Volatility and Systematic Risks in Financial Markets

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ABSTRACT

This thesis investigates different volatility risk measures, interdependencies between the risk measures and macroeconomic determinants, and the connection between systematic risk and market power in financial markets. In Chapter 1, I introduce the overall concept of the thesis and present an overview of the subsequent chapters. In Chapter 2, we comprehensively examine the volatility term structures in commodity markets. We model state-dependent spillovers in principal components (PCs) of the volatility term structures of different commodities, as well as that of the equity market. We detect strong economic links and a substantial interconnectedness of the volatility term structures of commodities. Accounting for intra-commodity-market spillovers significantly improves out-of-sample forecasts of the components of the volatility term structure. Spillovers following macroeconomic news announcements account for a large proportion of this forecast power. There thus seems to be substantial information transmission between different commodity markets.

The option-implied variance is calculated based on the entire option surface. Option-implied tail risk represents only a proportion of the left tail (or right tail) of the option surface. As for the calculation of the variance there are a plethora of tail risk measures to choose from, to evaluate the different tail risk measures. We compare them in Chapter 3. It comprehensively investigates the usefulness of the tail risk measures proposed in the literature. We evaluate the tail risk measures on the basis of their statistical and economic validity. Our main conclusion is that the option-implied measure of Bollerslev and Todorov (2011b) outperforms all others. It performs well for all tests and can predict not only the occurrence but also the size of future crash events. In addition, the measure is priced in the market: it predicts returns both in the time-series and in the cross-section. Finally, it also has an impact on real economic activity.

Using the tail risk measure found to be best for the equity markets in Chapter 3, we investigate the cross-section of tail risks in commodity markets in Chapter 4. In contrast to findings from equity indices, left and right tail risk implied by option markets are both

large. Moreover, we find that, both, left and right tail risk are priced in the cross-section of commodity futures returns. The variance risk premium is the main driver for the left tail and the right tail risk. We find strong links to between the tail risk and the tail risk of equity markets as well as to speculation in commodity markets. In general, commodity-specific variables exert the largest influence on tail risk. There is no evidence of commodity market factors that are linked to tail risk.

In Chapter 5, we examine the impact of product market competition on another risk factor, the systematic risk. Using a measure of total product market similarity, we document a strong negative link between market power and market betas. There is a more than threefold increase in the effect during the most recent low-competition period. Announcements of anti-competitive mergers lead to a significant reduction in market betas, underlining the causality of the market power–systematic risk relationship. Firms that face less competition appear to be partly insulated from systematic discount-rate shocks. Lower equity costs therefore mean that market power is in part self-reinforcing.

In Chapter 6, I conclude and outline possible future directions for research.

Keywords: Market power, systematic risk, Return Predictability, Commodity Market, Volatility, Tail Risk

ZUSAMMENFASSUNG

In dieser Arbeit werden verschiedene Volatilitätsrisikomaße, Intedependenzen zwischen den Risikomaßen und makroökonomischen Determinanten, sowie der Zusammenhang zwischen systematischem Risiko und Marktmacht auf den Finanzmärkten untersucht. In Kapitel 1 stelle ich das Gesamtkonzept der Arbeit vor und gebe einen Überblick über die nachfolgenden Kapitel. In Kapitel 2 untersuchen wir umfassend die Volatilitäts-Termstrukturen auf den Rohstoffmärkten. Wir modellieren zustandsabhängige Spillovers in den Hauptkomponenten (PCs) der Volatilitäts-Termstrukturen verschiedener Rohstoffe, sowie die des Aktienmarktes. Wir stellen starke wirtschaftliche Verbindungen und eine beträchtliche Verflechtung der Volatilitätstermstrukturen von Rohstoffen fest. Die Berücksichtigung von Spillover-Effekten innerhalb des Rohstoffmarktes verbessert die Prognosen der Komponenten der Volatilitäts-Termstruktur out-of sample erheblich. Ein großer Teil dieser Vorhersagekraft ist auf Spillover-Effekte im Anschluss an die Bekanntgabe makroökonomischer Nachrichten zurückzuführen. Es scheint also eine erhebliche Informationstransmission zwischen verschiedenen Rohstoffmärkten zu geben.

Die optionsimplizierte Varianz wird auf der Grundlage aller Optionen berechnet. Das durch Optionen implizierte Extrem-Risiko stellt nur einen Teil des linken (oder rechten) Endes der Optionen dar. Wie bei der Berechnung der Varianz gibt es eine Fülle von Maßzahlen für das Extrem-Risiko, aus denen man wählen kann, um das Extrem-Risiko zu berechnen. Wir vergleichen sie in Kapitel 3. Es untersucht umfassend die Nützlichkeit der in der Literatur vorgeschlagenen Extrem-Risikomaße. Wir bewerten die Extrem-Risikomaße auf der Grundlage ihrer statistischen und ökonomischen Validität. Unsere wichtigste Schlussfolgerung ist, dass das optionsimplizite Maß von Bollerslev and Todorov (2011b) alle anderen übertrifft. Es schneidet bei allen Tests gut ab und kann nicht nur das Auftreten, sondern auch das Ausmaß künftiger Crash-Ereignisse vorhersagen. Darüber hinaus wird das Maß auf dem Markt eingepreist: Es sagt die Renditen sowohl in der Zeitreihe als auch im Querschnitt voraus. Schließlich hat es auch Auswirkungen auf die reale Wirtschaftstätigkeit.

Unter Verwendung des Maßes für das Extrem-Risiko, das sich in Kapitel 3 als das beste für die Aktienmärkte erwiesen hat, untersuchen wir in Kapitel 4 den Querschnitt der Extrem-Risiken auf den Rohstoffmärkten. Im Gegensatz zu den Erkenntnissen aus den Aktienindizes sind sowohl das linke als auch das rechte Extrem-Risiko, das von den Optionsmärkten impliziert wird, groß. Außerdem stellen wir fest, dass sowohl das linke als auch das rechte Extrem-Risiko im Querschnitt der Renditen von Rohstoff-Futures eingepreist sind. Die Varianzrisikoprämie ist der Hauptfaktor für das linke Extrem- und das rechte Extrem-Risiko. Wir finden starke Zusammenhänge zwischen dem Extrem-Risiko der Rohstoffmärkte und dem Extrem-Risiko der Aktienmärkte sowie der Spekulation auf den Rohstoffmärkten. Im Allgemeinen üben rohstoffspezifische Variablen den größten Einfluss auf das Extrem-Risiko aus. Es gibt keine Hinweise auf Rohstoffmarktfaktoren, die mit dem Extrem-Risiko verbunden sind.

In Kapitel 5 untersuchen wir die Auswirkungen des Produktmarktwettbewerbs auf einen anderen Risikofaktor, das systematische Risiko. Unter Verwendung eines Maßes der gesamten Produktmarktähnlichkeit dokumentieren wir einen starken negativen Zusammenhang zwischen Marktmacht und Marktbetas. Dieser Effekt hat sich in der letzten wettbewerbsarmen Periode mehr als verdreifacht. Die Ankündigung wettbewerbsfeindlicher Fusionen führt zu einem deutlichen Rückgang der Marktbetas, was die Kausalität der Beziehung zwischen Marktmacht und systematischem Risiko unterstreicht. Unternehmen, die mit weniger Wettbewerb konfrontiert sind, scheinen teilweise von systematischen discount-rate Schocks abgeschirmt zu sein. Geringere Eigenkapitalkosten bedeuten daher, dass sich Marktmacht zum Teil selbstverstärkt.

In Kapitel 6 ziehe ich ein Fazit und skizziere mögliche zukünftige Forschungsrichtungen.

Schlagwörter: Marktmacht, Systematisches Risiko, Vorhersage von Aktienrenditen, Rohstoffmärkte, Volatilität, Extrem-Risiko

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Volatility as a measure of risk has been intensively studied for multiple markets, for example in Ang, Hodrick, Xing, and Zhang (2006b); Bollerslev, Hood, Huss, and Pedersen (2018); Jackwerth and Vilkov (2019). Volatility risk has severe consequences for the risk of a portfolio and serves as the main risk proxy for most market participants. Most studies infer the conditional volatility from options and interpolate between time to maturities. A recent study by Feunou, Fontaine, Taamouti, and Tédongap (2013) finds that the entire volatility term structure reveals risk factors that are not observed directly. The volatility term structure captures empirically the following risk factors from the equity market: risk premia, measures of real economic activity, business cycle risk, and the tightness of financial constraints. Compared to the volatility from a single maturity, the term structure captures the market expectation over longer horizons and thus should contain helpful information to evaluate longer term risks. This can be helpful for market participants to obtain more accurate evaluations their portfolio risk.

Chapter 2 analyses the volatility term structure of a large cross-section of commodities. The volatility term structure is of special interest for commodity markets because of its relation with the so called Samuelson (1965) effect. This effect states that volatility generally decreases with increasing time to maturity. Furthermore, it reveals connections in a market that some authors argue is due to the financialization getting increasingly integrated. For this purpose we summarize the main components of the term structure with their principal components. We first use the term structure to uncover spillovers, as well as contemporary connections between different commodities. Uncovering the connections between commodities has relevance, if this improves the forecast power for the term structure of volatility. We furthermore connect the spillovers between commodities to news announcements, which reveals that spillovers occur due to information transmission in the commodity market.

Chapter 2 contributes by providing a comprehensive study of the volatility term structure of different commodity markets. We can enhance our understanding of the determinants and dynamics of the volatility term structure. We uncover large inter-dependencies between commodities and connect these to information transmission between commodities via macroeconomic announcements. We show that accounting for intra-commodity market spillovers increases the out-of sample predictability substantially. Additionally, we show that a majority of the explanatory forecast power, up to 70% for the level, is achieved at macroeconomic news announcement days.

The volatility represents the risk an investor faces, when they invest into financial assets. Of particular interest for investors are extreme crashes, where marginal utility is highest. These can be as well approximated by a variety of different methods and datasets. Then one can estimate tail risk as well with a variety of different methods: parametric methods with strong assumptions about the stochastic process, semi-parametric, or non-parametric with no assumptions about the stochastic process. Tail risks can be estimated with different datasets for example: return-, macroeconomic-, or option-data.

In Chapter 3 we aim to find out which method is the best to capture tail risk. For this reason we find out about the correlation of the different tail risk measures and devise tests which identify a good tail risk measure. Identifying the best tail risk measure is very important for market participants and politicians. An inaccurate measure could lead to extreme investment and welfare losses.

The main contribution of this chapter is a systematic, coherent, and comprehensive evaluation of the tail risk measures proposed in the literature. For this analyses we employ targeted tests that are aimed to comprehensively evaluate the tail risk measures proposed in the literature.

In Chapter 3, we first find a large heterogeneity between the tail risk measures. The first two principal components can only explain 49% of the variation. This sends a clear warning to the profession, to not treat these tail risk measures as interchangable. For our analysis, we devise three main tests: (i) a probit predictive regression, predicting two-sigma events, and (ii) a prediction of the future left tail variation. These two tests measure how much the tail risk measures can predict (i) a crash and (ii) the quadratic variation of the market. The final test (iii) is an economic test. We test if the tail risk measures can predict the return of the market. In most analyses authors claim that the tail risk is a priced factor, thus this analysis tests which measure performs best in this regard. Our analysis produces a clear winner: The Bollerslev and Todorov (2011b) option-implied left tail measure ($BT11Q$) performs best overall. While there are measures that outperform $BT11Q$ in a particular test, $BT11Q$ is the measure that performs consistently well throughout our analyses.

In the next chapter, we are interested to find out, what are the common components of tail risk in the commodity market. For this purpose we use the result of the prior chapter and use $BT11Q$ as the best performing tail risk measure in the equity market, in order calculate the tail risk measure for the commodity market. We investigate the tail risk for the cross-section of commodities and the determinants of these tail risks. Furthermore we test if tail risk is priced in the cross-section of the commodity market.

Tail risk is particularly important for the commodity market. Tail risks in commodity markets has a large influence on inflation and consumer spending, (Garratt and Petrella, 2019). Typically in equity markets left tail risk plays the most important role (Bollerslev, Todorov, and Xu, 2015), therefore most literature focuses on the left tail risk. In commodity markets however, left and right tail risk play an equally important role. For commodity producers, that are typically long in commodities, left tail risk is more important to hedge against declines in commodity prices. For consumers of commodities, that are typically short in commodities, right tail risk is more important to hedge against increases in commodity prices.

In Chapter 4, we first seek to determine which factors determine tail risk in commodity markets, for both left and right tail risk. Second, we analyze if tail risk is priced in the cross-section in the commodity market.

In Chapter 4 we find that, both left and right tail risk are large in commodity markets. The variance risk premium is the largest determinant of tail risk. Speculation reduces the tail risk for many commodity markets. But many commodities also have links to the volatility index and tail risk from the equity market, large tail risk in equity markets are associated with large tail risks in commodity markets, indicating a large degree of integration between these markets. Tail risk is as well a priced factor in the cross-section of the commodity market. This indicates the economic importance of tail risk for commodity markets.

Another risk factor to consider is the market beta which should under the CAPM be the only priced factor in the market and therefore determines the cost-of capital. Additionally, recent studies find that market power might be responsible for some recent stylized facts in the macroeconomy: a decrease in labor share (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020), lower investment and lower productivity growth (Covarrubias, Gutiérrez, and Philippon, 2020), an increase in capital share, a decrease in low-skill wages, a decrease in labor force participation, a decrease in labor flows, and a decrease in migration rates (De Loecker, Eeckhout, and Unger, 2020), lagging innovation and a slowdown in aggregate output (Bae, Bailey, and Kang, 2021). Cairó and Sim (2020) show that these observed recent trends in the macro economy can be generated by market power in product and labor markets and these can lead to financial instability. Market power stabilizes cash flows, and lowers the idiosyncratic volatility (Gaspar and Massa, 2006; Hoberg and Phillips, 2010b; Gutiérrez and Philippon, 2019; De Loecker et al., 2020).

We investigate if market power has as well an influence on beta and thus the cost of capital. In addition we study the influences on partial beta, discount rate beta and cash flow beta. A negative relation would be an indication that companies that have high market power might as well have advantages to raise money in capital markets (lower market beta), this can therefore be an indication for market power being a perpetual cycle. In Chapter 5 we investigate the impact of competition in the product market on the systematic risk of a company. The market beta (i.e. systematic risk) implies severe consequences for the cost of capital of a company and therefore requires attention by regulators and market participants alike.

In Chapter 5 we use the measure of total product market similarity, introduced by Hoberg, Phillips, and Prabhala (2014), that arguably captures market power at the firm level substantially better than the measures used in previous studies, such as the industry-wide sales concentration and even rougher measures like firm size or Tobin's q. To examine any impact of the recent downward trend in competition, we analyze different subsamples. We also establish causality in the market power–beta relationship by analyzing the effect of anti-competitive mergers on market betas.

Our main finding is that total product market similarity is significantly negatively related to market betas. The results are not only statistically but also economically significant. For example, the difference between the market beta of a company with a total product market similarity that is two standard deviations below the average to an otherwise similar company with average total product market similarity amounts to up to 0.26, which implies a substantial difference in expected returns and, thus, the cost of capital. We find that the effect of a two-standard-deviation decrease in market power from the average on market betas increases more than threefold when comparing the post-2005 period to the first 16 years of our sample period between 1989 and 2004. Thus, (i) the effect of market power on betas appears to be substantially stronger in the current low-competition market environment. (ii) This result delivers an explanation for the conflicting results of previous studies: the effect was substantially weaker. If market power causally leads to lower market betas, the announcement of an anti-competitive merger should lead to a significant drop in a firm's market beta estimates. We analyze the relationship in more detail, and show that the starkest drop indeed occurs directly after the announcement, while controlling for other effects.

This thesis proceeds as follows. Chapter 2 studies the interdependencies of the volatility term structure in the commodity market and links to information transmission. In Chapter 3 we study a variety of different tail risk measure and devise tests to evaluate the best performing tail risk measure. In Chapter 4 we investigate how tail risk is in the commodity markets, we connect tail risk and possible determinants of tail risk and evaluate if tail risk is priced in the cross-section. Chapter 5 analyses the connection between market power and systematic risk. Finally in Chapter 6 we summarize the main findings of the thesis and suggest several directions for future research.

To improve the readability, especially of the separate parts of this thesis, each chapter is self-contained. This means that we generally redefine the variables and acronyms in each chapter, but use a consistent notation, whenever possible.

Chapter 2

Volatility Term Structures in the Commodity Market*

2.1 Introduction

A large set of external events and conditions has the potential to affect commodity markets. Important drivers of commodity prices are, inter alia, weather, investor flows and macroeconomic conditions. While the level of commodity prices is certainly important, understanding the volatility of commodity prices is at least as crucial. For example, Pindyck (2004) shows that, because storage helps to smooth production and deliveries, the marginal value of storage increases with volatility. Further applications where volatility is of special concern include risk management decisions, margin calculations, or the valuation of options contracts. While

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previous studies have examined the impact of commodity spot volatility, the entire volatility term structure provides additional important information for the above mentioned issues, since short-term and long-term options embed partly differential information and provide market expectations of future volatility over various horizons.

The importance of considering the entire term structure has been widely documented for equity markets (e.g. Adrian and Rosenberg, 2008; Bakshi, Panayotov, and Skoulakis, 2011; Feunou et al., 2013). In particular, these studies show that the volatility term structure is informative about, inter alia, risk premia, measures of real economic activity, business cycle risk and the tightness of financial constraints. Investigating the interconnectedness of the term structure and its relation with macroeconomic variables and announcements can be crucial to help understand the interdependencies and macroeconomic links of the commodity markets. This can be particularly helpful for practitioners that can use predictability of the entire volatility term structure for more accurate risk evaluations of their portfolios.

Our main contribution is to provide a comprehensive study of the volatility term structure of different commodity markets. The volatility term structure is of special interest for commodity markets because of its relation with the so called Samuelson (1965) effect. This effect states that volatility generally decreases with increasing time to maturity. In appreciating this, we can enhance our understanding of the determinants and dynamics of the volatility term structure.

First, we decompose the volatility term structure into its principal components (PCs) and study their economic drivers. We focus on the first three PCs: the level, the slope and the curvature of the term structure. This analysis allows us to understand how volatility dynamics change for contracts with different expiry dates.

When we investigate the macroeconomic determinants of the commodity volatility term structure, we uncover two main results. (i) Macroeconomic variables can explain a large proportion of the variation in the level factor, and typically a somewhat smaller share for the slope and curvature factors. (ii) An increase in the proportion of speculative open interest reduces the volatility level for various markets, while employment is positively related to the volatility level.

Second, we use a state-dependent autoregressive (AR) model to examine volatility spillovers between commodity markets. We compare a model using only the past lags of one commodity volatility term structure to a state-dependent unrestricted AR-model which also includes the lagged volatility PCs of another commodity, following the causality model by Granger (1969, 1988). We define economic states based on the forecast of the Engle and Manganelli (2004) conditional autoregressive Value at Risk (CaViaR). Using the Granger (1969, 1988) causality model to make out-of-sample predictions of the implied volatility term structure generally yields sizable forecast improvements over the predictions of the simple state-dependent AR-model. Accounting for spillover effects for the level and the slope yields out-of-sample R^2s of up to 5%. Intra-commodity effects are more important for the commodity market than spillover effects originating from the equity market. Finally, spillovers are state-dependent: they are strongest during market distress and smallest during normal periods.

One possible explanation for these findings is information transmission. To isolate the effects originating from this channel, we investigate the impact of scheduled macroeconomic news announcements on spillovers. If spillovers are larger after macroeconomic news announcements, this would indicate that some commodity markets capture information on macroeconomic news earlier than others. This could lead to subsequent changes in the volatility term structure of the cross-section of the commodity market. We find that macroeconomic news announcements models do indeed explain up to 70% of the spillovers for the level. News announcements associated with consumer income or consumer sentiment have a particularly large influence on spillovers for all components of the term structure.

We also investigate the impact of the financialization of commodity markets, which leads to a stronger co-movement across commodities in recent years due to the increased use of commodities as an investment (Tang and Xiong, 2012; Christoffersen, Lunde, and Olesen, 2019). We conduct a sub-sample analysis by studying changes in the lead/lag relationship between commodity markets pre-and post-financialization, which reveals two main findings: First, the volatility term structure for commodity and equity markets is strongly integrated for the post-financialization period. Second, there are two effects that affect spillovers post-financialization: (i) the increase in contemporaneous movements lowers spillovers for the level and (ii) more common factors for the slope and the curvature lead to overall higher spillovers.

