3.8673**	5.6609**	7.4067**	13.2254**
	(0.3533)	(0.8795)	(1.7587)	(2.1925)	(2.8755)	(6.5209)
	[0.3838]	[1.0505]	[2.0674]	[2.9472]	[3.7316]	[6.9681]
VRP	0.4548*	0.6511***	0.6012***	0.7115**	1.1931***	1.9257*
	(0.2631)	(0.1730)	(0.1780)	(0.2777)	(0.3210)	(1.0202)
	[0.2781]	[0.3608]	[0.4928]	[0.5355]	[0.6745]	[1.0198]
adj. R^2	0.0465	0.0646	0.0784	0.0991	0.1339	0.1514
Wald	(5.6427)	(19.2089)	(22.8497)	(15.3677)	(26.1202)	(9.4064)
	[6.1591]	[7.2024]	[4.9038]	[5.3547]	[6.6457]	[8.1298]
Panel B: Out-of-Sample						
Gold	0.0253	0.0597***	0.0721**	0.0878***	0.1244***	0.1283***
	{0.1026}	{0.0093}	{0.0114}	{0.0055}	{0.0003}	{0.0004}

The table shows that both the LJP and the VRP of gold are statistically significant predictors of futures excess returns for all horizons. The VRP is positively related to future returns while LJP is positively related as well.[5] When relying on Hodrick (1992) standard errors, at least one explanatory variable is statistically significant and both coefficients for three of the six horizons, while the Wald test rejects the null of joint insignificance of the predictors for all horizons. The explanatory power in terms of adj. R^2 varies from 4.65% to 15.14%.

We find that the contribution of individual predictor variables to the explanatory power depends on the return horizon. The time-series of the individual t-statistics from both simple and multiple regressions as well as the corresponding adjusted R^2 are illustrated in Figure 4.1. The VRP (dotted line) shows generally larger t-statistics than the LJP (solid line) while both are statistically significant throughout all horizons, for both simple and multiple regressions. While both predictors contribute equally to the relatively high adj. R^2 for short horizons, the additional explanatory power from the VRP when added to the LJP is much lower for longer horizons.[6]

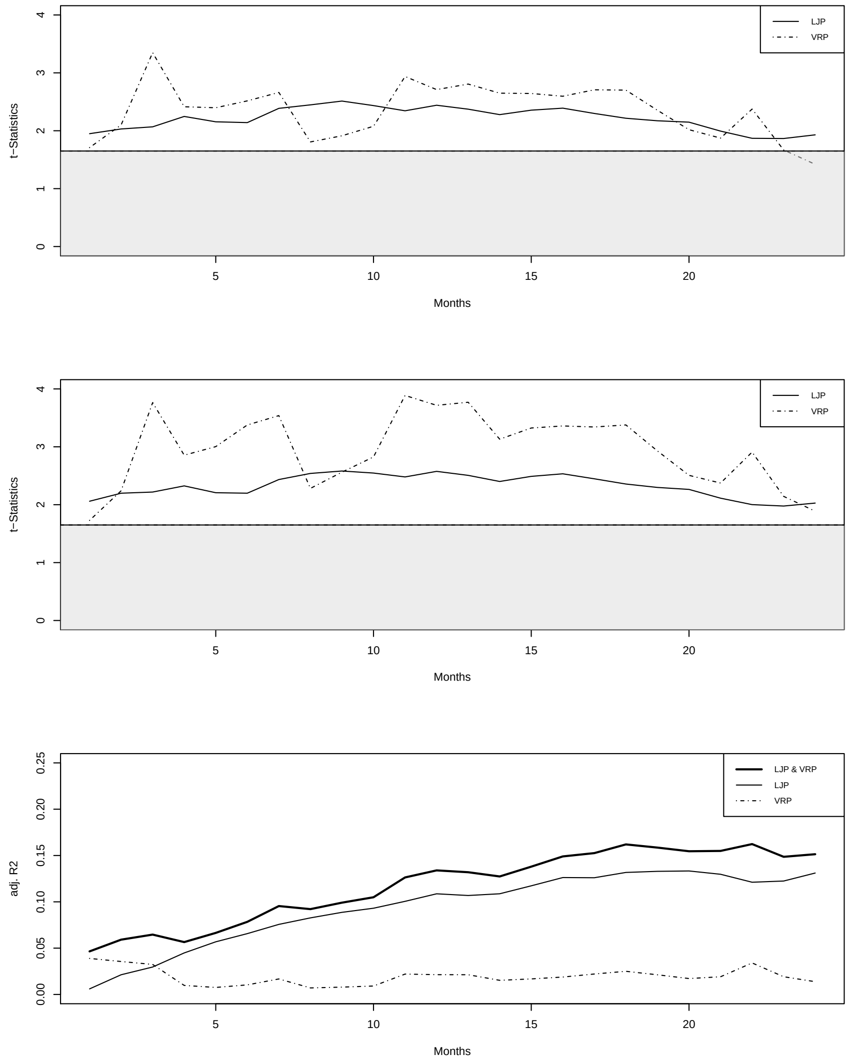
In summary, the predictors in our prediction models have both

[5] LJP presents the risk-neutral left part of the jump risk premium. Since the physical part is dwarfed by the risk-neutral component, the left jump tail premium can be expressed as $-LJP$. Hence higher jump tail premia lead to lower future gold returns. In times of financial distress, gold might suffer losses simultaneously with the stock market but of lower magnitude. Investors then have the incentive to reallocate their investments form the stock market into the gold market, which also leads to higher prices and lower returns in the gold market.

[6] Our findings for the VRP are consistent with the literature. Bollerslev et al. (2009) find that the explanatory power of the VRP for the U.S. concentrates at the horizon between three and six months and generally tapers off for longer return horizons, which is in line with the implications from their theoretical model. Further, they show that there is a positive relationship between the VRP and future expected returns, which is also consistent with our results. Bollerslev et al. (2014) extend these patterns to major economies including Belgium, France, Germany, Japan, the Netherlands, Switzerland and the U.K. These studies focus on the stock market while we focus on the gold market in this section. In Section 4.4 we show similar results for the equity market as well.

Figure 4.1: Predictability Regressions: Gold

This figure presents Newey & West (1987) t-statistics from the return predictability regressions for the gold futures returns. The independent variables are the LJP (solid line) and the VRP (dotted line). The first (second) panel reports t-statistics from simple (multiple) return predictability regressions. The shaded areas indicate statistical significance at the 10% level. The third panel shows the corresponding adj. R^2 for the simple regression (solid and dotted lines) and the multiple regression (bold solid line).



statistically and economically significant impact on future excess futures returns in the gold market. While their contribution to the explanatory power of the predictors depends on the prediction horizon, they jointly ensure a generally increasing pattern for longer horizons.

4.3.2 Out-of-sample Prediction

Having investigated the in-sample predictability, we now turn to an out-of-sample setting. As argued by Welch & Goyal (2008), it is not sufficient to only investigate in-sample tests since most of the predictors are unable to consistently forecast the excess returns out-of-sample. Most of their examined models underperform the recursive mean model out-of-sample when forecasting the equity risk premium. Similar to them, we use the recursive mean as a benchmark for our models. The historical mean is simply given by:

$$\bar{r}_{t+h} = \frac{1}{N}\sum_{j=1}^{t} r_j \tag{4.13}$$

using N return observations until t. Following Campbell & Thompson (2008), we evaluate our models using the expanding out-of-sample R^2 which compares mean squared prediction errors (MSPE) for the predictive model and the historical mean model, and is given by:

$$R^2_{OOS} = 1 - \frac{\sum_{t=s}^{T}(r_{t+1} - \hat{r}_{t+1})^2}{\sum_{t=s}^{T}(r_{t+1} - \bar{r}_{t+1})^2} \tag{4.14}$$

where $\hat{r}_{t+1}$ stands for the out-of-sample forecast obtained from the model in Equation (4.12) using the data until t and s is the break point splitting the whole sample for the out-of-sample analysis. Positive values for R^2_{OOS} indicate that the predictor outperforms the historical mean model in terms of the MSPE. We further formally test whether our models significantly outperform the historical mean model using the Clark & West (2007) augmented test, i.e. testing the null of $R^2_{OOS} \leq 0$. Under the null hypothesis, the MSPE-adjusted test statistic of Clark & West (2007) follows a standard normal distribution. Defining

$$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})^2 - \left[(r_{t+1} - \hat{r}_{t+1})^2 - (\bar{r}_{t+1} - \hat{r}_{t+1})^2\right] \tag{4.15}$$

and regressing f_{t+1} on a constant, i.e. $f_{t+1} = \alpha + \epsilon_{t+1}$, the MSPE-adjusted test statistic is equal to the t-statistic of the constant.

Panel B of Table 4.2 reports the results for the out-of-sample predictability analysis using five years of monthly observations for the initial estimation. Our prediction model shows good out-of-sample forecasting performance across all horizons, where it is able to outperform the historical mean model ($R^2_{OOS} > 0$). The higher performance relative to the historical mean is statistically significant for five of the six horizons. The R^2_{OOS} reaches values as high as 12.83% at the two-year horizon. In accordance with our previous results, our model is able to predict excess futures returns not only in-sample but is also able to beat the historical mean model out-of-sample. As such, as a first major result, we provide evidence that the excess return of gold is time-varying and predictable.

4.4 Gold and the Stock Market

In this section we investigate the relationship of the gold and equity market. In particular, we analyze the expected hedge and safe haven properties of gold, i.e. the expected co-movement of the gold and equity risk premia.

4.4.1 Equity Premium Prediction Model

In order to study co-movement between the gold and the equity risk premia, we first also need to obtain predictions for the latter. We follow the same approach as for the gold risk premium and consider the same variables as

Table 4.3: Comparison of Predictors for the Equity Premium

This table compares the significance of the introduced predictors. We regress S&P 500 futures excess returns on the explanatory variables in simple regressions for horizons from one month to two years. The check marks indicate whether the explanatory variable is statistically significant (at the 5% level).

	1-month	3-month	6-month	9-month	12-month	24-month
Basis		✓	✓			
Dollar						
Empl.	✓					✓
FFR						✓
Inflation						
IP		✓	✓			
log(D/P)				✓	✓	✓
log(E/P)						
LJP (Gold)						
LJP (S&P)						
LTR						
MFIV (Gold)						
Oil						
RJP (Gold)		✓	✓	✓	✓	✓
RJP (S&P)						
Stock Var.						
Tbill						
VRP (Gold)						
VRP (S&P)	✓	✓	✓	✓		

discussed in Section 4.3. Table 4.3 shows the significance of the individual explanatory variables in simple regressions from the one-month horizon to the two-year horizon. Even though RJP^{Gold} seems to show relatively good forecasting performance in simple regressions for the S&P 500 futures excess returns, it is insignificant in multiple regressions and hence is excluded from the model. The best model for the equity risk premium includes the dividend yield and the S&P 500 variance risk premium:

$$r_{t+h}^{S\&P} = a_h + b_{1,h} log(D/P)_t + b_{2,h} VRP_t^{S\&P} + \epsilon_{t+h} \tag{4.16}$$

The results for the predictability regressions using this model are reported in Panel A of Table 4.4.

Table 4.4: Predictive Regressions: Equity Premium

This table presents the results for monthly predictive regressions for the period from 1996 until 2015 in Panel A. The investigated predictors are the VRP of the S&P 500 and the dividend yield. The dependent variables are the S&P 500 futures excess returns. Robust Newey & West (1987) standard errors are reported in parentheses below using lags equal to the return horizon expressed in months. We also report Hodrick (1992) standard errors in square brackets for the slope coefficients. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$ according to the Newey & West (1987) standard errors. The last row reports Wald test statistics for the joint significance of the predictor variables using Newey & West (1987) standard errors in parentheses and Hodrick (1992) standard errors in square brackets. Panel B presents results for monthly out-of-sample predictive regressions for horizons from one month to two years for the S&P 500. The investigated predictors are the VRP of the S&P 500 and the dividend yield. The dependent variables are the S&P 500 futures excess returns. We rely on expanding rolling windows and include five years of data for the initial regression. To obtain statistical significance we conduct a Clark & West (2007) MSPE test. The null hypothesis is the recursive mean model outperforming the predictive model, i.e. $R_{OOS} \leq 0$. The p-values are reported in braces below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	1-month	3-month	6-month	9-month	12-month	24-month
Panel A: In-Sample						
Intercept	0.1651**	0.4714**	0.9200**	1.3635**	1.8231**	3.5464***
	(0.0716)	(0.1720)	(0.3374)	(0.5053)	(0.5795)	(0.7395)
log(D/P)	0.0411**	0.1165**	0.2248**	0.3307**	0.4415**	0.8597***
	(0.0176)	(0.0421)	(0.0809)	(0.1197)	(0.1369)	(0.1794)
	[0.0174]	[0.0503]	[0.0933]	[0.1344]	[0.1753]	[0.3255]
VRP	0.4105***	0.9432***	1.0419***	0.8332***	0.7997**	1.1937**
	(0.0752)	(0.1121)	(0.2024)	(0.2248)	(0.2710)	(0.5146)
	[0.1637]	[0.2876]	[0.4832]	[0.5366]	[0.5765]	[0.6933]
adj. R^2	0.1158	0.2136	0.1946	0.2034	0.2484	0.4164
Wald	(36.6227)	(86.7176)	(51.6379)	(26.4963)	(23.1149)	(23.6173)
	[12.9924]	[16.5738]	[16.4435]	[11.9341]	[12.1866]	[16.3726]
Panel B: Out-of-Sample						
S&P 500	0.0646**	0.1544**	0.0603**	0.0312*	0.0501*	0.0942*
	{0.0306}	{0.0147}	{0.0105}	{0.0787}	{0.0979}	{0.0624}

We find that all coefficients are statistically significant at the 5% level or lower according to Newey & West (1987) standard errors and the signs make sense economically, just as for the gold market. A higher VRP leads to higher future returns. The VRP can be interpreted as a measure of aggregate economic uncertainty and the positive sign is consistent with the results of Bollerslev et al. (2009) and Bollerslev et al. (2014). Bloom (2009) shows that higher uncertainty impacts the aggregate real economy by lowering industrial production and employment rates, which again influences asset prices. The positive sign of the dividend yield slope coefficient is consistent with the literature. As argued by Lewellen (2004), the ratios should positively impact expected returns. This positive relationship is prescribed by a present value model (Campbell & Shiller, 1988). Our (best) model is able to explain 19.46% of the variation in expected returns at the six-month horizon.[7] The Wald test of joint significance rejects the null in favor of the prediction model. Looking at the more conservative Hodrick (1992) standard errors, the slope coefficients both remain statistically significant for four of the six horizons, similar to the results for gold. For the nine-month and twelve-month horizon, the VRP is not significant but the Wald statistic indicates the joint significance of both predictors with all values being above 10. We find a generally increasing pattern for the adjusted R^2 starting with 11.58% at the one-month horizon and reaching values as high as 41.64% for the two-year horizon.[8]

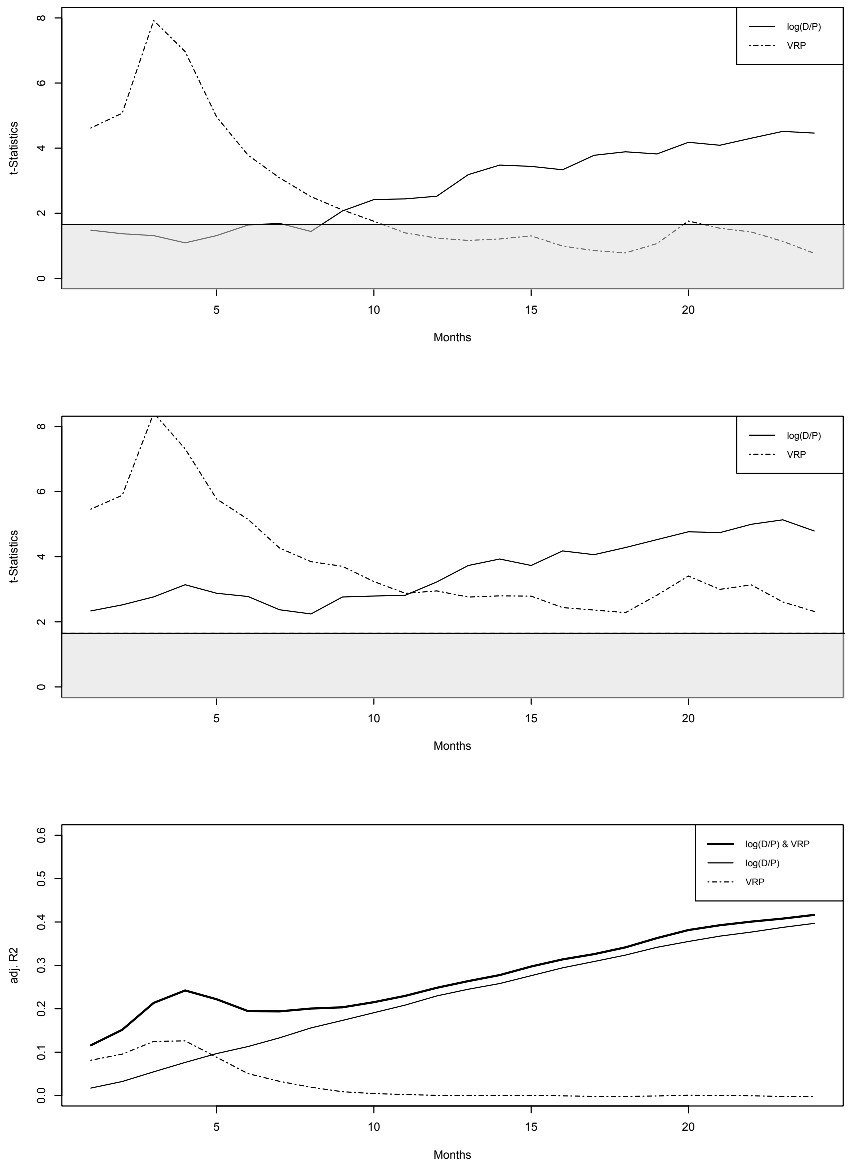
Turning next to the term structures of t-statistics and adj. R^2 in Figure 4.2, we find that the t-statistics of the VRP (dotted line) are generally

[7]This high adjusted R^2 is comparable to the 21.39% of Bollerslev et al. (2015), who include the left jump tail variation and the dividend yield as predictors for the period from 1996 until 2013.

[8]Our model delivers a higher explanatory power than proposed models of Welch & Goyal (2008), Kelly & Jiang (2014) and Bollerslev et al. (2015) for the one-month and the one-year horizon. For the one-year horizon, the authors find an adjusted R^2 of 16.98% (LJV and continuous VRP), 13.81% (kitchen sink regression) and 13.80% (Tail risk and dividend yield), respectively, compared to our R^2 of 24.84%.

Figure 4.2: Predictability Regressions: S&P 500

This figure presents Newey & West (1987) t-statistics from the return predictability regressions for the S&P 500 futures returns. The independent variables are the $log(D/P)$ (solid line) and the VRP (dotted line). The first (second) panel reports t-statistics from simple (multiple) return predictability regressions. The shaded areas indicate statistical significance at the 10% level. The third panel shows the corresponding adj. R^2 for the simple regression (solid and dotted lines) and the multiple regression (bold solid line).



higher for short horizons up to nine months while the t-statistics of the $log(D/P)$ dominate for longer horizons. This is true for both simple and multiple regressions. In addition, the explanatory power is slightly higher when relying on the VRP for short horizons while it almost vanishes for longer horizons. This is manifested in the third plot showing the adj. R^2. There is a large increase for short-term horizons, where both the $log(D/P)$ and the VRP contribute significantly to a high explanatory power while the explanatory power mainly comes from the $log(D/P)$ for long horizons.

Panel B of Table 4.4 demonstrates that the equity risk premium prediction model shows good out-of-sample forecasting performance across all horizons. It is able to outperform the historical mean model ($R^2_{OOS} > 0$). The higher performance relative to the historical mean is statistically significant for all horizons. The R^2_{OOS} reaches values as high as 9.42% for the S&P 500.[9] Just as for the gold market, our equity risk premium model is also able to predict excess futures returns not only in-sample but is also able to beat the historical mean model out-of-sample.

4.4.2 Gold as a Hedge and Safe Haven for the Equity Market

We test the performance of gold as a hedge or safe haven asset following the approach of Baur & McDermott (2010). However, we rely on expected premia rather than realized returns as Baur & McDermott (2010) do. Thus, we analyze whether gold can be expected to serve as a hedge or safe haven asset. The model differentiates between co-movements on average and in times of extreme market movements. More formally, we jointly estimate the

[9] For comparison, Welch & Goyal (2008) and Kelly & Jiang (2014) find R^2_{OOS} of 0.2% and 0.3% for the one-month horizon and 2.04% and 4.5% for the one-year horizon when predicting the equity premium. The best performing models of Welch & Goyal (2008) rely on the Term Spread (tms) and the Percent Equity Issuing ($eqis$) while Kelly & Jiang (2014) rely on their tail risk estimate λ.

following regressions using the maximum likelihood method:

$$\hat{r}_t^{Gold} = a + b_t \hat{r}_t^{Stock} + \epsilon_t \tag{4.17}$$

$$b_t = c_0 + c_1 D(\hat{r}^{Stock} q_{10}) \tag{4.18}$$

$$h_t = \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1} \tag{4.19}$$

where Equation (4.17) models the relation of the expected premia and ϵ_t is the error term.[10] The slope coefficient b_t is a dynamic process and depends on c_0 and c_1, the parameters of interest. $D(\hat{r}^{Stock} q_{10})$ is a dummy variable which captures extreme stock market movements and equals one if the expected premium $\hat{r}^{Stock}$ falls below the 10% quantile of the distribution. Equation (4.19) presents a GARCH(1,1) model and allows for heteroskedasticity.

The regressions are based on conditional estimates of the expected returns and hence answer the question whether gold is expected to be a hedge or safe haven from an ex-ante perspective. For comparison, we also reestimate the Equations (4.17)-(4.19) using realized returns. This allows us to compare the perception of gold from investors both ex-ante and ex-post.[11]

The parameters of interest (c_0 and c_1) indicate whether gold serves as a hedge and/or a safe haven. If c_0 is zero (negative and statistically significant) and c_1 is not positive, exceeding the value of c_0, gold is a weak (strong) hedge. If both parameters are non-positive (and statistically significant), gold acts as a weak (strong) safe haven.

The results of our analysis are reported in Table 4.5. We focus on the following four time horizons: one-month, six-month, one-year and

[10] Normality is assumed for the error term. Our conclusions remain qualitatively similar when assuming a t-distribution.

[11] We only include the 10% quantile (and exclude the 5% and 1% quantiles) as a proxy for extreme movements since our sample is much smaller, with a sample size of 230 observations. Figure 4.4 of the appendix plots the expected premia against the risk premia of the gold and stock market for the one-, six-, twelve- and twenty-four-month horizons.

Table 4.5: Hedge and Safe Haven

This table presents the estimation results for the role of gold as a hedge and safe haven relying on expected premia (columns (2)-(3)) or the risk premia (columns (4)-(5)). Negative coefficients in columns (2) and (4) indicate that gold is a hedge against the stock market while zero (negative) coefficients in columns (3) and (5) indicate that gold is a weak (strong) safe haven. We report Wald test statistics for the significance of the coefficients below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Expected Premium		Realized Returns	
	Hedge	10%	Hedge	10%
1-month	0.2432**	−0.1469	−0.0118	0.1187
	6.0221	0.9250	0.0192	0.9868
6-month	−0.1561	0.2430***	−0.2003	0.0131
	2.6767	13.7804	1.1012	0.0244
12-month	−0.1405	1.2301***	−0.1978	0.0033
	0.6117	16.2719	2.0724	0.0018
24-month	−0.1891***	1.1917***	−0.1155	−0.0730
	19.2115	32.2851	0.2957	0.5571

two-year, which include horizons of short-, mid- and long-term investors, respectively. In Table 4.5, columns (1) and (2) report the coefficients estimated from Equations (4.17)-(4.19) relying on the expected premia, while columns (3) and (4) show the coefficients estimated using the realized returns as dependent variables. The statistical significance of the coefficients is obtained from the Wald test statistics which are reported below the coefficients.[12]

One can observe that gold is not expected to serve as a hedge or safe haven throughout all horizons. At the one-month horizon, the coefficient c_0 is positive and statistically significant and hence movements in the same direction are expected for both gold and the stock market. For longer horizons the hedge coefficient c_0 is negative and even statistically significant

[12] Again, we control for overlapping observations by relying on Newey & West (1987) standard errors.

at the two-year horizons but is dwarfed by the co-movement during times of tumult in the stock market. The crisis coefficient $(c_0 + c_1)$ is positive and statistically significant for horizons longer than one month.

Turning next to the results based on the realized returns, we find that gold acts ex-post as both a weak hedge and weak safe haven for all horizons. All coefficients are statistically insignificant but all hedge coefficients are negative and of smaller absolute magnitude than the crisis coefficient. The results are similar to those of Baur & McDermott (2010), who show that gold serves as both a hedge and a safe haven for the U.S. stock market for the period from March 1979 until March 2009. The performance of gold as a a weak or strong hedge/safe haven depends on the frequency (daily, weekly, monthly). The findings of Baur & Lucey (2010) also suggest that gold acts as a hedge and safe haven for the U.S. stock market, where their empirical analysis includes both stock and bond returns in the regressions.

In summary, the high expected co-movement between gold and the stock market during times of stock market tumult offsets the expected hedging ability of gold. Economically, the role of gold as a hedge and safe haven is perceived by investors differently (ex-ante) compared to its actual role (ex-post). Even if investors are able to predict future movements of realized returns both in-sample and out-of-sample, and hence obtain a good conditional estimate of the expected return, the co-movement forecastability is limited.

4.5 Gold and Bond Risk Premia

4.5.1 Bond Premium Prediction Model

Next, we investigate the role of gold as a hedge against bonds. Again, we consider an ex-ante point of view as opposed to the ex-post realization.

We rely on forecast regressions of bond excess returns on forward rates in order to obtain an estimate for the bond risk premium following Cochrane & Piazzesi (2005):

$$r^{Bond}_{n,t+1} = \beta_{n,0} + \beta_{n,1} y_{1,t} + \beta_{n,2} f_{2,t} + ... + +\beta_{n,5} f_{5,t} + \epsilon_{n,t+1} \tag{4.20}$$

where $r^{Bond}_{n,t+1}$ is the holding period excess return from buying an n-year bond at time t and selling it as an $n-1$-year bond at time $t+1$, $y_{1,t}$ is the yield at time t and $f_{n,t}$ is the forward at time t for loans between time $t+n-1$ and $t+n$. We also estimate a restricted specification in the two-step procedure. In the first step, the average bond return across the different maturities is regressed on the forward rates:

$$\bar{r}^{Bond}_{n,t+1} = \gamma_{n,0} + \gamma_{n,1} y_{1,t} + \gamma_{n,2} f_{2,t} + ... + +\gamma_{n,5} f_{5,t} + \epsilon_{n,t+1} \tag{4.21}$$

In a second step, a single-factor b_n is estimated:

$$r^{Bond}_{n,t+1} = b_n(\gamma^T f_t) + \epsilon_{n,t+1} \tag{4.22}$$

$$\gamma^T f_t = \gamma_{n,0} + \gamma_{n,1} y_{1,t} + \gamma_{n,2} f_{2,t} + ... + +\gamma_{n,5} f_{5,t} \tag{4.23}$$

Cochrane & Piazzesi (2005) show that the linear combination of forward rates $\gamma^T f_t$ is a state variable for the expected returns of all maturities, while the restriction has only a minor impact on the forecasting performance. We obtain monthly bond yields with maturities from one year to five years from the Board of Governors of the Federal Reserve System.[13] Since our data consist of monthly bond data with maturities varying from one to five years, we can only conduct the analysis for one-year bond excess returns, just as Cochrane & Piazzesi (2005).

[13] Website: https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html. Unlike the data sets of Fama & Bliss (1987) or McCulloch & Kwon (1993), the data are available at a daily frequency and include estimates out to thirty-year maturities. For our analysis, we work with the coarser monthly frequency, where monthly observations are obtained as either the end-of-month observation or the mean of daily observations within that month. The results are qualitatively similar for both specifications.