Our study is related to several strands of the literature. For equity and bond markets a variety of articles show that the variance term structure is important and can capture unobserved risk factors. Adrian and Rosenberg (2008) and Bakshi et al. (2011) show that factors that describe the volatility term structure can predict various economic and financial measures. Bakshi et al. (2011) draw on an analogy with the term structure of interest rates and argue that the variance term structure embodies expected variances by both the financial and the real sector, as perceived by the index option market.[1]

For commodity markets, there is a vast literature that finds a factor structure in returns. Rotemberg and Pindyck (1990), Yang (2013), Szymanowska, De Roon, Nijman, and Van Den Goorbergh (2014) and Bakshi, Gao, and Rossi (2017) argue that common factors in commodity markets can explain a large part of cross-sectional return variation. For their analyses, these studies use the cross-section of commodity returns. Brunetti, Büyükşahin, and Harris (2016) show that hedge funds positions are negatively related to the volatility in corn, crude oil and natural gas futures markets. Hammoudeh and Yuan (2008) investigate the effects of oil and interest rate shocks on the volatility of metals markets, using various GARCH model specifications.

[1] Further studies on the volatility term structure in equity markets include: Campa and Chang (1995), Mixon (2007), Johnson (2017) and Hollstein, Prokopczuk, and Wese Simen (2019b).

Our study extends this literature by investigating the entire volatility term structure for a large cross-section of commodity markets. Leveraging the various expiration dates of commodity futures and options enables us to study the term structure and analyze whether there is a common factor structure in the volatility term structure.

The central contribution of our paper is the analysis of the lead/lag factor structure of commodity markets. Volatility spillovers of the commodity market have been investigated in several studies, but only in relation to specific markets and to the volatility of the spot market. Diebold and Yilmaz (2012) investigate volatility spillovers across different markets using a generalized vector autoregressive (VAR) framework. Du and He (2015) investigate Granger causality in risk between the returns of the crude oil market and stock market returns. They find that after the financial crisis the crude oil market was positively linked to the stock market, while it was negatively linked to the stock market beforehand. Nazlioglu, Erdem, and Soytas (2013) investigate spillovers in spot volatility between oil and agricultural markets. In the literature, spillovers are usually only investigated for certain events that trigger an increased dependency between the markets – for example, the food crisis. One reason for this might be that it is difficult to link spillovers to a particular cause. In this study, we examine macroeconomic news announcements for exactly this purpose.

In doing so, we add to the literature that uses macroeconomic news announcements to investigate the impact on returns or volatilities (Savor and Wilson, 2013; Lucca and Moench, 2015; Wachter and Zhu, 2018).

Finally, our study is related to the literature on financialization. Tang and Xiong (2012) investigate the correlation between crude oil returns and other commodities, and find that these correlations increase for a post-financialization period starting in 2004. Christoffersen et al. (2019) investigate returns and variances of commodities in the post-financialization period. They find that the factor structure is stronger for volatility, and that volatilities are strongly related to stock market volatility and the business cycle. We extend this literature by providing insights about the financialization of the entire commodity volatility term structure and are able to capture a more complete picture than the previous literature. The existing studies focus on contemporaneous movements, but not on the lead/lag relations in the commodity market. We are the first study to investigate the impact of financialization on the lead/lag structure of the commodity market volatility.

The remainder of this paper is organized as follows: In Section 2.2 we describe the data and methodology. In Section 2.3 we present our main analysis and in Section 2.4 we provide robustness tests. Section 2.5 concludes.

2.2 Data and Methodology

2.2.1 Volatility Term Structures in Commodity Markets

We obtain the commodity futures and options dataset from the Commodity Research Bureau (CRB). Our data covers the period from January 1st 1996 until December 31st 2015. We consider the following commodities: cocoa, coffee, copper, corn, cotton, crude oil, gold, natural gas, silver, soybeans and sugar. The selection of these commodities is based on the need for a sufficient range of options over a reasonably long time period. Because we want to study the impact of financialization on the lead/lag structure in the volatility term structure, we require that commodities have option data before 2000. We exclude a commodity for a certain year if the data coverage is below 70% of trading days.

We handle and filter the dataset following Prokopczuk, Symeonidis, and Wese Simen (2017) and Hollstein, Prokopczuk, and Tharann (2021) and remove all options that are in-the-money, have a time to maturity of less than one week or have a price lower than five times the minimum tick size. As risk-free rate, we use the daily Treasury yield.[2] We further remove

[2] https://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yield.

observations that violate standard no-arbitrage conditions, as in Aït-Sahalia and Duarte (2003). Each day, we need to observe at least two out-of-the-money call- and put-options, otherwise we remove this particular day from the sample. We follow Chang, Christoffersen, Jacobs, and Vainberg (2011) and Hollstein and Prokopczuk (2016) to interpolate the implied volatilities of options via cubic splines by moneyness ($\frac{K}{F}$), where K is the strike price and F is the price of a future with the same maturity as the option. From this set of options we calculate option prices using the Black (1976) formula. We use a constant extrapolation for the moneyness levels above and below the daily maximum and minimum levels. As a result we obtain a fine grid of 1000 implied volatilities between a moneyness of 1% and 300%. With this dataset, we compute model–free implied volatilities. For the S&P 500, we use options data from OptionMetrics and apply the same procedure.

We compute model-free option-implied volatility for various maturities using the non-parametric approach of Demeterfi, Derman, Kamal, and Zou (1999) and Britten-Jones and Neuberger (2000) as:

$$VIX_t^2 = \frac{2R_t^f}{T-t}\left[\int_0^{F_{t,T}} \frac{1}{K^2}\mathrm{p}_{t,T}(K)dK + \int_{F_{t,T}}^{\infty} \frac{1}{K^2}\mathrm{c}_{t,T}(K)dK\right]. \tag{2.1}$$

R_t^f is the continuously compounded risk-free rate and $F_{t,T}$ is the futures price at date t for maturity T. $p_{t,T}$ the put price and $c_{t,T}$ is the call price with strike K of respective out-of-the-money options. For some commodities, volatility exhibits seasonality, which could have a mechanical impact on the term structure as well as on spillover effects. To remove seasonal effects, we use a trigonometric function, following Back, Prokopczuk, and Rudolf (2013):

$$k_i cos(\omega g_i(t,\tau) - \omega\theta_i), \tag{2.2}$$

where $\omega = \frac{2\pi}{12}$ is the cycle length and $g_i(t,\tau) = t + 12\tau - S_i[\frac{t+12\tau}{S_i}]$. The operator $[X]$

returns the largest integer which is not greater than x. k_i is the specific exposure to the season, θ_i is the peak of the seasonal structure and τ is the contract maturity. We set S_i to 12 corresponding to monthly seasonality. $g_i(t,\tau)$ results therefore in integers from 0 to 11 representing the corresponding months. For each commodity, we regress the implied volatility on the mechanical model implied by Equation (2.2) and retain the residual series.

Table 2.1 shows the summary statistics of the volatility term structures. One can observe that the average volatility is decreasing with increasing maturity. This effect is strongest for non-metal commodities. For metals, the term structure is relatively flat. For the equity market, the volatility slightly increases with maturity. Thus the implied volatility term structure for commodity markets has unique features which makes it interesting to investigate. The standard deviation of the volatilities is lower for the annual maturities, except for gold, where the standard deviation is constant. The first autoregressive component is usually larger for longer-term volatilities, indicating a stronger persistence. This is not the case for energies, where long-term volatilities are less persistent.

2.2.2 Macroeconomic Data

We use a similar approach as Stock and Watson (2012) to investigate the macroeconomic determinants of the commodity volatility term structure. Specifically, we order various macroeconomic variables into groups and obtain the first PC of each macroeconomic group. In Table A1 of the Appendix, we describe the sources of our dataset as well as the applied standardization technique. We obtain factors representing the following macroeconomic groups: GDP components, Industrial production, Employment, Consumer expectations, Housing, Unemployment rate, Business inventories, Prices, Money supply, Interest rates, Wages, Exchange rates, Stock prices and Financial conditions.

Additionally, we also consider the variance risk premium (VRP) of the equity market

(Bollerslev, Tauchen, and Zhou, 2009; Hollstein and Wese Simen, 2020). We use the monthly VRP provided by Zhou (2018).[3] The author defines the VRP as de-annualized VIX^2 minus the realized variance from 5-minute returns over the past month. For our set of macroeconomic news announcements we use the most relevant macroeconomic news identified by the Thompson Reuters Eikon Economic Monitor. We retain the announcement dates from the webpages of the relevant institutions. We provide further details in Table A1 of the Appendix.

2.2.3 Commodity-Specific Measures

Following Gorton, Hayashi, and Rouwenhorst (2012), we use the inventory data for the commodity markets and several commodity-specific variables which are presented in Table A1 of the Appendix. First, we use the volatility of the commodity market as a whole. As a proxy we use the standard deviation of the CRB Commodity Index. Second, we use a unique inventory variable for each commodity market, that is retained from the sources presented in Table A1 of the Appendix. Third, motivated by Hong (2000) we use the Commodity Futures Trading Commission (CFTC) dataset to calculate Working's (1960) T, as a measure of speculation. We use data on trader positions from the CFTC to calculate the speculation factors. We use the historical dataset provided by the CFTC with data from 1995 until 2015 that only distinguishes between commercial and non-commercial traders. Table A1 of the Appendix shows the CFTC contract codes and associated commodities. Following Gorton et al. (2012), we choose the newer contract when both series are overlapping and we use the last value for the monthly observation. Speculation is represented by the number of open interest from speculators, both long and short, N_L and N_S divided by the open interest of hedgers (C_L, C_S). Working's (1960) T is defined as follows:

[3] `https://sites.google.com/site/haozhouspersonalhomepage`.

$$\text{Working's T} = \begin{cases} 1 + \dfrac{N_S}{C_S + C_L} & if \quad C_S \geq C_L \\ 1 + \dfrac{N_L}{C_S + C_L} & if \quad C_S < C_L \ . \end{cases} \tag{2.3}$$

If the market is short (long), only short (long) speculators determine Working's T.

Fourth, we use the basis of each commodity. Bakshi et al. (2017) show that this factor helps to price the cross-section of commodities. To calculate the basis for every commodity, we use the approach following Gorton et al. (2012) and Yang (2013) and define basis as the log difference between the one-month futures price and the twelve-month futures price scaled by the difference in time to maturity:

$$B_{i,t} = \frac{log(F_{i,t,T_1}) - log(F_{i,t,T_2})}{T_2 - T_1} \ . \tag{2.4}$$

The commodity basis reflects risk related to the convenience yield.

This results in the following factors: speculation, basis, commodity inventory and commodity volatility. For the purpose of calculating the basis, the dataset of futures is obtained from the CRB and presented in Table A1 of the Appendix.

2.3 Main Analysis

2.3.1 Descriptive Analysis

Motivated by Cochrane and Piazzesi (2005), Feunou et al. (2013) and Johnson (2017), we use information on the entire term structure to obtain unique factors of the implied commodity volatility term structure. Option markets carry forward-looking information about the underlying asset. Long-term and short-term options carry different information. Schwartz and Smith (2000) argue that long-term futures contracts carry information about the long-term equilibrium price level and short-term futures contracts provide information about the short-term price variations. Long- and short-term option-implied volatility can be interpreted in a similar vein.

We decompose the implied volatility term structure into three factors. The level factor can be seen as average volatility and is influenced less by short-term fluctuations than the slope, which loads positively on short-term volatility. In addition, we examine a curvature factor. Dissecting the different effects of the volatility term structure will help to reduce noise and provide insight into the information transmission and causal links of volatility for the commodity market.

We calculate the factors with principal component analysis (PCA), which disentangles term structure effects and creates uncorrelated orthogonal factors. All PCs are calculated by singular value decomposition of the scaled data matrix. They are standardized to have a mean of zero. Table 2.2 presents summary statistics that show that, combined, the three PCs explain from 82% to 95% of the total variation of the term structure of option-implied volatilities for the different commodities. In the following we separately examine the PCs.

Panel A of Table 2.2 shows that the **level** factor (first PC) captures 48% to 72% of the variation in the term structure of option-implied volatilities. It captures most of the variation for metals, where the Samuelson effect is not present (Bessembinder, Coughenour, Seguin, and Smoller, 1996; Duong and Kalev, 2008). This factor is highly persistent, as evidenced by the large AR(1) component. We use a factor rotation to ensure that the loadings on the first PC are positive. Figure A1 of the Appendix shows the loadings of the level factor on the components of the volatility term structure in black circles. The level factor has a loading that is almost constant over time for all observed markets.

In Panel B of Table 2.2 we see that the **slope** factor (second PC) captures 15% to 21% of the variation in the term structure of option-implied volatilities. The first-order autocorrelation is lower compared to the level. However, while for the equity market the AR(1)

Table 2.1: Summary Statistics Variance Term Structure

This table presents the summary statistics for the option-implied volatility term structure. It shows the annualized model-free estimate of option-implied volatility for the commodity market for monthly and annual volatilities. The volatilities are seasonally adjusted via a trigonometric function. The sample starts from 1996 through 2015. Vol_1 is the one-month volatility, Vol_{12} is the twelve-month volatility. The column sd presents the standard deviation, 10%, 15% and 90% denote the respective percentiles of the distribution. Finally $AR(1)$ reports the first-order autocorrelation coefficient (in percentage points).

		mean	*sd*	10%	50%	90%	$AR(1)$
Cocoa	Vol_1	0.25	0.08	0.15	0.23	0.35	95.92
	Vol_{12}	0.24	0.07	0.17	0.22	0.36	97.77
Coffee	Vol_1	0.42	0.13	0.28	0.41	0.58	96.33
	Vol_{12}	0.37	0.09	0.27	0.36	0.48	98.56
Copper	Vol_1	0.31	0.11	0.19	0.30	0.43	95.55
	Vol_{12}	0.27	0.10	0.17	0.24	0.41	99.23
Corn	Vol_1	0.29	0.10	0.17	0.28	0.42	91.76
	Vol_{12}	0.26	0.06	0.18	0.25	0.35	96.57
Cotton	Vol_1	0.27	0.10	0.18	0.25	0.40	97.28
	Vol_{12}	0.23	0.07	0.16	0.21	0.32	99.10
Crude Oil	Vol_1	0.36	0.14	0.22	0.34	0.50	97.95
	Vol_{12}	0.29	0.08	0.18	0.28	0.38	96.99
Gold	Vol_1	0.18	0.07	0.10	0.17	0.25	97.80
	Vol_{12}	0.18	0.07	0.10	0.18	0.27	99.77
Natural Gas	Vol_1	0.50	0.16	0.32	0.49	0.71	97.48
	Vol_{12}	0.36	0.10	0.26	0.35	0.45	93.58
Silver	Vol_1	0.32	0.12	0.20	0.30	0.46	97.82
	Vol_{12}	0.29	0.11	0.17	0.30	0.42	99.75
Soybeans	Vol_1	0.25	0.08	0.15	0.23	0.35	95.92
	Vol_{12}	0.24	0.07	0.17	0.22	0.36	97.77
Sugar	Vol_1	0.38	0.13	0.23	0.36	0.54	96.48
	Vol_{12}	0.27	0.07	0.18	0.27	0.36	98.58
Equity	Vol_1	0.22	0.09	0.13	0.20	0.32	88.49
	Vol_{12}	0.23	0.06	0.16	0.22	0.30	99.18

coefficient is only 0.79, for the commodity markets, the slope shows a higher autocorrelation of above 0.90. The loadings of the slope on the different contracts is displayed in blue triangles in Figure A1 of the Appendix.[4] These are consistently decreasing for all commodities,

[4]To have a consistent interpretation of the slope estimate for all markets, we require the slope of the term structure to be downward sloping with maturity, otherwise we multiply the current rotation by −1.

Table 2.2: Principal Components Summary Statistics

This table displays the summary statistics of the first three PCs, the level, the slope and curvature, of the commodity markets and the equity market. Panel A presents the summary statistics for the level, while Panels B and Panel C present those for the slope and the curvature, respectively. $expl.Var.(\%)$ shows the variation that is explained in percent, the mean is standardized at zero and thus not reported. The column sd presents the standard deviation. 10%, 25%, 50%, 75% and 90% denote the different percentiles of the distribution. Finally, $AR(1)$ reports the first-order autocorrelation coefficient(in percentage points).

	$expl.Var.(\%)$	sd	$skewness$	$kurtosis$	10%	25%	50%	75%	90%	$AR(1)$
Panel A - Level										
Cocoa	61	2.32	0.22	2.63	−3.06	−1.85	−0.01	1.53	2.98	99.38
Coffee	56	2.26	0.49	3.55	−2.86	−1.45	−0.21	1.39	2.88	99.01
Copper	67	2.35	1.63	6.65	−2.23	−1.65	−0.42	0.95	2.55	99.19
Corn	53	2.20	1.00	3.92	−2.38	−1.56	−0.51	1.18	3.23	98.58
Cotton	64	2.34	1.34	4.97	−2.29	−1.53	−0.65	1.04	3.13	99.37
Crude	64	2.33	1.13	5.66	−2.87	−1.55	−0.12	1.12	2.77	99.31
Gold	71	2.36	1.21	6.06	−2.87	−1.40	−0.20	1.03	2.67	99.51
Natural Gas	48	2.15	0.41	2.87	−2.82	−1.69	−0.07	1.40	3.01	99.15
Silver	75	2.39	0.84	3.92	−2.90	−1.91	−0.15	1.30	3.00	99.44
Soybeans	61	2.33	1.20	3.97	−2.26	−1.68	−0.64	1.01	3.62	98.98
Sugar	65	2.35	0.45	2.91	−2.94	−1.75	−0.20	1.70	2.90	99.14
Equity	72	2.38	1.54	7.21	−2.58	−1.78	−0.33	1.15	2.69	98.59
Panel B - Slope										
Cocoa	16	0.60	−1.20	10.16	−0.58	−0.27	0.01	0.32	0.63	89.22
Coffee	18	0.74	0.23	4.21	−0.90	−0.47	0.01	0.43	0.89	94.50
Copper	17	0.61	0.32	4.78	−0.66	−0.39	−0.05	0.36	0.74	90.08
Corn	21	0.88	−0.47	3.12	−1.29	−0.58	0.19	0.62	0.98	90.70
Cotton	16	0.60	0.62	6.04	−0.63	−0.34	−0.04	0.30	0.69	93.88
Crude	16	0.59	0.47	4.24	−0.75	−0.37	−0.03	0.32	0.78	95.44
Gold	19	0.63	0.32	4.29	−0.86	−0.37	0.00	0.38	0.76	96.72
Natural Gas	19	0.65	−0.21	5.15	−0.73	−0.42	0.01	0.38	0.78	90.43
Silver	16	0.51	0.66	4.92	−0.61	−0.31	−0.04	0.32	0.60	95.42
Soybeans	15	0.57	−0.61	4.11	−0.74	−0.29	0.09	0.34	0.62	91.56
Sugar	16	0.58	0.50	5.22	−0.65	−0.35	−0.02	0.31	0.70	91.41
Equity	16	0.53	1.58	11.49	−0.63	−0.30	−0.01	0.27	0.51	78.66
Panel C - Curvature										
Cocoa	10	0.38	1.58	9.44	−0.38	−0.25	−0.03	0.18	0.39	93.72
Coffee	10	0.40	−0.97	4.37	−0.58	−0.20	0.08	0.28	0.44	95.49
Copper	7	0.23	0.28	6.00	−0.25	−0.15	0.00	0.12	0.27	86.14
Corn	11	0.45	−0.14	2.63	−0.55	−0.31	−0.02	0.35	0.59	96.52
Cotton	9	0.31	−0.29	3.76	−0.41	−0.19	0.02	0.21	0.37	94.61
Crude	11	0.42	−3.53	22.50	−0.53	−0.01	0.12	0.21	0.28	92.93
Gold	4	0.14	0.57	5.03	−0.17	−0.08	−0.01	0.08	0.17	85.71
Natural Gas	15	0.84	−1.12	6.17	−0.92	−0.43	0.07	0.53	1.00	96.93
Silver	4	0.13	−0.72	7.89	−0.15	−0.08	0.00	0.08	0.15	87.01
Soybeans	9	0.35	−1.86	9.09	−0.34	−0.11	0.04	0.21	0.34	94.02
Sugar	10	0.34	−0.31	4.96	−0.42	−0.26	−0.02	0.29	0.44	93.92
Equity	7	0.22	−4.20	43.00	−0.19	−0.08	0.03	0.12	0.19	37.47

except for natural gas. The slope should be positive when the Samuelson effect is present and negative if it is not.

Panel C of Table 2.2 reveals that the **curvature** factor (third PC) can explain between 4% and 15% of the variation in the option-implied commodity volatility term structure. It explains the highest share of the variation for softs and agricultural commodities, where the Samuelson effect is strongest (Duong and Kalev, 2008). Surprisingly, the curvature factor seems for most commodities not to be less persistent than the slope factor. Especially for softs and agricultural commodities it has a higher persistence than for other sectors. The first-order autocorrelation is larger than 0.9. In contrast, for the equity market the curvature shows little first-order autocorrelation, with only 0.37. The loadings of the curvature factor are displayed with an orange plus in Figure A1 of the Appendix.[5] One can observe that it displays a tent-shaped factor loading on the volatility term structure. The factor loading is almost always highest for the nine-month implied volatility, with copper and gold peaking at three and sugar peaking at six months.

[5] We require the curvature to have a larger loading for medium volatility compared to long- and short-term volatility.

Table 2.3: Correlations

This table presents the correlation of the PCs across different commodities as well as that of the S&P 500. In Panel A, we show the correlations for the level factor, in Panel B those for the slope factor and in Panel C those for the curvature factor. Below each panel. PC_1 displays the correlation of the PCs with the first PC of the respective factor over all commodity markets.

Panel A - Level

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa	1.00	0.33	0.29	0.43	0.47	0.58	0.47	0.41	0.09	0.59	0.62	0.46
Coffee		1.00	−0.15	−0.15	−0.02	0.14	−0.17	0.29	−0.34	0.04	0.23	0.15
Copper			1.00	0.63	0.40	0.50	0.63	0.40	0.71	0.62	0.33	0.42
Corn				1.00	0.68	0.50	0.65	0.11	0.68	0.79	0.52	0.49
Cotton					1.00	0.51	0.51	0.04	0.57	0.59	0.63	0.39
Crude						1.00	0.57	0.43	0.39	0.53	0.52	0.68
Gold							1.00	0.23	0.78	0.56	0.41	0.54
Natural								1.00	0.00	0.25	0.33	0.20
Silver									1.00	0.49	0.26	0.41
Soybean										1.00	0.52	0.42
Sugar											1.00	0.52
Equity												1.00
PC_1	0.73	0.18	0.79	0.84	0.72	0.77	0.80	0.45	0.72	0.81	0.77	0.77

Panel B - Slope

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa	1.00	0.28	0.06	0.27	0.04	0.09	0.10	0.11	0.07	0.20	0.09	0.14
Coffee		1.00	0.09	0.36	0.03	−0.13	0.10	0.17	−0.02	0.34	0.23	−0.02
Copper			1.00	0.13	0.12	0.36	0.34	−0.06	0.34	0.13	0.16	0.29
Corn				1.00	0.26	−0.12	0.20	−0.14	0.01	0.68	0.19	0.07
Cotton					1.00	0.00	0.06	−0.03	0.01	0.27	0.21	0.02
Crude						1.00	0.44	−0.02	0.45	−0.08	0.02	0.42
Gold							1.00	−0.10	0.74	0.16	0.25	0.48
Natural								1.00	−0.07	−0.05	−0.04	−0.05
Silver									1.00	0.02	0.18	0.50
Soybean										1.00	0.23	0.03
Sugar											1.00	−0.01
Equity												1.00
PC_1	0.42	0.15	0.44	0.47	0.22	0.55	0.85	−0.15	0.73	0.35	0.28	0.73

Panel C - Curvature

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa	1.00	0.41	0.33	−0.54	−0.27	0.20	−0.03	0.00	0.25	−0.19	0.68	−0.00
Coffee		1.00	0.09	−0.09	−0.16	0.17	0.00	0.13	0.18	−0.08	0.30	0.09
Copper			1.00	−0.38	−0.19	0.05	−0.04	−0.13	0.09	−0.16	0.33	0.02
Corn				1.00	0.41	−0.04	0.02	0.09	−0.16	0.49	−0.55	−0.06
Cotton					1.00	0.13	−0.06	0.14	−0.19	0.37	−0.37	−0.08
Crude						1.00	−0.12	0.09	−0.03	0.06	0.15	−0.02
Gold							1.00	0.05	0.11	0.02	−0.12	0.17
Natural								1.00	0.13	−0.09	−0.03	0.07
Silver									1.00	−0.10	0.22	0.10
Soybean										1.00	−0.28	−0.08
Sugar											1.00	−0.05
Equity												1.00
PC_1	0.85	0.71	0.52	−0.80	−0.61	0.01	−0.04	−0.15	0.34	−0.48	0.83	0.06

To get an initial understanding of the dependence structure of the volatility term structure across commodities, Table 2.3 presents the correlations of the level, slope and curvature factors of different commodities. Additionally we investigate the correlation with the level factor of each asset and the first PC of the entire cross-section. There is a strong factor structure for the level of the volatility term structures. However, while there seems to be a strong overall common factor structure, there are also cases of negative correlations in the level factor across commodities. There is negative bi-variate correlation between coffee and commodities in the metal market (copper, silver and gold). These results are consistent with Christoffersen et al. (2019), who show that the common PC of the commodity market realized volatility cannot explain a large degree of the realized volatility of coffee. The correlations of the PCs of the volatility term structure of one commodity with those of other commodities in the same sector are high for the metal market and the agricultural market. The sector components in the market for softs and energies are not as strong. We see a strong factor structure in the slope of the volatility term structure with the first PC of the slope: this correlation exceeds 0.2 for most commodities. The level and slope factors of the equity market are also positively correlated with those of most commodity markets.

There are several questions that we seek to answer in the remainder of this paper: Are the term-structure factors related to macroeconomic factors, sector-specific factors, or commodity market factors? What are the determinants of the commodity volatility term structure? Can the knowledge about today's volatility term structure of one commodity help improve forecasts for that of other commodities? What effect does financialization have on the common factor structure and the lead/lag factor structure? And, finally, does information transmission contribute to spillovers?

2.3.2 Macroeconomic Determinants

To shed light on the relationship of commodity volatility and the macroeconomy, we conduct contemporaneous multivariate regressions of the level, slope and curvature factors of each commodity on the macroeconomic variables discussed above. Several previous studies show that there is a relation between commodity volatility and macroeconmic variables. Nguyen and Walther (2019) investigate the macroeconomic drivers of long- and short-term volatility components. They find significant drivers for global real economic activity and changes in consumer sentiment. Prokopczuk, Stancu, and Symeonidis (2019) and Kang, Nikitopoulos, and Prokopczuk (2019) analyze economic drivers of commodity market volatility and crude oil volatility and find that volatility shows strong comovement with economic and financial uncertainty, especially during crisis periods. For the softs and the agricultural market Covindassamy, Robe, and Wallen (2017) and Adjemian, Bruno, Robe, and Wallen (2018) show that macroeconomic variables and commodity-specific variables matter for the volatility.

With certain variables – for example unemployment and employment – there could be concerns about multicollinearity. To address this, we conduct the multicollinearity test of Kovács, Petres, and Tóth (2005) and compute variance inflation factors (VIF). The Kovács et al. (2005) red indicator is a measure of redundancy, using the average correlation of the data. For our sample, the average of this measure is 0.22, which is far below the threshold of 0.5 usually applied to diagnose multicollinearity. None of the VIFs exceeds 3.1 on average, which is far below typical thresholds of 5 and 10 employed by the literature. Thus, these tests indicate that the that multicollinearity does not pose a problem in the regressions.[6]

The results are shown Tables 2.4, 2.5 and 2.6, and we can see that certain macroeconomic factors do indeed influence the volatility term structure.

[6]The detailed test results are available upon request.

Table 2.4: Macroeconomic Determinants – Level

We conduct month-end contemporaneous regressions of the commodities' level factors on macroeconomic components. These are computed using the first PC of the macroeconomic groups in Table A1 of the Appendix as independent variables. *, **, ***, respectively indicate significance at the 10%, 5% and 1% level, using Newey and West (1986) standard errors with 10 lags.

	Cocoa	Coffee	Cotton	Sugar	Corn	Soybeans	Copper	Gold	Silver	Crude	Natural Gas
Business Inventory	−0.39**	−0.17	−0.40**	−0.19	0.08	−0.34**	0.31**	−0.40**	0.37	0.14	0.04
	(0.16)	(0.16)	(0.19)	(0.29)	(0.17)	(0.14)	(0.14)	(0.16)	(0.25)	(0.10)	(0.10)
Commodity Volatility	0.01	0.34**	0.33**	−0.67*	0.04	0.07	0.43**	−0.19	0.50***	0.27**	−0.02
	(0.18)	(0.14)	(0.14)	(0.39)	(0.26)	(0.26)	(0.21)	(0.24)	(0.16)	(0.13)	(0.11)
Consumer Expectations	0.06	0.22**	0.01	−0.11	−0.11	−0.24	0.09	0.04	−0.07	0.11	0.06
	(0.09)	(0.09)	(0.11)	(0.21)	(0.10)	(0.17)	(0.11)	(0.10)	(0.11)	(0.08)	(0.09)
Employment	0.79***	0.53***	0.34***	0.26	0.03	0.33**	0.33**	0.26**	−0.35***	0.61***	0.63***
	(0.14)	(0.12)	(0.12)	(0.23)	(0.10)	(0.14)	(0.13)	(0.10)	(0.13)	(0.07)	(0.10)
Exchange Rates	−0.00	0.00	−0.01	0.13	−0.10	−0.17	−0.10	−0.07	0.01	−0.03	−0.16***
	(0.09)	(0.06)	(0.09)	(0.13)	(0.06)	(0.13)	(0.10)	(0.07)	(0.13)	(0.07)	(0.06)
Financial Conditions	−0.05	−0.97***	0.05	1.74**	0.40	0.08	0.37**	0.32	0.63***	−0.09	−0.27
	(0.34)	(0.22)	(0.28)	(0.74)	(0.25)	(0.20)	(0.18)	(0.23)	(0.23)	(0.15)	(0.18)
GDP	0.29	0.12	0.07	1.01***	0.19	0.22	−0.13	0.12	−0.29	0.10	0.19
	(0.21)	(0.16)	(0.22)	(0.37)	(0.19)	(0.27)	(0.23)	(0.23)	(0.24)	(0.13)	(0.19)
Housing	−0.06	−0.48***	0.20	−3.58***	0.73**	1.01***	0.17	0.38	0.39**	−0.02	−0.37***
	(0.09)	(0.10)	(0.21)	(1.10)	(0.29)	(0.23)	(0.13)	(0.25)	(0.17)	(0.09)	(0.09)
Industrial Production	−0.05	−0.02	−0.19*	−0.36**	−0.32***	−0.02	0.18*	−0.19	−0.13	0.04	0.22**
	(0.09)	(0.07)	(0.10)	(0.16)	(0.12)	(0.08)	(0.11)	(0.12)	(0.11)	(0.08)	(0.10)
Interest Rates	−0.20	−0.21	−0.43**	0.12	−0.30	−0.86**	−0.69**	0.34	−0.99***	−0.75***	0.26
	(0.36)	(0.21)	(0.20)	(0.42)	(0.24)	(0.36)	(0.29)	(0.21)	(0.34)	(0.18)	(0.22)
Money	−0.02	−0.00	−0.02	0.06	−0.11***	−0.01	−0.03	−0.12***	−0.01	−0.04	0.03
	(0.03)	(0.05)	(0.04)	(0.09)	(0.02)	(0.02)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
Prices	−0.07	0.07	0.04	−0.51***	−0.02	0.12	0.09	−0.10	0.08	0.01	−0.04
	(0.08)	(0.06)	(0.11)	(0.14)	(0.08)	(0.09)	(0.08)	(0.06)	(0.09)	(0.05)	(0.05)
Stock Prices	−0.02	0.05	0.12	−0.01	−0.03	−0.05	−0.04	0.02	0.09	0.01	−0.10*
	(0.08)	(0.07)	(0.08)	(0.14)	(0.05)	(0.06)	(0.07)	(0.08)	(0.10)	(0.06)	(0.06)
Unemployment	0.23**	0.26***	0.24*	−0.04	−0.43***	0.14	−0.02	0.04	−0.23*	0.17*	0.20*
	(0.11)	(0.10)	(0.13)	(0.15)	(0.13)	(0.10)	(0.13)	(0.08)	(0.13)	(0.09)	(0.11)
Wages	−0.43*	0.23	−0.44**	−0.76	−0.11	0.37*	−0.84***	−0.28	−0.38	−0.22	0.19
	(0.25)	(0.20)	(0.18)	(0.52)	(0.14)	(0.20)	(0.24)	(0.24)	(0.35)	(0.18)	(0.18)
Working's T	−0.19**	−0.04	−0.03	0.15	−0.15	−0.07	−0.05	−0.02	−0.10	−0.00	−0.06
	(0.08)	(0.10)	(0.11)	(0.23)	(0.19)	(0.09)	(0.16)	(0.05)	(0.10)	(0.12)	(0.08)
Basis	−0.34	0.17	0.10	0.39	−0.09	−0.60***	0.51**	−0.02	0.25	−0.11	−0.46**
	(0.43)	(0.32)	(0.44)	(0.36)	(0.17)	(0.15)	(0.24)	(0.33)	(0.52)	(0.22)	(0.21)
Commodity Inventory	0.15	0.13	−0.04	−0.29**	0.09	0.06	0.05	−0.44***	0.00	−0.14	0.10
	(0.18)	(0.11)	(0.11)	(0.14)	(0.11)	(0.10)	(0.13)	(0.13)	(0.20)	(0.15)	(0.19)
Adj.R^2in %	36.55	40.23	44.48	55.47	55.65	45.44	42.16	34.52	52.23	57.75	46.47

Volatility Level:

In Table 2.4 we see that the level factor is in many cases negatively related to the change in speculation, represented by Working's T, albeit this change is insignificant.

There are several macroeconomic factors that influence the volatility term structure. Employment is significantly positively related to the level factors of most commodities. For sugar and corn, though, this effect is insignificant and for silver even negative. For the softs market this also holds for unemployment, showing that the overall employment situation seems to have a V-shaped influence on the level of volatilities for this market. High employment (unemployment) implies a high (low) available income and high (low) demand, which results in increasing (increasing) expected variation in prices. These commodities are most affected by direct consumer demand. Financial conditions are positively related to volatilities of the metals market and sugar. They are negatively related to coffee, which might explain the low correlation. This result is similar to those of Kilian (2009). The housing market has a negative relationship with coffee, sugar and natural gas for the volatility level, while the relation with the agricultural market and silver is positive. For interest rates, we see a largely negative effect on the level of volatility. It is particularly large for metals that are used for industrial purposes, e.g. copper and silver. Larger interest rates indicate larger borrowing costs with, ceteris paribus, lower expected demand and lower variation. For gold, an increase in interest rates increases opportunity costs and thus might result in decreasing market demand. However, because gold is used primarily as a financial commodity, it does not benefit from the positive signal of higher interest rates with regard to the stability of the economy. This effect can, on the contrary, indicate that prices of gold fall further, because the demand for hedges against an economic crisis decreases. This will likely result in increasing volatilities. For other commodities this will not occur in the same magnitude when inventories are not so low. For the volatility level of corn and gold, we see a negative relation with money supply.

Table 2.5: Macroeconomic Determinants – Slope

We conduct month-end contemporaneous regressions of the commodities' slope factors on macroeconomic components. These are computed, using the first PC of the macroeconomic groups in Table A1 of the Appendix as independent variables. *, **, ***, respectively indicate significance at the 10%, 5% and 1% level, using Newey and West (1986) standard errors with 10 lags.

	Cocoa	Coffee	Cotton	Sugar	Corn	Soybeans	Copper	Gold	Silver	Crude	Natural Gas
Business Inventory	−0.05	−0.02	−0.05	0.06	−0.10	−0.20**	−0.00	−0.03	0.03	0.17***	−0.02
	(0.04)	(0.06)	(0.08)	(0.04)	(0.19)	(0.09)	(0.04)	(0.06)	(0.04)	(0.06)	(0.05)
Commodity Volatility	0.07**	0.05	−0.03	−0.08	0.31**	0.08	0.13***	−0.07	0.14***	0.01	−0.05
	(0.03)	(0.04)	(0.04)	(0.07)	(0.15)	(0.12)	(0.03)	(0.07)	(0.04)	(0.04)	(0.04)
Consumer Expectations	−0.02	0.01	0.02	−0.00	−0.08	0.05	−0.00	−0.06	−0.02	−0.03	0.05
	(0.03)	(0.04)	(0.03)	(0.08)	(0.16)	(0.09)	(0.03)	(0.03)	(0.02)	(0.03)	(0.05)
Employment	0.03	−0.07	0.03	−0.14***	−0.04	0.05	0.10***	0.09**	0.05*	0.01	0.03
	(0.02)	(0.04)	(0.05)	(0.05)	(0.13)	(0.07)	(0.03)	(0.04)	(0.03)	(0.03)	(0.05)
Exchange Rates	0.01	−0.03	−0.04	0.02	0.00	−0.08	0.02	−0.02	−0.01	−0.01	−0.06*
	(0.02)	(0.04)	(0.03)	(0.06)	(0.08)	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Financial Conditions	0.03	0.03	0.01	0.04	−0.21	−0.06	−0.29***	−0.08	−0.07*	−0.01	0.03
	(0.04)	(0.07)	(0.05)	(0.07)	(0.15)	(0.09)	(0.05)	(0.06)	(0.04)	(0.07)	(0.08)
GDP	−0.05	0.00	−0.08	0.02	0.31	−0.11	0.05	−0.08	−0.01	−0.02	−0.07
	(0.05)	(0.06)	(0.05)	(0.10)	(0.26)	(0.10)	(0.05)	(0.05)	(0.06)	(0.06)	(0.08)
Housing	−0.08***	−0.02	−0.03	−0.38***	−0.19	0.10	−0.12***	−0.03	−0.14***	−0.06**	0.03
	(0.02)	(0.03)	(0.05)	(0.12)	(0.28)	(0.11)	(0.03)	(0.06)	(0.02)	(0.03)	(0.04)
Industrial Production	−0.01	−0.01	0.01	0.01	−0.05	0.00	0.01	0.07**	−0.04	0.00	0.04
	(0.02)	(0.04)	(0.03)	(0.05)	(0.13)	(0.05)	(0.03)	(0.03)	(0.02)	(0.03)	(0.05)
Interest Rates	0.01	0.04	0.08	−0.30***	0.28	0.10	−0.03	0.02	0.00	−0.09	−0.17
	(0.05)	(0.10)	(0.08)	(0.10)	(0.17)	(0.18)	(0.08)	(0.07)	(0.06)	(0.11)	(0.13)
Money	0.01	0.04***	−0.02***	0.10**	−0.07**	−0.02	−0.02	−0.06**	−0.02**	−0.03**	0.02
	(0.01)	(0.01)	(0.01)	(0.04)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Prices	0.02	0.00	−0.03	0.07	−0.04	−0.02	0.01	−0.00	0.00	0.02	−0.03
	(0.02)	(0.03)	(0.03)	(0.06)	(0.10)	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Stock Prices	0.01	0.09***	−0.02	−0.05*	0.00	0.03	0.02	−0.03	0.05***	−0.04**	0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Unemployment	−0.03	−0.02	0.02	−0.01	0.12	−0.02	0.02	0.02	−0.02	0.03	0.03
	(0.03)	(0.04)	(0.04)	(0.06)	(0.12)	(0.09)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)
Wages	0.06	−0.12	−0.07	0.04	−0.01	0.02	−0.01	0.22***	0.01	−0.07	−0.11
	(0.05)	(0.08)	(0.05)	(0.08)	(0.26)	(0.13)	(0.07)	(0.06)	(0.09)	(0.07)	(0.10)
Working's T	−0.02	−0.11***	−0.03	−0.16	0.19	−0.02	0.03	0.00	0.03	0.15***	−0.01
	(0.03)	(0.04)	(0.03)	(0.12)	(0.17)	(0.06)	(0.05)	(0.02)	(0.03)	(0.04)	(0.03)
Basis	0.14***	0.06	0.09	0.00	−0.22*	−0.20**	0.00	−0.09	0.14***	0.11	0.04
	(0.05)	(0.09)	(0.11)	(0.11)	(0.11)	(0.08)	(0.06)	(0.08)	(0.05)	(0.08)	(0.09)
Commodity Inventory	−0.00	0.03	0.03	0.08	−0.12	−0.09	−0.15***	0.07*	0.01	0.08*	−0.12*
	(0.04)	(0.04)	(0.03)	(0.06)	(0.08)	(0.06)	(0.05)	(0.04)	(0.04)	(0.05)	(0.07)
Adj.R^2in %	12.49	5.409	−1.858	28.83	−0.6	−9.961	32.73	30.36	39.50	32.65	3.254

The macroeconomic and commodity-specific factors are generally able to explain a large part of the variation in the level factor. The R^2s range between 34.52% for gold and up to 57.75% for corn.