Table 4.6: Bond Single-Factor Model

This table presents the estimation results for the regressions of one-year excess bond returns on forward rates. Panel A and B report results for the restricted and unrestricted model, respectively. The significance of the coefficients b_n and the Wald test statistics are based on Newey & West (1987) corrected standard errors with 18 lags. Stars indicate significance of the estimates: * significant at $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

	$Bond_{n=2}$	$Bond_{n=3}$	$Bond_{n=4}$	$Bond_{n=5}$
Panel A: Restricted Model				
b_n	0.3957**	0.8069***	1.2072***	1.5902***
	(0.1401)	(0.2250)	(0.2788)	(0.3146)
R^2	0.1211	0.1489	0.1876	0.2274
adj. R^2	0.1170	0.1450	0.1839	0.2239
Panel B: Unrestricted Model				
Wald	6.6953	10.5108	16.8167	24.5810
R^2	0.1497	0.1531	0.1879	0.2333
adj. R^2	0.1296	0.1331	0.1687	0.2152

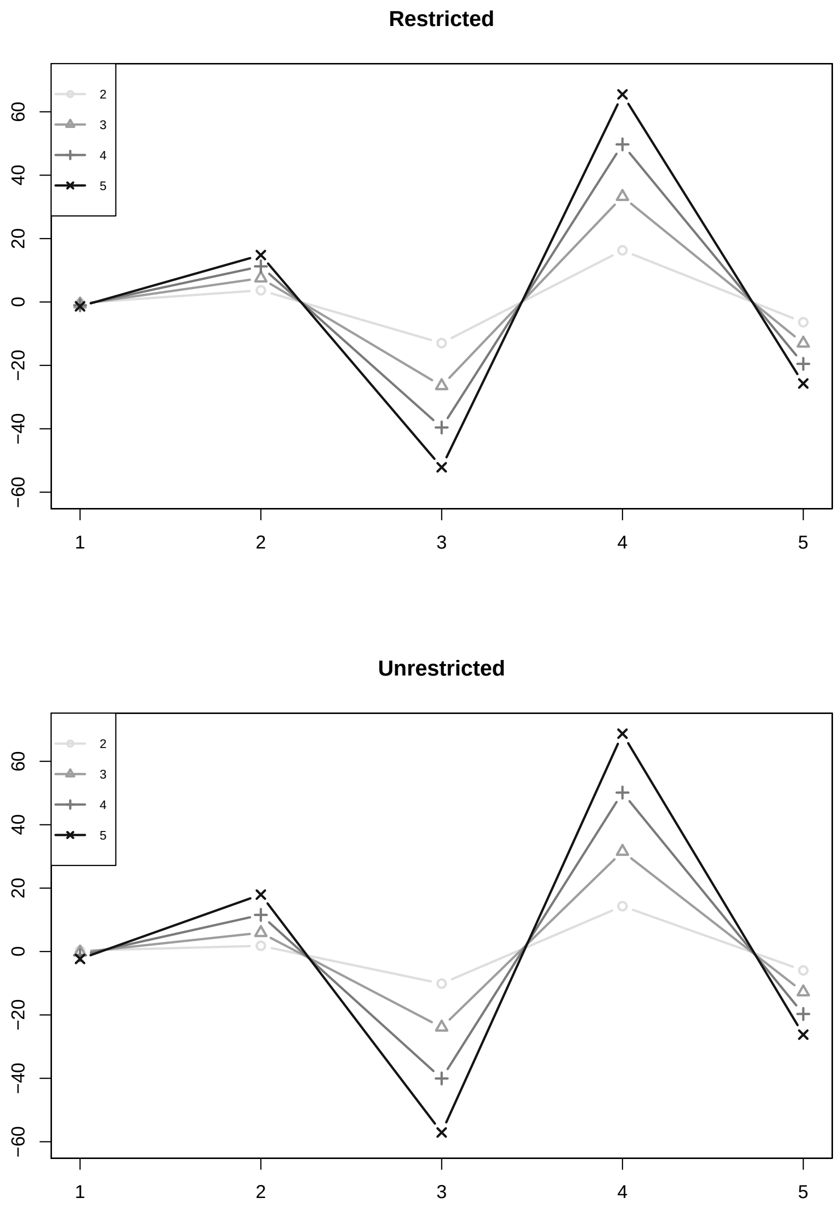
The results are summarized in Table 4.6. We find that the adj. R^2 values are similar for both the restricted and unrestricted model varying between 11.70% and 22.39% and 12.96% and 21.52%, respectively.[14]

We find that the loadings b_n of expected returns on the forecasting factor $\gamma^T f$ are statistically significant and are increasing in maturity. We apply the Newey & West (1987) correction with 18 lags following Cochrane & Piazzesi (2005). The coefficients implied by the restricted model for each maturity n and the slope coefficients of the unrestricted model are displayed in Figure 4.3 in the top and bottom panel, respectively. We find that the parameters are very similar for both models and hence the single factor of the restricted model is able to mimic the unrestricted model. The coefficients

[14] The explanatory power is somewhat lower than those of Cochrane & Piazzesi (2005) or Kessler & Scherer (2009), but neither includes the recent financial crisis. The magnitudes of our adj. R^2 are similar to Dahlquist & Hasseltoft (2013), who include the financial crisis and investigate the period from January 1975 to December 2009. They find adj. R^2 values between 20% and 24%. When excluding the financial crisis, we also find much higher adj. R^2, indicating that times of market tumult have an important impact on the predictability of bond excess returns.

Figure 4.3: Regression Coefficients of Bond Excess Returns

This figure plots the estimates of β from the unrestricted regressions of bond excess returns and restricted estimates $b\gamma^T$ in the top and bottom panel, respectively. The numbers in the legend indicate the maturity of the bonds, which is used as dependent variable, while the numbers on the horizontal axis are the maturity of the independent variables (forward rates).



do not follow a tent shape for either model and none of the maturities, which is consistent with the results of Kessler & Scherer (2009).[15] Even though there is no clear pattern of the coefficients, we find that they are statistically significant overall, which supports the strong link between forward rates and bond excess returns. For the unrestricted model we rely on Wald tests using also Newey & West (1987) 18 lags correction (Cochrane & Piazzesi, 2005). The null of zero coefficients can be rejected for all models except for the short-maturity bonds (n=2). When using the long-maturity bonds (n=4,5), the null test statistic χ^2 is even higher than the 1% critical value 15. All in all, our empirical findings suggest that we can be confident about our model(s) and we work with the estimates of expected bond risk premia as proxied by the fitted values of either the restricted or unrestricted model.

4.5.2 Gold as a Hedge for the Bond Market

We test the ability of gold as a hedge or safe haven against bond risk premia in the same manner as for the stock market:

$$\hat{r}_t^{Gold} = a + b_t \hat{r}_t^{Bond} + \epsilon_t \tag{4.24}$$

$$b_t = c_0 + c_1 D(\hat{r}^{Bond} q_{10}) \tag{4.25}$$

$$h_t = \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1} \tag{4.26}$$

The results are reported Table 4.7. Overall, they are quite similar to those for the stock market. The results are both qualitatively similar for the restricted and unrestricted model and all maturities and we focus our discussion on the restricted model in the following. From an ex-ante point of view, the hedge coefficient is negative and statistically insignificant, indicating that gold might serve as a hedge for bonds. But the positive 10%

[15]The authors show that the tent shape is only found in certain time frames rather than being a consistent pattern. Their finding is supported by data from both Datastream and CRSP (Fama & Bliss, 1987, data).

Table 4.7: Gold as a Hedge for Bonds

This table presents the estimation results for the role of gold as a hedge and safe haven relying on expected premia (columns (2)-(5)) or the risk premia (columns (6)-(7)) both for the one-year horizon. All results are based on the one-year horizon relying on two- to five-year zero bonds. Negative coefficients in columns (2), (4) and (6) indicate that gold is a hedge against the bond market while zero (negative) coefficients in columns (3), (5) and (7) indicate that gold is a weak (strong) safe haven. We report Wald test statistics for the significance of the coefficients below. Stars indicate significance of the estimates: * significant at $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

	Expected Premium				Realized Returns	
	Restricted		Unrestricted			
	Hedge	10%	Hedge	10%	Hedge	10%
$Bond_{n=2}$	−0.0040	0.2113***	−0.0106	0.1858***	0.0089	0.0151
	0.1716	17.7382	1.7380	33.2884	0.2293	0.0907
$Bond_{n=3}$	−0.0020	0.1036***	−0.0016	0.1084***	0.0061	0.0097
	0.1716	17.7384	0.1023	16.0364	0.2089	0.0982
$Bond_{n=4}$	−0.0013	0.0692***	−0.0010	0.0732***	0.0043	0.0091
	0.1716	17.7384	0.1029	16.3356	0.4134	0.3251
$Bond_{n=5}$	−0.0010	0.0526***	−0.0009	0.0511***	0.0044	0.0068
	0.1716	17.7387	0.1561	14.0398	0.7025	0.3260

coefficient, which is highly statistically significant, shows high co-movement of bond and gold risk premia during times of (bond) market stress and offsets the overall hedging performance of gold.

The analysis of realized returns suggests that gold acts as both a weak hedge and safe haven. Both the hedge and 10% coefficients are slightly above zero but statistically insignificant. Again, the results are similar across all bond maturities. The results are in line with Baur & Lucey (2010), who apply a similar methodology in order to investigate the relationship between gold and bonds for the period from November 1995 until November 2005. They also show that both the hedge and crisis coefficients are statistically insignificant.

In summary, we show that the high positive co-movement during times of (bond) market stress offsets the hedging property of gold. Ex-post, we show that gold serves as both a hedge and safe haven against bonds.

4.6 Gold as an Inflation Hedge

The findings concerning gold as an inflation hedge in the literature are mixed. Chua & Woodward (1982) find that gold is an inflation hedge for the U.S. and not for other major countries but consider only the period from 1975 until 1980. Batten et al. (2014) investigate the dynamic inflation-beta of gold for the period from 1985 until 2012 and find that the relationship is time-varying. Before the 1990s, the beta is generally positive and quite high, reaching values above 2.5. Throughout the 1990s, they show evidence of very small, close to zero, inflation-betas, and then a significant increase in the 2000s. For more research on gold and inflation, we refer to the literature survey of Blose (2010).

We want to explore the extent to which gold is expected to serve as an inflation hedge. To do so, we follow the approach of Chua & Woodward (1982) and estimate the following regression:

$$\hat{r}_t^{Gold} = \alpha + \beta \hat{I}_t + \epsilon_t \tag{4.27}$$

where $\hat{I}_t$ is the expected inflation rate at time t and ϵ_t is the error term. If the slope coefficient β is positive and statistically significant, gold is expected to act as a hedge against inflation. When there is an increase in inflation, there is a contemporaneous increase in the gold return. We also repeat the analysis, but replace the expected risk premium and the expected inflation with the realized excess returns r_t^{Gold} and the actual inflation rate, respectively. We focus on the same horizons h as in the stock market analysis: one month, six months, one year and two years.

Similar to our analysis for the stock market, we first need to obtain an estimate of the expected inflation. Ang et al. (2007) compare 39 forecasting models, and show that the time-series of inflation rate can be well described by time-series models such as Autoregressive (AR) models, Random Walk (RW) models or Autoregressive Moving Average (ARMA) models. We follow their advice and rely on an ARMA(1,1) model and AR models. The order of the AR-order p is chosen according to the Bayesian information criterion (BIC).[16] We evaluate the forecasting performance of the three models for the horizons from one month to two years by comparing the Root Mean Squared Error (RMSE). Each month, we estimate the models using all the observations available until that month and obtain forecasts of the inflation over the next h months. The initial estimation uses the first 60 observations. We then compare the expected inflation over the h months with the realized inflation over the h months and compute the RMSE.

Table 4.8 reports the results. One can observe in Panel A that both the AR and ARMA(1,1) models outperform the historical mean for all horizons except for the twenty-four-month horizon. The AR model shows the lowest overall RMSE. Only at the three-month horizon does the ARMA model show a slightly smaller RMSE. Panel B reports out-of-sample R^2 and the relevant p-values following Clark & West (2007) and Campbell & Thompson (2008), where the AR model is the benchmark model. The results support the choice of the AR model, since none of the models is able to outperform the the AR model for all horizons. Only the ARMA model is able to beat the AR model at the three-month horizon but the outperformance is statistically insignificant. For our hedging analysis we thus rely on the AR model in the following.

[16] Ang et al. (2007) show that expected inflation obtained from surveys is a strong competitor to the time-series models. We consider most of the competing models as advocated by the authors. Details of this analysis are reported in Section 4.7.4.

Table 4.8: Predictive Regressions: Inflation

This table presents the results for monthly predictive regressions for the period from 1996 until 2015. Forecasts for the next one, three, six, nine, twelve and twenty-four months are obtained from expanding window estimation, where the initial estimation takes into account the first sixty observations, using the following models: Autoregressive (AR) model, Random Walk (RW), Autoregressive Moving average (ARMA) and Historical Mean (HM). We report the Root Mean Squared Error (RMSE) for each model and horizon in Panel A. We also report out-of-sample R^2 and the relevant p-values following Clark & West (2007) and Campbell & Thompson (2008) in Panel B.

	1-month	3-month	6-month	9-month	12-month	24-month
Panel A: RMSE						
AR	0.0385	0.0309	0.0215	0.0169	0.0141	0.0092
RW	0.0479	0.0496	0.0471	0.0465	0.0454	0.0439
ARMA	0.0386	0.0305	0.0217	0.0171	0.0143	0.0093
HM	0.0442	0.0316	0.0222	0.0174	0.0145	0.0092
Panel B: Out-of-Sample R^2						
RW	−0.5522	−1.5731	−3.7991	−6.5316	−9.3570	−21.8170
	0.9174	0.8333	0.6279	0.5974	0.6604	0.6272
ARMA	−0.0040	0.0252	−0.0158	−0.0230	−0.0301	−0.0203
	0.7964	0.1675	0.5031	0.6471	0.7896	0.7114
HM	−0.3180	−0.0433	−0.0620	−0.0522	−0.0541	−0.0073
	0.6891	0.9226	0.8231	0.8234	0.8179	0.7900

After computing the expected inflation as the forecast of the AR model:

$$I_{t+1} = \phi_0 + \sum_{i=1}^{p} \phi_i I_{t+1-i} + \epsilon_{t+1} \tag{4.28}$$

we regress the expected gold premium on the former as in Equation (4.27) and report the coefficients in Table 4.9. We find that gold is not expected to serve as an inflation hedge across all horizons. From an ex-post point of view, gold does not act as an inflation hedge either.

The insignificant relationship between actual inflation and the gold risk premium is similar to the findings of our prediction model, where we show that inflation is an insignificant predictor of gold futures returns.

Table 4.9: Gold as an Inflation Hedge

This table presents the estimation results for the role of gold as a hedge against inflation relying on expected premia (columns (2)-(3)) or the risk premia (columns (4)-(5)). We report Newey & West (1987) robust standard errors in parentheses below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Expected Premium		Realized Returns	
	Intercept	β	Intercept	β
1-month	0.0086*	−1.1832	0.0022	1.4309
	(0.0047)	(2.0942)	(0.0045)	(1.6856)
6-month	0.0042	1.0848	0.0009	2.2005
	(0.0041)	(1.9923)	(0.0059)	(2.3333)
12-month	0.0022	2.2535	−0.0026	4.2211
	(0.0081)	(3.8844)	(0.0074)	(3.0123)
24-month	0.0106	−1.3830	−0.0033	4.9833
	(0.0089)	(4.3364)	(0.0194)	(8.3049)

4.7 Robustness

We provide additional evidence in favor of our prediction models by obtaining p-values of both slope coefficients and R^2 (in-sample and out-of-sample) with a parametric bootstrap. Further, we acknowledge the potential issues of errors-in-variables and finite sample bias for our empirical analysis. The former is relevant since various regressions rely on estimated values as explanatory variables. The potential finite sample bias is related to our relatively short sample period from 1996 until 2015, which leads to 230 monthly observations. In the following we present robustness tests which mitigate these potential issues. We focus on our main results for the stock market. Lastly, we show results for competing models for the inflation rate, following Ang et al. (2007).

4.7.1 Statistical Inferences of the Prediction Model

We follow Welch & Goyal (2008) and apply a parametric bootstrap in order to obtain the statistical significance of our OLS coefficients in Equations (4.12) and (4.16). The data generating process under the null is assumed to be

$$r_{t+h} = a_h + u_{1,t+h} \tag{4.29}$$

$$X_{t+1} = \alpha + \beta X_t + u_{2,t+h} \tag{4.30}$$

where X_t includes LJP and VRP^{Gold} for gold and $log(D/P)$ and $VRP^{S\&P}$ for the S&P 500. The data generating process under the alternative is given by:

$$r_{t+h} = a_h + b_h X_t + u_{1,t+h} \tag{4.31}$$

$$X_{t+1} = \alpha + \beta X_t + u_{2,t+h} \tag{4.32}$$

By allowing for an autoregressive structure for the predictors we control for the potential Stambaugh (1999) bias. We obtain pseudo time-series for both the returns and predictor time series under the null by drawing with replacement from the residuals simultaneously. This procedure thus preserves the cross-correlation structure of the residuals in the predictive regression and the two autoregressive models. We then compute and store the t-statistics of the coefficients, in-sample adjusted R^2, out-of-sample R^2_{OOS} and the MSPE-adjusted test statistic related to Equations (4.12) and (4.16). We repeat this process 5,000 times, which gives us empirical distributions for the test statistics and the R^2. After ordering the distribution for each statistic, critical values and p-values are obtained by the quantiles.

The results for the in-sample and out-of-sample analyses are reported in Panels A and B of Table B.1 of the appendix, respectively. We find that the p-values of all slope coefficients are all statistically significant for both the gold and S&P 500 prediction models, just as in our main analysis (when relying on Newey & West, 1987, standard errors). The LJP is significant at the 10% level at the one-month horizon while the VRP is significant at the 5% level for the one-, six-, nine- and twenty-four-month horizons. The remaining p-values are all below 1%. For the S&P 500, the coefficients are all statistically significant at the 1% level.[17] The p-values for the in-sample adj. R^2 are all smaller than 0.001 for the S&P 500 as well. For gold, the p-value is 2.18% for the one-month horizon and smaller than 1% for the remaining values.

The bootstrapped p-values for the out-of-sample R_{OOS} and the MSFE-adjusted test statistic also confirm the results in our main analysis. The MSFE-statistics show that our prediction model performs better than the historical mean model for all horizons at a significance level of 1%. Only for the S&P 500 and the one-month horizon is the statistical significance at the 5% level. The R_{OOS} are statistically significant at the 5% level or lower for both gold and the S&P 500 for all horizons.

We thus verify the performance of our prediction models concerning both the statistical significance of the predictors and the explanatory power (in-sample and out-of-sample) by relying on bootstrapping methods instead of corrections for heteroskedasticity and autocorrelation (Newey & West, 1987; Hodrick, 1992).

[17]The results are consistent with our main findings when relying on Newey & West (1987) and Hodrick (1992) standard errors in Tables 4.2 and 4.4. The VRP slope coefficient shows the lowest statistical significance at the one-, nine- and twenty-four-month horizon for gold as well, while the S&P 500 coefficients generally show higher t-statistics than those of gold.

4.7.2 Errors-in-Variables

We account for the possible errors-in-variables (EIV) problem since our expected premia in Equation (4.17) and (4.18) are estimates obtained from linear regressions. The standard econometric approach to deal with the EIV problem is the use of instrumental variables (Greene, 1998; Christensen & Prabhala, 1998). Christensen & Prabhala (1998) propose using lagged observations as an instrument. Algebraically, we estimate the following equation:

$$\hat{r}_t^{Gold} = a + b_t \hat{r}_t^{Stock} + \epsilon_t \tag{4.33}$$

$$b_t = c_0 + c_1 D(\hat{r}^{Stock} q_{10}) \tag{4.34}$$

$$h_t = \omega + \alpha \epsilon_{t-1}^2 + \beta h_{t-1} \tag{4.35}$$

$$\hat{r}_t^{Stock} = \beta_0 + \beta_1 \hat{r}_{t-1}^{Stock} + \eta_t \tag{4.36}$$

where η_t denotes the measurement error which is uncorrelated with $\hat{r}_t^{Stock}$. In the first-stage regression, Equation (4.36), the expected equity premium $\hat{r}_t^{Stock}$ is regressed on an instrument, its lagged observation $\hat{r}_{t-1}^{Stock}$. Fitted values from this regression then replace the expected equity premium $\hat{r}_t^{Stock}$ in the second-stage regression in Equation (4.33).[18]

Table B.2 of the appendix reports the IV estimates in the second-stage regression. The coefficients are of slightly higher magnitudes than in Table 4.5 but the conclusions remain the same. The hedge coefficient is negative for horizons of six months and more, while there is statistically significant positive co-movement during times of stock market tumult.

[18] We also conducted the analysis with the exclusion of Equation (4.35) and the relevant least squares (OLS) estimation as in Baur & Lucey (2010), which leads to qualitatively similar results. By doing so we reduce the number of parameters to be estimated from six to three compared to our sample size of 230. We further investigate the potential finite sample bias in Section 4.7.3.

4.7.3 Finite Sample Bias

In a two-step approach we investigate the robustness of our hedge and safe haven results against finite sample bias, as discussed in the literature. The use of Monte Carlo or bootstrap simulations is documented in recent studies and for various applications. Nelson & Kim (1993) rely on annual returns from 1872 until 1927 for stock return predictability regressions, and argue that the biases should be accounted for. Mark (1995) accounts for small–sample biases in his multiple-period regressions of exchange rates by relying on bootstrap distributions under the null. Bekaert et al. (1997) examine the expectations hypothesis of the term structure of interest rates and show evidence of extreme bias in the small-sample distribution of their regression-based tests.

In the first step we quantify the small-sample bias. In a second step we obtain critical values for our test statistics from a bootstrap approach, which does not rely on asymptotic results that may not be valid for finite samples.

First, we conduct a residual resampling bootstrap approach. For this purpose residuals are estimated from Equation (4.17). Block-bootstraps of the dependent variable are then generated by sampling from the residuals with replacement, which are then added to the fitted values from Equation (4.17). This leads to the same number of observations as in the initial model.[19] The coefficients of interest are then estimated from the Equation (4.17) using the simulated data. We repeat this procedure 5,000 times.[20] The small-sample bias of a coefficient is estimated as the difference between

[19] We follow Hall et al. (1995) using a block length of $n^{1/3}$, where n is the total sample size. We also consider non-block bootstraps, leading to qualitatively similar results.

[20] Efron & Tibshirani (1986), Kho (1996) and Kosowski et al. (2006) show by means of different applications that their results are not sensitive for repetitions larger than 500-1,000. By the choice of 5,000 replications we strike the right balance between our computational capacity and sufficient repetitions.

the original coefficient estimate and the average across the 5,000 simulated coefficients.

In a second step, new residuals are computed from the bias-corrected coefficients. New dependent variables under the null hypotheses are obtained by sampling the residuals. The original regression model in Equation (4.17) is then estimated again in order to obtain the Wald statistics. The procedure is repeated 5,000 times, which leads to a distribution of the statistics. From the percentiles of the distribution of simulated test statistics we obtain the critical values and p-values and conclude on the statistical significance of c_0 and the sum $c_0 + c_1$.

We present the results of the two steps in Panels A and B of Table B.3 of the appendix. The results suggest that our main conclusions are generally robust to potential finite sample bias. The absolute bias in coefficient estimates is negligible and varies between 0.01 and 2.14 percentage points, which should not overturn our results on the hedging and safe haven performance of gold. In Panel B, we report the bias-corrected coefficients, and show results for the finite sample distributions of the test statistics. The results are qualitatively similar to the results when relying on asymptotic critical values for the tests. Overall, the first coefficient c_0 speaks in favor of gold as a hedge but the high and statistically significant co-movement during the crisis offsets the hedging ability. In conclusion, it is unlikely that finite sample bias and distortions significantly affect our main results.

4.7.4 Modeling Inflation

In our main analysis we rely on time-series models for the expected inflation. Our choice is supported by the findings of Ang et al. (2007) but is also motivated by the available data frequency of potential explanatory variables. The competing non-time-series models of the authors use data at a coarser frequency and hence monthly forecasts of the inflation cannot be estimated. More specifically, their analysis focuses at the quarterly and yearly horizon and one-year-ahead inflation forecasts.

In this section, we investigate the forecasting performance of alternative inflation models. We include most of the models investigated by Ang et al. (2007) relying on quarterly data.[21] We also focus on one-year-ahead inflation forecasts, which is mainly due to the non-availability of alternative forecast horizons for the survey data.

Similar to our previous analyses we obtain out-of-sample forecasts using the different models, where the initial estimation takes into account the first five years of observations. We also compare the out-of-sample forecasting performance with respect to the AR model, following Stock & Watson (1989):

$$I_{t,t+4} = \lambda \hat{I}_t^{AR} + (1-\lambda)\hat{I}_t^{X} + \epsilon_{t,t+4} \tag{4.37}$$

where $\hat{I}_t^{AR}$ is the forecast of the inflation over the next year from the AR time-series model, $\hat{I}_t^{X}$ is the forecast from an alternative model and $\epsilon_{t,t+4}$ is the error term associated with the combined forecast. If $\lambda = 1$, then the forecasting model X does not add anything to the forecast from the AR time-series benchmark. If $\lambda = 0$, then forecasts from the AR model add nothing to the alternative model. We correct the standard errors of

[21] We exclude the random walk on annual inflation (AORW) and the models based on the Livingston survey (LIV1, LIV2, LIV3), since these are of yearly and semi-yearly frequency, respectively. Further we exclude regime-switching models and the empirical term structure model and the term structure model suggested by Ang et al. (2008). When estimating a regime-switching model for the inflation rate in a short sample with 76 quarterly observations, the algorithm fails to converge. We exclude models which include the Bernanke–Boivin–Eliasz FAC measure since the data is only available until the end of 2001. For the term structure data, we rely on the same data set as for our bond analysis in Section 4.5. Lastly, the Stock & Watson (1989) experimental leading indices were discontinued. Following the advice of the authors, we rely on the "most direct successor", the Chicago Fed National Activity Index (CFNAI and CFNAIMA3), obtained from the Federal Reserve Bank of St. Lous.

the coefficients due to the overlapping observations using 4 lags and the procedure of Newey & West (1987).[22]

Table B.4 of the appendix reports the results. In accordance with our main results, we find that the AR model shows relatively strong out-of-sample forecasting performance in the means of RMSE. Only 3 out of the 29 models (PC1, PC6 and PC7) show slightly smaller RMSE with ratios of 0.9870, 0.9701 and 0.9990, respectively. Nonetheless, the additional information added by these models is not statistically significant, where the coefficient $1 - \lambda$ in Equation (4.37) varies between 0.06 and 0.48.[23]

We repeat our regression analysis, which tests whether gold serves as an inflation hedge using the alternative inflation models and at the quarterly horizon. Table B.5 of the appendix reports the results. From an ex-post point of view, inflation does not serve as a hedge at the quarterly horizon, which shows that our main results are robust against the choice of frequency. From an ex-ante point of view, we find that gold does not serve as a hedge either. The coefficient is insignificant when relying on the AR model or PC1 and even negative and statistically significant when relying on PC6 or PC7. All in all, this subsection supports our main results: gold does not serve as a hedge for inflation. Even though the coefficients (and the significance) differ when using alternative models, the conclusion remains the same.

4.8 Conclusion

This chapter provides new evidence of gold as a hedge and safe haven asset for the stock market and inflation from a forward-looking perspective. In the first step we provide a strong prediction model, which is able to forecast

[22]Using Hodrick (1992) standard errors yields qualitatively similar results.

[23]In unreported results we find that the coefficient λ in Equation (4.37) is close to 1 or higher in most cases and statistically significant in 21 of the 29 cases.

the gold risk premium both in-sample and out-of-sample. Thus, our first major result is that the risk premium of gold is predictable.

Based on the conditional risk premium estimate and the realized excess returns, we compare the investors' perception of gold as a hedge and safe haven. We apply state of the art models in order to estimate expected stock and bond risk premia as well as expected inflation. For the bond and stock market, gold is not expected to serve as a hedge and safe haven but it is realized as both ex-post. For inflation, gold is not expected to be a hedge asset, which is also realized ex-post.

B Appendix

Figure 4.4: Expected Premium vs. Risk Premium

This figure plots the realized futures excess returns (black) against the expected premium (fitted values in red) of gold and the S&P 500. The first, second, third and forth panel report results for the 1-month, 6-month, 12-month and 24-month prediction horizon, respectively.

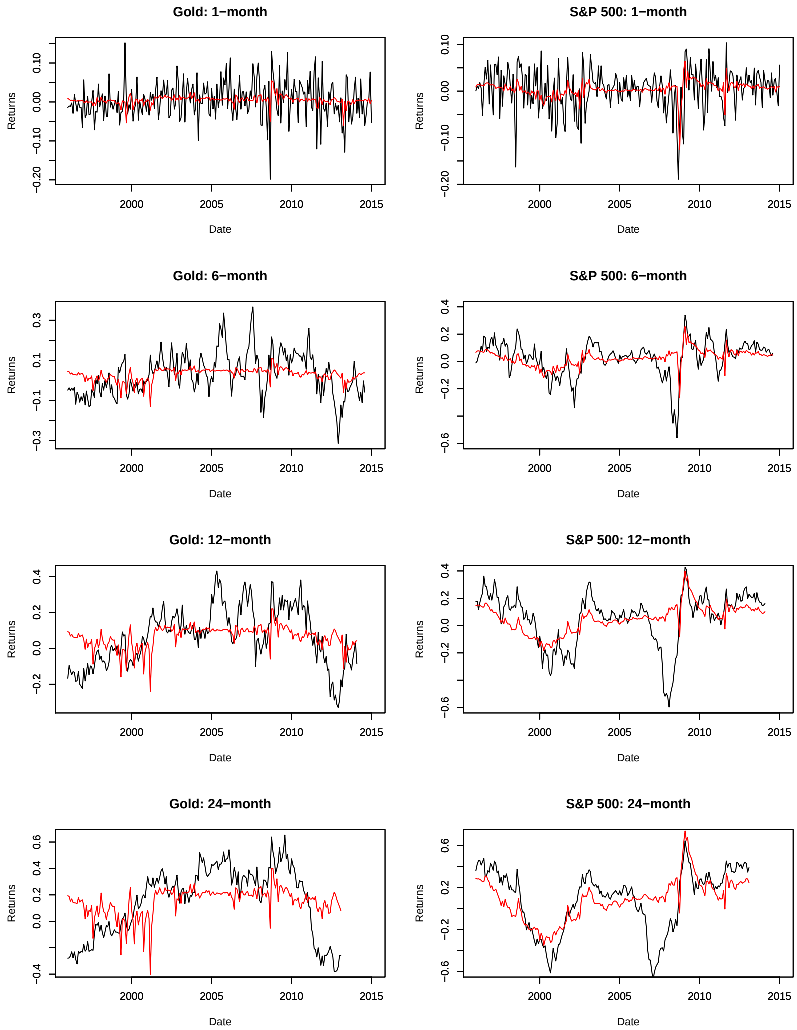


Table B.1: Statistical Inference of the Prediction Model

This table presents the results accounting for potential Stambaugh (1999) biases. In Panel A, we report the bootstrapped p-values for the slope coefficients and the in-sample adj. R^2. In Panel B, we report the bootstrapped p-values for the out-of-sample R^2_{OOS} and the MSPE-adjusted test statistic. The bootstrap procedure is repeated 5,000 times and the p-values are obtained from the empirical distributions of the statistics.