Volatility Slope:

Table 2.5 shows the results for the slope of the implied commodity volatility term structures. According to the theory of storage, we would expect to have either a significant positive relationship with the basis or a negative relationship with the inventory variables. There are three hypothesis that explain when the Samuelson (1965) theory holds. Hong (2000) states that information asymmetry in markets can lead to violations of the Samuelson hypothesis. Fama and French (1988) argue that around business cycle peaks, when inventory is low, the Samuelson hypothesis should hold, while the theory can be violated if inventory is high and marginal convenience yields are low. Bessembinder et al. (1996) argue that the existence of a temporary component that is reversed over time is the main factor that determines if the Samuelson hypothesis holds in a market. A positive shock leads to a reversal over time. They find that the Samuelson hypothesis is empirically supported in markets where spot price changes and the slope of the term structure co-vary negatively. Tightening inventories reduces the possibility for markets to react to increases in demand or supply shortages. Therefore we should investigate the basis, the inventory and Working's T with regard to their expected relation with the slope of the volatility term structure.

The basis is seen as a proxy for inventory levels. It is positive if the price of a one-month contract is larger than the price of a twelve-month contract. This occurs when the commodity is in backwardation, a state which is associated with tighter inventories. Contango, on the other hand, is associated with abundant inventories. The theory of storage can be supported for cocoa, silver, copper and natural gas. For these commodities we have either a significant positive relationship with the basis or a negative relationship with the inventory variable. The observations for gold, crude oil, corn and soybeans are not consistent with the theory of storage.

For the slope, we see a negative relation of financial conditions for copper and silver. As we have seen before, in good financial conditions the level of the volatility term structure increases, while the term structure becomes increasingly flat. The market expects long-term inventory to decrease, which leads to an increasing volatility in the future. We also observe a significant negative relationship between many of the commodities and the housing market. A housing crisis leads to a larger slope for sugar, cocoa, industrial metals and crude oil.

For the money supply, the largest relation can be seen in the slope. For coffee and sugar there is a positive relationship. Corn, cotton, gold, silver and crude oil have a negative relationship. The higher the money supply the lower is the slope, so a higher money supply could increase inflation expectations and long-term volatilities. For corn and gold an increasing money supply leads to a lower overall level of the volatility term structure: the lower slope indicates that the money supply particularly affects short-term volatilities for corn and gold.

For the slope, most variables have high explanatory value. However, part of the markets for which the Samuelson hypothesis typically holds appear to be driven driven by idiosyncratic factors (e.g. cocoa, coffee, cotton, corn and soybeans). For speculation we can observe no effect for the entire market, in contrast to Hong (2000), who finds that information asymmetry could lead to a violation of the Samuelson effect. He captures this effect in a model, where hedgers trade without fundamental market information and speculators trade on their information advantage. Uninformed hedgers trade for hedging reasons, which is why they are willing to trade with informed investors. Due to a larger impact of non-marketed risk in shorter-term futures. Hong (2000) further argues that cost in trading increases for the uninformed investor and they will trade less. He terms this effect a “speculative effect” that can overwhelm the Samuelson effect, and this holds even assuming a homogeneous information flow.

Table 2.6: Macroeconomic Determinants – Curvature

We conduct month-end contemporaneous regressions of the commodities' curvature factors on macroeconomic components. These are computed, using the first PC of the macroeconomic groups in Table A1 of the Appendix as independent variables. *, **, ***, respectively indicate significance at the 10%, 5% and 1% level, using Newey and West (1986) standard errors with 10 lags.

	Cocoa	Coffee	Cotton	Sugar	Corn	Soybeans	Copper	Gold	Silver	Crude	Natural Gas
Business Inventory	0.01	−0.01	0.07*	−0.02	−0.11	−0.12	0.01	0.01*	−0.01	0.00	−0.11*
	(0.02)	(0.02)	(0.04)	(0.05)	(0.10)	(0.10)	(0.02)	(0.01)	(0.01)	(0.02)	(0.07)
Commodity Volatility	0.01	0.03	−0.01	−0.04	0.06	−0.12	−0.01	0.01	0.01	0.01	−0.00
	(0.02)	(0.02)	(0.03)	(0.05)	(0.12)	(0.13)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)
Consumer Expectations	0.01	−0.00	0.00	0.06	0.04	0.10	−0.01	0.01	−0.02*	−0.00	0.05
	(0.02)	(0.02)	(0.02)	(0.04)	(0.07)	(0.12)	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)
Employment	0.01	0.05**	−0.05**	0.02	−0.07	−0.07	−0.01	0.02***	0.02**	0.03**	0.06
	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)	(0.07)
Exchange Rates	−0.01	−0.03**	−0.01	−0.06*	0.14***	0.10	−0.01	0.01	0.01	−0.01	0.06
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.09)	(0.01)	(0.01)	(0.01)	(0.01)	(0.05)
Financial Conditions	0.02	0.02	0.04	0.12**	−0.04	0.01	0.00	0.00	−0.00	0.00	0.15
	(0.04)	(0.04)	(0.03)	(0.05)	(0.10)	(0.12)	(0.02)	(0.01)	(0.01)	(0.02)	(0.12)
GDP	0.02	−0.01	−0.00	−0.09	0.27**	0.04	0.00	0.00	0.01	0.05	0.05
	(0.02)	(0.04)	(0.03)	(0.10)	(0.12)	(0.11)	(0.02)	(0.01)	(0.02)	(0.05)	(0.09)
Housing	0.01	−0.01	0.06	−0.02	−0.23	−0.07	0.00	−0.02	−0.01**	0.03*	0.02
	(0.01)	(0.02)	(0.04)	(0.09)	(0.16)	(0.14)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)
Industrial Production	−0.01	0.02	0.01	0.02	−0.04	−0.13*	−0.01	−0.00	−0.00	0.01	−0.09
	(0.01)	(0.01)	(0.02)	(0.03)	(0.07)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)
Interest Rates	−0.04	−0.04	0.00	0.08	0.19	0.37**	0.00	−0.00	−0.01	0.01	−0.11
	(0.06)	(0.06)	(0.04)	(0.07)	(0.13)	(0.16)	(0.03)	(0.02)	(0.02)	(0.03)	(0.16)
Money	0.01	0.01	0.00	0.00	0.06***	0.00	0.01*	−0.00	−0.00	0.02**	−0.05
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)
Prices	−0.01	−0.00	0.00	0.02	−0.11	−0.07	−0.01	0.01	−0.01	−0.03	−0.02
	(0.01)	(0.01)	(0.02)	(0.04)	(0.06)	(0.05)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)
Stock Prices	0.02*	0.01	−0.02	0.04	−0.04*	−0.02	0.02	0.02**	0.01	0.00	0.05
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)
Unemployment	−0.01	0.00	0.01	0.01	0.15***	−0.03	−0.02	0.02*	−0.00	−0.01	−0.03
	(0.01)	(0.02)	(0.03)	(0.03)	(0.05)	(0.07)	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)
Wages	−0.04	0.06	−0.08**	−0.05	0.00	−0.07	−0.03	−0.02	0.05**	0.08***	−0.25**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)	(0.09)	(0.03)	(0.01)	(0.02)	(0.03)	(0.10)
Working's T	0.00	0.00	−0.01	0.02	0.17**	0.00	0.01	−0.00	−0.00	0.00	0.01
	(0.01)	(0.02)	(0.02)	(0.09)	(0.08)	(0.04)	(0.02)	(0.00)	(0.01)	(0.03)	(0.06)
Basis	0.03	−0.11**	−0.07	0.15**	0.07	0.05	−0.03	−0.02	0.00	0.01	−0.11
	(0.04)	(0.06)	(0.05)	(0.06)	(0.07)	(0.07)	(0.02)	(0.02)	(0.01)	(0.04)	(0.09)
Commodity Inventory	−0.11***	−0.01	−0.02	0.04	−0.00	−0.04	−0.02	0.01	0.01	0.05	−0.26**
	(0.02)	(0.03)	(0.02)	(0.03)	(0.05)	(0.05)	(0.02)	(0.01)	(0.01)	(0.04)	(0.12)
Adj. R^2 in %	24.88	19.78	16.16	12.81	4.863	−10.34	−1.896	24.40	8.223	15.54	18.63

Volatility Curvature:

The results for the curvature factor are shown in Table 2.6. The curvature shows a positive relation with speculation only for corn. An increase in speculation decreases the level of the term structure, and introduces a concave shape. For coffee, sugar and corn the curvature is related to the exchange rate, for coffee and sugar a depreciating US-Dollar is related to a concave term structure, and for corn this is related to a convex term structure. Assuming that the Samuelson effect holds, this implies a higher medium-term volatility for a negative relation and a lower medium-term volatility for a positive relation. For coffee and sugar, the United States is a net importer, a depreciating currency will only increase local demand and increase the price in US-Dollar. For corn the United States is also a major exporter, having an effect on the cost of supply. For supplies, a depreciating US-Dollar implies lower relative costs for producers in the United States, enabling them to better compete and possibly increase supply. This has calming effects on the price volatility for these commodities. The variables can generally explain a large share of the variation in the curvature for the softs market. For the remaining commodity markets, the R^2s are generally smaller.

In summary, we find that macroeconomic variables can explain a large proportion of the variation in the level factor, but typically somewhat smaller shares of the slope and curvature factors.

2.3.3 Spillovers

Having documented a strong linear contemporaneous relationship between the volatility term structure factors and macroeconomic determinants, we investigate whether there are spillovers, i.e. lead/lag effects, in the volatility term structures. Volatility spillovers might vary in different economic states. During periods of distress, macroeconomic effects likely lead to a strong positive lead/lag relationship for most commodities. But the role of some commodities during a crisis could be different. For example, gold is often seen as a hedge against the equity market and might react differently to a macroeconomic shock than other commodities.

We therefore investigate state-dependent spillovers in risk, using a Value at Risk (VaR) approach. To construct state-dependent indicator variables we use the returns of an equally weighted commodity portfolio with a 5% VaR. We use the resulting time series with the percentiles of distressed or tranquil periods as in Adams, Füss, and Gropp (2014). We therefore consider three indicator variables, I_D, I_T and I_N, for distress, tranquil and normal periods, respectively. The variables are 1 if the VaR is in the defined α percentile. We follow Adams et al. (2014) and define the lower bound as 12.5% and the upper bound as 75%. Thus every observation below the 12.5% percentile indicates distress. Every observation above the 75% percentile indicates tranquil periods and everything in between shows normal economic states.[7] Adams et al. (2014) argue that these percentiles represent a good trade-off between power and an accurate representation of the state of the relevant market.

To estimate the VaR we use the CAViaR introduced by Engle and Manganelli (2004), which is able to capture volatility clustering and time varying error distributions. Engle and Manganelli (2004) specify the approach as follows:

$$VaR_t(\theta) = \theta_0 + \sum_{j=1}^{q} \theta_j VaR_{t-j}(\theta) + \sum_{i=1}^{r} \theta_{(q+i)} L(Y_{t-i}). \tag{2.5}$$

The AR components $VaR_{t-j}(\theta)$ introduce persistence in the VaR series which assures its continuity. The lag operator $L(Y_{t-i})$ introduces the link to the underlying dataset. For our purpose we use the asymmetric slope model by Engle and Manganelli (2004) as a specification for $L(Y_{t-i})$. This model is also used by Hong, Liu, and Wang (2009) for the estimation of the

[7] This implies a transformation of the otherwise positively defined VaR, which we define to be negative.

VaR and is correctly specified for a GARCH process with asymmetrically modeled standard deviation and i.i.d. errors. This is the specification of the asymmetric slope model:

$$VaR_t(\theta_l) = \theta_0 + \theta_1 VaR_{t-1} + \theta_2 Y^+_{t-1} + \theta_3 Y^-_{t-1} \ , \tag{2.6}$$

where $Y^+_t = \max(Y_t, 0)$, $Y^-_t = -\min(Y_t, 0)$. The resulting 5% VaR estimate for an equally weighted commodity portfolio is shown in Figure A2 of the Appendix. To obtain coefficients for a spillover analysis, we estimate a regression following the spirit of Adams et al. (2014). Our conditioning variable is not the LHS variable, but a commodity VaR Index. Hence, we cannot use quantile regressions. Instead, as described above, we introduce different economic states using dummy variables.

As control variables, we use the variance risk premium and the corresponding PC of the equity market (PCE):[8]

$$\begin{aligned} PC_{i,t} = & \sum_{k=1}^{p} \beta^1_k PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta^2_k PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta^3_k PC_{i,t-k} \cdot I_D + \\ & \sum_{u=1}^{p} \gamma^1_u PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma^2_u PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma^3_u PC_{j,t-u} \cdot I_D + \\ & VRP_t + PCE_t + \epsilon_t. \end{aligned} \tag{2.7}$$

$PC_{i,t-k}$ is the PC of asset i with lag k. We conclude that the term structure components of assets j spill over to those of asset i if the following null hypotheses can be rejected. We conduct four separate tests, with $H_0 : \gamma^1_u = 0$ we test if we observe any significant spillover effects during normal periods. For γ^2_u and γ^3_u we conduct the same test for tranquil and distressed periods, respectively. Additionally, we conduct a test investigating whether all three variables are jointly zero, $H_0 : \gamma^1_u = \gamma^2_u = \gamma^3_u = 0$.

[8]To uncover the relationship with the stock market we conduct a regression with the stock market's PC. In this case, we treat it like a PC of a commodity and consequently drop the PC of the equity market (PCE) from the set of control variables.

We further test whether the results are economically significant by performing an out-of-sample test. We examine whether we can improve the forecast of the implied volatility term structure when we have knowledge of the implied volatility term structure of another commodity. We follow Goyal and Welch (2007) to conduct an out-of-sample analysis. We test the forecast from the unrestricted AR regression including the components of asset j against a restricted AR process that sets coefficients $H_0 : \gamma_u^1 = \gamma_u^2 = \gamma_u^3 = 0$. For the purpose of the out-of-sample analysis, we assign the dummies based on forecasts that use only information available at time $t-1$.

We measure the out-of-sample performance with the following formula:

$$R^2_{OOS} = 1 - \frac{MSE_{un}}{MSE_{re}} \ , \tag{2.8}$$

where MSE_{un} is the mean squared error of the unrestricted forecast and MSE_{re} is the mean squared error of the restricted forecast. The restricted model assumes that $\gamma_u^1 = \gamma_u^2 = \gamma_u^3 = 0$ cannot be rejected.

We present the results of the state-dependent spillover test in Table 2.7. The level factor is in Panel A, the slope factor in Panel B and the curvature factor in Panel C. If the numbers are **bold**, the null hypothesis of zero predictability is rejected out-of-sample, using the McCracken (2007) OOS-F statistics, with a significance level of 10%. The in-sample significance is displayed with Newey and West (1986) standard errors with 10 lags. As argued by Goyal and Welch (2007), in-sample predictability is a key requirement. Table 2.7 shows large bi-variate spillovers between commodity markets for the different term structure factors. They are significant for a large number of commodities and large in size.

Table 2.7: Spillovers Between Markets

This table presents in-sample and out-of-sample results for spillover tests for the different components of the volatility term structure. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = \gamma_u^2 = \gamma_u^3 = 0$. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,**,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Level

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**1.61*****	**1.21**	**2.09**	**2.90*****	**2.79*****	**3.78*****	**0.68*****	**2.10*****	**1.04**	**2.02*****	**1.86*****
Coffee	**1.54**		**0.63**	**1.62****	**3.86**	**3.49*****	**0.58*****	**3.63***	**1.37*****	**0.52**	**0.84****	**0.63***
Copper	**1.36*****	**0.45**		**1.33**	**0.80**	**1.92***	**2.66*****	**0.39***	**3.51*****	**1.60****	**1.78***	**2.22*****
Corn	**2.39****	**1.66**	**1.16***		**0.46**	**1.74*****	**2.12*****	**1.84**	**2.53*****	**1.74****	**1.40*****	**0.98**
Cotton	**0.73**	**1.00**	**1.36**	**1.48**		**1.28*****	**0.88**	**1.94**	**2.57**	**2.32*****	**1.71****	**0.68**
Crude	**1.11****	**1.39*****	**2.24****	**1.46**	**2.29****		**2.03*****	**0.26**	**2.11*****	**2.35*****	**2.85****	**2.63*****
Gold	**1.37*****	**0.95****	**2.58*****	**1.68****	**1.95*****	**1.93*****		**2.93**	**3.15*****	**0.79****	**1.35*****	**1.71*****
Natural	**0.79**	**2.36**	**0.35*****	**3.05****	**8.15*****	**1.17*****	**1.36**		**1.03*****	**2.30****	**0.34****	**1.49*****
Silver	**1.43***	**1.33**	**2.10****	**2.31**	**1.67*****	**3.24*****	**2.71*****	**1.41****		**0.30**	**1.73**	**2.80*****
Soybean	**0.89*****	**0.47*****	**2.81*****	**1.54**	**1.19****	**2.26****	**1.44*****	**3.44****	**0.52****		**0.57*****	**0.58***
Sugar	**1.49**	**0.36*****	**0.43**	**2.30***	**1.43*****	**4.09****	**0.56**	**0.33*****	**1.52*****	**0.11**		**0.20*****
Equity	−0.33***	−0.14***	**1.68*****	**0.43**	0.01***	**2.02*****	**0.13*****	**0.98*****	**2.91*****	**0.17**	**0.27*****	

Panel B - Slope

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.70*****	**0.99**	**0.68*****	−1.42	−0.75***	−0.92	−0.94***	**0.45**	−0.10***	−2.78	−1.67***
Coffee	**0.79*****		−0.37	**1.04*****	**2.94***	**3.53*****	**0.91**	**1.54*****	−0.30	**0.18***	**0.78*****	−0.04***
Copper	**0.67**	**0.48***		−0.06	**0.68***	**0.66*****	**1.65***	**0.19***	**1.60*****	**0.56**	**1.86**	**1.01**
Corn	**1.71*****	**3.16*****	**0.72**		−0.11	**1.66*****	**1.60**	**3.33*****	−2.24*	**2.23*****	**0.32****	**0.85*****
Cotton	**0.30****	**1.32**	**0.87*****	**1.35*****		**0.39**	**1.06**	**1.02*****	**1.10**	**0.98**	**2.61*****	**0.84*****
Crude	**1.22**	**0.68***	**1.12****	**2.14*****	**1.37**		**2.70***	**0.95*****	**1.90**	**0.51**	**0.51**	**0.01*****
Gold	**0.79***	**0.32***	**1.06**	**0.68*****	**1.03*****	**1.90*****		**2.89*****	**4.09*****	**1.65**	**1.28*****	**1.07*****
Natural	−0.93	−1.46	−0.04	**1.31****	**3.28**	**0.12*****	**1.41**		−0.31*	−2.26	−2.02	−0.77***
Silver	**1.18***	**1.45****	**0.27**	**0.72**	**1.22**	**0.72*****	**1.38****	**0.38*****		**0.61**	**3.75**	**2.29*****
Soybean	**0.49**	**2.30*****	**1.19**	**1.50*****	**0.38**	**0.40**	**0.98****	**1.19*****	0.08***		**0.88*****	**1.03***
Sugar	**1.30**	−0.43*	−2.03***	**0.46****	**2.09*****	**1.32*****	−1.27***	**0.21*****	**2.41*****	**0.20**		−1.61**
Equity	−11.16***	−6.43	−2.28	−7.42	−8.19	−2.56***	−13.13***	−2.70***	−0.07***	**0.13**	−5.05	

Panel C - Curvature

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		−0.18***	**1.29*****	**1.82****	**−0.54****	**0.90*****	**0.80**	**1.00**	**2.72*****	**1.04**	**3.60*****	**1.49*****
Coffee	**0.67***		**0.81**	**0.07****	**1.66**	**3.36**	**1.42**	**3.00*****	**1.98*****	**0.18*****	−0.06***	−0.38***
Copper	**1.12*****	**0.31**		**1.13*****	**1.04****	**0.48**	**0.62****	**0.25*****	**0.50***	**0.45**	**1.72*****	**0.83**
Corn	**2.49*****	**2.10**	**1.20*****		**4.17****	**0.61**	**1.15**	**4.09*****	**1.25***	**1.35**	−0.13***	**1.42*****
Cotton	**1.15**	**1.37***	**0.89*****	**0.31**		**1.17**	**0.55***	**0.74**	**2.35**	**1.69****	**2.39*****	**0.43***
Crude	**1.32**	**1.11**	**0.28*****	**2.39**	**0.98**		**0.32**	**0.08*****	0.02	−0.08	**0.73****	−1.31
Gold	**0.05**	**0.38**	0.03	**0.43**	**0.35**	**0.40*****		**0.80*****	**0.45****	**0.47****	**0.57**	**0.43*****
Natural	**2.38*****	**3.13**	−0.84**	**4.08*****	**4.08****	**1.05**	−0.66*		**0.50**	**2.68*****	**0.07**	**2.75*****
Silver	−0.51*	−0.39**	**1.12**	**0.97*****	−2.34***	**0.46*****	**0.31*****	**1.69*****		−0.06	−0.57	**0.31**
Soybean	**0.60**	**0.30**	**1.41*****	**1.76****	**1.75**	**0.65****	**0.22**	**2.55***	**1.14*****		**0.20**	−0.01*
Sugar	**0.56*****	−0.41***	−11.99***	**1.62*****	**5.07**	**2.05*****	−13.33	**0.34*****	**0.17*****	−0.47***		−9.51
Equity	−8.61**	−6.31***	−5.43***	−3.09	−3.05	−4.23	−6.82***	−2.69**	−0.20**	−2.07	−2.89***	

Table 2.8: State-Dependent Spillovers Between Markets

This table presents in-sample and out-of-sample results for spillover tests for the different components of the volatility term structure. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

We summarize the results for the respective commodities j (from which the spillovers originate) in the first column. We test the null hypothesis, $H_0 : \gamma_u^1 = 0$ ($H_0 : \gamma_u^2 = 0$, $H_0 : \gamma_u^3 = 0$) for normal (tranquil, distressed) periods. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the median out-of-sample R^2 for each panel ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. We count a significant observation only when both the out-of-sample R^2s based on McCracken (2007) test statistic and the in-sample Wald test with Newey and West (1986) standard errors are significant toward the 10% level.

Panel A - Level

	Normal		Tranquil		Distressed	
	median R^2	significant obs.	median R^2	significant obs.	median R^2	significant obs.
Cocoa	0.41	2	0.34	3	0.32	2
Coffee	0.27	3	0.20	3	0.32	1
Copper	0.33	0	0.21	4	0.89	2
Corn	0.59	3	0.28	1	0.76	3
Cotton	0.98	2	0.45	3	1.02	3
Crude	0.60	4	0.43	8	1.09	5
Gold	0.42	2	0.18	3	0.62	3
Natural Gas	0.40	1	0.25	4	0.59	1
Silver	0.74	1	0.22	6	1.14	2
Soybeans	0.23	3	0.20	5	0.44	2
Sugar	0.61	1	0.25	3	0.64	3
Equity	0.41	5	0.30	5	0.47	5

Panel B - Slope

	Normal		Tranquil		Distressed	
	median R^2	significant obs.	median R^2	significant obs.	median R^2	significant obs.
Cocoa	0.28	3	0.16	3	0.19	2
Coffee	0.27	3	0.03	2	0.12	6
Copper	0.17	3	0.06	2	0.31	1
Corn	0.18	3	0.09	5	0.54	4
Cotton	0.14	2	0.03	2	0.35	1
Crude	0.43	2	−0.05	3	0.38	3
Gold	0.30	2	−0.10	3	0.56	1
Natural Gas	0.10	3	0.35	8	0.30	2
Silver	0.24	3	0.17	3	0.62	0
Soybeans	0.11	3	0.21	1	0.17	2
Sugar	0.48	3	0.10	3	0.34	4
Equity	0.24	5	0.29	5	0.33	1

Panel C - Curvature

	Normal		Tranquil		Distressed	
	median R^2	significant obs.	median R^2	significant obs.	median R^2	significant obs.
Cocoa	0.14	5	0.05	2	0.46	1
Coffee	0.08	1	0.17	4	0.18	1
Copper	0.15	0	0.05	3	0.23	2
Corn	0.36	5	0.18	5	0.65	4
Cotton	0.02	2	−0.01	3	0.69	3
Crude	0.12	2	0.01	1	0.49	3
Gold	0.19	2	0.04	1	0.19	0
Natural Gas	0.11	4	0	2	0.33	3
Silver	0.12	2	0.14	4	0.47	3
Soybeans	0.06	1	0	3	0.20	2
Sugar	0.07	3	0.03	2	0.38	3
Equity	0.06	1	0.14	9	0.30	1

Tables A3, A4 and A5 of the Appendix further present the results of the out-of-sample tests for the different economic states. Table 2.8 summarizes the information in these tables. In general Table 2.8 shows that spillovers in distress are large in size, while during tranquil periods they are large in frequency. Thus a state-dependent approach unveils differences in spillovers between states.

Volatility Level: In the following, we discuss the spillovers in level (Panel A of Table 2.7) in more detail. The equity market shows spillovers especially to commodity markets that are related to the business cycle, like crude oil, silver, copper and gold. A prediction that accounts for spillovers from the equity market to the gold, copper, crude oil and silver markets yields out-of-sample R^2s of 1.71%, 2.22%, 2.63% and 2.80%, respectively. A potential explanation for this finding is that the equity market reacts in a more timely manner to changes in the business cycle. Robe and Wallen (2016) observe a similar linkage between the equity markets and crude oil. We observe lagged information transmission to the business cycle sensitive commodity markets. The spillovers are largest from the equity market in periods of distress and normal periods, which can be seen in Table A3. In tranquil periods there is a feedback effect with the commodity market, indicating that the commodity markets' volatilities mainly influence the equity market in periods of low storage and tight supply, that will likely occur in tranquil periods due to higher demand. For the level factor, spillovers from the equity market decrease during tranquil periods while those to the equity market are somewhat higher than in normal and distressed periods.

The term structure components of copper Granger cause those of commodities in the same sector, crude oil and the equity market, which are connections we would expect from a business cycle sensitive commodity like copper. Jacobsen, Marshall, and Visaltanachoti (2018) show that metal returns lead equity markets. This connection to the equity market can also be observed for the level of the volatility term structure. We also see substantial spillovers from the gold market. In distress there are significant spillovers from gold to copper and corn. In tranquil periods there are spillovers to cocoa and crude oil and during normal periods to copper. Gold only spills over to silver in all economic states. The spillover to cocoa might be linked to the influence of interest rates that the level of gold captures, as can be seen in Table 2.4. This transmits to changes in the expected convenience yield, which alters the expected level of inventory and results in changes for the level volatility of cocoa.

Corn and soybeans do not show a lot of sector commonalities for spillovers in level, but both spill over to natural gas and gold. The link to natural gas might have something to do with their role as a fertilizer and as a main energy source for drying crops after the harvest. The larger the volatility, the higher is the incentive to produce more crops to smooth production and deliveries, which results in the use of natural gas to dry crops faster. Cotton captures demand-driven volatility fairly fast and thus spills over to the gold market, especially during tranquil and distressed periods.

Cotton volatility Granger causes a lot of commodity markets and is, in turn, only Granger caused by the volatility of three markets: crude oil, soybeans and sugar. Cotton Granger causes especially natural gas, a link which is not obvious. However, there are several possibilities. First, cotton is a competitor in the clothing industry with synthetic fibers that are produced from natural gas. Second, both commodities are highly sensitive to the weather in the United States, or more particularly in the Midwest, where a majority of the production is located. Third, storms will increase the level for both commodities, introducing supply disruptions to the market. Fourth, heatwaves decrease the harvest estimated for cotton and increase energy demand due to cooling.

Sugar is linked to the softs market. The connection is especially large during distress. One reason for this link might be the strong relationship of sugar to the housing market in level that it shares with the rest of the softs market, for which the link is weaker. The level of sugar causes also causes the level of crude oil. Both are linked due to biofuel production, where sugar cane is an efficient alternative and Brazil can as a main producer of both ethanol and sugar canes circumvent export restrictions for sugar by exporting ethanol.

The spillovers from crude oil to natural gas are small. This is in line with Bachmeier and Griffin (2006), who find that there exists no common primary energy market. In level the crude oil market spills over to every market. One reason for the high spillover is the influence of institutional investors that invest more heavily in liquid business cycle related markets. An indication for this can also be that crude oil is linked to the metal market in all economic states. Evidence of that phenomenon can be seen in the literature on the financialization of the commodity market. Basak and Pavlova (2016) show in a model that shocks to index commodities spill over to prices and inventories of other index commodities. Due to the influence on prices and inventories on volatility, this will also result in volatility spillovers. Institutional investors can increase those spillovers via an increased correlation.

Volatility Slope: Panel B of Table 2.7 displays the results for the slope. The equity market is less connected to the commodity market, spilling over only to the agricultural market and to precious metals. The slope of the equity volatility term structure cannot capture the unique patterns of the commodity market. A majority of the spillovers occur in tranquil periods, when the economic expansion that is reflected first in the stock market leads to higher volatility in prices for the equity market and subsequently the commodity market, as can be seen in Table 2.8. Short-term volatility increases more strongly, when inventory is tight (Fama and French, 1988). This effect spills over to the equity market from the crude oil market and increases the slope as well, increasing the short-term uncertainty of equity markets.

For the slope, spillovers from the equity market are higher than from the commodity market. Copper, gold and silver all show spillovers that are lower for the slope compared to the spillovers in level. This might be due to the low informativeness of the term structure for metals compared to the level. The highest amount of spillovers can be seen during tranquil periods, when inventory is low.

Spillovers to the slope of corn are large from coffee and cocoa, which shows short-term macroeconomic information transmission. Coffee spills over to other markets especially during periods of distress, which is an indication that coffee captures macroeconomic information of the slope of the volatility term structure earlier, which influences other commodity markets in such periods. Gold and copper are likely Granger caused by cotton, because it can capture a variety of general macroeconomic variables that can serve as early indicators for the general economic activity as, for example, wages in the United States. Cotton is a labor-intensive product with a high production share in the United States. Increases or decreases in the wage will quickly be reflected in the volatility of the price and subsequently in the demand for metals, which will affect volatility as well.

For the slope of the term structure, we still see a high degree of spillovers from crude oil to other markets. The spillover to corn for the slope is large during normal periods and in distress. This indicates that the short-term volatility of natural gas has a high influence on the slope of corn, likely because of its use as a fertilizer. Large changes in the price of natural gas can lead to large short-term changes in the price of corn; we have seen before that the same holds for the level, where the effects on the average volatility seem to be stronger for short-term volatilities.

Volatility Curvature: The main results for the curvature are in Panel C of Table 2.7. As can be seen from Table 2.8, there are significant spillover effects from the equity market to all commodity markets in tranquil market periods. A shock to the term structure of the equity market always spills over to the term structure of the commodity market, but we can not observe spillover effects from the commodity market to the equity market. For the slope and the curvature of the agricultural market, we observe more spillovers for corn than for soybeans. The reason for this might be that corn captures relatively more macroeconomic variables for the shape of the volatility term structure, while the shape of the term structure of soybeans is idiosyncratic, as can be seen in Tables 2.5 and 2.6. Large links to natural gas from the agricultural and softs markets show the medium-term impact of the volatility of agricultural goods on the volatility of natural gas.

Summarizing the results, we see that spillovers are strongly dependent upon economic states. They are strongest during market distress and comparably smallest in normal periods. Furthermore, intra-commodity effects are more important for the commodity market than spillover effects originating from the equity market. Intra-commodity effects rarely spill over to the equity market.

2.3.4 Financialization

We now investigate the option-implied volatility term structure with regard to the financialization of the commodity market. To do so, we split our sample into two parts. January 2004 is often regarded as the break point of financialization (Hamilton and Wu, 2015; Christoffersen et al., 2019).[9] In Table 2.9 we display the correlations pre- and post-financialization. At the bottom of each table we report the correlation of each variable with the first PC of the entire market. We see that the difference between the two periods is stark. In the grey colored post-financialization period the negative correlations disappear entirely compared to the pre-financialization period. Correlations are mostly above 0.4. The correlations of the factors of the term structure of natural gas and coffee with other commodities are much lower – they are outliers in this regard. After financialization, the component is large across commodities and (with the exception of coffee) above 0.5. Investigating the remaining factors of the implied volatility term structure, we see a further integration for the slope factor for the post-financialization period. For the second sub-sample the first PC of the market shows consistently positive correlations with every single market, indicating a strong common factor structure (except for natural gas).

[9] This date roughly corresponds with a break point analysis we have conducted. The Chow test detects break points for the volatility term structure for all commodity markets around 2004−2005.

Table 2.9: Correlations – Pre- and Post-Financialization

This table presents the correlations, for the post-financialization (starting from 01 Jan 2004; in the top right in grey) and pre-financialization (before 01 Jan 2004; in the bottom left) periods. Before indicates the correlation of the PCs with the first PC of the respective factor over all commodity markets pre-financialization. After is the same measure for the post-financialization period.

Panel A - Level

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa	1.00	0.24	0.60	0.68	0.63	0.64	0.56	0.41	0.53	0.78	0.68	0.59
Coffee	0.39	1.00	0.15	0.15	0.26	0.26	0.04	0.15	0.10	0.27	0.27	0.09
Copper	−0.24	−0.22	1.00	0.62	0.39	0.64	0.71	0.71	0.67	0.62	0.53	0.57
Corn	0.07	0.05	0.19	1.00	0.70	0.61	0.68	0.30	0.66	0.79	0.69	0.69
Cotton	0.37	0.20	−0.17	0.12	1.00	0.52	0.45	0.07	0.61	0.60	0.69	0.54
Crude	0.57	0.17	−0.31	−0.17	0.55	1.00	0.62	0.44	0.59	0.60	0.52	0.73
Gold	0.70	0.23	−0.32	0.02	0.35	0.52	1.00	0.38	0.87	0.55	0.49	0.79
Natural	0.23	0.17	−0.25	−0.26	0.34	0.47	0.30	1.00	0.32	0.40	0.32	0.19
Silver	0.16	−0.37	0.20	0.05	0.19	−0.06	0.60	−0.28	1.00	0.49	0.55	0.69
Soybean	0.41	0.07	0.19	0.70	0.26	−0.05	0.32	−0.18	0.41	1.00	0.59	0.53
Sugar	0.52	0.17	−0.11	0.09	0.52	0.60	0.50	0.24	−0.12	0.16	1.00	0.53
Equity	0.21	0.01	−0.12	0.03	0.11	0.49	0.31	0.10	−0.23	−0.08	0.54	1.00
Before	−0.04	0.51	−0.25	−0.62	−0.11	0.53	−0.74	0.32	−0.81	−0.81	0.59	0.76
After	0.83	0.28	0.81	0.87	0.73	0.78	0.81	0.52	0.81	0.82	0.79	0.79

Panel B - Slope

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa	1.00	0.26	0.13	0.26	−0.02	0.18	0.31	−0.02	0.19	0.19	0.14	0.16
Coffee	0.29	1.00	0.08	0.23	0.06	−0.21	0.15	0.21	0.07	0.29	0.36	0.05
Copper	0.10	0.19	1.00	0.12	0.08	0.17	0.24	0.10	0.24	0.11	0.00	0.18
Corn	0.28	0.49	0.09	1.00	0.25	−0.11	0.19	−0.21	−0.01	0.67	0.28	0.12
Cotton	0.18	0.00	−0.03	0.23	1.00	−0.04	−0.03	−0.07	−0.06	0.24	0.23	−0.04
Crude	0.06	−0.11	0.25	−0.28	−0.16	1.00	0.43	−0.00	0.45	−0.06	−0.11	0.35
Gold	−0.10	0.09	−0.18	0.15	0.05	−0.02	1.00	−0.09	0.72	0.14	0.09	0.69
Natural	0.24	0.15	−0.07	−0.01	0.08	0.09	0.05	1.00	0.00	−0.06	−0.12	−0.14
Silver	−0.21	−0.10	−0.03	−0.17	−0.30	−0.02	0.29	−0.01	1.00	−0.00	0.08	0.48
Soybean	0.21	0.43	0.15	0.71	0.33	−0.27	0.16	0.01	−0.03	1.00	0.27	0.08
Sugar	0.06	0.16	0.14	0.01	0.04	−0.05	0.22	0.17	0.33	0.10	1.00	−0.03
Equity	0.17	−0.09	0.13	−0.08	−0.04	0.29	−0.08	0.16	−0.09	−0.21	−0.22	1.00
Before	0.29	0.31	0.22	0.64	0.63	−0.47	0.29	0.33	0.12	0.77	0.64	−0.08
After	0.43	0.11	0.34	0.34	0.05	0.62	0.89	−0.18	0.75	0.26	0.20	0.75

Panel C - Curvature

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa	1.00	0.60	0.36	−0.62	−0.37	−0.03	0.01	−0.31	0.21	−0.08	0.77	−0.01
Coffee	0.25	1.00	0.29	−0.50	−0.41	−0.17	0.02	−0.07	0.22	−0.20	0.62	0.07
Copper	0.31	−0.12	1.00	−0.35	−0.21	−0.04	−0.13	−0.09	0.08	−0.14	0.38	0.03
Corn	−0.54	0.20	−0.43	1.00	0.44	0.02	0.13	0.31	−0.08	0.35	−0.61	−0.04
Cotton	−0.19	0.10	−0.11	0.27	1.00	0.18	0.04	0.21	−0.22	0.39	−0.48	−0.09
Crude	0.28	0.22	0.19	−0.22	0.01	1.00	−0.03	−0.12	−0.13	0.12	−0.01	−0.19
Gold	0.07	0.13	0.03	0.06	−0.07	−0.01	1.00	0.19	0.08	0.06	−0.13	0.23
Natural	0.24	0.19	−0.13	−0.32	−0.11	0.04	0.17	1.00	0.07	−0.05	−0.39	0.16
Silver	0.41	0.08	0.11	−0.38	0.03	0.18	0.01	0.34	1.00	−0.05	0.17	0.08
Soybean	−0.50	0.11	−0.16	0.74	0.28	−0.06	0.03	−0.30	−0.35	1.00	−0.22	−0.10
Sugar	0.53	−0.01	0.30	−0.65	−0.35	0.21	0.04	0.32	0.46	−0.58	1.00	−0.12
Equity	0.05	0.16	−0.04	0.00	0.03	0.12	0.03	0.10	0.04	0.03	0.05	1.00
Before	0.89	0.41	0.34	−0.89	−0.12	0.45	0.19	0.68	0.56	−0.81	0.84	0.17
After	0.85	0.77	0.52	−0.79	−0.68	−0.14	−0.11	−0.43	0.31	−0.37	0.87	0.02

The correlations are high for the precious metals market, crude oil and the equity market. They are among the most relevant markets for institutional investors and should be the markets that we expect to show the highest degree of financial integration.

The curvature factor also exhibits different correlations in the two sub-samples, but they could be due to changing common factors for the commodity market. One key feature of financialization – a stronger integration with the equity and crude oil market – is not present for the curvature of the volatility term structure. We see especially high correlation for sugar, corn and soybeans, mostly with each other and copper. Sugar also displays high correlations within the softs sector. In summary, we see that the volatility term structure for commodity and equity markets is strongly integrated post-financialization.

With the effects of financialization on the commodity market, there might have been a substantial shift in spillovers. In order to investigate this, we conduct the spillover analysis separately for the pre- and post-financialization periods in Tables A6 and A7 of the Appendix. The test is the same as in Equation (2.7). We expect two opposing effects of the financialization on spillovers. First, we would expect larger spillovers, because we have more common factors that influence the commodity markets. Second, we would, on the other hand, expect lower spillovers, because more changes will occur contemporaneously, as the correlations in Table 2.9 indicate. In Table A7 for the post-financialization period we see that almost all out-of-sample R^2s are positive, while in Table A6 for the pre-financialization period, part of the coefficients are negative. The in-sample Wald test indicates stronger significance for the post-financialization period, which could just be a result of the lower power for the pre-financialization period. Post-financialization, the spillovers are more consistent across commodities and spillovers for the level from and to the equity market are larger than pre-financialization. However, for the level, spillovers within the commodity market decrease. This indicates, in combination with the correlations in Table 2.9, that due to similar investor groups and similar behavior, we see more contemporaneous movements of the commodity market and less lagged dependence. For spillovers in the slope and the curvature of the commodity term structure, we see that they actually increase after financialization. Those factors seem to be more influenced by short-term movements. The increase in common factors leads to more spillovers across commodity markets. We conclude that there are two effects that affect spillovers pre- and post-financialization: the increase in contemporaneous movements lowers spillovers for the level. For the slope and the curvature, the increase in common factors leads to higher spillovers overall.

2.3.5 Macroeconomic Announcements

A potential cause of the spillovers is information transmission. One commodity market will capture the macroeconomic or commodity-specific information earlier, which impacts the volatility term structure of other markets with a lag. A natural economic experiment is the investigation of scheduled macroeconomic news announcements. Savor and Wilson (2013, p. 343) state: "Investors do not know what the news will be, but they do know that there will be news. If asset prices respond to these news, the risk associated with holding the affected securities will be higher around announcements". If spillovers are larger following news announcements, then it is likely that one commodity market captures the information of the news first and this information will subsequently spill over to the other markets. Macroeconomic news announcements have been evaluated in the literature. Lucca and Moench (2015) find that the returns prior to scheduled news announcements are larger. Most recently, Wachter and Zhu (2018) find that the relation between market betas and expected returns are far stronger on announcement days.