	Gold			S&P 500		
Panel A: In-Sample						
	LJP	VRP	adj. R^2	$log(D/P)$	VRP	adj. R^2
1-month	0.0932	0.0288	0.0218	0.0042	0.0010	0.0008
3-month	0.0086	0.0018	0.0006	0.0000	0.0000	0.0000
6-month	0.0020	0.0106	0.0008	0.0000	0.0006	0.0000
9-month	0.0000	0.0174	0.0000	0.0000	0.0030	0.0000
12-month	0.0000	0.0010	0.0000	0.0000	0.0078	0.0000
24-month	0.0000	0.0266	0.0000	0.0000	0.0058	0.0000
Panel B: Out-of-Sample:						
	R^2_{OOS}	MSFE		R^2_{OOS}	MSFE	
1-month	0.0034	0.0056		0.0160	0.0370	
3-month	0.0004	0.0000		0.0022	0.0014	
6-month	0.0130	0.0000		0.0006	0.0000	
9-month	0.0218	0.0000		0.0002	0.0000	
12-month	0.0120	0.0000		0.0000	0.0000	
24-month	0.0000	0.0000		0.0000	0.0000	

Table B.2: Hedge and Safe Haven: Instrumental Variable Regression

This table presents the estimation results for the role of gold as a hedge and safe haven relying on expected premia and instrumental variables. Negative coefficients in column (2) indicate that gold is a hedge against the stock market while zero (negative) coefficients in the column (3) indicate that gold is a weak (strong) safe haven. We report Wald test statistics for the significance of the coefficients below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Hedge	10%
1-month	0.3861	0.2698
	1.0310	0.5493
6-month	−0.2106	0.3936***
	2.1282	9.9802
12-month	−0.1497	1.3669***
	0.5387	14.9951
24-month	−0.1999***	1.2804***
	18.8311	31.7491

Table B.3: Finite Sample Bias

This table presents the results accounting for potential finite sample biases for the coefficient c_0 and the sum $c_0 + c_1$. In Panel A, we report the results for the bias in coefficient estimates in percentage points. The bias is computed as the difference between the initial coefficient estimates and the mean of the coefficients obtained from a block-bootstrap of the dependent variable with 5,000 repetitions. Panel B reports the results for the hypothesis tests of the coefficients with bootstrapped critical values/p-values. Bias-corrected coefficient estimates are used to simulate the dependent variables under the null. We repeat this 5,000 times and obtain distributions of the Wald test statistics. We report the bias-corrected coefficients and the bootstrapped p-values below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Hedge	10%
Panel A: Coefficient Bias		
1-month	0.0827	0.0056
6-month	0.3773	−0.9272
12-month	0.4727	−2.1364
24-month	0.1022	−1.0532
Panel B: Finite Sample Distributions		
1-month	0.2433*	−0.1469
	0.0512	0.4854
6-month	−0.1485	0.2338**
	0.2034	0.0180
12-month	−0.1344	1.2087**
	0.5333	0.0301
24-month	−0.1833***	1.1811***
	0.0052	0.0066

Table B.4: Forecasting Annual Inflation

This table presents the results for the forecast of annual inflation at a quarterly frequency. The column labeled "Relative" reports the ratio of the RMSE relative to the AR model. The column labeled "$1-\lambda$" reports the coefficient from Equation (4.37), where Newey & West (1987) corrected standard errors and p-values are given in columns "NW SE" and "NW p", respectively. The abbreviations for the different models are as in Ang et al. (2007).

	RMSE	Relative	$1-\lambda$	NW SE	NW p
ARMA	0.1089	1.1005	−0.5563	1.1043	0.6162
AR	0.0990	1.0000			
RW	0.2610	2.6377	−0.0557	0.0390	0.1586
PC1	0.0977	0.9870	0.0580	0.3384	0.8646
PC2	0.1008	1.0182	0.1099	0.2541	0.6670
PC3	0.1036	1.0465	−0.1057	0.3238	0.7452
PC4	0.1002	1.0128	−1.7387	0.5905	0.0046
PC5	0.1090	1.1014	0.0634	0.2905	0.8279
PC6	0.0960	0.9701	0.4765	0.3479	0.1760
PC7	0.0989	0.9990	0.3051	0.4122	0.4620
PC9	0.1013	1.0240	0.0824	0.2374	0.7297
PC10	0.1042	1.0531	−0.0915	0.2774	0.7427
TS1	0.1039	1.0500	−0.2700	0.2466	0.2780
TS2	0.1121	1.1326	−0.1543	0.3263	0.6380
TS3	0.1208	1.2203	−0.3963	0.4459	0.3777
TS4	0.1082	1.0931	−0.3036	0.3302	0.3617
TS5	0.1149	1.1613	−0.0407	0.3785	0.9148
TS6	0.1004	1.0150	0.2717	0.2992	0.3676
TS7	0.1041	1.0520	0.1461	0.3267	0.6564
TS9	0.0992	1.0024	−0.1185	0.4161	0.7768
TS10	0.1081	1.0920	−0.1039	0.2130	0.6275
TS11	0.1076	1.0875	−0.0861	0.1337	0.5222
VAR	0.1157	1.1695	0.0183	0.1210	0.8800
SPF1	0.0998	1.0080	0.2553	0.5217	0.6263
SPF2	0.1038	1.0486	0.0684	0.6711	0.9191
SPF3	0.1062	1.0735	−0.0324	0.3889	0.9339
MICH1	0.1364	1.3786	−0.6637	0.3966	0.0992
MICH2	0.1032	1.0427	−0.4310	0.6081	0.4813
MICH3	0.1081	1.0920	−0.6198	0.6302	0.3295

Table B.5: Gold as an Inflation Hedge - Alternative Models

This table presents the estimation results for the role of gold as a hedge against inflation relying on expected premia (columns (2)-(3)) or the risk premia (columns (4)-(5)). The models used to obtain the expected inflation rate is reported are the AR model and three Phillips curve models (PC1, PC6 and PC7). We report Newey & West (1987) robust standard errors in parentheses below. Stars indicate significance of the estimates: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Expected Premium		Realized Returns	
	Intercept	β	Intercept	β
AR	0.0200	−0.7347	−0.0094	0.5102
	(0.0280)	(1.1995)	(0.0134)	(0.4098)
PC1	0.0016	0.0430		
	(0.0127)	(0.5184)		
PC6	0.0132***	−0.4575**		
	(0.0049)	(0.2210)		
PC7	0.0176***	−0.6412**		
	(0.0061)	(0.2795)		

Chapter 5

The Long Memory of Equity Volatility: International Evidence*

5.1 Introduction

In this chapter we investigate the long memory in stock market volatility for a large number of countries. We first show that long memory volatility is prevalent in almost every international equity index. We then exploit the cross-sectional and time-series variation of the memory parameter to identify the sources of long memory in volatility. We find that long memory volatility can be related to macroeconomic variables in both the time-series and the cross-sectional dimension. On the one hand, longer memory is related to lower unemployment and lower interest rates for the majority of countries. On the other hand, longer memory is found to be related to

*This chapter is based on the Working Paper 'The Long Memory of Equity Volatility: International Evidence" authored by Duc Binh Benno Nguyen, Marcel Prokopczuk and Philipp Sibbertsen, 2017.

more developed and stable countries.

We shed new light on long memory in volatility by exploiting and combining the methodologies of three strands of literature. First, we extend the current research, which only focuses on major economies and large firms by investigating eighty-two international countries including both developed and emerging countries. Second, we allow for a time-varying degree of long memory. Third, long memory so far has only been analyzed in the time-series dimension not in the cross-sectional. We closely investigate possible macroeconomic fundamentals which may explain the degree of long memory both in the time-series and cross-sectional dimension.

We find that 94% of the international countries possess long memory in volatility with an average memory parameter of 0.27, which is statistically significant.[1] In the time-series dimension, longer memory can be related to lower interest rates. In the cross-sectional dimension, higher memory parameter estimates can be related to economically stronger, i.e. developed countries. In contrast, lower memory parameter estimates are associated with emerging and frontier countries. Further, countries with higher interest rates, higher unemployment rates and fewer jumps possess shorter memory in volatility. We verify our memory estimates by showing that volatility in countries with higher memory parameters are more predictable than in countries with low memory parameters.

Long memory properties have been investigated in the dynamics of both stock returns and volatility. Typically, the autoregressive fractionally integrated moving average (ARFIMA) model by Granger & Joyeux (1980), Granger (1981) and Hosking (1981) and the fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model introduced by Baillie et al. (1996) are used and shown to provide better

[1] This value presents a cross-sectional means using the GPH estimator and a bandwidth parameter of $m = n^{0.5}$.

forecasts than the short memory ARMA and GARCH models.

Several studies investigate the long memory of returns and volatility both in the U.S. stock market and in international stock markets. Bollerslev & Mikkelsen (1996) and Ding & Granger (1996) show that the conditional variance and absolute returns of the S&P 500 index possess long memory, respectively. Both papers rely on the FIGARCH model. Breidt et al. (1998) also find long memory in the variance of equally weighted and value-weighted CRSP stock market index returns by fitting a long memory stochastic volatility model and relying on the ARFIMA model. Lobato & Savin (1998) investigate long memory properties of the U.S. stock market index and thirty individual stock returns in the U.S. They apply a semiparametric test to returns, squared and absolute returns and find that squared returns exhibit long memory properties while the levels of returns do not. Sadique & Silvapulle (2001) and Henry (2002) consider the long memory property of various international stock indices including Germany, Japan, Korea, Malaysia, New Zealand, Singapore, Taiwan and the U.S. Sadique & Silvapulle (2001) rely on both the modified rescaled range tests and the GPH estimator while Henry (2002) relies on both parametric and semiparametric estimation methods including the GPH estimator, the estimator of Robinson (1994) and the ARFIMA model. Kasman et al. (2009) show evidence of long memory dynamics in both the conditional mean and variance for eight Central and Eastern European countries' stock markets and also rely on the both semiparametric (GPH) and parametric (ARFIMA, FIGARCH and HYGARCH) estimation procedures. While long memory has been investigated extensively both in the U.S. and international stock markets, the works so far have mainly focus on the detection of long memory. We contribute to the existing literature by largely extending the sample of countries to eighty-two and examining the cross-sectional variation of long memory across countries and its link to macroeconomic variables. The next chapter, which is based on Nguyen et al. (2017), investigates the cross-sectional variation of long memory in volatility at the firm level. It provides evidence of long memory in volatility for the cross-section of U.S. stocks and find a negative price for long memory volatility.

The rest of the chapter is organized as follows. Section 5.2 describes our data set and estimation procedure for long memory. Section 5.3 investigates long memory in the cross-section of countries. Section 5.4 presents robustness tests. Section 5.5 concludes. In the appendix to this chapter, which can be found in Section C, we present the results of additional analyses.

5.2 Data and Methodology

5.2.1 Data

The data used for our analyses come from various sources. For our international stock index data we follow Pukthuanthong & Roll (2015) and include eighty-two countries for which we obtain the data from Datastream.[2] If available, we rely on daily observations of the total return indices which include the dividends, and use the price index otherwise.[3] The sample covers the period from December 1964 until December 2015.[4]

For each country we obtain country-specific macroeconomic variables from the Global Financial Database. We include the real gross domestic product (GDP), the consumer price index (CPI), unemployment, short

[2]Table C.1 in the appendix presents an overview of the countries, the selected indices and the sample period.

[3]Prices are cleaned of outliers by removing observations which deviate by more than 10 standard deviations from the median using a rolling window of 50 observations (Barndorff-Nielsen et al., 2009).

[4]For Bangladesh, Slovenia and Zimbabwe, the last available observations are from April 2013, October 2010 and October 2006, respectively.

maturity and long maturity interest rates.[5] Most of the short maturity yields are 3-month treasury bills and most of the long maturity yields are 10-year government bonds. Hence from now on we refer to them as treasury bills (Tbill) and government bonds (Gov.Bonds). Both are given in percentage form per annum. The Real GDP data is obtained in U.S. dollar currency converted using exchange rates from the Global Financial Database.[6]

5.2.2 Semiparametric Estimation of Long Memory

In our empirical analysis we work with the two most popular estimators, which are the GPH estimator and the Local Whittle estimator.

Geweke & Porter-Hudak (1983) introduce an estimator which is based on the log-periodogram. A linear regression is employed to the spectral density relying on the first m periodogram ordinates. Empirically, the spectral density of a stationary process X_t is estimated by the periodogram:

$$I_X(\lambda_j) = \frac{1}{2\pi N}\left|\sum_{t=1}^{N} X_t e^{-it\lambda}\right|^2, \quad t = 1, ..., N \tag{5.1}$$

where the periodogram is not affected by centering of the time series for Fourier frequencies $\lambda_j = 2\pi j/N$ ($j = 1, ..., [(N-1)/2]$). The negative slope coefficient β_1 in the regression presents the estimator:

$$log(I(\lambda_j)) = \beta_0 + \beta_1 log[4sin^2(\lambda_j/2)] + \epsilon_j, \quad j = 1, ..., m \tag{5.2}$$

The asymptotic standard errors for the long memory parameter can be obtained from the asymptotic distribution, which is derived by Robinson

[5] The data for the U.S. is supplemented by data provided by Amit Goyal (website: http://www.hec.unil.ch/agoyal/) and FRED.

[6] Unfortunately, the Global Financial Database does not cover our complete sample of countries with macroeconomic variables. GDP data is available for seventy-two countries, inflation data is available for eighty countries, unemployment data is available for sixty-nine countries, treasury bill rates are available for seventy-eight countries and government bond rates are available for seventy-three countries.

(1995b) under mild conditions ($m \to \infty, N \to \infty, \frac{m}{N} \to 0$) :

$$\sqrt{m}(\hat{d} - d) \underset{d}{\longrightarrow} N\left(0, \frac{\pi^2}{24}\right) \tag{5.3}$$

The choice of the bandwidth parameter m results into a bias–variance trade-off. If the m is chosen too low and hence too close to the origin, an increased variance is the result, while a m chosen too high and hence too far from the origin leads to bias.

In the following empirical analyses, we focus on the GPH estimator and the bandwidth $m = N^{0.5}$ following the existing literature (Geweke & Porter-Hudak, 1983; Diebold & Rudebusch, 1989; Hurvich & Deo, 1999; Henry, 2002).[7] Results with alternative bandwidth choices and the Local Whittle estimator are reported in the Section 5.4.

We refer to d as the memory parameter and differentiate between three cases: A time series has short memory if $d = 0$. A time series has negative memory or is anti-persistent if $d < 0$. A time series has long memory if $0 < d < 1$ where it is non-stationary if $0.5 < d < 1$.

5.3 Long Memory Volatility in International Equity Markets

In this section we provide evidence of long memory volatility in the cross-section of eighty-two countries. First, we show that long memory volatility is prevalent in most countries but that the memory parameter varies across countries in Section 5.3.1. Section 5.3.2 refers long memory to predictability and Section 5.3.3 relates the memory parameter to macroeconomic variables in the time-series dimension. Section 5.3.4 relates the memory parameter

[7] Typically, empirical researches rely on this bandwidth choice since it is robust against short-range dependencies in the data.

Table 5.1: Summary Statistics

This table presents the summary statistics for the long memory volatility of international countries. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. Obs. in column (1) stands for the number of observations, SD stands for the standard deviation, column (2) reports selected quantiles; t-statistic in column (3) reports the mean t-statistic, Sign. at 5% reports the proportion of significant long memory estimates, while the remainder of column (3) reports the proportion of the memory parameter being in a certain interval.

Descriptive		Quantiles		Memory	
Obs.	82	5%	0.01	t-statistic	3.95
Mean	0.27	25%	0.20	Sign. at 5%	0.87
SD	0.13	Median	0.28	-0.5<d<0.0	0.04
Skewness	-0.41	75%	0.35	0.0<d<0.5	0.94
Kurtosis	0.28	95%	0.46	0.5<d<1.0	0.02

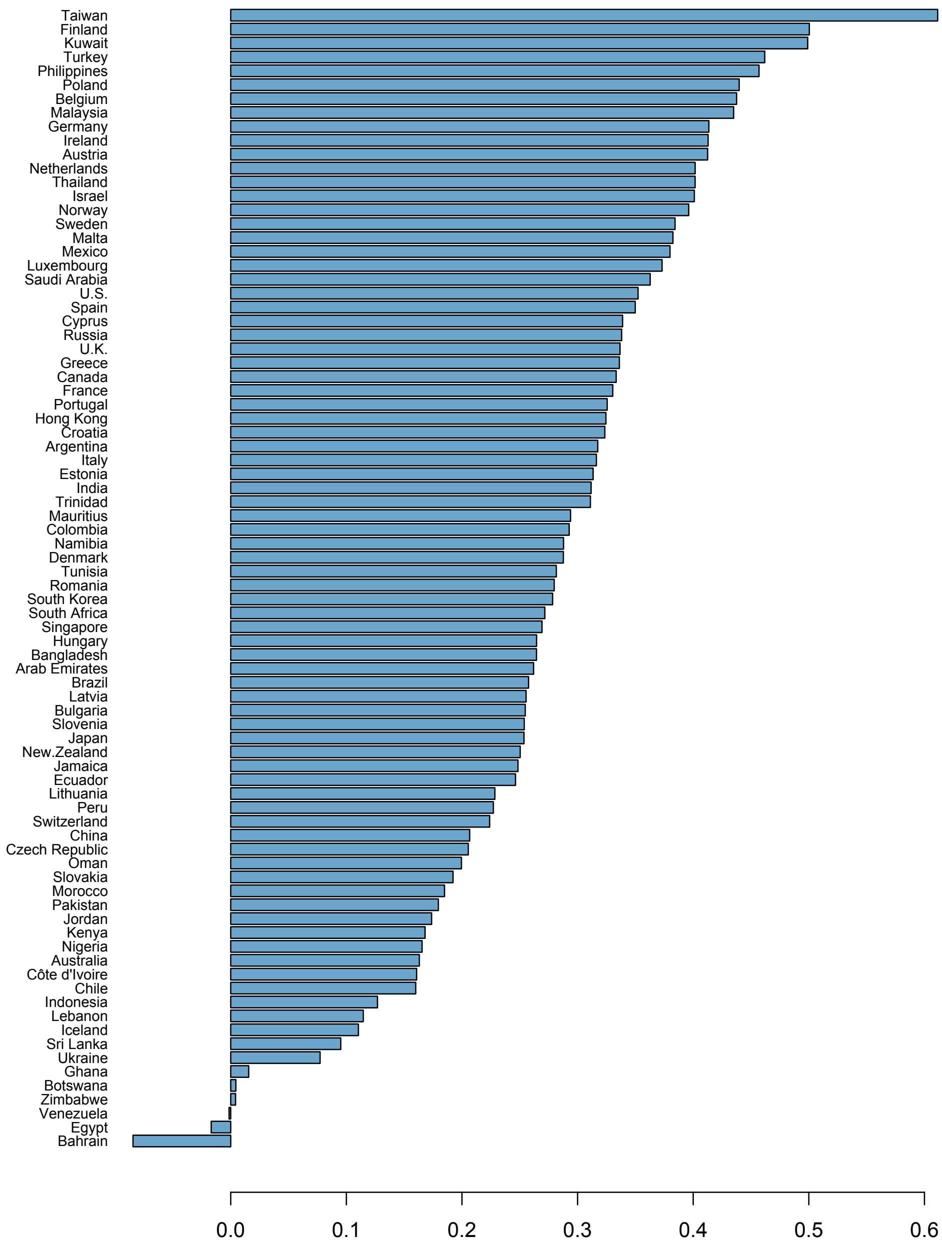
to macroeconomic variables in the cross-section of countries and separately investigates the memory in developed and emerging countries.

5.3.1 Descriptive Statistics

We apply the GPH estimator to the time series of squared returns for the selected eighty-two countries. Table 5.1 provides summary statistics for the memory parameter d. The mean memory parameter over the eighty-two countries is 0.27 and the mean standard deviation is 0.13. If the time series exhibit short memory, the mean should be approximately zero. The average t-statistic of 3.95 suggests that long memory is present in volatility. In fact, 87% of the parameters are positive and statistically significant at the 5% level or lower. Further, the 5% to 95% quantiles suggest that most parameters lie in the interval $(0, 0.5)$. We find that 94% of the countries exhibit long memory in volatility, where $0 < d < 0.5$, while 4% show anti-persistence and 2% show non-stationary long memory in volatility.

Figure 5.1: Memory Estimates of International Countries

This figure shows the memory parameter estimates applying the GPH estimator and a bandwidth parameter of $m = N^{0.5}$ to the eighty-two countries for the period from January 1964 until December 2015.



We hence conclude that most international stock markets exhibit long memory in volatility. These results extend the current literature which focuses on the U.S. and some major countries like Japan or the U.K. (Cheung & Lai, 1995; Sadique & Silvapulle, 2001; Henry, 2002).

The countries with the highest memory parameter are Taiwan, Finland and Kuwait, while countries with the lowest memory parameter are Bahrain and Egypt. Figure 5.1 displays the estimates for the eighty-two countries. The G-7 countries, representing the major advanced economies and those making the largest percentage of global wealth, do not possess the longest or shortest memory. But six of the seven major economies have a memory parameter higher than 0.3 while the ten countries with the shortest memory are all "frontier" countries.[8] In the following we closely investigate potential drivers of the memory parameter.

5.3.2 Long Memory and Predictability

Typically, long memory time series are described as highly persistent time series, for which the autocorrelation function is decaying at a hyperbolic rate rather than an exponential rate as for short memory processes. Intuitively, the higher persistence of the time series can be linked to higher predictability or lower uncertainty. In this section, we empirically show the link between long memory and predictability for the volatility of the stock indices.

At the same time, this exercise presents a validity check for our long memory estimates. A higher memory parameter should be associated with higher forecasting performance, if our memory estimates are correct and not biased by the quality of the data or spurious long memory.

We run monthly predictability regressions of the realized volatility

[8] Even though the beginning of the sample period varies across the countries, the memory parameters are comparable. In our empirical analysis we also consider the same sample size for all countries, which delivers qualitatively similar results.

for each country separately both in-sample and out-of-sample. We obtain monthly realized volatility observations by summing squared daily returns within each month (Bollerslev et al., 2014). We rely on the state of the art (Heterogeneous) Autoregressive models of Realized Volatility (HAR-RV) following Corsi (2009).[9] The independent variables are lagged observations of the realized volatility and we consider five different specifications by including the volatility from the previous month (HAR(1)), six months (HAR(2)), one year (HAR(3)), two years (HAR(4)) and 5 years (HAR(5)):

$$HAR(1) : RV_{t+1}^M = \alpha + \beta RV_t^M + \epsilon_{t+1} \tag{5.4}$$

$$HAR(2) : RV_{t+1}^M = \alpha + \beta RV_t^M + \beta RV_t^{6M} + \epsilon_{t+1} \tag{5.5}$$

$$HAR(3) : RV_{t+1}^M = \alpha + \beta RV_t^M + \beta RV_t^{6M} + \beta RV_t^{1Y} + \epsilon_{t+1} \tag{5.6}$$

$$HAR(4) : RV_{t+1}^M = \alpha + \beta RV_t^M + \beta RV_t^{6M} + \beta RV_t^{1Y} + \beta RV_t^{2Y} + \epsilon_{t+1} \tag{5.7}$$

$$\begin{aligned} HAR(5) : RV_{t+1}^M = \alpha + \beta RV_t^M + \beta RV_t^{6M} + \beta RV_t^{1Y} + \beta RV_t^{2Y} \\ + \beta RV_t^{5Y} + \epsilon_{t+1} \end{aligned} \tag{5.8}$$

The multiperiod volatilities are normalized sums of the one-month realized volatilities. The six-months' realized volatility is exemplarily given by:

$$RV_t^{6M} = \frac{1}{6}(RV_t^M + RV_{t-1}^M + ... + RV_{t-5}^M) \tag{5.9}$$

The models are able to mimic the behavior of long memory processes and exhibit strong forecasting performance, despite the simplicity of both the model and the estimation. We form tertile portfolios by sorting the cross-section of country stock market indices by the memory parameter. We then compute the average adjusted R^2, t-statistic, F-statistic and out-of-sample R_{OOS}^2 for each tertile portfolio.[10]

The results are reported in Table 5.2. Panel A shows the adjusted R^2 of the in-sample predictability regressions. There is a strictly monotonic

[9] We also considered simple Autoregressive models including the lags 1, 6, 12, 24 and 60, leading to qualitatively similar results.

[10] We report t-statistics of the slope coefficient for HAR(1) and F-statistics for the joint significance of the slope coefficients for the remaining models.

Table 5.2: Long Memory and Predictability – Cross-Section of Countries

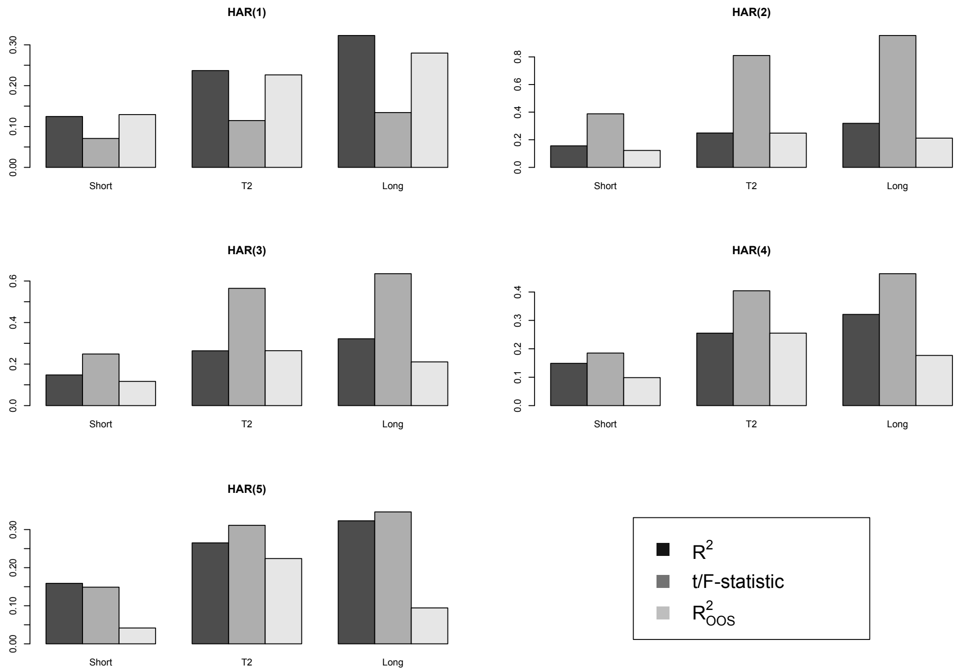
This table reports the results predictive regressions. We estimate the proposed HAR models by simple linear regressions including the previous 1, 6, 12, 24 and 60 observations. We form tertile portfolios where countries with the lowest memory parameter are in the first tertile and countries with the highest memory parameter are in the third tertile. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. We report average adjusted R^2 in Panel A, average t-statistics and F-statistics in Panel B and out-of-sample R^2 in Panel C.

	T1	T2	T3
Panel A: Adjusted R^2			
HAR(1)	0.1246	0.2370	0.3229
HAR(2)	0.1560	0.2491	0.3190
HAR(3)	0.1476	0.2638	0.3217
HAR(4)	0.1488	0.2552	0.3212
HAR(5)	0.1588	0.2651	0.3230
Panel B: T-statistic/F-statistic			
HAR(1)	7.0841	11.4621	13.4188
HAR(2)	38.7906	81.0082	95.4979
HAR(3)	24.8456	56.4617	63.5065
HAR(4)	18.5080	40.4269	46.4415
HAR(5)	14.8762	31.1230	34.6305
Panel C: R^2_{OOS}			
HAR(1)	0.1292	0.2265	0.2798
HAR(2)	0.1227	0.2482	0.2118
HAR(3)	0.1165	0.2645	0.2104
HAR(4)	0.0986	0.2552	0.1766
HAR(5)	0.0415	0.2239	0.0943

pattern of explanatory power, which is increasing in the memory parameter. This is further supported by the increasing t-statistics and F-statistics in Panel B. Countries with higher memory parameters have stronger explanatory power and the predictor variables are more statistically significant than countries with shorter memory in volatility. Lastly, in Panel C, the R^2_{OOS} also show that the out-of-sample forecasting performance of long memory countries is stronger than short memory countries. There is

Figure 5.2: Predictability of Tertile Portfolios

This figure reports adjusted R^2, t-statistics, F-statistics and R^2_{OOS} for tertile portfolios of the cross-section of countries. For a better presentation, the test statistics are all divided by 100.



a strictly monotonic pattern for the short horizon model, HAR(1), which diminishes when including more lags. A graphical illustration of the results is reported in Figure 5.2.

We thus show that the degree of memory in volatility is a proxy for predictability. At the same time this exercise validates our estimation approach of memory. Our results are true for both in-sample and out-of-sample, while we allow for various model specifications including short memory processes and long memory mimicking processes.

5.3.3 Time Variation of Long Memory Volatility

We first investigate the temporal variation of the memory parameter for the individual countries and their relationships with macroeconomic variables. For this purpose, we allow for a time-varying memory parameter. We estimate the memory parameter by applying the GPH estimator at a monthly frequency to a rolling window of five years of daily return data. We start with a separate analysis of the U.S. and consider the complete cross-section in a second step.

Evidence from the U.S.

Each month we regress the memory parameter of the U.S. on the following macroeconomic variables: inflation proxied by changes in Consumer Price Index (Inflation), log Unemployment rate (Unemployment), treasury bill rates (Tbill), government bond rates (Gov.Bonds), gross domestic product growth (GDP) and an indicator function for the recession (Recession) that represents periods of expansion and recession defined by the National Bureau of Economic Research (NBER):

$$d_{U.S.,t} = \alpha_{U.S.} + \beta_{U.S.} X_{U.S.,t} + \epsilon_t \tag{5.10}$$

where d_t stands for the memory parameter at time t, X_t contains one or more of the macroeconomic variables and ϵ_t is the error term.[11] All time series are at monthly frequency except for the GDP, which is quarterly.[12] Table 5.3 reports the results. Our interpretations refer to the terms predictability, uncertainty and low memory parameters interchangeably.