To investigate the influence of information transmission on spillovers, we analyze the influence of scheduled macroeconomic news. We estimate the following regression:

$$
\begin{aligned}
PC_{i,t} =& a + \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} I_D \\
&+ \sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} I_D \\
&+ \sum_{l=1}^{p} \tau_l^1 PC_{j,t-l} I_N I_{Ann} + \sum_{l=1}^{p} \tau_l^2 PC_{j,t-l} I_T I_{Ann} + \sum_{l=1}^{p} \tau_l^3 PC_{j,t-l} I_D I_{Ann} + \epsilon_t \ .
\end{aligned}
\tag{2.9}
$$

$PC_{i,t}$ represents a PC of commodity i and $PC_{j,t}$ the PC of commodity j at time t. I_{Ann} is 1 when we have an announcement date. We test the null hypothesis of: $\tau_j^1 = \tau_j^2 = \tau_j^3 = 0$. If the Wald test is significant, scheduled macroeconomic news will affect the spillover from the day of the announcement. To investigate how large the contribution of macroeconomic news announcements is, we decompose the R^2 using the method by Lindeman, Merenda, and Gold (1980). This measure uses a simple unweighted average of average contributions of different models of different sizes. The measure sums up to the original R^2.

We use the following macroeconomic news announcement categories: Employment (E), Consumer Confidence (CC), CPI (CPI), Durable (D), Factory Orders (FO), Federal Funds Rate (FFR), GDP (GDP), Housing (H), Industrial production (IP), Initial Jobless Claims (IJC), International Trade (IT), ISM Manufacturing PMI (ISM-M), ISM N-Mfg PMI (ISM N-M), Retail Sales (RS) and Michigan Consumer Sentiment (M).

Table A8 of the Appendix shows the summary statistics of the macroeconomic announcements. We find the percentage overlap for announcement observations is overall modest. This is relevant, particularly because a large overlap of announcement makes it impossible to separate the impact between the impact of those events. For example factory orders and the employment situation report are reported on the same day 16% of the time. For only few announcement pairs is this share higher, and for the vast majority substantially lower.

Tables 2.10 and 2.11 report the significant macroeconomic spillovers at the 10% level with

Newey and West (1986) standard errors. Table 2.10 shows how many scheduled macroeconomic news events are significant for any commodity pair. Table 2.11 shows which macroeconomic news yield spillovers for the different commodities. The numbers indicate how many observations are significant in-and out-of-sample. In the parentheses below, the maximum (Table 2.10) or median (Table 2.11) additional R^2 relative to the total R^2 explained by spillovers is reported. We choose the maximum relative R^2 because it is more important to have an idea how much additional explanatory power the most important macroeconomic news announcements have for each commodity pair. This is still a conservative estimate of the overall influence of scheduled news events, because there are several different announcement types that create these spillovers. To get an idea how large the influence of each scheduled news announcement is, while avoiding any large observations distorting the reported results, we report the median in Table 2.11.

We find that spillovers are vastly enhanced for news announcement days. For the level, macroeconomic announcement days are responsible for up to 70% of the total R^2 of all spillovers. Most commodity pairs have at least one macroeconomic news event accounts for at least 15% of the spillovers for the level of the volatility term structure. The share is significantly larger for the slope and the curvature, where macroeconomic news account mostly for at least above 25% of the spillovers. This is because the slope and curvature are influenced more strongly by short-term movements.

In Table 2.11 we show which macroeconomic events trigger spillovers in the volatility term structure of commodities. In this table, we see the dominant effect of the initial jobless claims report, that seems to introduce increases in spillover effects throughout the commodity market. We find that most important for the commodity market are news announcements that influence consumer sentiment or income directly, for example the Michigan Consumer Sentiment Index, or housing sales. All markets show substantial increases in spillovers for certain macroeconomic news announcements. The same holds for the slope and the curvature.

Table 2.10: Information Transmission – News Announcements

This table displays the number of significant macroeconomic variables. The influence is estimated with a Wald test based on the following regression:

$$
\begin{aligned}
PC_t^{(k)} =& a + \sum_{j=1}^{p} \beta_j^1 PC_{t-j}^{(k)} I_N + \sum_{j=1}^{p} \beta_j^2 PC_{t-j}^{(k)} I_T + \sum_{j=1}^{p} \beta_j^3 PC_{t-j}^{(k)} I_D \\
&+ \sum_{j=1}^{p} \gamma_j^1 PC_{t-j}^{(l)} I_N + \sum_{j=1}^{p} \gamma_j^2 PC_{t-j}^{(l)} I_T + \sum_{j=1}^{p} \gamma_j^3 PC_{t-j}^{(l)} I_D \\
&+ \sum_{j=1}^{p} \tau_j^1 PC_{t-j}^{(l)} I_N I_{Ann} + \sum_{j=1}^{p} \tau_j^2 PC_{t-j}^{(l)} I_T I_{Ann} + \sum_{j=1}^{p} \tau_j^3 PC_{t-j}^{(l)} I_D I_{Ann} + \epsilon_t.
\end{aligned}
$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, of $\tau_j^1 = \tau_j^2 = \tau_j^3 = 0$. For each commodity pair, we count the number of macroeconomic news series that yield a significant Wald test at 10%. We use Newey and West (1986) standard errors with 10 lags. Panels A-C represent the values for various PCs. In parentheses we display the result of a decomposition of the R^2. The method was introduced by Lindeman et al. (1980). We use the maximum R^2 of spillovers after macroeconomic news announcements relative to the R^2s from spillovers overall.

Panel A - Level

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equities
Cocoa		6	6	5	6	4	8	3	3	2	2	3
Max. R^2 (%)		(13.62)	(54.53)	(29.01)	(30.52)	(21.42)	(20.81)	(46.20)	(17.46)	(30.01)	(12.16)	(29.44)
Coffee	4		6	9	7	7	7	4	4	5	5	8
Max. R^2 (%)	(13.23)		(40.52)	(27.61)	(45.45)	(32.55)	(43.04)	(15.57)	(6.35)	(71.55)	(27.65)	(34.31)
Copper	3	2		1	8	3	5	5	5	3	0	6
Max. R^2 (%)	(38.47)	(50.74)		(25.51)	(23.97)	(25.92)	(25.19)	(26.72)	(25.27)	(30.35)	(18.16)	(33.41)
Corn	6	5	5		6	6	7	6	7	7	9	4
Max. R^2 (%)	(25.65)	(53.50)	(24.85)		(26.13)	(20.29)	(24.60)	(28.88)	(25.38)	(29.27)	(31.02)	(24.62)
Cotton	5	5	5	4		8	5	1	5	4	1	7
Max. R^2 (%)	(30.78)	(54.99)	(24.47)	(43.48)		(24.09)	(24.63)	(44.18)	(40.99)	(38.30)	(36.79)	(27.28)
Crude	3	1	2	5	9		6	5	6	4	3	8
Max. R^2 (%)	(20.56)	(67.24)	(34.34)	(20.53)	(29.52)		(19.07)	(38.75)	(26.35)	(7.29)	(29.22)	(26.81)
Gold	4	6	7	7	6	6		5	7	3	6	9
Max. R^2 (%)	(21.25)	(24.20)	(25.36)	(24.56)	(25.19)	(20.27)		(21.61)	(20.75)	(10.52)	(23.96)	(24.44)
Natural	2	1	5	5	3	7	4		6	0	3	6
Max. R^2 (%)	(46.65)	(22.93)	(48.38)	(38.80)	(57.73)	(31.42)	(23.06)		(18.53)	(19.42)	(40.21)	(50.99)
Silver	4	1	5	4	4	9	3	3		2	1	6
Max. R^2 (%)	(10.95)	(7.73)	(25.41)	(25.17)	(24.81)	(24.45)	(20.07)	(10.82)		(5.81)	(6.55)	(27.19)
Soybean	3	4	5	4	7	4	4	5	4		2	6
Max. R^2 (%)	(18.72)	(62.66)	(28.12)	(25.43)	(25.70)	(5.89)	(10.46)	(15.30)	(5.79)		(13.92)	(17.29)
Sugar	4	8	7	9	12	5	8	7	3	4		8
Max. R^2 (%)	(20.21)	(44.64)	(40.13)	(54.50)	(44.59)	(28.21)	(37.24)	(47.43)	(20.45)	(28.78)		(36.48)
Equities	5	4	5	3	6	4	9	0	8	1	6	
Max. R^2 (%)	(25.44)	(33.98)	(25.16)	(24.94)	(25.25)	(25.64)	(24.69)	(33.45)	(22.99)	(16.71)	(26.47)	

to be continued on the following page

Panel B - Slope

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equities
Cocoa		4	5	5	6	8	6	10	8	6	4	9
Max. R^2 (%)		(29.13)	(64.64)	(28.12)	(64.52)	(72.10)	(61.00)	(32.70)	(60.95)	(34.69)	(40.59)	(31.18)
Coffee	3		4	8	9	5	9	11	5	2	12	8
Max. R^2 (%)	(24.74)		(26.46)	(25.09)	(38.03)	(34.16)	(37.45)	(29.37)	(52.14)	(23.29)	(25.87)	(52.57)
Copper	9	3		3	4	3	5	6	1	8	6	9
Max. R^2 (%)	(45.62)	(37.50)		(60.01)	(37.54)	(29.42)	(34.13)	(39.98)	(25.38)	(53.31)	(27.89)	(40.56)
Corn	6	6	8		8	4	10	6	6	9	9	11
Max. R^2 (%)	(31.27)	(26.73)	(48.32)		(24.62)	(43.81)	(26.09)	(52.72)	(42.13)	(24.60)	(25.98)	(41.91)
Cotton	12	3	5	1		4	5	6	8	2	9	8
Max. R^2 (%)	(57.24)	(31.99)	(40.15)	(26.04)		(77.84)	(56.77)	(50.66)	(76.24)	(11.19)	(36.03)	(67.62)
Crude	7	5	5	8	6		7	8	8	6	5	12
Max. R^2 (%)	(50.40)	(30.33)	(33.50)	(48.90)	(58.88)		(51.75)	(51.01)	(31.78)	(40.23)	(37.68)	(46.82)
Gold	6	5	9	7	9	11		4	10	5	11	14
Max. R^2 (%)	(44.38)	(22.70)	(42.58)	(33.30)	(54.93)	(61.09)		(29.61)	(24.89)	(26.98)	(26.19)	(47.03)
Natural	4	6	4	9	2	10	4		8	7	0	5
Max. R^2 (%)	(36.34)	(28.09)	(42.27)	(57.46)	(39.49)	(57.63)	(43.36)		(32.72)	(35.63)	(41.74)	(42.03)
Silver	7	7	12	5	6	10	8	5		5	7	12
Max. R^2 (%)	(53.40)	(46.82)	(29.06)	(50.95)	(68.03)	(48.55)	(30.71)	(32.38)		(57.25)	(27.06)	(40.16)
Soybean	8	10	5	7	7	6	3	6	7		11	10
Max. R^2 (%)	(43.86)	(20.99)	(48.35)	(24.51)	(12.94)	(26.34)	(31.77)	(29.71)	(74.76)		(29.30)	(53.87)
Sugar	8	6	8	8	6	6	9	7	14	8		7
Max. R^2 (%)	(61.60)	(26.96)	(28.79)	(25.49)	(31.36)	(41.18)	(25.68)	(42.58)	(28.07)	(33.03)		(39.98)
Equities	3	3	10	4	4	8	8	6	13	2	6	
Max. R^2 (%)	(33.38)	(39.12)	(49.44)	(48.44)	(64.41)	(53.31)	(45.88)	(52.84)	(36.27)	(70.78)	(51.17)	

Panel C - Curvature

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equities
Cocoa		13	8	8	1	10	5	13	4	9	2	10
Max. R^2 (%)		(28.74)	(27.69)	(28.66)	(38.69)	(33.52)	(57.80)	(74.14)	(27.41)	(27.31)	(26.21)	(66.72)
Coffee	10		9	3	6	11	4	9	7	10	3	10
Max. R^2 (%)	(34.03)		(82.08)	(72.95)	(65.13)	(45.17)	(54.62)	(57.82)	(32.49)	(35.45)	(46.45)	(57.71)
Copper	5	4		4	5	6	6	8	4	9	3	7
Max. R^2 (%)	(25.52)	(73.18)		(23.20)	(27.30)	(61.06)	(52.52)	(52.34)	(38.75)	(32.31)	(29.05)	(43.24)
Corn	6	3	6		5	6	5	9	10	5	6	7
Max. R^2 (%)	(25.22)	(50.16)	(25.16)		(17.68)	(87.30)	(35.18)	(71.63)	(20.81)	(22.32)	(25.90)	(42.88)
Cotton	5	5	7	7		8	4	5	1	2	4	7
Max. R^2 (%)	(47.79)	(23.94)	(33.48)	(17.73)		(65.22)	(24.30)	(73.59)	(29.74)	(16.92)	(23.22)	(54.80)
Crude	3	5	1	5	1		3	8	4	5	4	9
Max. R^2 (%)	(39.96)	(31.18)	(65.78)	(55.40)	(34.64)		(29.11)	(43.81)	(62.14)	(70.42)	(51.84)	(68.85)
Gold	6	3	3	3	4	9		9	6	3	5	9
Max. R^2 (%)	(51.19)	(76.88)	(60.64)	(31.25)	(34.93)	(87.36)		(51.60)	(44.42)	(50.09)	(39.99)	(66.83)
Natural	7	1	2	8	4	7	3		6	1	1	7
Max. R^2 (%)	(74.88)	(46.24)	(34.52)	(40.33)	(44.87)	(48.00)	(40.72)		(40.07)	(32.39)	(51.32)	(36.72)
Silver	4	8	9	7	4	8	7	7		9	4	11
Max. R^2 (%)	(28.45)	(26.44)	(38.25)	(25.98)	(33.45)	(88.36)	(36.23)	(58.32)		(43.85)	(38.22)	(45.39)
Soybean	4	7	8	9	3	6	5	5	9		3	9
Max. R^2 (%)	(21.23)	(26.66)	(22.74)	(22.19)	(15.60)	(43.93)	(27.51)	(24.02)	(37.82)		(27.60)	(51.28)
Sugar	4	4	5	10	6	8	8	6	12	10		9
Max. R^2 (%)	(30.85)	(62.04)	(38.85)	(24.03)	(22.97)	(41.35)	(37.31)	(63.57)	(29.03)	(31.35)		(83.37)
Equities	2	4	1	3	5	7	4	2	8	5	1	
Max. R^2 (%)	(73.89)	(64.73)	(51.68)	(71.53)	(69.64)	(87.99)	(48.37)	(55.57)	(42.59)	(68.32)	(74.43)	

Table 2.11: Information Transmission – News

This table displays the number of significant commodities that are influenced by the commodities of the horizontal axis. The influence is estimated with a Wald test based on the following regression:

$$\begin{aligned} PC_{i,t} = & a + \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} I_D \\ & + \sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} I_D \\ & + \sum_{l=1}^{p} \tau_l^1 PC_{j,t-l} I_N I_{Ann} + \sum_{l=1}^{p} \tau_l^2 PC_{j,t-l} I_T I_{Ann} + \sum_{l=1}^{p} \tau_l^3 PC_{j,t-l} I_D I_{Ann} + \epsilon_t \ . \end{aligned}$$

We test the null hypothesis, of $\tau_j^1 = \tau_j^2 = \tau_j^3 = 0$. For each commodity pair, we count the number of macroeconomic news series that yield a significant Wald test at the 10% level. We use Newey and West (1986) standard errors with 10 lags. In parentheses we display the result of a decomposition of the R^2. We use the median R^2 of spillovers after macroeconomic news announcements relative to the R^2 from spillovers overall. The method was introduced by Lindeman et al. (1980). Panels A-C represent the values for various PCs. The abbreviations are presented in Section 2.3.5.

Panel A - Level												
	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equities
E	4	3	6	4	7	4	6	4	2	1	5	3
Median R^2 (%)	(10.54)	(12.06)	(12.99)	(13.85)	(12.54)	(11.82)	(12.17)	(12.18)	(10.91)	(7.00)	(13.25)	(13.38)
CC	2	3	5	3	7	1	4	4	7	1	2	6
Median R^2 (%)	(13.10)	(14.09)	(15.93)	(14.76)	(14.87)	(13.16)	(13.25)	(12.39)	(11.64)	(6.30)	(13.23)	(15.32)
CPI	5	3	4	4	4	5	4	2	4	7	1	3
Median R^2 (%)	(11.92)	(11.55)	(13.83)	(13.68)	(13.66)	(12.36)	(11.10)	(11.57)	(11.53)	(6.24)	(10.44)	(14.39)
D	1	4	4	6	4	4	5	1	6	1	1	7
Median R^2 (%)	(11.56)	(12.67)	(14.25)	(13.87)	(13.12)	(12.03)	(11.81)	(10.57)	(11.58)	(5.62)	(14.25)	(14.54)
FO	3	0	5	4	8	4	5	2	3	2	6	4
Median R^2 (%)	(12.25)	(12.19)	(14.48)	(13.55)	(13.84)	(12.75)	(12.41)	(13.20)	(11.44)	(6.55)	(13.62)	(13.63)
FFR	2	4	6	3	6	7	4	4	6	2	2	3
Median R^2 (%)	(10.31)	(13.14)	(13.84)	(13.77)	(15.62)	(12.37)	(12.29)	(10.73)	(11.78)	(7.35)	(10.06)	(12.58)
GDP	1	4	1	1	3	4	4	3	3	1	2	4
Median R^2 (%)	(10.67)	(13.86)	(14.32)	(14.07)	(15.06)	(13.12)	(12.99)	(13.37)	(11.22)	(7.68)	(14.12)	(15.23)
H	3	2	2	2	4	2	5	2	4	1	1	7
Median R^2 (%)	(20.56)	(21.66)	(24.15)	(23.32)	(22.90)	(22.38)	(22.48)	(20.63)	(19.90)	(11.01)	(21.75)	(24.44)
IP	2	3	2	0	5	2	4	3	2	1	1	2
Median R^2 (%)	(11.63)	(9.91)	(13.35)	(13.05)	(13.86)	(12.21)	(11.70)	(12.23)	(11.46)	(6.32)	(10.76)	(13.89)
IJC	7	2	7	8	7	8	3	8	3	5	7	8
Median R^2 (%)	(19.85)	(44.64)	(28.12)	(20.53)	(26.13)	(19.45)	(15.15)	(28.88)	(18.53)	(28.78)	(24.67)	(27.28)
IT	2	3	4	4	4	4	6	1	7	4	1	4
Median R^2 (%)	(11.59)	(11.63)	(12.11)	(13.94)	(13.88)	(12.74)	(11.74)	(12.60)	(11.71)	(6.08)	(11.97)	(14.06)
ISM-M	4	3	4	6	6	5	3	3	4	3	3	5
Median R^2 (%)	(14.51)	(13.48)	(14.67)	(15.08)	(15.66)	(13.03)	(14.14)	(13.43)	(12.12)	(6.37)	(14.00)	(16.00)
ISM-N-M	2	2	5	7	6	5	6	0	2	2	2	7
Median R^2 (%)	(13.02)	(11.67)	(14.85)	(14.13)	(14.37)	(13.15)	(14.16)	(14.13)	(11.81)	(6.90)	(14.07)	(14.11)
RS	1	4	1	0	1	2	1	4	1	0	2	2
Median R^2 (%)	(11.25)	(14.23)	(12.47)	(13.08)	(13.70)	(12.57)	(11.57)	(12.57)	(11.43)	(8.58)	(10.96)	(13.76)
M	4	3	2	4	2	6	6	3	4	4	2	6
Median R^2 (%)	(21.25)	(20.78)	(24.62)	(24.94)	(25.19)	(21.14)	(22.91)	(20.49)	(20.75)	(11.09)	(23.32)	(24.01)

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Panel B - Slope												
	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equities
E	8	4	3	4	3	4	6	2	9	3	5	8
Median R^2 (%)	(21.62)	(14.08)	(21.53)	(16.27)	(21.99)	(17.94)	(17.48)	(24.22)	(19.79)	(16.78)	(15.52)	(12.01)
CC	2	4	4	4	7	6	4	7	7	4	6	6
Median R^2 (%)	(24.86)	(16.51)	(18.20)	(13.78)	(18.99)	(15.83)	(14.92)	(20.78)	(17.20)	(8.79)	(15.24)	(14.84)
CPI	3	3	5	5	0	6	4	6	2	4	5	7
Median R^2 (%)	(19.90)	(13.95)	(16.40)	(15.88)	(16.84)	(16.81)	(16.35)	(18.87)	(15.19)	(12.76)	(13.62)	(19.32)
D	6	5	6	7	7	4	10	8	8	6	5	6
Median R^2 (%)	(16.20)	(15.83)	(17.59)	(14.18)	(24.21)	(15.71)	(14.39)	(21.31)	(16.03)	(12.95)	(15.41)	(18.69)
FO	8	4	4	6	9	4	6	7	9	4	8	4
Median R^2 (%)	(18.11)	(16.82)	(20.64)	(17.55)	(16.65)	(14.56)	(18.72)	(12.70)	(16.88)	(13.59)	(18.93)	(14.20)
FFR	9	3	5	3	6	5	5	3	8	7	7	10
Median R^2 (%)	(12.54)	(12.03)	(16.36)	(12.52)	(16.92)	(18.78)	(14.85)	(19.16)	(26.40)	(16.28)	(16.72)	(24.10)
GDP	8	6	7	4	4	5	6	4	7	1	5	9
Median R^2 (%)	(13.53)	(12.36)	(19.77)	(16.25)	(27.57)	(13.14)	(14.47)	(13.33)	(18.57)	(9.37)	(15.97)	(14.95)
H	2	2	0	3	1	3	3	6	6	1	6	6
Median R^2 (%)	(24.76)	(25.87)	(23.49)	(25.49)	(30.30)	(26.69)	(24.42)	(27.28)	(24.18)	(18.11)	(23.78)	(25.94)
IP	2	4	5	5	3	6	5	6	3	3	4	10
Median R^2 (%)	(21.70)	(14.83)	(14.55)	(15.40)	(18.97)	(17.22)	(15.59)	(16.55)	(15.55)	(19.68)	(17.10)	(18.96)
IJC	6	5	10	6	4	10	9	4	7	3	3	9
Median R^2 (%)	(43.86)	(26.96)	(39.97)	(33.30)	(23.93)	(48.55)	(30.71)	(32.70)	(31.78)	(33.03)	(23.45)	(40.56)
IT	2	5	4	4	4	5	2	6	2	8	5	7
Median R^2 (%)	(15.19)	(12.26)	(13.57)	(17.38)	(22.10)	(16.79)	(18.14)	(18.46)	(17.89)	(14.33)	(16.93)	(15.29)
ISM-M	6	2	3	4	4	5	5	6	7	3	8	5
Median R^2 (%)	(14.10)	(14.65)	(18.03)	(17.57)	(23.98)	(16.52)	(18.86)	(17.75)	(25.47)	(14.66)	(17.95)	(18.18)
ISM-N-M	5	5	6	3	4	7	3	5	6	3	4	6
Median R^2 (%)	(20.30)	(16.43)	(20.23)	(17.12)	(16.32)	(15.25)	(17.95)	(16.65)	(18.26)	(18.29)	(17.78)	(11.97)
RS	2	3	7	5	5	2	3	4	3	6	5	8
Median R^2 (%)	(23.31)	(15.45)	(14.36)	(14.92)	(27.66)	(16.39)	(16.47)	(18.86)	(18.04)	(14.19)	(14.58)	(17.54)
M	4	3	6	2	6	3	3	1	4	4	4	4
Median R^2 (%)	(25.82)	(22.03)	(24.06)	(25.09)	(29.82)	(25.56)	(27.32)	(29.37)	(26.23)	(21.94)	(24.85)	(24.54)

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Panel C - Curvature

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equities
E	3	3	6	6	2	10	5	5	4	3	4	8
Median R^2 (%)	(14.20)	(14.19)	(15.35)	(13.35)	(12.53)	(19.97)	(14.15)	(17.24)	(17.33)	(11.17)	(14.12)	(20.18)
CC	4	4	2	4	4	5	0	6	5	5	4	8
Median R^2 (%)	(14.96)	(16.25)	(16.65)	(14.22)	(12.49)	(19.40)	(13.96)	(15.40)	(16.01)	(12.23)	(14.44)	(17.23)
CPI	5	4	6	2	2	4	1	5	6	5	2	7
Median R^2 (%)	(13.88)	(14.07)	(15.19)	(14.57)	(13.22)	(16.19)	(17.29)	(14.51)	(14.57)	(16.51)	(13.30)	(26.56)
D	5	3	7	5	4	6	5	7	8	5	4	9
Median R^2 (%)	(15.31)	(10.76)	(18.95)	(14.71)	(11.91)	(18.73)	(17.34)	(13.32)	(13.21)	(15.76)	(13.40)	(18.18)
FO	3	4	6	4	7	6	6	5	7	2	2	8
Median R^2 (%)	(15.20)	(16.23)	(19.56)	(13.04)	(14.23)	(24.47)	(13.98)	(16.07)	(18.01)	(9.43)	(14.94)	(21.99)
FFR	6	4	4	7	4	6	2	3	4	5	3	7
Median R^2 (%)	(10.70)	(10.60)	(18.03)	(12.64)	(7.69)	(25.20)	(16.45)	(15.20)	(13.69)	(13.57)	(11.35)	(18.06)
GDP	5	5	7	8	2	4	4	7	4	6	3	7
Median R^2 (%)	(14.61)	(14.25)	(15.38)	(10.09)	(11.00)	(19.29)	(18.85)	(15.42)	(16.79)	(17.04)	(12.59)	(17.50)
H	2	2	1	3	3	7	2	4	3	5	1	2
Median R^2 (%)	(25.63)	(25.76)	(27.69)	(25.98)	(23.06)	(26.51)	(24.30)	(24.48)	(20.94)	(30.24)	(25.90)	(23.75)
IP	4	3	3	4	2	6	3	3	3	6	1	2
Median R^2 (%)	(13.98)	(17.29)	(18.17)	(15.55)	(13.64)	(24.12)	(21.59)	(17.43)	(18.69)	(21.35)	(16.83)	(30.19)
IJC	2	7	3	7	5	9	5	6	3	5	5	7
Median R^2 (%)	(30.85)	(46.24)	(33.48)	(21.71)	(33.45)	(61.06)	(26.78)	(57.82)	(32.35)	(12.87)	(29.05)	(51.28)
IT	5	6	4	4	2	5	5	6	7	6	0	8
Median R^2 (%)	(15.23)	(17.60)	(19.69)	(15.45)	(15.24)	(24.43)	(20.61)	(16.67)	(15.94)	(17.52)	(13.71)	(22.55)
ISM-M	3	3	4	2	2	1	3	8	4	3	3	4
Median R^2 (%)	(13.27)	(14.96)	(14.98)	(14.54)	(13.87)	(24.94)	(23.46)	(20.65)	(14.07)	(14.31)	(14.48)	(16.47)
ISM-N-M	2	2	2	3	4	8	8	4	5	1	2	6
Median R^2 (%)	(14.16)	(16.03)	(17.27)	(15.29)	(12.57)	(20.59)	(27.57)	(19.08)	(15.81)	(11.34)	(14.36)	(26.75)
RS	2	5	3	3	0	4	2	5	4	5	1	7
Median R^2 (%)	(16.17)	(18.38)	(18.96)	(17.76)	(15.46)	(24.59)	(19.97)	(20.08)	(16.84)	(20.67)	(15.91)	(25.71)
M	5	2	1	5	1	5	3	7	4	6	1	5
Median R^2 (%)	(22.37)	(22.26)	(25.16)	(23.20)	(21.06)	(26.81)	(25.14)	(22.92)	(23.10)	(24.80)	(24.18)	(26.56)

To summarize, we find that macroeconomic news announcements induce a substantial amount of spillovers. There this is thus evidence of information transmission in commodity markets. Moreover, news announcements associated with consumer income or sentiment have a particularly large influence on spillovers for the entire term structure.

2.4 Robustness

In this section, we examine the robustness of our findings. We change several specifications. First, we also conduct the main analysis with the SVIX by Martin (2017), the summary table is presented in Table A9 of the Appendix. The author claims that the SVIX is the true measure of variance, while the VIX is a risk-neutral measure of entropy. The SVIX and the VIX differ by the weighting scheme imposed on the different option prices. The $SVIX^2$ is described as:

$$SVIX_t^2 = \frac{2R_t^f}{(T-t)F_{t,T}^2}\left[\int_0^{F_{t,T}} \mathrm{p}_{t,T}(K)dK + \int_{F_{t,T}}^{\infty} \mathrm{c}_{t,T}(K)dK\right].$$

The results for the SVIX, presented in Table A10 of the Appendix, show a more consistently positive dependence between commodity markets than for the VIX. This underlines its interpretation as the variance, while the VIX might overweigh the negative tails. This probably leads to more erratic movements in the term structure of the VIX, compared to that of the SVIX, which enables us to uncover even more spillovers. The dynamics are, however, similar compared to the dynamics observed for the VIX. Our main conclusions remain unchanged.

Second, we define the PCs not via an eigenvalue decomposition but parametrically. Aligning with the representation of each component, we use for the first PC the average over all maturities. For the second PC we use the difference between the short-term volatility and the long-term volatility and for the third PC we use the difference between the medium volatility and the short- and long-term volatility:

$$
\begin{aligned}
PC_1 =& \frac{1}{6}(VIX_1 + VIX_2 + VIX_3 + VIX_6 + VIX_9 + VIX_{12}) \ , \\
PC_2 =& VIX_1 - VIX_{12} \ , \\
PC_3 =& - VIX_1 + 2VIX_6 - VIX_{12} \ .
\end{aligned}
$$

For the parametric specification of the PCs in Table A11 of the Appendix, we obtain very similar results. The dynamics differ more for higher order components, for which the correlation decreases. This behavior is to be expected due to the high correlation between both specifications, of an average over 95% for the first component, 85% for the second component and 60% for the third PC.

Finally, we change the estimation level of the VaR from 5% to 1%. The results are in Table A12 of the Appendix. Changing the VaR from 5% to the 1% results in different periods being defined as distress, tranquil and normal periods. In periods when the entire commodity market has been under large distress, the VaR will be high only for the most extreme tail events. With the new definition of the VaR, the new time series shows an estimate of the 1% most extreme events and the dummy variables change slightly. But the change does not alter the previous results of the spillover effects. In particular for the level, the results are very similar. For the slope and the curvature, a change in the dummy variables has a larger effect; however, the results are still qualitatively similar.

2.5 Conclusion

Investigating the term structure of option-implied volatilities, we address the following questions: What are the macroeconomic determinants of the volatility term structure? How high is the interdependence in the commodity market, and why is there interdependence? How has the volatility term structure changed due to financialization?

We uncover several results. Macroeconomic variables are an important determinant, in particular for the level of the volatility term structure: speculation and employment influence the level the most. We also show that it is important to consider the cross-sectional variation of commodity markets when aiming to predict future volatility. Observing the rich dynamics of the volatility term structure reveals the benefit of studying the entire volatility term structure. Financialization has led to an increase in contemporaneous movement, which leads to a decrease in long-term spillovers. Spillovers of a short-term nature increase due to the larger number of common factors. Finally, we find that spillovers can, to a large extent, be ascribed to information transmission. Spillovers are substantially stronger when related to macroeconomic news announcements.

As a result, for derivative pricing or risk assessment in the commodity market, it is necessary to study the market as a whole. Fundamental factors can capture a part of the volatility term structure. A better volatility forecast will improve production planning, inventory decisions and risk management.

A1 Appendix

A1.1 Additional Figures

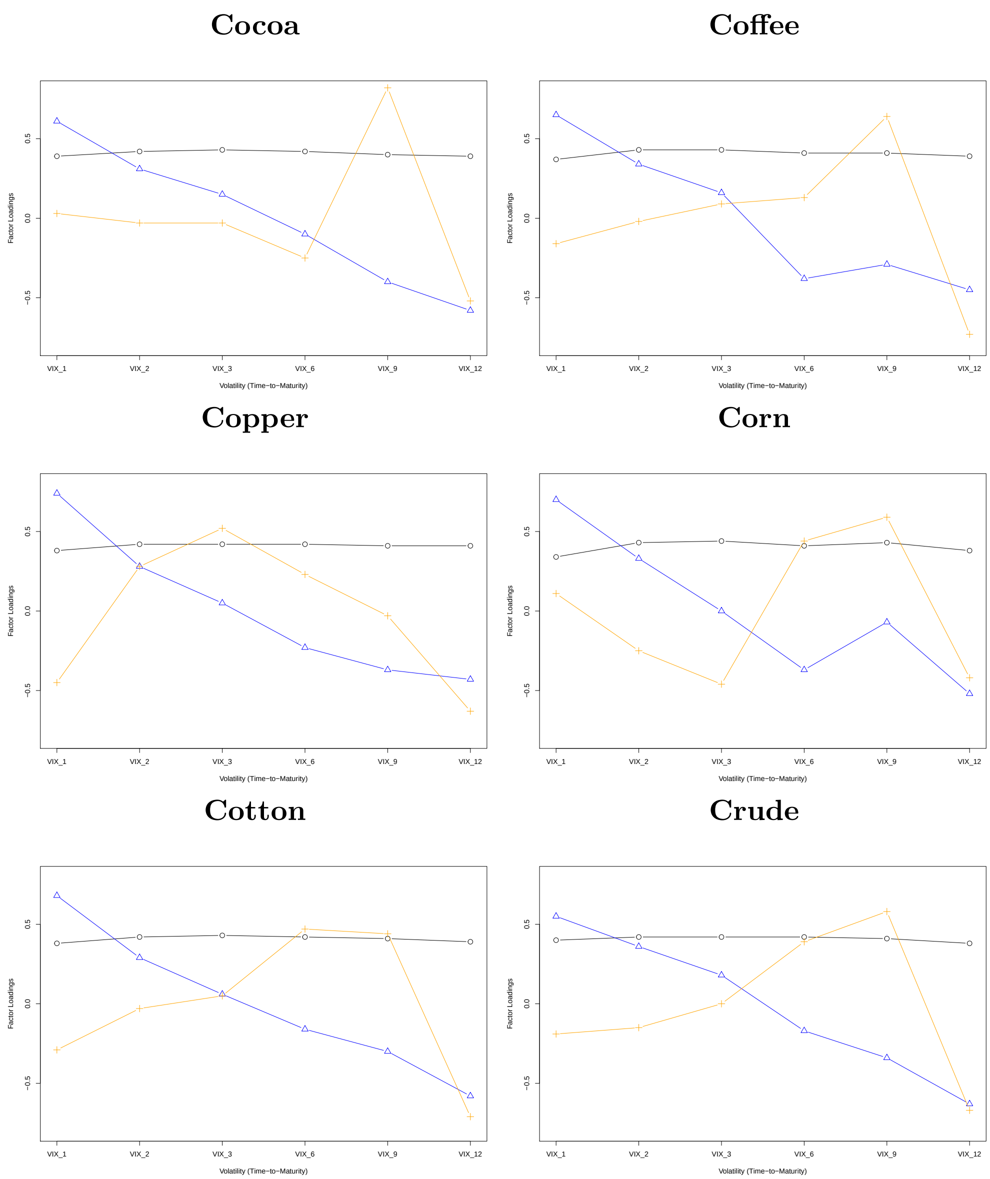
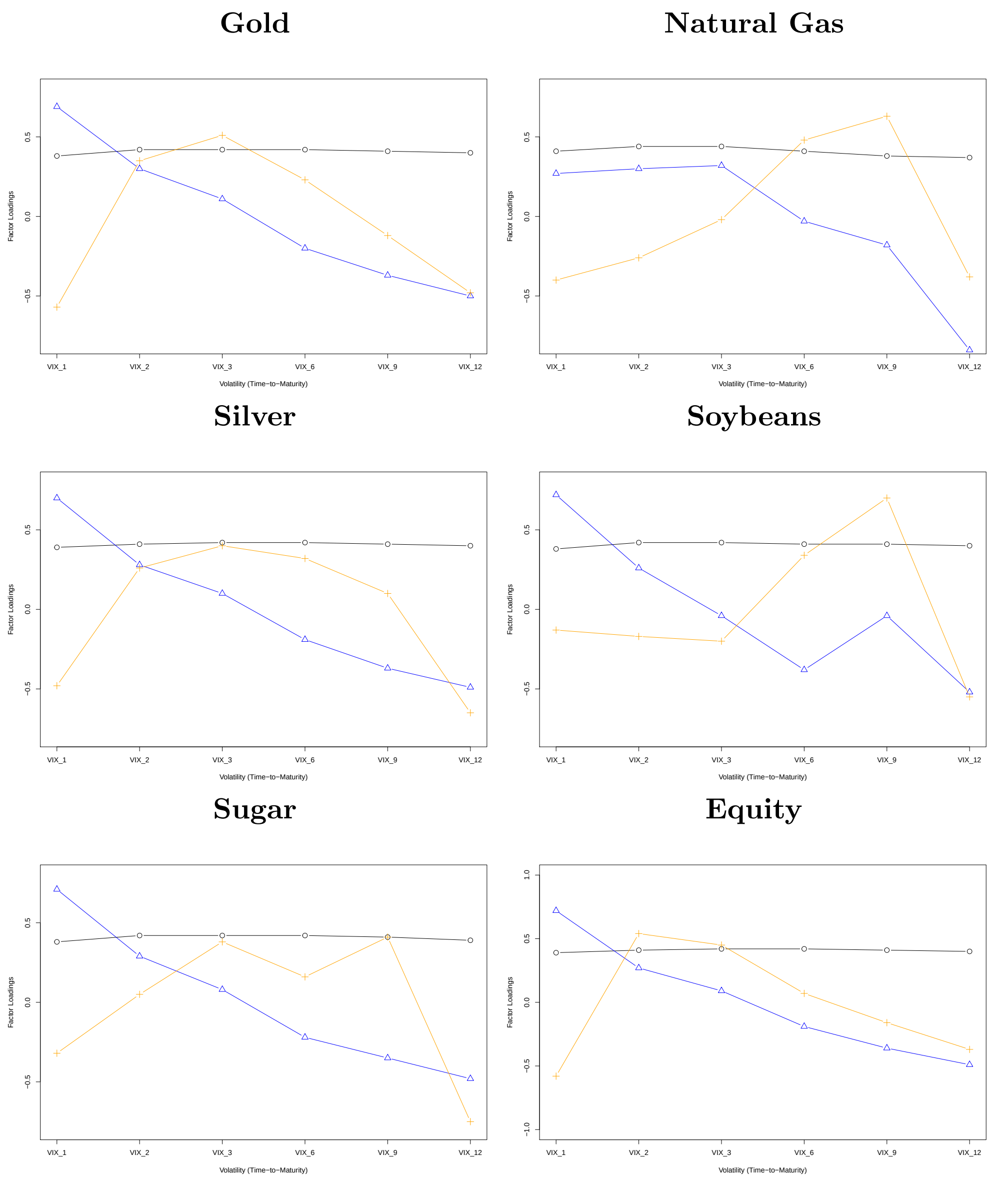


Figure A1: Principal Component Factor loadings

This figure shows the factor loadings of the first three PCs for each commodity. The level factor uses a black line with circles as dots, the slope is presented by a blue line and a triangle and the curvature is an orange line with a plus.



Continued Figure A1

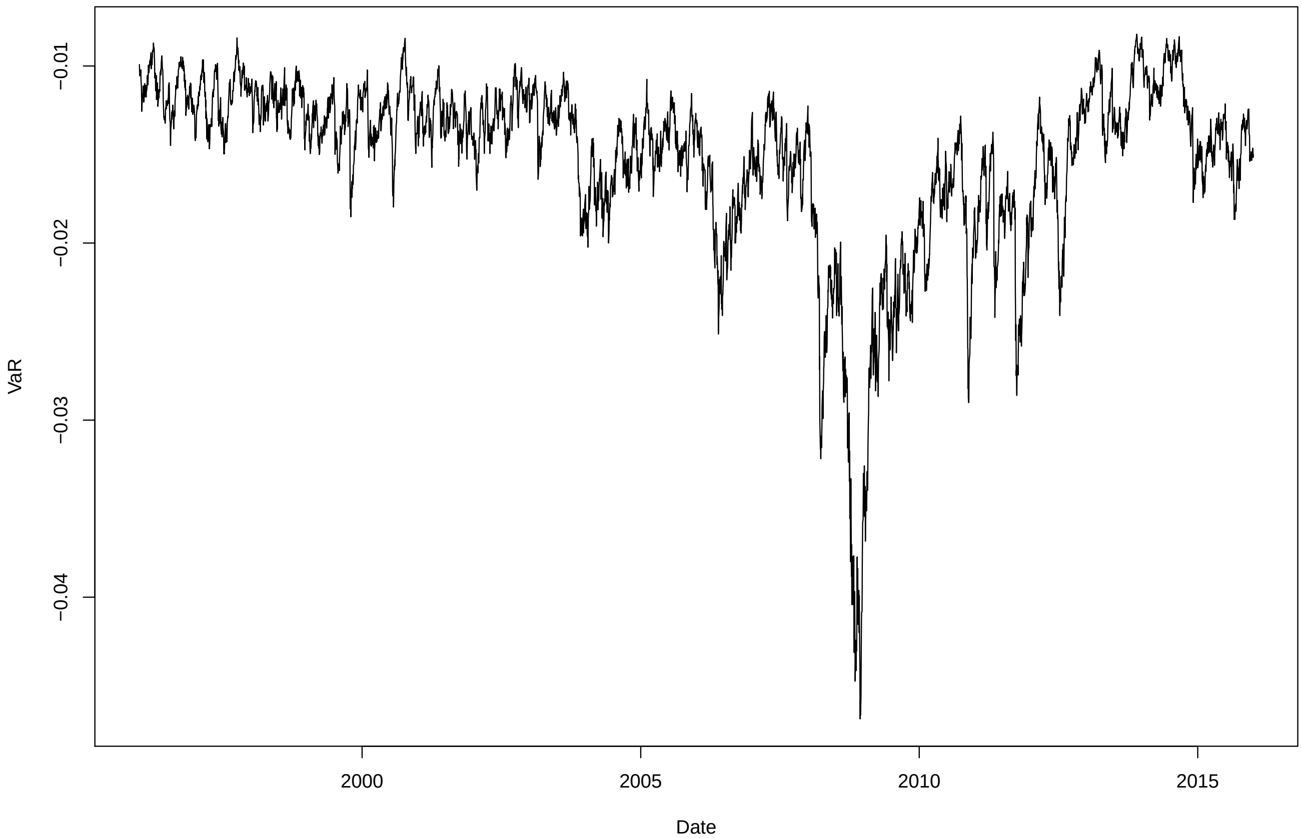


Figure A2: 5% Value at Risk (VaR) of an Equally Weighted Portfolio of All Commodities
The VaR estimation follows the estimation of Engle and Manganelli (2004). This estimation captures volatility clustering and can be constructed entirely out-of-sample.