[11]Since our memory estimates d_t rely on rolling window estimates, one might argue that there is barely temporal variation in our estimates. If this is true, this should work against our empirical analysis and we should not find any significant drivers of the memory parameter, but we do. In addition, we repeat the analysis relying on smaller rolling windows using 12 months of daily return data. The results are qualitatively similar.

[12]We follow Bloom (2009) and detrend the time series using the Hodrick–Prescott filter with $\lambda = 129,600$.

Table 5.3: Long Memory of the U.S.

This table presents the coefficients from the regressions of the memory parameter on macroeconomic variables for the U.S. for the period from 1964 until 2015. The regressors are the inflation, the log unemployment, the treasury bill and the government bond rates and the GDP growth. Recession is the indicator function that represents periods of expansion and recession defined by the NBER. All the macroeconomic variables are monthly except for GDP, hence Model 5 and Model 8 are on a quarterly basis. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$ applied to squared returns. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
(Intercept)	0.4244^{***}	0.4070^{***}	0.5356^{***}	0.7847^{***}	0.4352^{***}	0.4125^{***}	0.9302^{***}	1.0393^{***}
	(0.0142)	(0.0114)	(0.0161)	(0.0299)	(0.0275)	(0.0121)	(0.0434)	(0.0566)
Inflation	-7.9649^{*}						3.9341	2.1536
	(4.2795)						(3.3853)	(4.9511)
Unemployment		0.2143^{**}					0.7310^{***}	0.7641^{***}
		(0.0998)					(0.1290)	(0.0925)
Tbill			-0.0452^{***}				0.0501^{***}	0.0930^{***}
			(0.0045)				(0.0115)	(0.0150)
Gov.Bonds				-0.0711^{***}			-0.1283^{***}	-0.1719^{***}
				(0.0054)			(0.0137)	(0.0178)
GDP					-5.0221			1.4630
					(3.1868)			(2.7594)
Recession						-0.0344	0.0270	-0.0084
						(0.0363)	(0.0286)	(0.0533)
adj. R^2	0.0080	0.0117	0.2453	0.3630	0.0145	-0.0003	0.4181	0.6271

We find that inflation proxied by the changes in the CPI has a negative relationship with the degree of long memory, which is statistically significant at the 10% level (Model 1). However, the explanatory power is rather low for inflation rates with an adjusted R^2 of 0.8%. Economically, the negative sign of the coefficient implies that in times of lower inflation, the memory of U.S. market volatility is rather longer. Ball (1992) argues that inflation is expected to be kept low by authorities when it is low. When inflation is high, on the other hand, there is a high degree of uncertainty since policymakers face the trade-off between deflation and the resulting recession. This uncertainty can be related to unpredictability in the U.S. market in general but more importantly also in the U.S.

stock market. This argument is supported by Fischer & Modigliani (1978), who suggest that higher inflation rates cause governments to announce unrealistic stabilization programs which leads to uncertainty for market prices. The lower predictability in times of high inflation is reflected by the shorter memory.

The unemployment rate impacts the memory parameter positively and is statistically significant at the 5% level (Model 2). The adjusted R^2 is of similar magnitude when including the inflation as a regressor with a value of only 1.17%. Veronesi (1999) shows that good news in bad times (and bad news in good times) is generally related to increased uncertainty. Similarly, Boyd et al. (2005) argue that the impact of unemployment for stocks depends on the business cycle but the economy is usually in an expansion phase. Hence, the average relationship of higher unemployment and higher uncertainty is consistent with the lower predictability proxied by shorter memory in volatility.

Both the short- and long- term interest rates given by Tbill and Gov.Bonds have a negative impact on the memory parameter which is statistically significant at the 1% level. The adjusted R^2 are the highest with values of 24.53% and 36.30%, respectively. A large literature has researched the impact of interest rates on real activity. Typically high interest rates play a key role in (inflation) stabilization programs for the government in order to decrease inflation rates. As discussed above, high inflation rates are related to lower predictability. The lower predictability given by lower memory parameters coupled with higher interest rates can be confirmed from our regression analysis for the U.S.

Similar to inflation, GDP has a negative coefficient, but it is statistically insignificant. The same is true for the recession indicator as defined by the

NBER, which does not help explain the memory parameter.[13] Intuitively, one would expect recessions to be associated with low memory parameters due to the high uncertainty and low predictability in these times.

We also conduct regressions including all variables. Model 7 is a multiple regression without GDP at a monthly frequency while Model 8 is a multiple regression including GDP at a quarterly frequency. While the signs and the significance of Unemployment and Gov.Bonds in Model 7 are similar to the univariate regressions, the adjusted R^2 increase to remarkable magnitudes of 41.81% and 62.71% for Model 7 and 8, respectively. In summary, the direction of the relationships between the memory parameter and macroeconomic variables makes sense economically and the variables jointly have high explanatory power for the memory parameter.

Evidence from the Complete Cross-Section

We repeat the analysis from above and estimate the same regression as Equation (5.10) for each of the countries individually. For overview purposes we do not report the same output as Table 5.3 for each country but report median estimates for the cross-section, the percentage of countries for which we find a negative (positive) and statistically significant coefficient and the average t-statistic and adjusted R^2 across all countries. The results are presented in Table 5.4.

Overall, the median values deliver the same results for the entire cross-section as for the U.S. All macroeconomic variables except for unemployment have a negative impact on the memory parameter for the cross-section. Nonetheless, only for Tbill and Gov.Bonds we find strong statistical evidence. For 63% (55%) of the countries, Tbill (Gov.Bonds)

[13] Note that there are much fewer observations for the regression including the GDP and hence plausibly less power due to the quarterly frequency, while the recession variable is just a dummy variable.

Table 5.4: Long Memory of the Cross-Section of Countries

This table presents the statistics from the regressions of the memory parameter on the macroeconomic variables for eighty-two countries for the period from 1964 until 2015. The regressors are the inflation, the log unemployment, treasury bill and the government bond rates, and the GDP growth. Recession is the indicator function that represents periods of expansion and recession defined by the NBER. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. The first row reports the median of the coefficients over the cross-section. The second (third) row reports the percentage of countries for which the slope is negative (positive) and statistically significant at a 5% level. The fourth row reports the average absolute t-statistic across all countries and the fifth row reports the average adjusted R^2 over all countries.

	Inflation	Unemployment	Tbill	Gov.Bonds	GDP	Recession	KS ex. GDP	KS
Median	−0.15	0.07	−0.01	−0.02	−0.05	−0.01		
$\beta < 0$ (significant)	6.49%	18.97%	62.69%	55.00%	2.50%	18.99%		
$\beta > 0$ (significant)	3.90%	24.14%	23.88%	21.67%	0.00%	13.92%		
t-statistic	0.97	2.16	8.04	8.02	0.81	1.61		
Adj. R^2	0.01	0.04	0.20	0.19	0.01	0.02	0.37	0.37

shows a negative and statistical significant relationship with the memory parameter, which is consistent with our results for the U.S. This is supported by average t-statistics above 8 and the highest adj. R^2 value of 20% (19%).

For the remaining macroeconomic variables, we do not find any consistent pattern across countries. Both the explanatory power and the statistical significance of the slope coefficients are relatively low, where the R^2 vary between 1% and 4%.

Using the kitchensink regression, excluding or including the GDP increases the adjusted R^2 to 37% and 37%, respectively, indicating that the macroeconomic variables jointly have explanatory power for the memory parameter. While the sign of inflation, unemployment, interest rates, GDP and Recession are generally consistent with the analysis of the U.S., it is not true for the complete cross-section (proportion is less than 100%) and not statistically significant for many countries.

5.3.4 Cross-Sectional Variation and Macroeconomic Variables

Instead of investigating the temporal relationship between the long memory parameter and the macroeconomic variables for each country separately, we now examine the complete cross-section over the sample period. We employ two different approaches relying on either portfolio sorts or cross-sectional regressions. Since we are interested in country-specific variables, we exclude the recession dummy variable. Instead, we include a measure of stability directly obtained from the return time series: Jumps. Intuitively, a stable country should exhibit fewer stock market jumps. We apply the common jump test proposed by Barndorff-Nielsen & Shephard (2006).[14] The test relies on the bipower variation, which decomposes the quadratic variation into its part due to continuous movements and a jump part. The jump test statistic is given by:

$$BNS_t = \frac{(\pi/2)B_t - S_t}{\sqrt{((\pi^2/4)+\pi-5)(\pi/2)^2 Q_t}} \tag{5.11}$$

$$Q_t = \frac{1}{K_t-3}\sum_{k=4}^{K_t} |r_{t,k}||r_{t,k-1}||r_{t,k-2}||r_{t,k-3}| \tag{5.12}$$

$$S_t = \frac{1}{K_t}\sum_{k=1}^{K_t} r_{t,k}^2 \tag{5.13}$$

$$B_t = \frac{1}{K_t-1}\sum_{k=2}^{K_t} |r_{t,k}||r_{t,k-1}| \tag{5.14}$$

where K_t is the number of observations over the examined period, $r_{t,k}$ is the kth daily observation over the examined period t and BNS_t is normally distributed under the null. We rely on two measures of jumps. First, we compute the BNS jump statistic for each month and country using a pool

[14] Pukthuanthong & Roll (2015) show, with the help of simulations using different jump size and frequency, that this test is preferable compared to the ones proposed by Jiang & Oomen (2008), Lee & Mykland (2008) and Jacod & Todorov (2009).

Table 5.5: International Portfolio Sorts

This table presents the average macroeconomic variables of the tertile portfolios sorted by the memory parameter. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015. Long memory is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. The column *LMS* reports the difference of the third and first portfolio with t-statistics in squared brackets.

	T1	T2	T3	T3-T1 (LMS)	
Inflation	0.0039	0.0034	0.0034	−0.0005	[−1.2397]
Unemployment	7.7295	7.3664	6.9280	−0.8015	[−3.0940]
Tbill	12.0172	10.5784	9.5123	−2.5048	[−1.0116]
Gov.Bonds	9.8846	8.5284	7.7230	−2.1616	[−3.2466]
GDP	0.0034	0.0033	0.0067	0.0034	[1.8528]
BNS	−3.9505	−0.3542	−0.2565	3.6940	[2.0753]
BNS-I	0.0843	0.0299	0.0180	−0.0662	[−4.5159]

of daily returns following Pukthuanthong & Roll (2015). The first measure is given by the jump statistic for each month. Our second measure presents an indicator function which shows whether the current month exhibits a statistically significant jump at a 5% significance level.

Each month, we sort the countries by their memory parameter and form tertile portfolios where the countries with the lowest memory parameter are in the first tertile and countries with the highest memory parameter are in the third tertile. We then compare averages of macroeconomic variables for the tertile portfolios. Table 5.5 reports average inflation, unemployment, treasury bill rates, government bond rates, GDP and jump measures for the tertile portfolios.[15] There is a monotonic pattern in all of the tertile portfolios (except for GDP) which are increasing or decreasing with the memory parameter.

[15] Looking at the cross-section of countries, one might argue that GDP per capita is a more appropriate measure of comparison than GDP. Our main results rely on real GDP but we also repeated the analysis using GDP per capita, which leads to qualitatively similar results.

We find that the unemployment and government bond rates are lower for countries with long memory. The average spread of the high minus low (LMS) portfolio, which holds the country indices with the longest memory and writes the country indices with the shortest memory, is statistically significant with t-statistics of –3.09 and –3.25, respectively. This stands in contrast of our time-series analysis. While unemployment has a positive impact on the memory parameter in the time-series dimension for most countries, it has a negative impact on the memory parameter in the cross-sectional dimension. Moreover, countries with higher memory parameters have statistically significantly fewer jumps according to both the BNS statistic and the indicator function.[16] Lastly, countries with long memory show higher GDP growth than countries with short memory, which is weakly statistically significant (t-statistic of 1.85).

We also conduct cross-sectional regressions of the memory parameter by estimating the following regression:

$$d_{i,t} = \alpha_{i,t} + \beta_{i,t} X_{i,t} + \epsilon_{i,t} \tag{5.15}$$

where d_i is the memory parameter of country i, X_i contains one or more macroeconomic variables and ϵ_i is the error term. Table 5.6 reports the average coefficient estimates. The slope coefficients of Unemployment, Tbill and Gov.Bonds are all negative and statistically significant at the 1% level while the BNS coefficient is positive and statistically significant (1%) as well. For inflation and GDP, we do not find any significant relationship. The results are generally consistent with our sorting exercise.[17]

[16]The BNS statistic is generally negative and falls below −1.96 if there is a significant (5%) jump, hence lower statistics indicate more significant jumps.

[17]We also conduct panel regressions and find qualitatively similar results. The slope coefficients of Unemployment, Tbill and Gov.Bonds are negative and statistically significant at the 1% level while the BNS coefficient is positive and statistically significant as well. We account for both fixed effects and heteroskedasticity in the regression. Detailed results are reported in Table C.2 of the appendix.

Table 5.6: Cross-Sectional Regressions

This table presents results from the cross-sectional regressions. The dependent variable is the memory parameter for each country and the regressors are the inflation, the log unemployment, treasury bill and government bond rates, GDP growth and jumps measured by BNS. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015. Long memory is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. We report time-series averages and standard errors in parentheses below. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	0.0036^{***}	8.3460^{***}	11.9472^{***}	10.6636^{***}	0.0015	-4.3354^{***}	0.2287^{***}
	(0.0009)	(0.0663)	(0.4604)	(0.1186)	(0.0042)	(0.8375)	(0.0197)
Inflation	-0.0003						-0.1006
	(0.0017)						(0.4048)
Unemployment		-3.7159^{***}					-0.0008
		(0.1661)					(0.0011)
Tbill			-4.3856^{***}				-0.0047^{**}
			(1.3340)				(0.0021)
Gov.Bonds				-5.4660^{***}			0.0068^{**}
				(0.3698)			(0.0030)
GDP					-0.0086		
					(0.0088)		
BNS						10.1832^{***}	0.0308^{***}
						(2.0815)	(0.0055)

Our results suggest that countries with stable economies possess longer memory volatility compared to less stable countries. Intuitively, a stable country should hence exhibit fewer jumps as well. Long-term interest rates as proxied by government bonds can also be related to the stability of a country. These tend to be lower in safer countries. Since the value of money might be unpredictable in unstable environments, people prefer to spend their money, which is counteracted with higher interest rates by the government. The U.S. has an average short term interest rate of 5.36% over the sample period compared to Brazil (22.60%), Romania (45%) and Turkey (45%).

We directly test whether developed countries possess longer memory than undeveloped countries. In the following we do not rely on proxies for the economic strength of a country, such as macroeconomic variables, but we use existing specifications. We differentiate between Organisation for Economic Co-operation and Development (OECD) countries and emerging countries as defined by Thomson Reuters Tickhistory (TRTH). We also differentiate between developed, emerging and frontier countries, as defined by the classification of Morgan Stanley Capital International (MSCI). We estimate the following cross-sectional regression:

$$d_i = \alpha_i + \beta_i D_i + \epsilon_i \tag{5.16}$$

where d_i is the memory parameter of country i, D_i is a dummy variable indicating whether a country is part of group of countries and ϵ_i is the error term. If frontier countries have a shorter memory than developed countries, the coefficient is expected to be negative and statistically significant.

We run three distinct analyses. First, we estimate the memory parameter over the complete sample from 1964 until 2015, resulting in a cross-sectional regression with eighty-two observations. Since the classification of MSCI and the inclusion in the OECD group has changed within our sample period, one could argue that the first analysis leads to biased results. We hence repeat the same analysis, but estimate the memory parameter only for the most recent eight years for the period from 2008 until 2015. Lastly, we use the time series of memory parameters from the previous sections estimated from rolling windows and estimate the cross-sectional regression in each month. The regression equation is then modified as:

$$d_{i,t} = \alpha_{i,t} + \beta_{i,t} D_{i,t} + \epsilon_{i,t} \tag{5.17}$$

We are interested in the temporal variation of the slope coefficient $\beta_{i,t}$ and report time-series averages for these.

The results for the three analyses are presented in Table 5.7 in Panel A, B and C, respectively.

Table 5.7: Long Memory in Developed and Emerging Countries

This table presents the cross-sectional regressions of the memory estimates on the dummy variables. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015 in Panel A. Panel B investigates the subperiod from 2008 until 2015. OECD, Emerging, Developed and Frontier indicate whether a country is part of the OECD group, an emerging, developed or a frontier country according to the definition of Thomson Reuters Tickhistory (TRTH) or Morgan Stanley Capital International (MSCI). We repeat the estimation of the memory parameter at a monthly frequency relying on rolling windows of five years of daily observations. Each month we run the same cross-sectional regression as in Panel A and B and report the time-series averages of the coefficients in Panel C with the standard errors in parentheses below. We also report the average of the adjusted R^2 over the sample period. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: 1964-2015						
(Intercept)	0.2444***	0.3250***	0.2472***	0.2609***	0.3115***	0.2428***
	(0.0170)	(0.0246)	(0.0160)	(0.0167)	(0.0160)	(0.0388)
OECD (TRTH)	0.0836**					
	(0.0286)					
Emerging (TRTH)		−0.0748**				
		(0.0298)				
Developed (MSCI)			0.0953**			0.0997**
			(0.0302)			(0.0457)
Emerging (MSCI)				0.0466		0.0646
				(0.0316)		(0.0457)
Frontier (MSCI)					−0.1142***	−0.0455
					(0.0278)	(0.0448)
adj. R^2	0.0853	0.0616	0.0996	0.0143	0.1636	0.1919
Panel B: 2008-2015						
(Intercept)	0.3608***	0.5255***	0.3548***	0.4279***	0.4496***	0.2177***
	(0.0268)	(0.0386)	(0.0237)	(0.0275)	(0.0277)	(0.0584)
OECD (TRTH)	0.1675***					
	(0.0448)					
Emerging (TRTH)		−0.1542**				
		(0.0468)				
Developed (MSCI)			0.2324***			0.3694***
			(0.0446)			(0.0689)
Emerging (MSCI)				−0.0252		0.1850**
				(0.0516)		(0.0689)
Frontier (MSCI)					−0.0898*	0.1420**
					(0.0489)	(0.0677)
adj. R^2	0.1396	0.1098	0.2466	−0.0096	0.0288	0.2936

Table 5.7: Long Memory in Developed and Emerging Countries continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: Time-Series Averages						
Coefficient	0.0455***	−0.0120**	0.0402***	0.0363***	−0.0552***	
	(0.0048)	(0.0054)	(0.0067)	(0.0038)	(0.0065)	
adj.R^2	0.0518	0.0551	0.0947	0.0125	0.0463	

We can confirm the presumption that economically stronger countries have higher memory parameters than weaker countries for the period from 1964 until 2015 in Panel A. This holds true for both definitions of either TRTH or MSCI. OECD and developed countries exhibit a higher memory parameter which is statistically significant at the 5% level while emerging (TRTH) and frontier countries possess a shorter memory in volatility, which is also statistically significant at the 5% level or lower. The adjusted R^2 vary from 1.43% to 16.36%. The results remain qualitatively similar when considering the subsample from 2008 until 2015 in Panel B. OECD and developed countries possess statistically higher memory parameters while emerging (TRTH) and frontier countries possess statistically shorter memory in volatility. Lastly, the time series averages of the slope coefficients deliver the same message. All coefficients are statistically significant at the 5% level or lower, and exhibit the same signs as for the other two analyses.

An economically strong country tends to be more stable and less sensitive to sudden shocks. Therefore, it is intuitive that stock market volatility in these countries will be more persistent. We can relate the memory of a country to its economic importance proxied by classifications such as OECD, MSCI or continents.

5.4 Robustness

In this section we run various robustness tests including alternative long memory estimates and predictive regressions. All results are reported in the appendix to this chapter.

5.4.1 Estimation of the Memory Parameter

For our main analysis we follow the existing literature and choose the ad hoc bandwidth parameter of $m = N^{0.5}$. We repeat the exercises using a bandwidth parameter of $m = N^{0.6}$ and $m = N^{0.7}$. Further, we apply the GPH estimator to absolute returns rather than squared returns as in our main analysis (Bollerslev & Wright, 2000). Lastly, we follow another commonly used approach to estimate long memory, the Local Whittle estimator. The Local Whittle estimator is obtained by minimizing the following objective function:

$$\hat{d}_{LW} = \arg\min_{d \in \theta} \left[log\left(\frac{1}{m} \sum_{j=1}^{m} \frac{I(\lambda_j)}{\lambda_j^{2d}} \right) - \frac{2d}{m} \sum_{j=1}^{m} log\lambda_j \right], \quad \theta \subseteq (-0.5, 0.5) \tag{5.18}$$

where m is restricted to $m < \frac{N}{2}$. The originally proposed estimator by Whittle (1951) presents an approximate maximum likelihood approach, which is extended by the Local Whittle estimator. Under mild assumptions similar to those for the GPH estimator, Robinson (1995a) derives the asymptotic distribution:

$$\sqrt{m}(\hat{d}_{LW} - d_0) \underset{d}{\longrightarrow} N\left(0, \frac{1}{4}\right) \tag{5.19}$$

Table C.3 reports the time-series regression of the memory parameter on macroeconomic variables for the U.S. The table presents results based on the four alternative memory estimators in Panel A, B, C and D, respectively. Even though the magnitudes of the slope coefficients slightly differ, the relationship between the variables and the memory parameter remains qualitatively similar. Generally, inflation, short and long interest rates have a negative impact on the memory parameter while unemployment has a positive relationship with the memory parameter.[18] The adjusted R^2 vary from 0%–41%, 0%–63%, 0%–34% and 0%–52% in the univariate regressions for the four alternative estimators, respectively. For comparison, the adjusted R^2 varies from 0%-36% in our main analysis using the GPH estimator and $m = N^{0.5}$.

Table C.4 compares the memory parameter in developed and emerging countries for the alternative memory estimators. OECD countries and developed (MSCI) countries have statistically significantly higher memory parameters while emerging countries (TRTH) and frontier countries have statistically significantly shorter memory in volatility for all four estimators. The adjusted R^2 vary from 1%–16%, 1%–23%, 2%–16% and 0%–8% in the univariate regressions for the four estimators, respectively. For comparison, the adjusted R^2 varies from 1%–16% in our main analysis using the GPH estimator and $m = N^{0.5}$.

Table C.5 investigates the average macroeconomic variables of tertile portfolios sorted by the memory parameter. Countries with higher memory parameters exhibit fewer jumps (higher BNS and lower BNS-I) and show lower government bond rates. This result is true and statistically significant for all four estimators. Additionally, countries with a higher memory parameter have lower unemployment rates, which is statistically significant for three of the four estimators.

[18] There is one exception. Unemployment has a negative and statistically significant impact on the memory parameter when using the bandwidth of $m = N^{0.7}$.

5.4.2 Predictive Regresssions

In Section 5.3.4, we investigate the contemporaneous relationship between the memory parameter and macroeconomic variables' cross-section of countries. It is argued in the literature that changes in macroeconomic variables do not directly impact the real economy and the stock market, but it takes several months or more. Paye (2012) investigates the predictability of stock return volatility by multiple macroeconomic variables including up to two lags while Engle et al. (2013) show that macroeconomic fundamentals are important for both short- and long-horizon forecasting of stock market volatility. We hence repeat our time-series analysis but investigate a lagged relationship rather than a contemporaneous one for the U.S. Equation (5.10) is modified as follows:

$$d_{U.S.,t} = \alpha_{U.S.} + \beta_{U.S.} X_{U.S.,t-h} + \epsilon_t \tag{5.20}$$

considering lags from one quarter, half a year and one year ($h = 1, 2, 4$).[19] Table C.6 presents the results for the three horizons in the three panels. Consistent with our main results, we find that inflation, short and long interest rates and GDP have a negative impact on the memory parameter while unemployment has a positive relationship with the memory parameter. The relationship between GDP and the memory parameter diminishes for longer horizons and the slope coefficient is no longer statistically significant. The adjusted R^2 varies between 0% and 39% for the univariate regressions. Hence, the relationship between memory and macroeconomic variables found in our main contemporaneous analysis persists into the future for up to one year.

[19] We conduct this analysis in quarterly frequency because GDP data is only available at this frequency.

5.5 Conclusion

In Chapter 5 we shed new light on long memory in the volatility of international equity markets. With the help of portfolio sorts and cross-sectional regressions, we demonstrate how the memory parameter of a country stock index volatility can be explained by country-specific macroeconomic variables such as inflation, unemployment rates, interest rates and jumps. We show that macroeconomic variables help explain the memory parameter, both in the time-series and the cross-sectional dimension. Following the existing literature, we provide economically reasonable explanations for the sign of the relationships. In addition, classifications such as OECD, developed, emerging or frontier countries also matter for the memory parameter. More developed countries possess a higher memory parameter while frontier and emerging countries possess a shorter memory in volatility. Our results are robust against various variations of the examined models.

C Appendix

Table C.1: Overview of Country Sample

This table presents the eighty-two countries and their availability from Datastream. We rely on a common currency, the U.S. dollar, for all values. We work with either the total return index ("RI") or the pure price index ("PI").

Country	Datastream Availability		Index Identification	Datastream Mnemonic	Country	Datastream Availability		Index Identification	Datastream Mnemonic
Argentina	2-Aug-93	31-Dec-15	ARGENTINA MERVAL	ARGMERV(PI)~U$	Lithuania	31-Dec-99	31-Dec-15	OMX VILNIUS (OMXV)	LNVILSE(RI)~U$
Australia	1-Jan-73	31-Dec-15	AUSTRALIA-DS MarKET	TOTMAU$(RI)	Luxembourg	2-Jan-92	31-Dec-15	LUXEMBURG-DS MarKET	TOTMKLX(RI)
Austria	1-Jan-73	31-Dec-15	AUSTRIA-DS Market	TOTMKOE(RI)~U$	Malaysia	2-Jan-80	31-Dec-15	KLCI COMPOSITE	KLPCOMP(PI)~U$
Bahrain	31-Dec-99	31-Dec-15	DOW JONES BAHRAIN	DJBAHR$(PI)	Malta	27-Dec-95	31-Dec-15	MALTA SE MSE -	MALTAIX(PI)~U$
Bangladesh	1-Jan-90	1-Apr-13	BANGLADESH SE ALL SHARE	BDTALSH(PI)~U$	Mauritius	29-Dec-95	31-Dec-15	S&P/IFCF M MAURITIUS	IFFMMAL(PI)~U$
Belgium	1-Jan-73	31-Dec-15	BELGIUM-DS Market	TOTMKBG(RI)~U$	Mexico	4-Jan-88	31-Dec-15	MEXICO IPC (BOLSA)	MXIPC35(PI)~U$
Botswana	29-Dec-95	31-Dec-15	S&P/IFCF M BOTSWA0.	IFFMBOL(PI)~U$	Morocco	31-Dec-87	31-Dec-15	MOROCCO SE CFG25	MDCFG25(PI)~U$
Brazil	7-Apr-83	31-Dec-15	BRAZIL BOVESPA	BRBOVES(RI)~U$	Namibia	31-Jan-00	31-Dec-15	S&P/IFCF M NAMBIA	IFFMNAL(PI)~U$
Bulgaria	20-Oct-00	31-Dec-15	BSE SOFIX	BSSOFIX(PI)~U$	Netherlands	1-Jan-73	31-Dec-15	NETHERLAND-DS Market	TOTMKNL(RI)~U$
Canada	31-Dec-64	31-Dec-15	S&P/TSX COMPOSITE INDEX	TTOCOMP(RI)~U$	New Zealand	4-Jan-88	31-Dec-15	NEW ZEALAND-DS MarKET	TOTMNZ$(RI)
Chile	2-Jan-87	31-Dec-15	CHILE GENERAL (IGPA)	IGPAGEN(PI)~U$	Nigeria	30-Jun-95	31-Dec-15	S&P/IFCG D NIGERIA	IFGDNGL(PI)~U$
China	3-Apr-91	31-Dec-15	SHENZHEN SE COMPOSITE	CHZCOMP(PI)~U$	Norway	2-Jan-80	31-Dec-15	NORWAY-DS MarKET	TOTMNW$(RI)
Colombia	10-Mar-92	31-Dec-15	COLOMBIA-DS Market	TOTMKCB(RI)~U$	Oman	22-Oct-96	31-Dec-15	OMAN MUSCAT SECURITIES MKT.	OMANMSM(PI)~U$
Côte d'Ivoire	29-Dec-95	31-Dec-15	S&P/IFCF M CÔTE D'IVOIRE	IFFMCIL(RI)~U$	Pakistan	30-Dec-88	31-Dec-15	KARACHI SE 100	PKSE100(PI)~U$
Croatia	2-Jan-97	31-Dec-15	CROATIA CROBEX	CTCROBE(PI)~U$	Peru	2-Jan-91	31-Dec-15	LIMA SE GENERAL(IGBL)	PEGENRL(PI)~U$
Cyprus	3-Sep-04	31-Dec-15	CYPRUS GENERAL	CYPMAPM(PI)~U$	Philippines	2-Jan-86	31-Dec-15	PHILIPPINE SE I(PSEi)	PSECOMP(PI)~U$
Czech Republic	9-Nov-93	31-Dec-15	CZECH REP.-DS NON-FINCIAL	TOTLICZ(RI)~U$	Poland	16-Apr-91	31-Dec-15	WARSAW GENERALINDEX	POLWIGI(RI)~U$
Denmark	31-Dec-69	31-Dec-15	MSCI DENMARK	MSDNMKL(RI)~U$	Portugal	5-Jan-88	31-Dec-15	PORTUGAL PSI GENERAL	POPSIGN(PI)~U$
Ecuador	2-Aug-93	31-Dec-15	ECUADOR ECU (U$)	ECUECUI(PI)	Romania	19-Sep-97	31-Dec-15	ROMANIA BET (L)	RMBETRL(PI)~U$
Egypt	2-Jan-95	31-Dec-15	EGYPT HERMES FINANCIAL	EGHFINC(PI)~U$	Russia	1-Sep-95	31-Dec-15	RUSSIA RTS INDEX	RSRTSIN(PI)~U$
Estonia	3-Jun-96	31-Dec-15	OMX TALLINN (OMXT)	ESTALSE(PI)~U$	Saudi Arabia	31-Dec-97	31-Dec-15	S&P/IFCG D SAUDI ARABIA	IFGDSB$(RI)
Finland	2-Jan-91	31-Dec-15	OMX HELSINKI (OMXH)	HEXINDX(RI)~U$	Singapore	1-Jan-73	31-Dec-15	SINGAPORE-DS MarKET EX TMT	TOTXTSG(RI)~U$
France	1-Jan-73	31-Dec-15	FRANCE-DS Market	TOTMKFR(RI)~U$	Slovakia	14-Sep-93	31-Dec-15	SLOVAKIA SAX 16	SXSAX16(PI)~U$
Germany	31-Dec-64	31-Dec-15	DAX 30 PERFORMANCE	DAXINDX(RI)~U$	Slovenia	31-Dec-93	14-Oct-10	SLOVENIAN EXCH. STOCK (SBI)	SLOESBI(PI)~U$
Ghana	29-Dec-95	31-Dec-15	S&P/IFCF M GHA0.	IFFMGHL(PI)~U$	South Africa	1-Jan-73	31-Dec-15	SOUTH AFRICA-DS MarKET	TOTMSA$(RI)
Greece	26-Jan-06	31-Dec-15	ATHEX COMPOSITE	GRAGENL(RI)~U$	South Korea	31-Dec-74	31-Dec-15	KOREA SE COMPOSITE (KOSPI)	KORCOMP(PI)~U$
Hong Kong	2-Jan-90	31-Dec-15	HANG SENG	HNGKNGI(RI)~U$	Spain	2-Jan-74	31-Dec-15	MADRID SE GENERAL	MADRIDI(PI)~U$
Hungary	2-Jan-91	31-Dec-15	BUDAPEST (BUX)	BUXINDX(PI)~U$	Sri Lanka	2-Jan-85	31-Dec-15	COLOMBO SE ALLSHARE	SRALLSH(PI)~U$
Iceland	31-Dec-92	31-Dec-15	OMX ICELAND ALLSHARE	ICEXALL(PI)~U$	Sweden	28-Dec-79	31-Dec-15	OMX STOCKHOLM (OMXS)	SWSEALI(PI)~U$
India	2-Jan-87	31-Dec-15	INDIA BSE (100) NATIONAL	IBOMBSE(PI)~U$	Switzerland	1-Jan-73	31-Dec-15	SWITZ-DS Market	TOTMKSW(RI)~U$
Indonesia	2-Apr-90	31-Dec-15	INDONESIA-DS Market	TOTMKID(RI)~U$	Taiwan	31-Dec-84	31-Dec-15	TAIWAN SE WEIGHTED	TAIWGHT(PI)~U$
Ireland	1-Jan-73	31-Dec-15	IRELAND-DS MarKET	TOTMIR$(RI)	Thailand	2-Jan-87	31-Dec-15	THAILAND-DS MarKET	TOTMTH$(RI)
Israel	23-Apr-87	31-Dec-15	ISRAEL TA 100	ISTA100(PI)~U$	Trinidad	29-Dec-95	31-Dec-15	S&P/IFCF M TRINIDAD & TOBAGO	IFFMTTL(PI)~U$
Italy	1-Jan-73	31-Dec-15	ITALY-DS MarKET	TOTMIT$(RI)	Tunisia	31-Dec-97	31-Dec-15	TUNISIA TUNINDEX	TUTUNIN(PI)~U$
Jamaica	29-Dec-95	31-Dec-15	S&P/IFCF M JAMAICA	IFFMJAL(PI)~U$	Turkey	4-Jan-88	31-Dec-15	ISE TIOL 100	TRKISTB(PI)~U$
Japan	1-Jan-73	31-Dec-15	TOPIX	TOKYOSE(RI)~U$	Ukraine	30-Jan-98	31-Dec-15	S&P/IFCF M UKRAINE	IFFMURL(PI)~U$
Jordan	21-Nov-88	31-Dec-15	AMMAN SE FINANCIAL MarKET	AMMANFM(PI)~U$	Utd. Arab	1-June-05	31-Dec-15	MSCI UAE	MSUAE$
Kenya	11-Jan-90	31-Dec-15	KENYA NAIROBI SE	NSEINDX(PI)~U$	United Kingdom	1-Jan-65	31-Dec-15	UK-DS MarKET	TOTMUK$(RI)
Kuwait	28-Dec-94	31-Dec-15	KUWAIT KIC GENERAL	KWKICGN(PI)~U$	United States	4-Jan-68	31-Dec-15	S&P 500 COMPOSITE	S&PCOMP(RI)~U$
Latvia	3-Jan-00	31-Dec-15	OMX RIGA (OMXR)	RIGSEIN(RI)~U$	Venezuela	2-Jan-90	31-Dec-15	VENEZUELA-DS MarKET	TOTMVE$(RI)
Lebanon	31-Jan-00	31-Dec-15	S&P/IFCF M LEBANON	IFFMLEL(PI)~U$	Zimbabwe	6-Apr-88	6-Oct-06	ZIMBABWE INDUSTRIALS	ZIMINDS(PI)

Table C.2: Long Memory for the Cross-Section of Countries – Panel Regression

This table presents the statistics from the panel regressions of the memory parameter on macroeconomic variables for eighty-two countries for the period from 1964 until 2015. The regressors are the inflation, the log unemployment, treasury bill and the government bond rates, and the GDP growth. Recession is the indicator function that represents periods of expansion and recession defined by the NBER and BNS presents the Barndorff-Nielsen et al. (2009) jump test statistic. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Inflation	−0.0027						−0.0425	−0.0680
	(0.0227)						(0.0927)	(0.1472)
Unemployment		−0.0057***					−0.0014***	−0.0267
		(0.0002)					(0.0003)	(0.0530)
Tbill			−0.0003***				−0.0008	−0.0024
			(0.0001)				(0.0007)	(0.0015)
Gov				−0.0046***			−0.0078***	−0.0070***
				(0.0003)			(0.0008)	(0.0014)
GDP					−0.0138			−0.1210*
					(0.0304)			(0.0706)
BNS						0.0001**	0.0009***	0.0034***
						(0.0000)	(0.0004)	(0.0010)

Table C.3: Long Memory of the U.S. – Alternative Long Memory Estimates

This table presents the coefficients from the regressions of the memory parameter on the macroeconomic variables for the U.S. for the period from 1964 until 2015. The regressors are the inflation, the log unemployment, treasury bills and government bond rates and GDP growth. Recession is the indicator function that represents periods of expansion and recession defined by the NBER. All macroeconomic variables are monthly except for GDP, hence Model 5 and Model 8 are on a quarterly basis. Long memory is estimated with the GPH estimator and a bandwidth choice of $m = N^{0.6}$ and $m = N^{0.7}$ in Panel A and B, respectively. The GPH estimator is applied to absolute returns and a bandwidth of $m = N^{0.5}$ in Panel C and Panel D shows results relying on the LW estimator and $m = N^{0.5}$. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A: GPH estimator ($m = N^{0.6}$)								
(Intercept)	0.4373^{***}	0.4148^{***}	0.5999^{***}	0.9142^{***}	0.4136^{***}	0.4117^{***}	0.9819^{***}	1.1624^{***}
	(0.0176)	(0.0142)	(0.0189)	(0.0358)	(0.0244)	(0.0151)	(0.0527)	(0.0604)
Inflation	-10.3997^{*}						5.3654	2.0343
	(5.3207)						(4.1047)	(5.2583)
Unemployment		0.2539^{**}					0.5740^{***}	1.1672^{***}
		(0.1242)					(0.1564)	(0.1170)
Tbill			-0.0652^{***}				0.0240^{*}	0.0975^{***}
			(0.0053)				(0.0139)	(0.0158)
Gov.Bonds				-0.0940^{***}			-0.1246^{***}	-0.1951^{***}
				(0.0064)			(0.0166)	(0.0184)
GDP					-1.3916			2.9567^{***}
					(1.0635)			(0.8567)
Recession						0.0454	0.1032^{**}	0.0575
						(0.0451)	(0.0346)	(0.0425)
adj. R^2	0.0092	0.0104	0.3308	0.4108	0.0070	0.0000	0.4472	0.7193
Panel B: GPH estimator ($m = N^{0.7}$)								
(Intercept)	0.2889^{***}	0.2790^{***}	0.3745^{***}	0.5912^{***}	0.2772^{***}	0.2793^{***}	0.5961^{***}	0.6656^{***}
	(0.0089)	(0.0072)	(0.0094)	(0.0143)	(0.0127)	(0.0077)	(0.0215)	(0.0323)
Inflation	-5.6173^{**}						2.5356	1.9762
	(2.6987)						(1.6747)	(2.8152)
Unemployment		-0.1573^{**}					-0.0811	0.2652^{***}
		(0.0628)					(0.0638)	(0.0626)
Tbill			-0.0345^{***}				0.0024	0.0264^{**}
			(0.0026)				(0.0057)	(0.0085)
Gov.Bonds				-0.0592^{***}			-0.0624^{***}	-0.0881^{***}
				(0.0026)			(0.0068)	(0.0098)
GDP					0.4833			1.2870^{**}
					(0.5524)			(0.4587)
Recession						-0.0132	0.0083	-0.0060
						(0.0229)	(0.0141)	(0.0228)
adj. R^2	0.0108	0.0170	0.3587	0.6349	-0.0023	-0.0022	0.6429	0.6990

Long Memory of the U.S. – Alternative Long Memory Estimates Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel C: GPH estimator (absolute returns; $m = N^{0.5}$)								
(Intercept)	0.5223***	0.5059***	0.6125***	0.8071***	0.5037***	0.5100***	0.9182***	1.0064***
	(0.0116)	(0.0093)	(0.0131)	(0.0248)	(0.0157)	(0.0099)	(0.0361)	(0.0455)
Inflation	−7.4465**						2.1738	0.2664
	(3.4964)						(2.8094)	(3.9656)
Unemployment		0.2155**					0.6103***	0.6458***
		(0.0813)					(0.1070)	(0.0882)
Tbill			−0.0374***				0.0381***	0.0737***
			(0.0037)				(0.0095)	(0.0119)
Gov.Bonds				−0.0566***			−0.1001***	−0.1342***
				(0.0045)			(0.0114)	(0.0139)
GDP					−1.8885**			−0.0508
					(0.6830)			(0.6461)
Recession						−0.0211	0.0273	−0.0044
						(0.0297)	(0.0237)	(0.0321)
adj. R^2	0.0115	0.0194	0.2501	0.3435	0.0617	−0.0016	0.4017	0.6342
Panel D: LW estimator ($m = N^{0.5}$)								
(Intercept)	0.3837***	0.3567***	0.4945***	0.7241***	0.3528***	0.3526***	0.7975***	0.8827***
	(0.0120)	(0.0094)	(0.0123)	(0.0203)	(0.0164)	(0.0100)	(0.0299)	(0.0404)
Inflation	−12.9398***						2.3408	1.0516
	(3.5222)						(2.5542)	(3.7541)
Unemployment		0.2536**					0.3982***	0.6321***
		(0.0821)					(0.0925)	(0.0825)
Tbill			−0.0428***				0.0303***	0.0610***
			(0.0030)				(0.0082)	(0.0107)
Gov.Bonds				−0.0655***			−0.0976***	−0.1289***
				(0.0034)			(0.0094)	(0.0123)
GDP					−1.5143**			1.3986**
					(0.7193)			(0.6124)
Recession						0.0321	0.0494**	−0.0035
						(0.0315)	(0.0217)	(0.0305)
adj. R^2	0.0360	0.0248	0.3775	0.5215	0.0300	0.0001	0.5449	0.7117

Table C.4: Long Memory in Developed and Emerging Countries – Alternative Estimates

This table presents the cross-sectional regressions of the memory estimates on the dummy variables. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015. Long memory is estimated with the GPH estimator and a bandwidth choice of $m = N^{0.6}$ and $m = N^{0.7}$ in Panel A and B, respectively. The GPH estimator is applied to absolute returns and a bandwidth of $m = N^{0.5}$ in Panel C and Panel D shows results relying on the LW estimator and $m = N^{0.5}$. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: GPH estimator ($m = N^{0.6}$)						
(Intercept)	0.2515^{***}	0.3573^{***}	0.2616^{***}	0.2814^{***}	0.3345^{***}	0.2209^{***}
	(0.0183)	(0.0275)	(0.0177)	(0.0188)	(0.0182)	(0.0428)
OECD (TRTH)	0.1242^{***}					
	(0.0308)					
Emerging (TRTH)		-0.0907^{**}				
		(0.0332)				
Developed (MSCI)			0.1206^{***}			0.1612^{**}
			(0.0334)			(0.0505)
Emerging (MSCI)				0.0500		0.1104^{**}
				(0.0355)		(0.0505)
Frontier (MSCI)					-0.1189^{***}	-0.0053
					(0.0317)	(0.0495)
adj. R^2	0.1583	0.0738	0.1297	0.0119	0.1388	0.2189
Panel B: GPH estimator ($m = N^{0.7}$)						
(Intercept)	0.2083^{***}	0.3166^{***}	0.2225^{***}	0.2462^{***}	0.3022^{***}	0.2112^{***}
	(0.0167)	(0.0262)	(0.0165)	(0.0180)	(0.0168)	(0.0397)
OECD (TRTH)	0.1415^{***}					
	(0.0281)					
Emerging (TRTH)		-0.0853^{**}				
		(0.0317)				
Developed (MSCI)			0.1278^{***}			0.1391^{**}
			(0.0312)			(0.0468)
Emerging (MSCI)				0.0434		0.0785^{*}
				(0.0339)		(0.0468)
Frontier (MSCI)					-0.1330^{***}	-0.0420
					(0.0292)	(0.0458)
adj. R^2	0.2318	0.0715	0.1632	0.0078	0.1959	0.2630

Long Memory in Developed and Emerging Countries – Alternative Estimates Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: LW estimator ($m = N^{0.5}$)						
(Intercept)	0.2546***	0.3028***	0.2551***	0.2587***	0.3054***	0.2449***
	(0.0147)	(0.0212)	(0.0137)	(0.0139)	(0.0135)	(0.0329)
OECD (TRTH)	0.0544**					
	(0.0246)					
Emerging (TRTH)		−0.0423				
		(0.0256)				
Developed (MSCI)			0.0667**			0.0769*
			(0.0260)			(0.0388)
Emerging (MSCI)				0.0540**		0.0678*
				(0.0263)		(0.0388)
Frontier (MSCI)					−0.0958***	−0.0353
					(0.0235)	(0.0380)
adj. R^2	0.0456	0.0209	0.0646	0.0380	0.1618	0.1838
Panel D: GPH estimator (absolute returns; $m = N^{0.5}$)						
(Intercept)	0.3938***	0.4584***	0.3932***	0.4154***	0.4228***	0.3842***
	(0.0140)	(0.0195)	(0.0131)	(0.0136)	(0.0139)	(0.0338)
OECD (TRTH)	0.0502**					
	(0.0235)					
Emerging (TRTH)		−0.0685**				
		(0.0236)				
Developed (MSCI)			0.0657**			0.0747*
			(0.0247)			(0.0399)
Emerging (MSCI)				−0.0136		0.0177
				(0.0257)		(0.0399)
Frontier (MSCI)					−0.0340	0.0046
					(0.0243)	(0.0390)
adj. R^2	0.0422	0.0839	0.0701	−0.0090	0.0117	0.0498

Table C.5: International Portfolio Sorts – Alternative Long Memory Estimates

This table presents the average macroeconomic variables of the tertile portfolios sorted by the memory parameter. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015. Long memory is estimated with the GPH estimator and a bandwidth choice of $m = N^{0.6}$ and $m = N^{0.7}$ in Panel A and B, respectively. The GPH estimator is applied to absolute returns and a bandwidth of $m = N^{0.5}$ in Panel C and Panel D shows results relying on the LW estimator and $m = N^{0.5}$. The column *LMS* reports the difference of the third and first portfolio with t-statistics in squared brackets.

	T1	T2	T3	T3- T1 (LMS)	
Panel A: GPH estimator ($m = N^{0.6}$)					
Inflation	0.0038	0.0035	0.0033	−0.0005	[−0.6361]
Unemployment	7.7592	7.5606	6.8455	−0.9137	[−2.4542]
Tbill	11.9322	8.4317	11.3281	−0.6040	[−0.2547]
Gov.Bonds	10.2931	8.0374	8.0045	−2.2886	[−3.4877]
GDP	0.0018	0.0059	0.0038	0.0020	[1.7396]
BNS	−3.7743	−0.2091	−0.1562	3.6182	[2.0425]
BNS-I	0.0955	0.0148	0.0095	−0.0860	[−3.9556]
Panel B: GPH estimator ($m = N^{0.7}$)					
Inflation	0.0037	0.0031	0.0034	−0.0003	[−0.4056]
Unemployment	7.5144	7.4730	6.8688	−0.6456	[−1.3959]
Tbill	13.4881	9.9356	8.6620	−4.8262	[−1.4858]
Gov.Bonds	10.1239	8.4567	7.3953	−2.7287	[−6.3381]
GDP	0.0037	0.0033	0.0083	0.0046	[4.0613]
BNS	−3.6394	−0.2806	−0.1811	3.4583	[2.0498]
BNS-I	0.0904	0.0197	0.0113	−0.0791	[−3.5078]
Panel C: GPH estimator (absolute returns; $m = N^{0.5}$)					
Inflation	0.0037	0.0031	0.0033	−0.0004	[−0.5899]
Unemployment	7.7897	7.5074	6.7241	−1.0656	[−3.0034]
Tbill	13.6766	9.4347	8.6176	−5.0591	[−1.4161]
Gov.Bonds	9.5664	8.9168	7.8552	−1.7113	[−3.1334]
GDP	0.0044	0.0041	0.0066	0.0022	[1.7534]
BNS	−2.5185	−1.5721	−0.4765	2.0419	[2.8122]
BNS-I	0.0698	0.0382	0.0242	−0.0456	[−4.2736]
Panel D: LW estimator ($m = N^{0.5}$)					
Inflation	0.0042	0.0041	0.0047	0.0005	[0.8343]
Unemployment	7.3763	7.1598	6.6214	−0.7549	[−3.2149]
Tbill	13.0206	10.3177	9.8895	−3.1312	[−1.2597]
Gov.Bonds	9.9875	8.6120	7.9389	−2.0485	[−3.7036]
GDP	−0.0011	0.0056	0.0069	0.0079	[2.5104]
BNS	−4.0822	−0.9068	−0.4097	3.6724	[2.3223]
BNS-I	0.1148	0.0323	0.0203	−0.0945	[−4.4816]

Table C.6: Long Memory of the U.S. – Predictive Regressions

This table presents the coefficients from the regressions of the memory parameter on the macroeconomic variables for the U.S. for the period from 1964 until 2015. The regressors are the log consumer price index, the log unemployment, treasury bill and the government bond rates and GDP growth lagged by h quarters. Recession is the indicator function that represents periods of expansion and recession defined by the NBER. All macroeconomic variables are monthly except for GDP, hence Model 5 and Model 8 are on a quarterly basis. Long memory is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A: $h = 1$								
(Intercept)	0.4141^{***}	-0.2506^{***}	0.5431^{***}	0.7936^{***}	0.4041^{***}	0.4106^{***}	-0.0709	-0.5865^{**}
	(0.0110)	(0.0748)	(0.0159)	(0.0298)	(0.0197)	(0.0121)	(0.0817)	(0.2577)
Inflation	-7.0080^{***}						-5.9748^{***}	-2.9321^{**}
	(1.3868)						(1.0603)	(1.3907)
Unemployment		0.3704^{***}					0.5207^{***}	0.8053^{***}
		(0.0416)					(0.0471)	(0.1399)
Tbill			-4.6635^{***}				7.1164^{***}	8.0271^{***}
			(0.4380)				(0.8769)	(1.7104)
Gov.Bonds				-7.1906^{***}			-12.2448^{***}	-12.7036^{***}
				(0.5306)			(0.9129)	(1.7059)
GDP					-1.5167^{*}			2.4658^{**}
					(0.8577)			(1.0392)
Recession						-0.0174	0.0706^{**}	0.0094
						(0.0363)	(0.0261)	(0.0477)
adj. R^2	0.0747	0.2044	0.2699	0.3754	0.0206	-0.0025	0.5744	0.5654
Panel B: $h = 2$								
(Intercept)	0.4130^{***}	-0.2238^{**}	0.5758^{***}	0.8045^{***}	0.4051^{***}	0.3989^{***}	0.3890^{***}	0.0728
	(0.0113)	(0.0756)	(0.0149)	(0.0309)	(0.0198)	(0.0120)	(0.0924)	(0.2718)
Inflation	-4.7089^{**}						-4.3664^{***}	0.5189
	(1.4380)						(1.1830)	(1.5008)
Unemployment		0.3554^{***}					0.1884^{***}	0.3474^{**}
		(0.0421)					(0.0522)	(0.1456)
Tbill			-5.3730^{***}				-0.2507	-1.1136
			(0.3853)				(0.9404)	(1.7749)
Gov.Bonds				-7.1496^{***}			-5.7493^{***}	-4.6440^{**}
				(0.5328)			(1.0173)	(1.8860)
GDP					-1.2340			2.2171^{*}
					(0.8512)			(1.1180)
Recession						0.0876^{**}	0.1299^{***}	0.0509
						(0.0360)	(0.0291)	(0.0527)
adj. R^2	0.0310	0.1878	0.3889	0.3707	0.0108	0.0160	0.4704	0.4701

Table C.6: Long Memory of the U.S. – Predictive Regressions continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel C: $h = 4$								
(Intercept)	0.4134^{***}	-0.2527^{***}	0.5527^{***}	0.7942^{***}	0.4045^{***}	0.4070^{***}	0.0494	-0.4678^{*}
	(0.0112)	(0.0749)	(0.0157)	(0.0300)	(0.0198)	(0.0121)	(0.0887)	(0.2687)
Inflation	-5.6349^{***}						-4.4262^{***}	-1.8303
	(1.4095)						(1.1396)	(1.4541)
Unemployment		0.3715^{***}					0.4305^{***}	0.7147^{***}
		(0.0417)					(0.0508)	(0.1455)
Tbill			-4.8666^{***}				4.9223^{***}	5.7397^{**}
			(0.4214)				(0.9381)	(1.7702)
Gov.Bonds				-7.1153^{***}			-10.2998^{***}	-10.6401^{***}
				(0.5280)			(0.9809)	(1.7865)
GDP					-1.3775			2.6813^{**}
					(0.8563)			(1.0822)
Recession						0.0153	0.0795^{**}	0.0347
						(0.0363)	(0.0280)	(0.0499)
adj. R^2	0.0470	0.2053	0.3033	0.3727	0.0155	-0.0027	0.5086	0.5244

Chapter 6

The Memory of Stock Return Volatility: Asset Pricing Implications*

6.1 Introduction

In this chapter we investigate the memory of volatility in the cross-section of U.S. stocks. To the best of our knowledge, we are the first to analyze the asset pricing implications of long memory volatility. We show that long memory is prevalent in the volatility of individual stock returns. Long memory can be related to the size, past performance and jump intensity of a firm. Moreover, we provide time-series and cross-sectional evidence for a negative price of long memory volatility in the cross-section of stock returns.

We shed new light on the implication of long memory by combining three strands of literature. First, we extend the research on documenting

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long memory, which, so far, has only focused on indices or some large firms by investigating the complete cross-section of U.S. stocks. Second, we analyze the time-variation of long memory in volatility. Third, long memory has so far only been analyzed in the time-series dimension, not in the cross-sectional one. We discuss and investigate possible microeconomic fundamentals, which may explain long memory and examine whether memory is a priced factor.

We find that 95% of stocks possesses long memory in volatility with an average memory parameter of 0.22. At the firm level, higher volatility memory estimates are related to larger size, worse prior performance and fewer price jumps. Following the investment strategy of holding stocks with shorter memory in volatility and shorting stocks with longer memory in volatility generates excess returns of 1.71% per annum. This result is supported by cross-sectional regression tests. We find a significant risk premium for the memory parameter where stocks with anti-persistent volatility can earn up to 4.7% per annum more than stocks with long memory in volatility. We show that the volatility of stocks with higher memory parameters is more predictable than stocks with low memory parameters. This indicates that lower uncertainty of stocks with longer memory, i.e. more persistent volatility, results in the negative premium.[1] Our results are robust to controling for idiosyncratic volatility, size, and other characteristics, as well as to various further tests. At the same time we verify our memory estimates by showing that forecasting volatility for stocks with longer memory works better than for stocks with shorter memory. We also relate our results to existing theoretical models, which show how long memory is generated through heterogeneity in the market.

[1] In recent studies, Baltussen et al. (2017) and Hollstein & Prokopczuk (2017) show that volatility-of-volatility is priced in the cross-section of stock returns. Although one might think that volatility-of-volatility is related to the degree of long memory in volatility, we empirically show that (i) it is not, and (ii) it is priced separately.

Long memory processes (also referred to as long-range dependent processes) are present in numerous sciences and fields such as physics, geophysics, hydrology, climatology, biology and, most importantly for the subject of this project, economics and finance. Long memory processes can be described as long-range dependent time series with a hyperbolic decaying autocorrelation function, as opposed to the exponential function of short memory processes such as autoregressive processes. The introduction of long memory processes created a huge wave of new time-series models and methodologies to analyze, estimate, and predict them, since the old methods used for short memory time series were no longer appropriate. The first study to mention is perhaps Hurst (1951), who examines the Nile River in order to understand the persistence of stream flow data. There also exist several papers dealing with long memory in economics and finance. Baillie (1996) provides a detailed survey and review for this purpose. The most common models are the autoregressive fractionally integrated moving average (ARFIMA) model by Granger & Joyeux (1980), Granger (1981) and Hosking (1981) and the fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model introduced by Baillie et al. (1996). These are extensions of the short memory ARMA and GARCH models, respectively. Long memory properties have been analyzed comprehensively in returns and volatilities and Chapter 6 draws from several strands of literature.

The first focuses on the estimation and detection of long memory in the volatility of stock returns. Shortly after the introduction of the FIGARCH model, Bollerslev & Mikkelsen (1996) and Ding & Granger (1996) show that the conditional variance and absolute returns of the S&P 500 index, respectively, possess long memory. Breidt et al. (1998) also find long memory in the variance of equally weighted and value-weighted Center for Research in Security Prices (CRSP) stock market index returns. Lobato & Savin

(1998) investigate the long memory properties of the U.S. stock market index and thirty individual stock returns in the U.S., while Sadique & Silvapulle (2001) and Henry (2002) consider the long memory property of various international stock indices, including Germany, Japan, Korea, New Zealand, Malaysia, Singapore, Taiwan and the U.S.

Another strand of the literature analyzes breaks in the long memory parameter, and hence allows memory to vary over time. Leybourne et al. (2007) consider long memory dynamics and introduce a test for a break from stationary long memory to non-stationary long memory. Their test is improved by Sibbertsen & Kruse (2009), since the results may be distorted when the data-generating process exhibits long memory. They apply the test to U.S. inflation data and find a break in the early 1980s. Sibbertsen et al. (2014) test for the persistence of EMU government bond yields for France, Italy and Spain, using the same methodology, and find breaks between 2006 and 2008.

This chapter is mostly related to the asset pricing literature. The research and discovery of anomalies and effects that can explain the cross-section of expected returns is constantly growing since the introduction of the capital asset pricing model (CAPM) (Sharpe, 1964; Lintner, 1965; Mossin, 1966; Black, 1972). In addition to the market portfolio, Fama & French (1993) show that size and book-to-market ratio are better able to capture the cross-sectional variation in average stock returns. Carhart (1997) adds a momentum factor, and more recently, Fama & French (2015) extend their three-factor model by profitability and investment factors. The list of potential explanatory variables for the cross-sectional variation of stock returns is ongoing. For example, to name only two, Amihud (2002) finds a positive relationship between the illiquidity of stocks and future excess returns while Ang et al. (2006b) show that idiosyncratic volatility is negatively priced in the cross-section. Hou et al. (2014) propose the q-factor model including market, size, investment and profitability factors, and show that the performance of their model is at least as good as the models proposed by Fama & French (1993) and Carhart (1997).

The rest of the chapter is organized as follows. Section 6.2 describes our data set and estimation procedure for long memory. Section 6.3 examines the cross-section of U.S. stocks. Section 6.4 relates long memory to predictability. Section 6.5 theoretically discusses the origin of long memory. Section 6.6 presents robustness tests and Section 6.7 concludes. In the appendix to this chapter, which can be found in Section D, we present the results of additional analyses.

6.2 Data and Methodology

6.2.1 Data

The data used for our analyses come from various sources. For our cross-sectional analysis of U.S. stock returns, we obtain equity prices, returns, market capitalization and volume data from the CRSP for the period from January 1926 until December 2015. In our main analysis we investigate four different firm characteristics which have been shown in the existing literature to be priced in the cross-section of stock returns. They include size, value, momentum effects and the liquidity factor. The construction of the variables, which we from now on refer to as Size, Book-to-Market, Momentum and Illiquidity, follows the convention of the literature (see Jegadeesh & Titman, 1993; Amihud, 2002; Fama & French, 2008; Jiang & Yao, 2013, among others) and are based on market capitalizations, returns and trading volumes from CRSP and balance-sheet information from COMPUSTAT.[2]

High-frequency price data are obtained from Thomson Reuters Tick History. When employing high-frequency data, the analysis is restricted to the period from January 1996 until December 2015 and on the S&P 500 constituents only.[3]

6.2.2 Semiparametric Estimation of Long Memory in Volatility

Our estimation of the long memory parameter relies on two of the most popular estimators, the GPH estimator and the Local Whittle estimator.

The first is based on the log-periodogram and was developed by Geweke & Porter-Hudak (1983). The GPH estimator employs a linear regression using the first m periodogram ordinates and exploits the shape of the spectral density around the origin. The spectral density of a stationary process X_t is estimated empirically by the periodogram:

$$I_X(\lambda_j) = \frac{1}{2\pi N} \left| \sum_{t=1}^{N} X_t e^{-it\lambda} \right|^2, \quad t = 1, ..., N \tag{6.1}$$

where the periodogram is not affected by centering of the time series for Fourier frequencies $\lambda_j = 2\pi j/N$ $(j = 1, ..., [(N-1)/2])$. The estimator is given by the negative slope estimate β_1 in the regression:

$$log(I(\lambda_j)) = \beta_0 + \beta_1 log[4sin^2(\lambda_j/2)] + \epsilon_j, \quad j = 1, ..., m \tag{6.2}$$

Under mild conditions $(m \to \infty, N \to \infty, \frac{m}{N} \to 0)$, Robinson (1995b) derives the asymptotic distribution:

$$\sqrt{m}(\hat{d} - d) \xrightarrow[d]{} N\left(0, \frac{\pi^2}{24}\right) \tag{6.3}$$

[2] Even though the size factor is constructed by calculating the logarithm of the market capitalization we refer to this factor as Size rather than log(Size).

[3] This choice is due to the restricted availability of high-frequency data for the complete cross-section, which is crucial for our long memory estimates.

which provides the asymptotic standard errors for the long memory parameter. The estimator is narrowband since the bandwidth parameter m leads to a bias–variance trade-off. While a high m far from the origin leads to bias, a low m too close to the origin leads to a rise in the variance.

The second estimator is the Local Whittle estimator, which is obtained by minimizing the following objective function:

$$\hat{d}_{LW} = \arg\min_{d \in \theta} \left[log\left(\frac{1}{m}\sum_{j=1}^{m}\frac{I(\lambda_j)}{\lambda_j^{2d}}\right) - \frac{2d}{m}\sum_{j=1}^{m} log\lambda_j \right], \quad \theta \subseteq (-0.5, 0.5) \tag{6.4}$$

where m is restricted to $m < \frac{N}{2}$. The Local Whittle estimator is an extension of the one originally proposed by Whittle (1951) which relies on an approximate maximum likelihood approach. Under mild assumptions similar to those for the GPH estimator, Robinson (1995a) derives the asymptotic distribution:

$$\sqrt{m}(\hat{d}_{LW} - d_0) \underset{d}{\longrightarrow} N\left(0, \frac{1}{4}\right) \tag{6.5}$$

For our main analysis we focus on the GPH estimator and the bandwidth $m = N^{0.5}$ following the existing literature (Geweke & Porter-Hudak, 1983; Diebold & Rudebusch, 1989; Hurvich & Deo, 1999; Henry, 2002).[4] Results with alternative bandwidth choices and the Local Whittle estimator are reported in the robustness section, Section 6.6.3.

We refer to d as the memory parameter and differentiate between three cases: A time series has short memory if $d = 0$. A time series has negative memory or is anti-persistent if $d < 0$. A time series has long memory if $0 < d < 1$ where it is non-stationary if $0.5 < d < 1$.

[4]Typically, empirical researchers rely on this bandwidth choice since it is robust against short-range dependencies in the data. In terms of mean squared error (MSE) improvement, Beran et al. (2013) argue that the bandwidth $m = O(N^{0.8})$ is the optimal choice.

6.3 Long Memory Volatility in the Cross-Section of Stock Returns

In this section we provide evidence of long memory volatility in the cross-section of U.S. stock returns. First, we show in Section 6.3.1 that long memory volatility is prevalent in most stocks but that the degree varies across stocks. Section 6.3.2 relates the memory parameter to firm characteristics. Sections 6.3.3 and 6.3.4 investigate whether long memory volatility is a priced factor.

6.3.1 Descriptive Statistics

We apply the GPH estimator to the time series of squared returns for the cross-section of U.S. stocks. Since we are interested in the relationship between memory, firm characteristics and expected returns, we allow for a time-varying memory parameter. More specifically, we estimate the memory parameter at a monthly frequency using a rolling window, which includes the most recent five years of daily return observations.[5] Table 6.1 provides summary statistics for the memory parameter estimates.

In our sample period we have on average 2480 memory parameter estimates at each point of time. The average estimate is 0.22 with a standard deviation of 0.12. The mean t-statistic of 23.34 suggests that the memory parameter is statistically significant on average. Also, we find that most of the stocks exhibit long memory in volatility. 95% of the stocks show a memory parameter with $0.0 < d < 0.5$, while 3% of the stocks are anti-persistent and only 2% show non-stationary long memory.

[5]We require at least non-missing return observations on 50% of the days over the examined period for a stock to be included in our analysis.

Table 6.1: Summary Statistics

This table presents summary statistics for the memory estimates of individual stocks' volatility. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. In our sample we have an average number of 2480 long memory estimates per month. AR(1) stands for the cross-sectional average of first-order autocorrelation coefficients. SD stands for the standard deviation. The second column reports selected quantiles of the averages. t-statistic reports the mean t-statistic. Sign. at 5% reports the proportion of significant long memory estimates, while the remainder of the last column reports the proportion of the memory parameter being in a certain interval.

Descriptive		Quantiles		Memory	
AR(1)	0.87	5%	0.04	t-statistic	23.34
Mean	0.22	25%	0.15	Sign. at 5%	0.96
SD	0.12	Median	0.22	$-0.5 < d < 0.0$	0.03
Skewness	0.40	75%	0.29	$0.0 < d < 0.5$	0.95
Kurtosis	1.48	95%	0.43	$0.5 < d < 1$	0.02

Our results are consistent with the literature and extend the evidence of long memory in stock return volatility to a broader cross-section. Lobato & Savin (1998), for example, find that components of the Dow Jones Index show strong evidence of long memory in squared returns for the period from July 1962 until December 1994. Breidt et al. (1998) find for the equally weighted CRSP portfolio for the period from 1962 until 1989 a memory parameter of $d = 0.22$, which coincides with both the mean and the median from our analysis of the complete cross-section of the U.S. stocks.

6.3.2 Explaining Long Memory with Firm Characteristics

In this section we relate the memory parameter of a stock's volatility to firm characteristics. We include Size, Book-to-Market, Momentum and Illiquidity. These variables have been shown to be priced in the cross-section of stock returns (Jegadeesh & Titman, 1993; Amihud, 2002; Fama & French, 2008; Jiang & Yao, 2013). We further include two jump measures since recent studies have shown that jumps are an important factor in the cross-section of stock returns. Jiang & Yao (2013) analyze the predictability of cross-sectional stock returns and find that once controling for jumps firm characteristics such as size and liquidity are no longer predictive. Kelly & Jiang (2014) and Cremers et al. (2015) show that the sensitivity of stocks to market tail and jump risk helps to explain the cross-sectional variation in expected returns. We apply the common jump test proposed by Barndorff-Nielsen & Shephard (2006) (BNS).[6] The test relies on the bipower variation, which decomposes the quadratic variation into its parts due to continuous movements and a jump part. The jump test statistic is given by

$$BNS_t = \frac{(\pi/2)B_t - S_t}{\sqrt{((\pi^2/4)+\pi-5)(\pi/2)^2 Q_t}} \tag{6.6}$$

$$Q_t = \frac{1}{K_t - 3}\sum_{k=4}^{K_t} |r_{t,k}||r_{t,k-1}||r_{t,k-2}||r_{t,k-3}| \tag{6.7}$$

$$S_t = \frac{1}{K_t}\sum_{k=1}^{K_t} r_{t,k}^2 \tag{6.8}$$

$$B_t = \frac{1}{K_t - 1}\sum_{k=2}^{K_t} |r_{t,k}||r_{t,k-1}| \tag{6.9}$$

where K_t is the number of observations over the examined period, $r_{t,k}$ is the kth daily observation over the examined period t and BNS_t is normally distributed under the null. First, we compute the BNS jump statistic for each month and stock using daily return data within each calender month following Pukthuanthong & Roll (2015). The first measure of jump intensity is given by the jump test statistic (BNS). Our second measure is a dummy variable indicating whether the current month includes a significant jump at the 5% level, which we denote as BNS-I.

[6] Pukthuanthong & Roll (2015) show with the help of simulations using different jump size and frequency, that this test is preferable to those proposed by Lee & Mykland (2008), Jiang & Oomen (2008) and Jacod & Todorov (2009).

Table 6.2: Portfolio Sorts and Characteristics

This table presents firm characteristics of portfolios sorted by the memory of volatility. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. From 1950 until 2015 we sort stocks each month and form and hold the portfolio for one month. We report the average long memory parameter, size, momentum and illiquidity, BNS statistic and BNS indicator function of quintile portfolios. The Q5-Q1 column reports the averages for the long memory minus short memory portfolio (LMS) with the according t-statistics in square brackets.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1 (LMS)	
Memory	0.0044	0.1295	0.2118	0.2975	0.4471	0.4427	[202.7567]
Size	11.6610	11.8630	12.0161	12.1707	12.3560	0.6950	[23.3435]
Book-to-Market	0.8934	0.9168	0.8993	0.8758	0.8996	0.0062	[0.5910]
Momentum	0.1681	0.1558	0.1522	0.1483	0.1284	−0.0397	[−14.2697]
Illiquidity	0.0044	0.0040	0.0038	0.0040	0.0055	0.0010	[3.9205]
BNS	−0.1994	−0.0620	−0.0255	−0.0110	0.0036	0.2030	[12.5035]
BNS-I	0.0177	0.0126	0.0106	0.0087	0.0074	−0.0103	[−24.2588]

Each month for the period from January 1950 until December 2015, we sort all stocks into quintile portfolios where stocks with the lowest memory parameter are in the first quintile and stocks with the highest memory parameter are in the fifth quintile. We then track the average firm characteristics of these quintile portfolios.[7]

Table 6.2 shows the results. We report the average memory and firm characteristics for each quintile and for the long memory minus short memory (LMS) portfolio. For the latter we also present t-statistics in square brackets in the last column. Average portfolio size, momentum, and jump measures demonstrate a monotonic pattern that is increasing/decreasing in the memory parameter. Stocks with higher market capitalization, worse past performance and fewer jumps (higher jump statistics and fewer significant jumps) exhibit longer memory in volatility. These differences are highly statistically significant with absolute t-statistics above 12. There is no monotonic pattern for Book-to-Market and Illiquidity but the hedge

[7]We start our analysis in 1950 because book-to-market data is available only from 1950 in COMPUSTAT.

Table 6.3: Cross-sectional Regression

This table presents the results from cross-sectional regressions for the period from 1950 until 2015. Each month, we regress the memory parameter of the cross-section on size, book-to-market, momentum, illiquidity and BNS. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. We report the average β coefficients and the according standard errors in parentheses below. The first row excludes any jump measures. The second row includes the BNS jump statistic while the third row includes the BNS jump indicator. Stars indicate significance: * significant at $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

	Intercept	Size	Book-to-Market	Momentum	Illiquidity	BNS	BNS-I
β	0.0292***	0.0160***	0.0019***	−0.0186***	0.3126		
	(0.0061)	(0.0006)	(0.0006)	(0.0013)	(0.2696)		
β	0.0286***	0.0161***	0.0017***	−0.0184***	0.3720	0.0052***	
	(0.0061)	(0.0006)	(0.0006)	(0.0013)	(0.2738)	(0.0005)	
β	0.0301***	0.0160***	0.0018***	−0.0185***	0.3701		−0.0491***
	(0.0061)	(0.0006)	(0.0006)	(0.0013)	(0.2754)		(0.0025)

portfolio shows positive values for both and the t-statistic is statistically significant for Illiquidity.

We complement the above analysis with cross-sectional regressions. At each point of time, we regress the memory parameter of each firm on the predictor variables in the following regression:

$$d_{i,t} = \alpha_t + \beta_t X_{i,t} + \epsilon_{i,t} \tag{6.10}$$

where $d_{i,t}$ is the memory estimate of stock i at time t, $X_{i,t}$ is the vector containing the firm characteristics of stock i at time t and ϵ_i is the error term.[8] The slope coefficients are expected to have signs as the LMS portfolio spreads. The coefficients are reported in Table 6.3 for three regressions. The first row excludes the jump measures, the second includes the BNS jump statistic and the third includes the jump dummy variable.

In accordance with our portfolio sorts, stocks with large Size, worse prior performance and fewer jumps (higher jump statistics and fewer

[8] We experiment with multiple alternative estimation methods for long memory in order to make sure that the results are robust with respect to the estimation approach. The methods and results are reported in Section 6.6.3 and are qualitatively similar.

significant jumps) exhibit higher memory parameters. The coefficients are all statistically significant at the 1% level. We additionally find that value stocks possess higher memory parameters, while illiquidity is not able to explain the degree of memory in volatility. Intuitively, stocks which tend to exhibit jumps more frequently, are less persistent and predictable and should possess lower memory parameters. We show the close connection of long memory and predictability in Section 6.4 and provide some intuition for how memory is generated for small (large) and loser (winner) stocks in Section 6.5.

6.3.3 Long Memory Volatility and Expected Stock Returns: Portfolio Sorts

In previous sections we relate the memory of volatility to firm-specific variables, trying to explain the degree of long memory. In the next step, we investigate whether investors demand a compensation for holding assets with higher exposure to this factor by looking at the relationship between the degree of memory in volatility and realized future excess stock returns. Assuming that the degree of memory in volatility is related to the predictability of a stock return's volatility, a highly predictable stock should be less uncertain than an unpredictable stock. We hence expect a negative price for long memory in order to compensate investors for the additional volatility risk of short memory stocks.[9]

As in Section 6.3.2, each month, we sort all stocks into quintile portfolios where stocks with the lowest memory parameter are in the first quintile and stocks with the highest memory parameter are in the fifth quintile. Excess returns of the equally weighted portfolios are tracked over

[9]Section 6.4 confirms the intuitive relationship of memory and predictability of a stock's volatility in a validity check.

the subsequent month.[10] The analysis is out-of-sample in the sense that there is no overlap between the data used for the memory estimation and the data used to compute the excess returns of the portfolios. The LMS portfolio returns are then regressed on risk factors in order to test whether these returns merely reflect passive exposure to standard factors. We include the market portfolio of the CAPM, which controls for systematic risk and the Fama & French (1993) three-factor model (FF3), which additionally includes the size and value effects. Further, we employ the state-of-the art Fama & French (2015) five-factor model (FF5) and the Hou et al. (2014) q-factor model (HXZ).[11] We investigate three different sample periods, which start in 1926, 1963 and 1967, respectively. All periods end in December 2015.[12]

The results are presented in Table 6.4. We report the mean return of the quintile portfolios and the LMS portfolio (Q5-Q1) in the first row. Below we report the alphas of the three different models. We find that the annualized mean return generally adheres to a decreasing pattern from 13.57% in the first quintile to 11.86% in the fifth quintile. All quintile portfolio returns are statistically significant, just like the difference of -1.71% between the long memory quintile and the short memory quintile (LMS). Controling for risk factors leads to alphas of -2.23%, -2.47%, -2.84% and -2.52% for the CAPM, Fama & French (1993) three-factor model, Fama & French (2015) five-factor and Hou et al. (2014) q-factor model, respectively. The

[10] Since our memory estimates $d_{i,t}$ rely on rolling window estimates, one might argue that there is barely temporal variation in our estimates. If this is true, this should work against our empirical analysis and we should not find any significant relationship between memory and expected returns, but we do. In the robustness section, Section 6.6.5, we repeat the analysis, relying on monthly memory parameters estimated from high-frequency data in that month. The results are qualitatively similar.

[11] The factors for the first three models are available from the Kenneth R. French's data library, website:mba.tuck.dartmouth.edu/pages/faculty/ken.french. The factors of the Hou et al. (2014) model were kindly provided by the authors.

[12] The choice of different sample periods is motivated by the availability of the factor models. The Fama & French (2015) factors are available starting in 1963 while the Hou et al. (2014) factors are available starting in 1967.

Table 6.4: Sorted Portfolio Returns

This table reports average returns and risk-adjusted returns of equally weighted quintile portfolios for the period from 1926 until 2015. Each month, stocks are sorted by the degree of long memory in volatility and we track the portfolio returns over the subsequent month. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. The one-month-ahead portfolio returns are regressed on risk factors in the Capital Asset Pricing Model (CAPM), the Fama & French (1993) 3-factor model (FF3), the Fama & French (2015) 5-factor model (period starts in 1963) (FF5) and the Hou et al. (2014) q-model (period starts in 1967) (HXZ). The corresponding alphas are reported. We report Newey & West (1987) using lags equal to the return horizon in parentheses. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1 (LMS)
Mean return	0.1357***	0.1288***	0.1344***	0.1263***	0.1186***	−0.0171**
	(0.0334)	(0.0326)	(0.0343)	(0.0346)	(0.0356)	(0.0086)
CAPM	0.0385***	0.0328***	0.0337***	0.0238**	0.0162	−0.0223***
	(0.0125)	(0.0115)	(0.0110)	(0.0103)	(0.0108)	(0.0083)
FF3	0.0136**	0.0103**	0.0084*	−0.0016	−0.0111*	−0.0247***
	(0.0062)	(0.0051)	(0.0048)	(0.0048)	(0.0062)	(0.0077)
FF5	0.0238**	0.0146*	0.0137*	0.0045	−0.0046	−0.0284***
	(0.0108)	(0.0087)	(0.0076)	(0.0075)	(0.0095)	(0.0099)
HXZ	0.0450***	0.0340***	0.0335***	0.0270**	0.0198	−0.0252*
	(0.0160)	(0.0129)	(0.0114)	(0.0113)	(0.0133)	(0.0129)

risk adjusted returns are all statistically significant.[13]

Consequently, controling for standard risk factors does not affect our main result that the long memory volatility excess return trade-off is priced with a negative sign.[14]

[13] We focus on equally weighted portfolios. We have redone the analysis with value-weighted portfolios, which leads to a spread return of −2.27% and a FF5 alpha of −2.19%. Both are statistically significant at the 10% level.

[14] As shown in Section 6.3.2, the memory parameter can be explained by firm characteristics such as size, jumps and momentum. Nonetheless, controling for the risk factors delivers statistically significant alphas. As an additional robustness check we investigate whether the isolated effect of long memory, which is orthogonal to firm size and other firm characteristics, is priced in the cross-section as well. Residual long memory is obtained by regressing the memory parameter on the firm characteristics at each point of time following Hong et al. (2000), Nagel (2005) and Hillert et al. (2014). We find a CAPM (FF5) alpha of −1.2% (−1.5%), which is statistically significant at the 10% level or lower. Results are reported in Table D.1 in the appendix.

6.3.4 Long Memory Volatility and Expected Stock Returns: Regression Tests

The portfolio sorts present strong evidence that the degree of long memory in volatility is (negatively) related to future excess returns. We now estimate Fama & MacBeth (1973) regressions that simultaneously control for different variables and test if the degree of memory of a stock's volatility contains information about future excess returns beyond that of various other firm characteristics. This exercise, which relies on individual stock returns rather than stock portfolios, presents an alternative method in order to estimate the cross-sectional risk premium associated with long memory volatility. We rely on individual stocks rather than portfolio returns since the formation of portfolios in cross-sectional regressions is shown to influence the results and lead to higher standard errors of the risk premium estimates (Lo & MacKinlay, 1990; Ang et al., 2010; Lewellen et al., 2010). Each month, we regress excess stock returns over the following month on the stock characteristics of the current month:

$$r_{i,t+1} - r_{f,t+1} = \alpha_t + \gamma_t^M d_{i,t} + \gamma_t^C X_{i,t} + \epsilon_{i,t+1} \tag{6.11}$$

where $r_{i,t}$ is the return of stock i and $r_{f,t}$ is the risk-free rate at time t. $X_{i,t}$ is a vector containing the firm characteristics Size, Book-to-Market, Momentum, Illiquidity and Jumps.[15] γ_t^M and γ_t^C are the risk premia associated with the memory parameter and the remaining firm characteristics, respectively, and $\epsilon_{i,t}$ is the error term. In a second step we perform tests on the time-series averages of the estimated monthly intercept and slope coefficients in order to test for significance of the risk premia $\hat{\gamma}_t^M$ and $\hat{\gamma}_t^C$ over the sample period.

[15] We use the same firm characteristics as in our portfolio sorts in Section 6.3.2. We include further control variables such as the market beta, idiosyncratic volatility and more in the robustness section, Section 6.6.6.

Table 6.5: Fama–MacBeth Regressions

This table reports results from Fama & MacBeth (1973) regressions for the period from 1950 until 2015. Each month, excess stock returns are regressed on lagged firm characteristics including the memory parameters, market capitalization (Size), book-to-market values, prior returns (Momentum), illiquidity and jump statistics (BNS). The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	0.0091^{***}	0.0144^{***}	0.0075^{***}	0.0076^{***}	0.0087^{***}	0.0091^{***}	0.0106^{*}
	(0.0025)	(0.0051)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0056)
Long Memory	-0.0039^{**}	-0.0021^{*}	-0.0038^{**}	-0.0038^{**}	-0.0044^{***}	-0.0043^{***}	-0.0024^{**}
	(0.0016)	(0.0012)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0011)
Size		-0.0006^{*}					-0.0005
		(0.0003)					(0.0003)
Book-to-Market			0.0019^{***}				0.0024^{***}
			(0.0005)				(0.0006)
Momentum				0.0067^{***}			0.0095^{***}
				(0.0016)			(0.0013)
Illiquidity					0.2010^{**}		0.0991
					(0.1010)		(0.1768)
BNS						0.0024^{***}	0.0020^{***}
						(0.0004)	(0.0003)

Table 6.5 reports the results of the Fama & MacBeth (1973) regressions presenting the time-series averages of the coefficients, $\hat{\alpha}_t$, $\hat{\gamma}_t^M$ and $\hat{\gamma}_t^C$.

Model 1 regresses the excess return of stocks over the following month on the memory parameter only. The market price of long memory is -0.0039, which is statistically significant at the 5% level. Consequently, a stock with anti-persistent volatility can earn average annualized returns of up to 4.7% higher than a stock with long memory volatility.[16] Models 2 to 6 additionally include one of the firm characteristics in the cross-sectional regression. The magnitude and significance of the memory risk premium is slightly reduced when adding Size but barely changes when

[16]The lowest possible memory parameter for a anti-persistent stock is given by the lower bound of the interval $(-0.5; 0)$ while the highest possible stationary memory parameter is given by the upper bound of the interval $(0; 0.5)$. The highest possible annualized spread returns can thus be approximated by $1 * (-0.0039) * 12 = -0.0468$.

adding Book-to-Market, Momentum, Illiquidity or Jumps. Nonetheless, the coefficient $\hat{\gamma}^M$ remains statistically significant for all models. The negative (positive) risk premium for Size (Book-to-Market, Momentum and Illiquidity) is consistent with the literature (Fama & French, 1992; Jegadeesh & Titman, 1993; Amihud, 2002). Results are qualitatively similar for the kitchen sink regression (Model 7) where the coefficient of the memory parameter remains statistically significant.

6.4 Long Memory Volatility and Predictability

A possible explanation for the negative relationship between long memory volatility and expected stock returns is the uncertainty around a stock's volatility. As discussed earlier, long memory represents the hyperbolic decay of the autocorrelation function which on the other hand allows for (high and long-run) volatility predictability. One can argue that in times of financial distress large negative shocks are more persistent for stocks with long memory, which makes these stocks less favorable than short memory stocks. But even though negative shocks are more persistent, the volatility predictability is still higher for long memory stocks, which makes them less uncertain regarding their level of risk.

In Sections 6.3.3 and 6.3.4, we provide evidence that stocks with long memory volatility earn on average lower returns than stocks with short memory using both portfolio sorts and cross-sectional regressions. In this section, we supply empirical evidence that long memory is associated with predictability and hence confirm our channel of negative expected returns through volatility uncertainty. Further, this exercise is a validity check of our long memory estimates. If our memory estimates are not biased by data quality or spurious long memory, a higher memory parameter should be directly linked to higher forecasting performance.[17]

For each stock, we conduct monthly predictability regressions of realized volatility both in-sample and out-of-sample. The time series of monthly realized volatility is obtained by summing squared daily returns for each month (Bollerslev et al., 2014). Following the spirit of Corsi (2009), we use (heterogenous) autoregressive models of realized volatility (HAR-RV).[18] The regressions include lagged observations of the realized volatility and we allow for five different specifications by including the volatility from the previous month (HAR(1)), six months (HAR(2)), one year (HAR(3)), two years (HAR(4)) and 5 years (HAR(5)):[19]

$$HAR(1) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \epsilon_{t+1} \tag{6.12}$$

$$HAR(2) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \beta RV_t^{6M} + \epsilon_{t+1} \tag{6.13}$$

$$HAR(3) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \beta RV_t^{6M} + \beta RV_t^{1Y} + \epsilon_{t+1} \tag{6.14}$$

$$HAR(4) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \beta RV_t^{6M} + \beta RV_t^{1Y} + \beta RV_t^{2Y} + \epsilon_{t+1} \tag{6.15}$$

$$\begin{aligned} HAR(5) : RV_{t+1}^{M} = \alpha &+ \beta RV_t^{M} + \beta RV_t^{6M} + \beta RV_t^{1Y} + \beta RV_t^{2Y} \\ &+ \beta RV_t^{5Y} + \epsilon_{t+1} \end{aligned} \tag{6.16}$$

[17] We acknowledge the issue of spurious long memory where higher memory parameters can be caused by structural breaks. Even though we work with rolling window estimates, which should be only marginally affected by breaks, we control for this in three different ways. First, both our portfolio sorts and cross-sectional regressions include the BNS jump statistic and the alpha or long memory risk premium remain statistically significant. Hence, our results are not driven by the BNS variable. Second, the validity check in this section relates the memory parameter to predictability. If our parameters are biased by structural breaks or jumps, we should not find any clear relationship, however we do. Third, we repeat our portfolio sorts but rely on returns purged from jumps following Pukthuanthong & Roll (2015). Buying stocks with long memory volatility and selling stocks with short memory volatility, where long memory is estimated from raw returns, leads to a statistically significant spread return of −1.73% and a Fama & French (2015) five-factor alpha of −2.89%, which is statistically significant as well. Both are of similar magnitudes to those in our main analysis.

[18] We also experimented with simple autoregressive (AR) models including the lags 1, 6, 12, 24 and 60, leading to qualitatively similar results.

[19] Our frequency differs from the one of Corsi (2009), who relies on daily, weekly and monthly volatility in order to forecast the volatility over the next day, week or two weeks. Our goal is different. We are interested in the one month horizon, which is the holding period for our portfolio sorts and the horizon for the cross-sectional regressions.

Table 6.6: Long Memory and Predictability

This table reports results of predictive regressions. We run heterogenous autoregressive regressions of the monthly realized variance for each stock including the previous one, six, twelve, twenty-four and sixty observations. We form quintile portfolios where stocks with the lowest memory parameter are in the first quintile and stocks with the highest memory parameter in the fifth quintile portfolio. We report average adjusted R^2 in Panel A, average t-statistics and F-statistics in Panel B and out-of-sample R^2 in Panel C.

	Q1	Q2	Q3	Q4	Q5
Panel A: Adjusted R^2					
HAR(1)	0.0888	0.1507	0.1822	0.2343	0.3000
HAR(2)	0.1447	0.2111	0.2418	0.2897	0.3491
HAR(3)	0.1529	0.2185	0.2486	0.2946	0.3536
HAR(4)	0.1535	0.2184	0.2484	0.2958	0.3561
HAR(5)	0.1491	0.2132	0.2490	0.2931	0.3579
Panel B: T-statistic/F-statistic					
HAR(1)	5.6276	8.5058	9.7878	11.7858	12.9780
HAR(2)	41.2025	74.8700	89.9142	116.0092	123.2804
HAR(3)	29.4787	52.5572	61.9348	78.9834	82.9948
HAR(4)	22.3186	39.6614	46.0103	58.7847	61.2399
HAR(5)	16.2773	29.1439	34.9617	42.7776	45.3960
Panel C: R^2_{OOS}					
HAR(1)	0.0474	0.1306	0.1515	0.1967	0.2729
HAR(2)	0.1266	0.2139	0.2237	0.2546	0.3117
HAR(3)	0.1203	0.2090	0.2136	0.2424	0.2921
HAR(4)	0.1039	0.1896	0.1944	0.2233	0.2704
HAR(5)	0.0064	0.1147	0.1194	0.1475	0.1919

The multiperiod volatilities are normalized sums of the one-month realized volatilities. The six-months' realized volatility is exemplarily given by:

$$RV_t^{6M} = \frac{1}{6}(RV_t^M + RV_{t-1}^M + ... + RV_{t-5}^M) \tag{6.17}$$

Despite the simplicity of these models, they are shown to be able to mimic long memory behavior and exhibit good forecasting performance.

We form quintile portfolios by sorting the cross-section of stock returns by the memory parameter. We then compute the average adjusted

R^2, F-statistic and out-of-sample R^2_{OOS} for each quintile portfolio.[20] The calculation of the out-of-sample R^2_{OOS} follows Campbell & Thompson (2008), and measures the differences in mean squared prediction errors (MSPE) for the predictive model, Equations (6.12)-(6.16) and the historical mean.

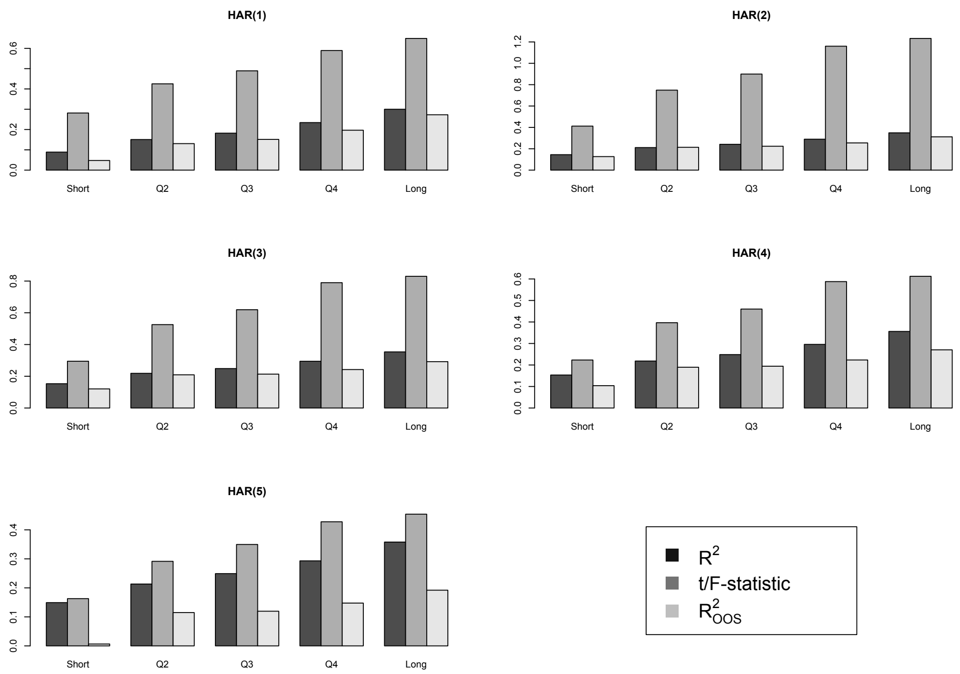
The results are reported in Table 6.6. Panel A shows the adjusted R^2 of the in-sample predictability regressions. There is a strictly monotonic pattern of explanatory power, which is increasing in the memory parameter. This is supported by the increasing t-statistics and F-statistics in Panel B. Stocks with higher memory parameters show stronger explanatory power and the predictor variables are more statistically significant than stocks with lower memory parameters. Lastly, the R^2_{OOS} also show that the out-of-sample forecasting performance of long memory stocks is stronger than short memory stocks and exhibits a generally monotonic pattern. A graphical illustration of the results is presented in Figure 6.1. One can see that the bars are monotonically increasing for all five models and all three colors (adj R^2, F-statistic and R^2_{OOS}).

We thus show that the memory of stocks is a proxy for predictability, which explains the negative spread returns of the LMS portfolio. At the same time, this exercise validates our estimation approach to memory. Our results are true for both in-sample and out-of-sample, while we allow for various model specifications including short memory processes and long memory mimicking processes.

[20] We report t-statistics of the slope coefficient for HAR(1) and F-statistics for the joint significance of the slope coefficients for the remaining models. For the out-of-sample analysis, the R^2_{OOS} for some stocks show extremely bad performance, with values below -100% due to large spikes. We winsorize the data at the 1% and 99% level to minimize the effect of these outliers. Cleaning the time series of the outliers delivers qualitatively similar results.

Figure 6.1: Predictability of Quintile Portfolios

This figure reports adjusted R^2, F-statistics and R^2_{OOS} for quintile portfolios of the cross-section of U.S. stock returns. For a better presentation, the test statistics are all divided by 100.



6.5 Implication for Existing Models

In this section we discuss the connection of our empirical results with theoretical models of how long memory in volatility is generated for individual stocks using the proposed "Agent-based" model of LeBaron (2006) and the "Interacting Agent View" of Alfarano & Lux (2007). These models rely on heterogeneity across market agents. Müller et al. (1993), Peters (1994) and Corsi (2009) also consider markets with heterogenous traders. Motivated by the memory-generating models, we discuss how large and loser stocks in these models differ from small and winner stocks.[21]

6.5.1 Interacting Agent View

Alfarano & Lux (2007) divide traders in a market into two groups – fundamentalists and chartists – whose interactions are based on the mechanism introduced by Kirman (1993). The noise traders (chartists) are driven by herd instincts and buy (sell) if they are optimistic (pessimistic). The long memory in volatility is then generated by the interaction of agents with heterogenous beliefs and strategies. The numbers of fundamentalists and chartists are fixed, but transition from optimists to pessimists and vice versa is allowed by a two-state model. They derive an equilibrium distribution with two equilibria where a transition between them has a finite probability. The average time for the transition is denoted as the mean first passage time T_0. From the ratio of mean first passage time T_0 and available data observations T, conclusions on the memory of the process can be drawn. For higher T_0 relative to T, the memory parameter of squared returns decreases starting with a Hurst exponent close to 1 and converging to 0 for $T >> T_0$. The mean first passage time is negatively related to the number of agents N in the market. We divide the cross-section of stock returns into several segments by firm characteristics. The relation of T and T_0 for each submarket allows for conclusions on the memory of the submarket. We focus on the effect of these two variables, assuming that all other variables are the same for the two markets in comparison.[22]

First, our main analysis shows that stocks with higher market capitalization exhibit longer memory in volatility. Gompers & Metrick (2001) find that the demand for large and liquid stocks has grown due

[21]For these characteristics, we find statistical significance concerning memory parameter spreads for both portfolio sorts and cross-sectional regressions.

[22]The impact of other variables is neglible, since the memory parameter is high for low T relative to T_0 and always converges to zero for $T \to \infty$.

to the increasing share of the U.S. equity market. Additionally, investment decisions in small stocks are harder to justify to sponsors by professional managers, as argued by Lakonishok et al. (1992). Further, Merton (1987) argues that small stocks exhibit incomplete information. This makes smaller stocks less favorable as well. All these findings suggest that the number of investors in large stocks dominates those of small stocks. The larger number of agents for large stocks leads to a higher mean first passage time and hence intuitively to longer memory in volatility, as we empirically document.

Second, we find that stocks with longer memory in volatility tend to be loser stocks. This result can be explained by the disposition effect, as labeled by Shefrin & Statman (1985). The effect states that investors tend to hold on their losing stocks too long and sell their winner stocks too soon in financial markets. This effect can be explained in the context of the prospect theory of Kahneman & Tversky (1979) and the mental accounting framework of Thaler (1980). The results suggest that the number of agents investing in winner stocks tends to decrease while the number for the loser stocks tends to remain constant or even increase. This leads to longer memory for loser stocks, as shown in our main analysis.

6.5.2 Agent-based Models

LeBaron (2006) divides the market into groups according to their investment horizon and hence considers a heterogenous agent framework. The agents rely on past information such as lagged returns, dividend–price ratios and trend indicators to evaluate rules for investment decisions. This evaluation varies across agents. Some agents rely only on more recent data, e.g. only the past six months (short memory investor), while others use thirty years' worth of data (long memory investor). The trading rules may evolve over time and a Walrasian equilibrium is reached by clearing the market.

The author shows that in a market consisting of homogeneous investors (long memory investors only), the price converges to the equilibrium price through the learning mechanism, which results in a short memory process for squared returns. If the market consists of all types of agents (all memory), on the other hand, the price takes large swings from the equilibrium and large crashes and shows long memory behavior for volatility. The persistence is driven by the short-term investors. As argued by Corsi (2009), short-term investors are influenced by the long-term variance, which again has an impact on the short-term variance while long-term investors are not influenced by changes in short-term volatility. The model can be transferred to parts of the complete market as proxied by the cross-section of U.S. stock returns. We compare the fraction of short- and long-term investors in various markets and conclude on the degree of memory in these markets.

Perez-Quiros & Timmermann (2000) argue that small firms with little collateral show the highest asymmetry in their risk across recession and expansion states. Their expected returns are thus more sensitive to credit market conditions. Chan & Chen (1991) present similar arguments for small firms being more sensitive to news about the state of the business cycle. This implies that investors in small firms are generally mid- to long-term oriented, while investors of large and better collateralized firms may be both short- and long-term oriented. This is supported by the argument from the "Interacting Agent View model". Large stocks are more favorable and hence attract all different kinds of agents. The higher degree of heterogeneity of large firm investors lead to the higher memory parameter compared to small firms.[23]

Daniel & Moskowitz (2016) argue that the momentum strategy

[23] Even though small firm investors are rather short-term oriented, this does not mean there are no long-term investors. The same is true for large firms. Hence we consider the relative proportion of long-term and short-term investors and talk about the degree of heterogeneity.

generates abnormally high returns on average, but at the same time experiences abnormally high losses. This is because the loser stocks embed features of a short call option on the market portfolio. Especially during times of volatile bear markets, past-loser stocks lose a large fraction of their market value and contain high financial leverage. The equity of theses firms is similar to out-of-the money call options on the underlying firm values, which are correlated with the market. This implies that loser stocks are much more sensitive to the state of the market (turbulent vs. calm), which may change quickly. Consequently, the fraction of short-term investors in the market of loser stocks should be larger than in the market of winner stocks, which leads to higher memory estimates for loser stocks. This is what we find empirically.

6.6 Extensions and Robustness Tests

In this section we run further analyses of long memory volatility in the cross-section and various robustness tests including alternative estimators and portfolio sorts, and extend our cross-sectional analysis with further control variables. Detailed results are reported in the appendix to this chapter.

6.6.1 Long Memory Volatility and Industries

In Section 6.3.2 we consider different firm characteristics and how they are able to explain the memory parameter of volatility in the cross-section of U.S. returns. We find that higher memory parameters can be related to large, loser stocks and stocks with fewer jumps. In this section, we investigate whether firms in certain industries possess higher or lower memory parameters. More specifically, we use the twelve industry portfolio identifiers obtained from Kenneth R. French's data library. The industries are Consumer Non-Durables, Consumer Durables, Manufacturing, Energy, Chemicals, Business Equipment, Telecommunication, Utilities, Shops, Healthcare, Money & Finance and Others. We apply the GPH estimator and a bandwidth parameter of $m = N^{0.5}$ as in our main analysis. Table D.2 of the appendix reports the results. The mean and median are very close to the value for the complete cross-section (0.22). Since the degree of memory is similar for all industries, industry codes, unlike firm characteristics, are not able to explain the cross-sectional variation of the memory parameter.

6.6.2 Fama–French Portfolios

In Section 6.3.2 we sort stocks by their memory parameter and investigate the average firm characteristics of quintile portfolios. In this section, we validate our results by comparing the memory of Fama–French decile portfolios, which are sorted by size, book-to-market or momentum. There are two major differences with this approach. First, instead of sorting by the memory parameter, stocks are sorted by their firm characteristics. Second, we consider decile instead of quintile portfolios.[24] The portfolio returns are obtained from Kenneth R. French's data library. We apply the GPH estimator with the bandwidth parameter of $m = N^{0.5}$ as in our main analysis and report the memory parameter for each decile portfolio and the high-minus-low ($D10 - D1$) in Table D.3 of the appendix. Consistent with our main results, portfolios with larger size, higher book-to-market and worse prior performance exhibit higher memory parameters.[25] The book-to-market (momentum) portfolios demonstrate a monotonically increasing (decreasing) pattern in memory.

[24]The results for the Fama–French quintile portfolios are qualitatively similar.

[25]The magnitude of the memory parameters are somewhat higher than in our main analysis. This is because we here use the complete time series of daily returns over more than 60 years, compared to the 5 years in our main analysis.

6.6.3 Estimation of the Memory Parameter

For our main analysis we follow the existing literature and choose the ad hoc bandwidth parameter of $m = N^{0.5}$. We repeat the estimation using a bandwidth parameter of $m = N^{0.6}$, $m = N^{0.7}$ and $m = N^{0.8}$ and alternative estimators in this section and report the results in Tables D.4, D.5 and D.6 of the appendix.[26]

We report the portfolio sorts for the cross-section of U.S. returns using the GPH estimator and alternative parameters in Table D.4, Panels A, B and C. We find that sorting by the memory parameter and holding stocks with long memory and selling stocks with short memory still generates negative excess returns. Using the alternative bandwidth parameters $m = N^{0.6}$, $m = N^{0.7}$ and $m = N^{0.8}$ leads to returns of -1.80%, -2.71% and -2.32% per annum, respectively. Adjusting for the additional risk factors of the Fama & French (2015) model leads to significant alphas of similar magnitudes as in our main analysis.

Further, we apply the GPH estimator to the absolute returns rather than the squared returns as in our main analysis (Bollerslev & Wright, 2000). The results are reported in Panel D and are consistent with our main findings. Stocks with short memory earn on average 2.94% per annum more than stocks with long memory. This spread return is statistically significant at the 1% level and remains significant when controling for the Fama & French (2015) risk factors.

A commonly used alternative approach to estimate long memory is the Local Whittle (LW) estimator. We repeat the estimation with the LW estimator and the same bandwidth parameter as in our main results,

[26] These alternative bandwidth parameters are the most common choices in the literature, see Hurvich & Ray (2003), Hurvich et al. (2005), Bandi & Perron (2006), Berger et al. (2009), Hou & Perron (2014), among others, and include the MSE-optimal one for the GPH estimator.

$m = N^{0.5}$ (Bandi & Perron, 2006). Results are provided in Table D.5. For the portfolio sorts we find a negative spread return of 2.09% for the LMS portfolio which is statistically significant at the 5% level (Panel A). The Fama & French (2015) five-factor alpha with a value of -3.21% is statistically significant as well. In addition, we apply the LW estimator with bandwidth parameters of $m = N^{0.6}$, $m = N^{0.7}$ and $m = N^{0.8}$ to the squared returns and a bandwidth parameter of $m = N^{0.5}$ to the absolute returns. Panels B to E report the results. The spread returns are all negative, varying from -1.82% to -3.03%, and the Fama & French (2015) five-factor alphas vary from -2.54% to -3.93%, while all returns and risk-adjusted returns are statistically significant.

Table D.6 reports the coefficient estimates from the cross-sectional regressions in Equation (6.11) using the alternative long memory estimator and bandwidths. We rely on simple regressions where individual stock returns are regressed on the long memory parameter in Panel A and multiple regressions where we additionally include Size, Book-to-Market, Momentum, Illiquidity and the BNS jump test statistic as explanatory variables. The results are consistent with our main analysis. For the simple regressions we find that long memory is negatively priced in the cross-section with a risk premium estimate varying from -0.0104 to -0.0039, depending on the estimator and bandwidth, which is statistically significant. Including the control variables slightly changes the magnitude of the long memory premium but they remain statistically significant. In addition, we find a negative (positive) price for the size (book-to-market ratio and momentum) of a stock which is consistent with both our main analysis and the literature.

6.6.4 Holding Period Returns

In our main analysis, portfolios are rebalanced monthly and held for one month. We now track whether the negative risk premium associated with long memory volatility persists for longer holding periods. Each month, we sort all stocks into quintile portfolios where stocks with the lowest memory parameter are in the first quintile and stocks with the highest memory parameter are in the fifth quintile. Excess returns of the portfolios are tracked over the subsequent one, two, three, four and five years. To account for the overlapping returns, we adjust the standard errors following Newey & West (1987), using lags according to the return horizon expressed in months.

The results are reported in Table D.7 of the appendix. Average returns and Fama & French (2015) risk adjusted returns for the one-, two-, three-, four- and five-year holding period are reported in Panels A, B, C, D and E. The annualized mean returns are of similar magnitude as for the one-month holding period. The LMS spreads are -1.88%, -1.93%, -1.88%, -1.90% and -1.91%, respectively, and are all statistically significant at the 5% level or lower. The risk adjusted returns only change slightly, and vary between -1.66% to -2.29% and are generally statistically significant.

6.6.5 High-Frequency Data

We repeat our analysis, but rely on high-frequency instead of daily returns. We obtain 5-min returns for the S&P 500 constituents for the period from 1996 until 2015 from Thomson Reuters Tick History. Our choice of the sample period and stocks is restricted by their availability. The data is cleaned following Barndorff-Nielsen et al. (2009). Zhang et al. (2005) argue that high-frequency data should always result in a more accurate estimate when used correctly due to the basic statistical principle that more data are always better. Bollerslev & Wright (2000) show that the high-frequency data allow for a superior and nearly unbiased estimation of the long memory parameter using 5-min return observations. We apply the GPH estimator and a bandwidth parameter of $m = N^{0.5}$ to a month of 5-min returns, which counts up to 1738 ($= 22 * 79$) data points per estimation window. This window is comparable to 8 years of daily observations.

The results are reported in Table D.8 of the appendix. We find a negative return of -8.83% for the LMS portfolio, which is statistically significant at the 1% level. Controling for additional risk factors generally slightly mitigates the risk premium but the alphas remain significant. This section thus confirms our main results and shows that the negative risk premium is not dependent on the source and frequency of data and the sample period. We implicitly investigate four subsamples and thus show that our main results are robust against various sample periods. Our choice of subsamples is motivated by the availability of the data. The longest period from 1926 until 2015 is chosen according to the availability of the CRSP stock data. We control for Fama & French (2015) (Hou et al., 2014) risk factors, which are available from 1963 until 2015 (1967 until 2015). Lastly, we also investigate the most recent 20 years from 1996 until 2015, which is chosen due to the availability of high-frequency data from Thomson Reuters Tick History.

6.6.6 Additional Control Variables

In Section 6.3.4 we conduct regression tests including Size, Book-to-Market, Momentum, Illiquidity and Jumps. We now also control for further effects and anomalies which have been shown to be good predictors of expected returns. More specifically, we include the market beta (BETA), reversal (REV), cokurtosis with the market (CKT), coskewness with the market

(CSK), idiosyncratic volatility (IVOL), realized kurtosis (KURT), realized skewness (SKEW) and demand for lottery (MAX). Further, we include a stock's volatility-of-volatility (Vol-of-Vol). In our empirical analysis we relate the long memory of volatility to the predictability of volatility and uncertainty. We relate higher volatility predictability to lower uncertainty regarding a stock's level of risk. In the literature, uncertainty has been measured by the volatility-of-volatility for both individual stocks and the aggregate market (Baltussen et al., 2017; Hollstein & Prokopczuk, 2017).[27] We calculate the volatility-of-volatility as the 5-year rolling window volatility of monthly realized volatility.[28] We find an average cross-sectional correlation of 0.11 between the degree of long memory volatility of a stock and its volatility-of-volatility. While both are intuitively related to uncertainty, the measures are barely correlated and we hence do not expect that our findings can be explained by the volatility-of-volatility of a stock. The market beta is estimated from daily return regressions of excess stock returns on an intercept and the market excess return over the examined period. Following Ang et al. (2006b), idiosyncratic volatility equals the standard deviation of the residuals from the same regression as for the market beta, but additionally includes the size and book-to-market factors of the Fama & French (1993) model. The short-term reversal at the end of a month is defined as the return of that month following Jegadeesh (1990). The coskewness and cokurtosis of a stock at the end of a month is estimated from the daily returns in that month following Ang et al. (2006a). The kurtosis and skewness of a stock at the end of a month is given by the sample kurtosis and skewness estimated from the daily returns

[27]Both studies investigate the asset pricing implication of the volatility-of-volatility and find a negative price, just as we find for long memory.

[28]It is not possible to compute the measure of Baltussen et al. (2017) for our sample since they rely on options data of individual stocks which are available starting in 1996 from OptionMetrics. Our approach for calculating the volatility-of-volatility closely follows the approach for our long memory estimates.

in that month. Lastly, the demand for lottery is given by the maximum total daily return observation of a month (Bali et al., 2011).

Table D.9 of the appendix presents the results of the cross-sectional regressions.[29] Models 7 to 15 show the time-series averages of the additional coefficients in multiple regressions. Most importantly, the risk premium of the long memory volatility remains negative and statistically significant for all additional control variables, varying from -0.0043 to -0.0036. The signs of statistically significant risk premia for variables besides long memory are generally consistent with the literature. Frazzini & Pedersen (2014) find that portfolios with higher betas have lower alphas and Sharpe ratios than portfolios of low-beta assets. Amaya et al. (2015) show that buying stocks with low realized skewness and selling stocks with high realized skewness generates statistically significant and positive excess returns at a weekly frequency while there is no clear relationship for realized kurtosis. The negative and statistically significant premium for idiosyncratic volatility is consistent with the results of Ang et al. (2006b). Bali et al. (2011) argue that investors are willing to pay more for stocks that exhibit extreme positive returns. As a consequence, these stocks exhibit lower future returns, which is consistent with the negative premium we find. Model 16 includes the memory parameter and all additional control variables in this section while Model 17 presents the kitchen sink regression. The coefficient of the memory parameter remains statistically significant at the 5% level or lower.

We control for two further variables: Aggregate long memory and aggregate volatility. Following Ang et al. (2006b), we rely on changes in the volatility index as a proxy for innovations in aggregate volatility. The VIX index presents the implied volatility of a S&P 100 index contract over the next 30 days ,which is at-the-money. Since the data goes back only

[29] We also report mean values of each control variable in quintile portfolios, which are sorted by long memory volatility. The results are presented in Table D.10.

until 1986, we rely on U.S. stock market volatility following Bloom (2009) for the time before. We compute the monthly standard deviation of the daily market returns and normalize the time series of monthly return volatilities to the same mean and variance as the VIX index when they overlap from 1986 until 2015. For aggregate long memory, we follow the approach in our main analysis and apply the GPH estimator and the bandwidth parameter $m = N^{0.5}$ to squared market returns in the most recent 60 months. For each stock, we then estimate sensitivities to aggregate long memory and volatility (Ang et al., 2006b):

$$r_{i,t} - r_{f,t} = \beta_0 + \beta_{i,Mkt} MKT_t + \beta_{i,AF} \Delta AF_t + \epsilon_{i,t} \tag{6.18}$$

where MKT is the market excess return, ΔAF describes the innovations in the aggregate factor (long memory or volatility), $\beta_{i,Mkt}$ and $\beta_{i,AF}$ are loadings on the market risk and aggregate factor, respectively, and ϵ is the error term. For both, aggregate long memory and volatility, we estimate the loadings in time-series regressions using a rolling window of 60 observations.

We then repeat our regression tests and further include the loadings on aggregate long memory and volatility in the vector $X_{i,t}$. Table D.11 of the appendix reports the results. The first two columns extend our control variables from 6.3.4, while columns three and four include the control variables discussed above. The coefficient associated with the risk premium of long memory remains negative and statistically significant for all model specifications. Our findings thus show that aggregate volatility or aggregate long memory cannot explain our results.

6.6.7 International Evidence

In previous sections we show that long memory is priced in the cross-section of U.S. stock returns and that our results are robust to controlling further effects and anomalies, choices of sample periods and to the estimation approach of long memory. In this section we extend our findings to further major economies. We consider the remaining G-7 countries: Canada, France, Germany, Italy, Japan and the U.K. This choice is motivated by their economic relevance and the data availability for these countries. We obtain equity price and market capitalization data from Datastream and include the universe of stocks from the major exchanges for the six countries. The majority of the stocks are traded at the major exchanges. While Canada, France, Italy and the U.K. only have one major exchange, there are two for Germany (Frankfurt and Xetra) and Japan (Osaka and Tokyo). U.S. dollar returns are calculated using the total return indices and exchange rates from Datastream. Our sample period starts in January 1980 and ends in December 2015 just as for the U.S.[30] The number of firms varies for the six countries. U.K. includes the most firms with a median of 4185 firm observations over the investigation period while Italy has the fewest number of firms with a median value of 264.

We clean the data following existing studies. First, we exclude extreme observations as follows: If the past or current return observation r_t or r_{t-1} are higher than 300% and $(1+r_t)(1+r_{t-1})-1 < 50\%$, then both returns are set missing (Hou et al., 2011; Lee, 2011). We filter non-trading days, which are defined as days on which more than 90% of the stocks have zero returns (Amihud, 2002; Lesmond, 2005; Lee, 2011). Lastly, we set the minimum observation at 0.01 following Lee (2011) in order to exclude illiquid stocks.

We report our findings in Table D.12 of the appendix. Panel A provides summary statistics for the remaining G-7 countries. In accordance with our findings for the U.S. we find that most of the stocks exhibit long memory in volatility. For Canada, 74% of the stocks show a memory parameter in the interval $(0.0; 0.5)$ while the proportion varies between 97% and 98% for

[30] The data for Datastream does not go back as far as CRSP. To ensure sufficient data quality we decide to start the sample in 1980.

France, Germany, Italy, Japan and the U.K. The average estimates of 0.40, 0.27, 0.24, 0.28, 0.24 and 0.30 for Canada, France, Germany, Italy, Japan and the U.K., respectively, also supports long memory in stock return volatility for the non-U.S. countries.

We also repeat the sorting exercise and report the average and risk-adjusted returns of the hedge-portfolio (Q5-Q1) in Panel B. We find that sorting by long memory in volatility generates negative returns for all countries. This spread is statistically significant for all countries at the 5% level or lower except for Italy. We control for global risk factors in the CAPM, the Fama & French (1993) 3-factor model and the state-of-the-art Fama & French (2015) 5-factor model using the data provided by the Kenneth R. French data library.[31] The risk-adjusted returns are very similar to the raw average returns, and statistically significant as well for the same six countries. This suggests, that the returns cannot be explained by the risk factors from the common models above. Lastly, we repeat the cross-sectional regressions and report the average coefficient estimates of α_t and γ_t^M in Panel C. We find that long memory in volatility is also priced in the cross-section of stock returns for Canada, France, Germany, Japan and the U.K. The slope coefficients are statistically significant at the 5% at lower.

In summary, this section confirms that our findings are not restricted to the U.S. stock market but our conclusions on the asset pricing implications of long memory in volatility are more general and can be extended to major economies.

[31] Website: Http://mba.tuck.dartmouth.edu/pages/facult/ken.french. The sample period for the risk-adjusted returns starts in 1990 due to the availability of global factors.

6.7 Conclusion

In this chapter we shed new light on the asset pricing implication of long memory in stock return volatility. Using portfolio sorts and cross-sectional regressions, we analyze how the degree of long memory of a firm's return volatility can be explained by its size, book-to-market, prior performance or jumps. Based on existing theoretical models, we discuss how long memory is generated in high market capitalization (winner) stocks compared to low market capitalization (loser) stocks. We estimate a cross-sectional price of long memory of -4.7% per annum. This estimate is robust to controling for size, value, momentum, liquidity effects and more. We relate the compensation for holding short memory stocks to higher risk, which is given by the low predictability of short memory stocks. Our results are robust against different variations of the estimation approach and the examined models.

D Appendix

Table D.1: Sorted Portfolio Returns: Residual Long Memory

This table reports average returns and risk-adjusted returns of equally weighted quintile portfolios. Each month, stocks are sorted by their residual long memory and we track the portfolio returns over the subsequent month. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. Residual memory is calculated by regressing the memory parameter on size, book-to-market, momentum and illiquidity (Model 1). Model 2 additionally includes the BNS jump test statistic. The one-month-ahead portfolio returns are regressed on risk factors in the Capital Asset Pricing Model (CAPM) and the Fama & French (2015) five-factor model (FF5). The corresponding alphas are reported. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1 (LMS)
Panel A: Model 1						
CAPM	0.0261^{***}	0.0227^{**}	0.0286^{***}	0.0188^{*}	0.0146	-0.0115^{*}
	(0.0101)	(0.0100)	(0.0098)	(0.0101)	(0.0097)	(0.0060)
FF5	0.0049	-0.0007	0.0034	-0.0090^{*}	-0.0100^{*}	-0.0149^{**}
	(0.0047)	(0.0044)	(0.0041)	(0.0048)	(0.0058)	(0.0069)
Panel B: Model 2						
CAPM	0.0261^{***}	0.0236^{**}	0.0293^{***}	0.0176^{*}	0.0141	-0.0120^{**}
	(0.0100)	(0.0100)	(0.0099)	(0.0100)	(0.0097)	(0.0060)
FF5	0.0050	0.0006	0.0042	-0.0102^{**}	-0.0099^{*}	-0.0149^{**}
	(0.0047)	(0.0043)	(0.0041)	(0.0048)	(0.0058)	(0.0068)

Table D.2: Long Memory and Industries

This table reports descriptive statistics for the memory parameter of industry portfolios. for the period from 1926 until 2015. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. SD stands for the standard deviation. Min and Max stand for the minimum and maximum observation over the sample period.

	Non-Durables	Durables	Manufacturing	Energy	Chemicals	Business Equipment
Mean	0.21	0.22	0.22	0.21	0.24	0.19
Median	0.21	0.22	0.21	0.21	0.23	0.20
SD	0.06	0.05	0.06	0.08	0.10	0.08
Min	0.02	−0.02	0.11	−0.03	−0.04	−0.11
Max	0.37	0.39	0.44	0.55	0.80	0.56
Skewness	0.32	−0.06	1.64	0.34	1.08	−0.29
Kurtosis	3.48	4.22	6.33	4.00	6.13	4.22
	Telecommunication	Utilities	Shops	Healthcare	Money Finance	Other
Mean	0.20	0.21	0.23	0.23	0.21	0.21
Median	0.21	0.21	0.22	0.22	0.20	0.21
SD	0.09	0.08	0.05	0.08	0.07	0.07
Min	−0.30	−0.15	0.10	−0.01	−0.02	−0.05
Max	0.47	0.53	0.39	0.58	0.45	0.43
Skewness	−0.78	−0.29	0.82	1.08	0.03	−0.47
Kurtosis	5.77	5.39	3.53	5.39	3.92	5.10

Table D.3: Long Memory and Fama–French Portfolios

This table reports the memory parameter for decile portfolios sorted Size, Book-to-Market and Momentum for the period from 1950 until 2015. The last column reports the average of the High-Minus-Low ($D10 - D1$) portfolio. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-D1
Size	0.3425	0.5483	0.5162	0.4799	0.4955	0.4489	0.4349	0.4397	0.4159	0.3860	0.0436
Book-to-Market	0.3382	0.4249	0.4334	0.4544	0.4808	0.5062	0.5090	0.5326	0.4905	0.6149	0.2767
Momentum	0.6184	0.6202	0.6138	0.5527	0.5215	0.4896	0.4237	0.3635	0.3034	0.1952	−0.4232

Table D.4: Sorted Portfolio Returns: Alternative GPH Estimators

This table reports average returns and risk-adjusted returns of equally weighted quintile portfolios for the period from 1926 until 2015. Each month, stocks are sorted by their memory parameter estimate and we track the portfolio returns over the subsequent month. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.6}$, $m = N^{0.7}$ or $m = N^{0.8}$ in Panels A-C. The GPH estimator is applied to absolute returns and $m = N^{0.5}$ in Panel D. The one-month-ahead portfolio returns are regressed on risk factors in the Fama & French (2015) five-factor model (FF5). The average return and the corresponding alphas are reported. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1 (LMS)
Panel A: GPH $m = N^{0.6}$						
Mean return	0.1347***	0.1353***	0.1316***	0.1248***	0.1167***	−0.0180**
	(0.0345)	(0.0347)	(0.0338)	(0.0345)	(0.0331)	(0.0089)
FF5	0.0219**	0.0174*	0.0081	0.0052	−0.0009	−0.0228**
	(0.0106)	(0.0090)	(0.0074)	(0.0076)	(0.0094)	(0.0095)
Panel B: GPH $m = N^{0.7}$						
Mean return	0.1426***	0.1313***	0.1286***	0.1256***	0.1155***	−0.0271***
	(0.0357)	(0.0345)	(0.0343)	(0.0331)	(0.0330)	(0.0096)
FF5	0.0291***	0.0131	0.0074	0.0070	−0.0043	−0.0334***
	(0.0105)	(0.0093)	(0.0078)	(0.0076)	(0.0088)	(0.0097)
Panel C: GPH $m = N^{0.8}$						
Mean return	0.1415***	0.1379***	0.1248***	0.1208***	0.1183***	−0.0232**
	(0.0361)	(0.0361)	(0.0335)	(0.0335)	(0.0313)	(0.0099)
FF5	0.0293***	0.0170**	0.0090	−0.0010	−0.0022	−0.0314***
	(0.0103)	(0.0082)	(0.0086)	(0.0085)	(0.0084)	(0.0095)
Panel D: GPH Absolute Returns $m = N^{0.5}$						
Mean return	0.1417***	0.1321***	0.1306***	0.1264***	0.1123***	−0.0294***
	(0.0335)	(0.0331)	(0.0341)	(0.0342)	(0.0360)	(0.0103)
FF5	0.0202**	0.0145	0.0106	0.0074	−0.0026	−0.0228**
	(0.0102)	(0.0091)	(0.0074)	(0.0074)	(0.0105)	(0.0105)

Table D.5: Sorted Portfolio Returns: Alternative LW Estimators

This table reports average returns and risk-adjusted returns of equally weighted quintile portfolios for the period from 1926 until 2015. Each month, stocks are sorted by their memory parameter estimate and we track the portfolio returns over the subsequent month. The memory parameter is estimated with the LW estimator and a bandwidth parameter of $m = N^{0.5}$, $m = N^{0.6}$, $m = N^{0.7}$ or $m = N^{0.8}$ in Panels A-D. The LW estimator is applied to absolute returns and $m = N^{0.5}$ in Panel E. The one-month-ahead portfolio returns are regressed on risk factors in the Fama & French (2015) five-factor model (FF5). The average return and the corresponding alphas are reported. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1 (LMS)
Panel A: LW $m = N^{0.5}$						
Mean return	0.1391***	0.1299***	0.1309***	0.1256***	0.1181***	−0.0209**
	(0.0333)	(0.0332)	(0.0333)	(0.0351)	(0.0358)	(0.0100)
FF5	0.0309***	0.0133	0.0092	0.0009	−0.0012	−0.0321***
	(0.0115)	(0.0086)	(0.0077)	(0.0076)	(0.0097)	(0.0109)
Panel B: LW $m = N^{0.6}$						
Mean return	0.1363***	0.1355***	0.1309***	0.1227***	0.1182***	−0.0182*
	(0.0342)	(0.0344)	(0.0341)	(0.0345)	(0.0334)	(0.0099)
FF5	0.0254**	0.0176**	0.0079	0.0017	0.0000	−0.0254**
	(0.0110)	(0.0088)	(0.0079)	(0.0075)	(0.0094)	(0.0103)
Panel C: LW $m = N^{0.7}$						
Mean return	0.1435***	0.1324***	0.1307***	0.1238***	0.1137***	−0.0298***
	(0.0352)	(0.0349)	(0.0338)	(0.0343)	(0.0326)	(0.0101)
FF5	0.0324***	0.0131	0.0093	0.0054	−0.0069	−0.0393***
	(0.0106)	(0.0092)	(0.0081)	(0.0079)	(0.0090)	(0.0105)
Panel D: LW $m = N^{0.8}$						
Mean return	0.1427***	0.1370***	0.1275***	0.1230***	0.1135***	−0.0292***
	(0.0366)	(0.0351)	(0.0344)	(0.0334)	(0.0315)	(0.0112)
FF5	0.0298***	0.0191**	0.0080	0.0014	−0.0053	−0.0351***
	(0.0108)	(0.0088)	(0.0082)	(0.0078)	(0.0093)	(0.0106)
Panel E: LW Absolute Returns $m = N^{0.5}$						
Mean return	0.1445***	0.1327***	0.1336***	0.1175***	0.1141***	−0.0303**
	(0.0337)	(0.0324)	(0.0344)	(0.0337)	(0.0369)	(0.0121)
FF5	0.0264**	0.0147	0.0099	0.0021	−0.0029	−0.0293***
	(0.0103)	(0.0091)	(0.0075)	(0.0076)	(0.0108)	(0.0112)

Table D.6: Cross-sectional Regressions: Alternative Estimators

This table reports results from Fama & MacBeth (1973) regressions for the period from 1950 until 2015. Each month, excess stock returns are regressed on the lagged memory parameters in Panel A. Panel B further includes additional lagged firm characteristics, which are market capitalization (Size), book-to-market values, prior returns (Momentum), illiquidity and jump statistics (BNS). The memory parameter is estimated by applying the GPH or the LW estimator and a bandwidth parameter of $m = N^{0.5}$, $m = N^{0.6}$, $m = N^{0.7}$ or $m = N^{0.8}$ to squared or absolute returns. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. Stars indicate the significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	GPH				LW				
	$N^{0.6}$	$N^{0.7}$	$N^{0.8}$	Abs. $N^{0.5}$	$N^{0.5}$	$N^{0.6}$	$N^{0.7}$	$N^{0.8}$	Abs. $N^{0.5}$
Panel A: Simple Regressions									
Intercept	0.0089***	0.0091***	0.0091***	0.0094***	0.0092***	0.0091***	0.0094***	0.0095***	0.0097***
	(0.0026)	(0.0026)	(0.0027)	(0.0025)	(0.0026)	(0.0026)	(0.0027)	(0.0027)	(0.0025)
Long Memory	−0.0039*	−0.0062**	−0.0075**	−0.0045**	−0.0047**	−0.0053*	−0.0084**	−0.0104**	−0.0060**
	(0.0022)	(0.0028)	(0.0036)	(0.0019)	(0.0022)	(0.0029)	(0.0038)	(0.0049)	(0.0025)
Panel B: Multiple Regressions									
Intercept	0.0106*	0.0109*	0.0110*	0.0111**	0.0106*	0.0106*	0.0109*	0.0111*	0.0110*
	(0.0056)	(0.0056)	(0.0057)	(0.0056)	(0.0056)	(0.0056)	(0.0056)	(0.0057)	(0.0056)
Long Memory	−0.0026*	−0.0044**	−0.0047*	−0.0027**	−0.0030**	−0.0033*	−0.0063**	−0.0071*	−0.0036**
	(0.0015)	(0.0021)	(0.0028)	(0.0013)	(0.0015)	(0.0019)	(0.0028)	(0.0039)	(0.0017)
Size	−0.0005	−0.0005*	−0.0005*	−0.0005*	−0.0005	−0.0005	−0.0005	−0.0005	−0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Book-to-Market	0.0024***	0.0024***	0.0023***	0.0024***	0.0024***	0.0024***	0.0024***	0.0023***	0.0024***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Momentum	0.0094***	0.0095***	0.0094***	0.0095***	0.0095***	0.0095***	0.0094***	0.0094***	0.0095***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Illiquidity	0.0987	0.0952	0.0926	0.0927	0.0993	0.0991	0.0971	0.0924	0.0933
	(0.1764)	(0.1754)	(0.1752)	(0.1759)	(0.1763)	(0.1765)	(0.1753)	(0.1742)	(0.1752)
BNS	0.0020***	0.0020***	0.0020***	0.0020***	0.0020***	0.0020***	0.0020***	0.0020***	0.0020***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)

Table D.7: Sorted Portfolio Returns: Alternative Holding Periods

This table reports average returns and risk-adjusted returns of equally weighted quintile portfolios for the period from 1926 until 2015. Each month, stocks are sorted by their memory parameter estimate and we track the portfolio returns over the subsequent one, two, three, four and five years in Panel A, B, C, D and E, respectively. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. The one-month-ahead portfolio returns are regressed on risk factors in the Capital Asset Pricing Model (CAPM) and the Fama & French (2015) five-factor model (period starts in 1963) (FF5). The mean returns and the corresponding alphas are reported. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1 (LMS)
Panel A: One Year Holding Period						
Mean return	0.1404***	0.1371***	0.1384***	0.1329***	0.1216***	−0.0188**
	(0.0503)	(0.0504)	(0.0472)	(0.0438)	(0.0448)	(0.0095)
FF5	0.1566***	0.1592***	0.1616***	0.1478***	0.1400***	−0.0166
	(0.0502)	(0.0488)	(0.0477)	(0.0470)	(0.0473)	(0.0150)
Panel B: Two Years Holding Period						
Mean return	0.1453***	0.1431***	0.1412***	0.1371***	0.1260***	−0.0193**
	(0.0423)	(0.0403)	(0.0386)	(0.0359)	(0.0371)	(0.0097)
FF5	−0.0059	−0.0037	−0.0076	−0.0200**	−0.0288***	−0.0229**
	(0.0092)	(0.0079)	(0.0075)	(0.0087)	(0.0111)	(0.0100)
Panel C: Three Years Holding Period						
Mean return	0.1445***	0.1441***	0.1421***	0.1378***	0.1256***	−0.0188**
	(0.0390)	(0.0391)	(0.0357)	(0.0325)	(0.0332)	(0.0092)
FF5	−0.0072	−0.0025	−0.0093	−0.0202*	−0.0292**	−0.0219**
	(0.0089)	(0.0092)	(0.0078)	(0.0115)	(0.0119)	(0.0091)
Panel D: Four Years Holding Period						
Mean return	0.1510***	0.1509***	0.1478***	0.1438***	0.1319***	−0.0190**
	(0.0424)	(0.0434)	(0.0394)	(0.0352)	(0.0352)	(0.0094)
FF5	−0.0008	0.0017	−0.0031	−0.0152	−0.0212	−0.0204**
	(0.0188)	(0.0234)	(0.0292)	(0.0302)	(0.0224)	(0.0081)
Panel E: Five Years Holding Period						
Mean return	0.1534***	0.1537***	0.1493***	0.1464***	0.1343***	−0.0191**
	(0.0341)	(0.0379)	(0.0356)	(0.0321)	(0.0303)	(0.0093)
FF5	−0.0191	−0.0204	−0.0263*	−0.0352***	−0.0393***	−0.0203**
	(0.0141)	(0.0180)	(0.0142)	(0.0124)	(0.0122)	(0.0091)

Table D.8: Sorted Portfolio Returns: High Frequency Data

This table reports average returns and risk-adjusted returns of quintile portfolios for the period from 1996 until 2015. Each month, stocks are sorted by their long memory parameter estimate and we track the portfolio returns over the subsequent month. The one-month-ahead portfolio returns are regressed on risk factors in the Capital Asset Pricing Model (CAPM), the Fama & French (1993) 3-factor model (FF3), the Fama & French (2015) 5-factor model (FF5) and the Hou et al. (2014) q-model (HXZ). The corresponding alphas are reported. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. The memory parameter is estimated using a month of 5-min returns and the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1 (LMS)
Mean return	0.1638***	0.1246***	0.1091**	0.1025**	0.0754*	−0.0883***
	(0.0441)	(0.0474)	(0.0461)	(0.0438)	(0.0445)	(0.0176)
CAPM	0.1508***	0.1138***	0.0980**	0.0881**	0.0600	−0.0908***
	(0.0403)	(0.0432)	(0.0444)	(0.0405)	(0.0417)	(0.0182)
FF3	0.1369***	0.1040**	0.0798*	0.0768*	0.0633	−0.0736***
	(0.0429)	(0.0437)	(0.0457)	(0.0433)	(0.0434)	(0.0193)
FF5	0.0963	0.0643	0.0395	0.0558	0.0367	−0.0597**
	(0.0644)	(0.0638)	(0.0612)	(0.0581)	(0.0563)	(0.0257)
HXZ	0.0558	0.0194	−0.0088	0.0259	−0.0169	−0.0727**
	(0.0870)	(0.0845)	(0.0827)	(0.0785)	(0.0737)	(0.0302)

Table D.9: Fama–MacBeth Regressions: Additional Control Variables

This table reports results from Fama & MacBeth (1973) regressions for the period from 1950 until 2015. Each month, excess stock returns are regressed on lagged firm characteristics including, memory parameters, market capitalization (Size), book-to-market values, prior returns (Momentum), illiquidity and jump statistics (BNS). We further control for Beta, Cokurtosis (CKT), Coskewness (CSK), idiosyncratic volatility (IVOL), kurtosis (KURT), skewness (SKEW), demand for lottery (MAX) and volatility of volatility (Vol-of-Vol). We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17
Intercept	0.0091***	0.0144***	0.0075***	0.0076***	0.0087***	0.0091***	0.0096***	0.0095***	0.0087***	0.0089***	0.0116***	0.0114***	0.0096***	0.0122***	0.0089***	0.0106***	0.0267***
	(0.0025)	(0.0051)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0027)	(0.0024)	(0.0026)	(0.0026)	(0.0019)	(0.0025)	(0.0025)	(0.0021)	(0.0017)	(0.0019)	(0.0040)
Long Memory	−0.0039**	−0.0021*	−0.0038**	−0.0038**	−0.0044***	−0.0043***	−0.0040**	−0.0037**	−0.0036**	−0.0037**	−0.0042***	−0.0043***	−0.0039**	−0.0041***	−0.0038***	−0.0041***	−0.0021**
	(0.0016)	(0.0012)	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0014)	(0.0017)	(0.0016)	(0.0015)	(0.0014)	(0.0013)	(0.0010)
Size		−0.0006*															−0.0013***
		(0.0003)															(0.0002)
Book-to-Market			0.0019***														0.0012**
			(0.0005)														(0.0005)
Momentum				0.0067***													0.0096***
				(0.0016)													(0.0013)
Illiquidity					0.2010**												0.4686**
					(0.1010)												(0.1836)
BNS						0.0024***											−0.0001
						(0.0004)											(0.0003)
Beta							−0.0510***									−0.0006	−0.0006
							(0.0042)									(0.0005)	(0.0006)
REV								−0.0005								−0.0577***	−0.0395***
								(0.0005)								(0.0043)	(0.0037)
CKT									0.0000							0.0007	0.0011***
									(0.0005)							(0.0005)	(0.0004)
CSK										−0.0005						0.0003	−0.0010
										(0.0008)						(0.0007)	(0.0007)
IVOL											−0.1483***					−0.0725	−0.2892***
											(0.0447)					(0.0598)	(0.0535)
KURT												−0.0006***				−0.0003**	−0.0002**
												(0.0001)				(0.0001)	(0.0001)
SKEW													−0.0020***			0.0014***	0.0009***
													(0.0003)			(0.0003)	(0.0003)
MAX														−0.0610***		−0.0159	0.0156
														(0.0112)		(0.0164)	(0.0165)
Vol-of-Vol															−0.0074	0.0207	−0.0206
															(0.0309)	(0.0244)	(0.0244)

Table D.10: Portfolio Sorts and Additional Control Variables

This table presents firm characteristics of portfolios sorted by the memory of volatility. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. From 1950 until 2015 we sort stocks each month and form and hold the portfolio for one month. We report the average long memory parameter, memory parameters, market capitalization (Size), book-to-market values, prior returns (Momentum), illiquidity and jump statistics (BNS), Beta, Cokurtosis (CKT), Coskewness (CSK), idiosyncratic volatility (IVOL), kurtosis (KURT), skewness (SKEW), demand for lottery (MAX) and volatility of volatility (Vol-of-Vol) of quintile portfolios. The Q5-Q1 column reports the averages for the long memory minus short memory portfolio (LMS) with the according t-statistics in square brackets.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1 (LMS)	
Memory	0.0044	0.1295	0.2118	0.2975	0.4471	0.4427	[202.7567]
Size	11.6610	11.8630	12.0161	12.1707	12.3560	0.6950	[23.3435]
Book-to-Market	0.8934	0.9168	0.8993	0.8758	0.8996	0.0062	[0.5910]
Momentum	0.1681	0.1558	0.1522	0.1483	0.1284	−0.0397	[−14.2697]
Illiquidity	0.0044	0.0040	0.0038	0.0040	0.0055	0.0010	[3.9205]
BNS	−0.1994	−0.0620	−0.0255	−0.0110	0.0036	0.2030	[12.5035]
Beta	0.8044	0.8458	0.8668	0.8874	0.8998	0.0954	[13.5244]
REV	0.0151	0.0128	0.0124	0.0118	0.0108	−0.0043	[−6.2043]
CKT	0.7717	0.8385	0.8870	0.9271	0.9574	0.1857	[15.0266]
CSK	−0.0462	−0.0464	−0.0455	−0.0432	−0.0410	0.0052	[1.9815]
IVOL	0.0245	0.0233	0.0226	0.0224	0.0233	−0.0012	[−3.5765]
KURT	3.9543	3.8076	3.7205	3.6439	3.5518	−0.4024	[−40.4010]
SKEW	0.2678	0.2461	0.2337	0.2232	0.2074	−0.0604	[−16.6647]
Max	0.0672	0.0625	0.0602	0.0594	0.0609	−0.0063	[−7.1539]
Vol-of-Vol	0.0616	0.0551	0.0527	0.0528	0.0577	−0.0039	[−4.4344]

Table D.11: Exposure to Market Long Memory and Aggregate Volatility

This table reports results from Fama & MacBeth (1973) regressions for the period from 1950 until 2015. Each month, excess stock returns are regressed on lagged firm characteristics including, memory parameters, market capitalization (Size), book-to-market values, prior returns (Momentum), illiquidity and jump statistics (BNS). We further control for Beta, Cokurtosis (CKT), Coskewness (CSK), idiosyncratic volatility (IVOL), kurtosis (KURT), skewness (SKEW), demand for lottery (MAX) and volatility of volatility (Vol-of-Vol) and exposure to market memory and aggregate volatility. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.0114**	0.0107*	0.0239***	0.0239***
	(0.0053)	(0.0055)	(0.0049)	(0.0047)
Long Memory	−0.0017*	−0.0024**	−0.0018*	−0.0022**
	(0.0010)	(0.0011)	(0.0010)	(0.0010)
Size	−0.0004	−0.0005*	−0.0011***	−0.0012***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Book-to-Market	0.0020***	0.0023***	0.0012**	0.0013**
	(0.0005)	(0.0006)	(0.0005)	(0.0005)
Momentum	0.0093***	0.0094***	0.0093***	0.0094***
	(0.0012)	(0.0013)	(0.0013)	(0.0013)
Illiquidity	−0.0091	0.0770	0.4028***	0.4076**
	(0.1470)	(0.1716)	(0.1550)	(0.1693)
BNS	0.0020***	0.0019***	−0.0001	−0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Beta			−0.0004	−0.0007
			(0.0005)	(0.0006)
Rev			−0.0412***	−0.0381***
			(0.0037)	(0.0038)
CKT			0.0011***	0.0012***
			(0.0003)	(0.0004)
CSK			−0.0011	−0.0010
			(0.0007)	(0.0007)
KURT			−0.2973***	−0.0002**
			(0.0515)	(0.0001)
SKEW			−0.0003**	0.0009***
			(0.0001)	(0.0003)
MAX			0.0008***	0.0145
			(0.0002)	(0.0170)
Vol-of-Vol			0.0200	−0.2936***
			(0.0164)	(0.0585)
Market Long Memory	−0.0017		−0.0004	
	(0.0015)		(0.0014)	
Aggregate Volatility		−0.0008		0.0005
		(0.0009)		(0.0008)

Table D.12: Long Memory in Stock Return Volatility – International Evidence

We report the summary statistics for the memory estimates of individual stocks' volatility for Canada, France, Germany, Italy, Japan and the U.K. in Panel A. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. AR(1) stands for the cross-sectional average of the first-order autocorrelation coefficients. SD stands for the standard deviation. The last row reports the proportion of the memory parameter being in a certain interval. Panel B reports average and risk-adjusted returns of equally weighted hedge portfolios. Each month, stocks are sorted by the degree of long memory in volatility and we track the portfolio returns over the subsequent month. The one-month-ahead portfolio returns are regressed on risk factors in the Capital Asset Pricing Model (CAPM), the Fama & French (1993) 3-factor model (FF3), the Fama & French (2015) 5-factor model (FF5). The corresponding alphas are reported. We report Newey & West (1987) standard errors using lags equal to the return horizon in parentheses. We rely on global factors and the period for the alphas starts in November 1990. Panel C reports results from Fama & MacBeth (1973) regressions. Each month, excess stock returns are regressed on the lagged memory parameters. Stars indicate significance: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Canada	France	Germany	Italy	Japan	UK
Panel A: Descriptive Statistics						
AR(1)	0.92	0.90	0.88	0.88	0.89	0.91
Mean	0.40	0.27	0.24	0.28	0.24	0.30
SD	0.14	0.12	0.13	0.12	0.10	0.14
Skewness	−0.36	−0.21	0.40	−0.16	0.36	−0.49
Kurtosis	2.63	2.93	3.22	3.26	4.75	2.28
$0.0 < d < 0.5$	0.74	0.97	0.97	0.96	0.98	0.97
Panel B: Portfolio Sorts						
Mean Return	−0.0078***	−0.0127***	−0.0178**	−0.0001	−0.0022**	−0.0075***
	(0.0027)	(0.0036)	(0.0085)	(0.0019)	(0.0011)	(0.0024)
CAPM	−0.0088***	−0.0150***	−0.0214**	−0.0003	−0.0028***	−0.0037**
	(0.0024)	(0.0040)	(0.0101)	(0.0019)	(0.0011)	(0.0015)
FF3	−0.0077***	−0.0148***	−0.0201**	0.0005	−0.0027***	−0.0031**
	(0.0022)	(0.0044)	(0.0087)	(0.0019)	(0.0010)	(0.0013)
FF5	−0.0079***	−0.0131***	−0.0168**	0.0000	−0.0021**	−0.0028**
	(0.0023)	(0.0028)	(0.0075)	(0.0023)	(0.0010)	(0.0014)
Panel C: Cross-sectional Regressions						
Intercept	0.0191***	0.0169***	0.0197***	0.0058	0.0074*	0.0069**
	(0.0054)	(0.0035)	(0.0058)	(0.0041)	(0.0039)	(0.0034)
Long Memory	−0.0178***	−0.0261***	−0.0307**	−0.0011	−0.0060**	−0.0151***
	(0.0063)	(0.0068)	(0.0139)	(0.0038)	(0.0024)	(0.0050)

Chapter 7

Conclusion and Further Research

7.1 Summary and Conclusion

This thesis investigates the implications of asset's tail risk and long memory on expected returns and hedging properties in financial markets. Chapter 2 studies local and global tail risk in major economies and to what extent it is possible to predict future aggregate market returns and the cross-section of stock returns using tail risk measures. We find that future market returns mainly depend on our World Fear index, which is a proxy for global tail risk, rather than local tail risk. Furthermore, we find that World Fear is significantly priced with a positive sign across the countries. Specifically, we find that the portfolio of stocks with the highest sensitivity toward World Fear outperforms the stocks with the lowest exposure to World Fear by upto 2.72% per month in terms of average returns. Our results may be explained by the impact of World Fear on the real economy. We show that an increase in World Fear is followed by higher unemployment in subsequent months followed by a slow recovery.

Chapter 3 studies the relevance of tail risk in commodity markets. We present evidence on commodity sectors with both high and low jump correlations. This influences the choice of commodity-based portfolios directly if one is interested in the diversification of extreme movements. We link our results to further asset classes. Similar to the stock market, jumps in commodity markets are rare and extreme events but nonetheless appear much less frequently than in stock markets as found by Pukthuanthong & Roll (2015). Our analysis suggests that even though returns of commodities and stocks are correlated, jumps are generally diversifiable. In contrast, commodities are useful hedges for both normal and extreme price movements in the U.S. Dollar exchange rate and Treasures notes.

The most famous hedging asset, both promoted in the media and the academic literature, is the commodity gold. Chapter 4 comprehensively studies the gold risk premium and the hedging properties of gold from an ex-ante perspective. We find that the gold excess return is predictable both in-sample and out-of-sample. Relying on parsimonious models for the gold, equity and bond risk premia as well as expected inflation, we examine the expected and unexpected relationships. Our results suggest that gold is not expected to serve as a hedge for the stock and bond market but it does so ex-post, while it is neither expected to hedge against inflation nor does it do so.

Chapters 5 and 6 deal with a common stylized fact in financial data, long memory. We provide evidence of long memory in volatility for both a large set of countries and in the cross-section of U.S. stocks. Chapter 5 examines long memory at the aggregate level and relates the degree of memory in international equity index volatility to macroeconomic fundamentals both in the time-series and cross-sectional dimension. Longer memory in volatility is shown to be associated with lower unemployment and lower interest rates for most countries on the one hand and more developed countries on the other. Chapter 6 investigates the long memory at the firm level in U.S. stock return volatility and introduces the possible existence of an uncertainty-return trade-off in financial markets. Since long memory in volatility describes the slowly decaying autocorrelation function, it is a proxy for the predictability of volatility and hence can be interpreted as a measure of uncertainty. For the empirical analysis we use portfolio sorts as well as cross-sectional Fama & MacBeth (1973) regressions and find that long memory volatility is significantly priced with a negative sign. Specifically, we find that the quintile portfolio of stocks with the longest memory underperforms the quintile of stocks with the shortest memory by 2.84% per annum in terms of 5-factor alphas. In cross-sectional regressions we find that long memory is priced even after controlling for firm characteristics such as market capitalization, book-to-market ratios, momentum or liquidity. We link our findings to existing long memory models and show that our results are robust to the choice of long memory estimation, holding period, estimation windows and further control variables.

The findings presented in this thesis have important implications for both academics and market participants in practice.

First of all, World Fear and long memory are both important for many applications in asset pricing, portfolio choice and risk management. The methodology introduced by Kelly & Jiang (2014) allows financial managers to estimate a monthly time-series of tail risk while the most prominent long memory estimator introduced by Geweke & Porter-Hudak (1983) and rolling windows can be used to obtain a monthly time-series of memory estimates.

Showing that World Fear is priced in the stock market and more important than local tail risk provides an important contribution that may help understanding financial markets better. Investors should differentiate between local and global tail risk and decide whether they want to hedge against increases in those or expose their portfolios to the factors earning the substantial risk premium attached to those. Similarly, the negative uncertainty-return trade-off of long memory volatility in the cross-section of stock returns has to be taken into account by the managers. We show its importance and that the information content of long memory volatility about stock returns goes beyond those of known characteristics and anomalies such as size and momentum.

Financial managers should also consider commodities, especially gold, when aiming to diversify their portfolios. Even though returns of some commodities show quite high correlations with returns of other asset classes, extreme returns (jumps) are generally diversifiable. We also show that asset managers should carefully differentiate between hedging properties from an ex-ante and an ex-post perspective.

The findings presented here also have several implications for the academic literature. The tail risk measure obtained from returns is shown to have predictive power for future aggregate market returns and the cross-section of stock returns. The statistical evidence is comparable to measures those obtained from options data (such as the VIX or VRP) and the predictability and asset pricing effects are also channeled by uncertainty shocks. The feasible estimation allows for a broader application than option implied measures, since options data availability may be limited for many countries. For the estimation of long memory in volatility, we show that the simple GPH estimator and the bandwidth of $m = N^{0.5}$ is applicable and asset pricing implications derived from alternative bandwidths and estimators are qualitatively similar.

7.2 Suggestions for Further Research

Various methods have been introduced in order to estimate tail risk. The conclusions drawn on the relationship with market returns, stock returns and the aggregate economy are similar. But the question arises, which tail risk measure is most accurate and has the strongest predictive/explanatory power in a horse race, especially given the different natures of the measures such as the use of historical stock returns versus the use of forward-looking options data. Further, only little research is done dealing with the fundamental differences in the estimation methods and the economic interpretation of the tail risk measures.

Our findings related to long memory at both the aggregate market and the firm level give rise to several potentially interesting topics for future research.

First, are the explored asset pricing implications limited to the cross-section of stock returns of major economies or can they be generalized to further countries and asset classes such as currencies and commodities as well? As shown in this thesis, economically weaker countries, for example, tend to show shorter long memory volatility in the equity index. This finding combined with the "Agent-based" model of LeBaron (2006) and the "Interacting Agent View" of Alfarano & Lux (2007) may suggest different findings for weaker economies.

Second, this thesis only investigates long memory estimated in historical volatility and as such relies on historical stock return data. There has been a long debate about the information content of implied volatility compared to realized or historical volatility. Assuming efficient option markets, implied volatility as the "market" volatility forecast should be an efficient forecast for future volatility since it subsumes information of all other market variables, which are able to predict future volatility. We can thus study the asset implications of long memory in implied volatility and compare these to our existing findings.

Furthermore, since one main objective of our thesis is to study the dynamics of volatility, it seems highly profitable to employ not only time series data of equity returns or implied volatility, but to make use of securities that are very sensitive to changes in the volatility dynamics, i.e. options. An option pricing model may be calibrated allowing for long memory using monthly or quarterly subsamples of option prices of the S&P 500. The result of this approach will be again a time series of estimates of the long memory parameter, although now obtained under the risk-neutral measure. This methodology has the advantage that one has a large number of observations available, all coming from security prices that are sensitive to volatility. If there exists a risk premium, the estimates need not to be equal to the estimates from the first approach under the physical measure. Thus, the analysis will allow us to determine whether the long memory property of volatility originates from the volatility process itself or from the variance risk premium (VRP). For example, it might be that the volatility process under the risk-neutral measure does not exhibit long memory but the VRP does. Although multiple methods for the estimation of long memory exist, to the best of my knowledge, none of those has used options data in order to estimate long memory.

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