A1.2 Additional Tables

Table A1: Data Sources

This table presents the data sources. Panel A introduces the futures dataset. Panel B presents macroeconomic variables as in Stock and Watson (2012). Panel C introduces the series of macroeconomic announcements. In Panel B we indicate the transformation method for the time series. We present the transformation codes in Table A2. An explanation for the numbers can be found in Table A2. Abbreviations are: St. Louis Federal Reserve Economic Data (FRED), Commodity Futures Trading Commission (CFTC), Department of Energy (DOE), Intercontinental Exchange (ICE), U.S. Department of Agriculture (USDA), U.S. Department of Labor (DOL), University of Michigan (UM), Federal Reserve (FED), Archival FRED (ALFRED), Institute of Supply Management (ISM), United States Census (Census), New York Mercantile Exchange (NYMEX), New York Commodity Exchange (COMEX), Chicago Board of Trade (CBOT) and seasonally adjusted (SA).

Panel A	Sector	Symbol	Commodity	Exchange
	Softs	CC	Cocoa	ICE
		KC	Coffee	ICE
		CT	Cotton	ICE
		SB	Sugar	ICE
	Metals	HG	Copper	NYMEX/COMEX
		GC	Gold	NYMEX/COMEX
		SI	Silver	NYMEX
	Energies	CL	WTI Crude Oil	NYMEX
		NG	Natural Gas	NYMEX
	Agricultural	C	Corn	CBOT
		S	Soybeans	CBOT
Panel B	Name	T	Source	Description
GDP components	Cons-Dur	5	FRED	SA
	Cons-NonDur	5	FRED	SA
	Cons-Serv	5	FRED	SA
	Exports	5	Datastream	
	Imports	5	Datastream	
Industrial production	IP: cons dble	5	FRED	2007=100, SA
	IP: cons nondble	5	FRED	2007=100, SA
	IP: bus eqpt	5	FRED	2007=100, SA
	IP: dble mats	5	FRED	2007=100, SA
	IP: nondble mats	5	FRED	2007=100, SA
	IP: mfg	5	FRED	2007=100, SA
	IP: fuels	5	FRED	2007=100, SA
	NAPM prodn	1	FRED	SA; Discontinued in 2016-05
	Capacity Util	1	FRED	SA
Employment	Emp: mining	5	FRED	SA
	Emp: const	5	FRED	SA
	Emp: dble gds	5	FRED	SA
	Emp: nondbles	5	FRED	SA
	Emp: services	5	FRED	SA
	Emp: TTU	5	FRED	SA
	Emp: wholesale	5	FRED	SA
	Emp: retail	5	FRED	SA
	Emp: FIRE	5	FRED	SA
	Emp: Govt	5	FRED	SA
	Emp: Hours	5	FRED	2002=100, SA
	Avg hrs	1	FRED	SA
	Overtime: mfg	2	FRED	SA

to be continued on the following page

	Name	T	Source	Description
Consumer expectations	Consumer expect	2	FRED	1966; Q1=100
Housing	HStarts: NE	4	FRED	
	HStarts: MW	4	FRED	
	HStarts: S	4	FRED	
	HStarts: W	4	FRED	
Unemployment rate	U: all	2	FRED	SA
	U: mean	2	FRED	SA
	U: < 5 wks	5	FRED	SA
	U: 5-14 wks	5	FRED	SA
	U: 15+ wks	5	FRED	SA
	U: 15-26 wks	5	FRED	SA
	U: 27+ wks	5	FRED	SA
Business inventories	PMI	1	FRED	SA
	NAPM new orders	1	FRED	SA
	NAPM vendor del	1	FRED	SA
	NAPM Invent	1	FRED	SA
	Orders (ConsGoods)	5	FRED	SA
	Orders (NDCap-Goods)	5	FRED	SA
Prices	CPI-core	6	FRED	1982-84=100; SA
	PCED	6	FRED	2009=100; SA
Money	M1	6	FRED	SA
	M2	6	FRED	SA
	MB	6	FRED	SA
	Reserves tot.	6	FRED	
	BUSLOANS	6	FRED	SA
	Cons credit	6	FRED	SA
Interest rates	FedFunds	5	FRED	
	3mo T-bill	5	FRED	
	6mo T-bill	5	FRED	
Wages	AHE: const	5	FRED	SA
	AHE: mfg	5	FRED	SA
Exchange rates	Ex rate: avg	5	FRED	1973-03=100
	Ex rate: Switz	5	FRED	
	Ex rate: Japan	5	FRED	
	Ex rate: UK	5	FRED	
	Ex rate: Canada	5	FRED	
Stock prices	S&P 500	5	Datastream	1973-03=100
	DJIA	5	Datastream	
Financial conditions	ADS	1	FRED	
	Sentiment	1	FRED	
	Baltic Dry Index	1	FRED	
Commodity volatility	CRBSPOT	1	Datastream	
Cocoa	073732, 083731	2	CFTC	1996-2016; Speculation from CFTC dataset
Coffee	085691, 085692	2	CFTC	1996-2016; Speculation from CFTC dataset
Cotton	067651	2	CFTC	1996-2016; Speculation from CFTC dataset
Sugar	080732	2	CFTC	1996-2016; Speculation from CFTC dataset
Corn	002601, 002602	2	CFTC	1996-2016; Speculation from CFTC dataset
Soybeans	005601, 005602	2	CFTC	1996-2016; Speculation from CFTC dataset
Gold	088691, 088606	2	CFTC	1996-2016; Speculation from CFTC dataset
Silver	084691, 084605	2	CFTC	1996-2016; Speculation from CFTC dataset
Copper	085691, 085692	2	CFTC	1996-2016; Speculation from CFTC dataset
Natural gas	023651	2	CFTC	1996-2016; Speculation from CFTC dataset
Crude oil	067651	2	CFTC	1996-2016; Speculation from CFTC dataset
Inventory	Cocoa	5	ICE	Cocoa monthly total stocks from Jan 1986 until Dec 2016
	Coffee	5	ICE	Coffee monthly total stocks from Nov 1996 until Dec 2016

to be continued on the following page

	Name	T	Source	Description
	Cotton	5	ICE	Cotton month-end total stocks from Aug 2002 until Dec 2016
	Sugar	5	USDA	Sugar total quarterly stocks[a] from March 1990 until Dec 2016
	Corn	5	USDA	Corn total quarterly stocks[a] from Dec 1987 until Dec 2016
	Soybeans	5	USDA	Soybeans total quarterly stocks[a] Dec 1980 until Dec 2016
	Gold	5	COMEX	Gold total monthly stocks via Datastream from July 2002 until Dec 2016
	Silver	5	COMEX	Silver total monthly stocks via Datastream from July 2002 until Dec 2016
	Copper	5	LME	Copper monthly stocks in LME warehouses from Jan 1970 until Dec 2016
	Natural gas	5	EIA	Natural Gas monthly stocks from Jan 1979 until Dec 2016
	Crude oil	5	EIA	Crude Oil and Petroleum products month-end stocks from Jan 1990 until Dec 2016
	VRP	1	Webpage[3]	Difference between the risk-neutral and objective expectations of realized variance
Panel C				
Employment Situation Report		1	DOL	https://www.bls.gov/bls/archived_sched.htm
Consumer Confidence Index		1	Conference Board	https://www.conference-board.org/data/consumerconfidence.cfm
CPI		1	DOL	https://www.bls.gov/bls/archived_sched.htm
Durable Goods	Advance Report on Durable Goods Manufacturers' Shipments, Inventories, and Orders	1	Census	https://www.census.gov/manufacturing/m3/about_the_surveys/index.html
Factory Orders	Manufacturers' Shipments, Inventories, and Orders	1	Census	https://www.census.gov/manufacturing/m3/about_the_surveys/index.html
Federal Funds Rate		1	FED	https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm
GDP[b]		1	ALFRED	https://alfred.stlouisfed.org/release?rid=53
Housing[c]		1	Census	https://www.census.gov/construction/nrs/historical_data/historic_releases.html
Industrial Production	Industrial Production and Capacity Utilization - G.17	1	FED	https://www.federalreserve.gov/releases/g17/release_dates.htm
Initial Jobless Claims		1	ALFRED	https://alfred.stlouisfed.org/release/downloaddates?rid=180
International Trade	FT900: U.S. International Trade in Goods and Services	1	Census	https://www.census.gov/foreign-trade/Press-Release/ft900_index.html
ISM Manufacturing PMI		1	ISM	https://www.instituteforsupplymanagement.org/ISMReport/content.cfm?ItemNumber=10745&SSO=1
ISM N-Mfg PMI		1	ISM	https://www.instituteforsupplymanagement.org/ISMReport/content.cfm?ItemNumber=10745&SSO=1
Retail Sales[d]	Monthly Retail Trade	1	Census	https://www.census.gov/retail/mrts/historic_releases.html
Michigan Consumer Sentiment[e]	University of Michigan/Surveys of Consumers	1	UM	https://data.sca.isr.umich.edu/survey-info.php

[a]The weekly grain series was discontinued in Aug 26 2014 by the USDA, the National Agricultural Statistics Service (NASS) issues a quarterly series instead.

[b]Includes the advance, second estimate and final estimate.

[c]Includes residential construction and sales.

[d]We choose the later date, if the announcement is split on two dates.

[e]Includes both preliminary and final announcements.

Table A2: Data Handling

This table presents category codes and data transformations, following Stock and Watson (2012), presented in Table A1. Z_t denotes the raw series and X_t the transformed series.

Code	X_t
1	Z_t
2	$Z_t - Z_{t-1}$
3	$(Z_t - Z_{t-1}) - (Z_{t-1} - Z_{t-2})$
4	$ln(Z_t)$
5	$ln(\frac{Z_t}{Z_{t-1}})$
6	$ln(\frac{Z_t}{Z_{t-1}}) - ln(\frac{Z_{t-1}}{Z_{t-2}})$

Table A3: Spillovers Between Different Markets – Level Factor

This table presents in-sample and out-of-sample results for spillover tests for the level of the volatility term structure. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = 0$ ($H_0 : \gamma_u^2 = 0$, $H_0 : \gamma_u^3 = 0$) for normal (tranquil, distressed) periods. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,**,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Normal

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		1.20**	**0.10**	**0.94**	**1.63**	**0.67***	**1.17**	**0.54**	**1.14**	**0.23**	**0.94**	**0.40****
Coffee	**0.47**		**0.12**	**0.30****	**1.27**	**1.39**	**0.14**	**1.54**	**0.30**	0.05	**0.34**	**0.41**
Copper	**1.00**	**0.14**		**0.52**	**0.46**	**0.75**	**0.96****	**0.10**	**0.74****	**0.46**	**0.82**	**0.42**
Corn	**1.23**	**0.64**	**0.33**		−0.04	**0.58**	**0.77**	**0.40**	**0.92**	**0.39****	**1.04**	**0.34**
Cotton	**0.19**	**0.25**	**0.27**	**0.64****		**0.48****	**0.26**	**0.19**	**0.71**	**0.66****	**0.76*****	**0.16**
Crude	**0.30**	**0.52***	**0.96**	**0.59**	**1.32**		**0.66**	**0.38**	**0.74**	**0.77**	**1.11**	**1.09***
Gold	**0.41****	**0.34**	**0.84**	**0.57**	**0.81**	**0.60*****		**1.15**	**0.88**	**0.12**	**0.19**	**0.54*****
Natural	**0.13**	**0.77***	−0.16	**1.33***	**2.39****	**0.46**	−1.39		**0.25**	**1.70**	−0.18	**0.52***
Silver	**0.40**	**0.27**	**0.85**	**0.44**	**0.65****	**2.04*****	**0.60*****	**0.29*****		−0.10	**0.61**	**0.80****
Soybean	**0.42*****	−0.23	**1.06**	**0.63**	**1.09**	**0.58**	**0.42**	**1.66**	0.07		**0.44**	**0.31**
Sugar	**0.68**	**0.13**	**0.33**	**0.91**	**0.98**	**1.49**	**0.24**	**0.09**	**0.77**	**0.15****		**0.18**
Equity	−0.05	−0.45*	**0.20**	**0.10**	−0.75**	**0.39**	**0.11**	**0.62**	**0.65**	**0.15**	**0.24**	

Panel B - Tranquil

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.11**	**0.13**	**0.94**	**1.23*****	**1.57*****	**1.29*****	**0.25**	**0.22*****	**0.49**	−0.10***	**0.30*****
Coffee	**0.68**		**0.11**	**0.32**	**0.63**	**1.10**	**0.13**	**0.63**	**−0.05*****	**0.55**	**0.49**	0.04
Copper	**0.20*****	**0.20**		**0.28**	**0.20***	**0.25***	**0.29**	**0.20****	**0.67*****	**0.59****	**0.62**	**0.30**
Corn	**0.53**	**0.17**	**0.40*****		**0.56**	**0.37*****	**0.50**	0.00	**0.85**	**0.20****	−0.64***	**0.26**
Cotton	**0.17**	**0.21**	**0.30**	**0.16**		**0.39**	**0.14**	**0.92**	**0.47**	**0.30*****	**0.25****	**0.11**
Crude	**0.23**	**0.51*****	**0.21***	**0.27**	**0.45**		**0.43*****	−0.92	**0.24*****	**0.20****	**0.17**	**0.48*****
Gold	**0.49**	**0.10**	**0.26***	**0.64**	**0.44*****	**0.63***		**0.47**	0.04	**0.06**	**0.47**	**0.38*****
Natural	**0.47**	**0.49**	**0.08**	**1.23****	**1.34**	**0.26*****	−0.90		**0.10**	**0.08****	**0.45****	**0.62****
Silver	**0.36***	**0.61**	**0.54**	**1.38**	**0.68**	**0.59*****	**0.68****	**0.68*****		**0.24**	**0.44**	**0.44****
Soybean	**0.34*****	**0.16***	**0.40*****	**0.07**	−0.41**	**0.43***	**0.18**	**0.07**	**0.15**		**0.22**	**0.22**
Sugar	0.06	**0.20*****	0.04	**0.10**	**0.11***	**0.11***	**0.07**	**0.25*****	**0.13*****	**0.11**		**0.11*****
Equity	**0.24*****	**0.28**	−0.03***	**0.05**	−0.19***	**0.49*****	−0.19*	**0.29*****	**0.29*****	−0.32*	**0.07*****	

Panel C - Distressed

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.32*****	**1.23**	**0.89**	**1.56**	**0.87****	**1.49**	−0.59	**1.25**	**0.65**	**0.79*****	**0.94***
Coffee	**0.14**		**0.37**	**0.76*****	**2.64**	**1.62**	**0.09**	**1.53**	0.00	−0.37	**0.39****	**0.32**
Copper	**1.05**	**0.22**		**0.50***	**0.40**	**1.09***	**1.59****	**0.08**	**1.70*****	**0.44**	**0.68**	**0.94****
Corn	**1.83**	**1.17**	**0.61**		−0.05	**1.30**	**1.56***	**1.27**	**1.46**	**1.02**	**1.47**	**0.47**
Cotton	**0.32**	**0.60**	**0.89**	**0.74**		**0.86***	**0.42**	**0.59**	**1.35**	**1.46****	**0.64***	**0.31**
Crude	**0.32***	**0.26**	**1.05**	**0.74**	**1.18**		**0.75**	**0.68***	**0.72**	**1.54****	**1.74**	**1.21*****
Gold	**0.39****	**0.45**	**1.56****	**0.90**	**1.02***	**0.37****		**1.38**	**1.14**	**0.34**	**0.49**	**0.58****
Natural	−0.34	**0.87**	**0.55*****	**2.34***	**2.15***	**0.24***	−0.92		**0.33**	**1.47**	−0.14	−0.17***
Silver	**0.72**	**0.61**	**1.01**	**0.91**	**0.49***	**1.28*****	**0.62*****	**0.30**		**0.09**	**0.82**	**1.17***
Soybean	**0.30**	**0.29**	**2.07**	**1.10**	**1.49**	**1.54**	**0.65**	**1.55**	**0.16***		−0.01*	0.03**
Sugar	**0.69**	**0.08**	−0.13	**0.41**	**0.84**	**2.15**	−0.56	**0.18**	**0.93**	−0.09		−0.36
Equity	−0.29	**0.15**	**0.55**	−0.13	−0.25	**0.31**	−0.16	**0.19**	**1.15**	**0.34**	−0.04	

Table A4: Spillovers Between Different Markets – Slope Factor

This table presents in-sample and out-of-sample results for spillover tests for the slope of the volatility term structure. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = 0$ ($H_0 : \gamma_u^2 = 0$, $H_0 : \gamma_u^3 = 0$) for normal (tranquil, distressed) periods. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,** ,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Normal

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.27**	**0.31**	−0.11	−0.74	−0.33**	−1.37	0.05	**0.65**	−0.54**	−0.29	−0.29
Coffee	**0.28**		**0.12**	**0.18**	**1.13**	**0.98****	**0.30**	**0.97**	−0.13	−0.15	**0.55**	**0.07*****
Copper	0.05	**0.27***		−0.16	**0.32****	0.30	**0.72****	**0.15***	**0.87*****	0.74	0.89	**0.24****
Corn	**0.89*****	**1.68*****	0.12		−0.05	0.96	1.06	2.33	**−2.24****	**0.62*****	**0.65****	**0.29***
Cotton	**0.25*****	**0.78**	**0.29**	**0.44****		−0.13	**0.32**	0.04	**0.41**	**0.41****	**1.54****	**0.33**
Crude	**0.94**	**0.15**	**0.60**	**0.46***	**0.74**		**1.49**	**0.10****	**0.24**	**0.14**	0.04	**0.15**
Gold	**0.24**	0.04	**0.27**	−0.29***	**0.14**	**0.99*****		**1.38**	**1.78****	**0.84****	**0.48**	**0.30**
Natural	**0.11**	−1.59	−0.31	**0.78**	−0.90	**0.91**	**1.68**		0.01	−0.13	−0.48**	**0.92****
Silver	**0.44**	**0.56**	−0.10	0.07*	**0.09**	**0.43**	**0.17*****	0.01**		**0.11**	**1.20**	**0.72****
Soybean	**0.46**	**1.77*****	**0.57**	**0.39****	**0.53**	**0.48**	−0.01*	**1.35***	0.02*		**0.16*****	0.00
Sugar	**0.54****	−0.11	**0.17**	**0.37**	**0.38***	**0.30**	−0.42	**0.10**	**1.48**	−0.09		0.02
Equity	−2.67	−3.74	−1.35	−2.41*	−1.94	−1.39***	−4.94***	−0.75	**0.07**	−0.47	−3.87	

Panel B - Tranquil

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		−0.11**	−0.18**	−0.37***	−0.76	−0.05***	−0.19	**0.35*****	−0.26	**0.14**	−0.73	−0.11***
Coffee	**0.22*****		**0.09***	−0.02**	**0.43**	0.02	0.02	**0.75****	**0.21**	**0.21****	**0.07*****	**0.10*****
Copper	**0.19**	0.03**		**0.09**	0.03	0.05***	0.05	**0.06***	**0.14**	−0.01	**0.19**	**0.15**
Corn	**0.11*****	−0.01	−0.64		−0.25***	−0.07***	−0.35**	**0.84*****	**0.52***	**1.62**	−0.74	**0.39*****
Cotton	**0.16**	**0.20**	**0.37*****	**0.41****		−0.05	**0.49***	**0.73*****	**0.36**	−0.00	**0.42*****	**0.29*****
Crude	0.41	0.25	0.06	**0.45*****	0.03		**0.31****	**−0.43****	0.19	0.26	**0.36****	**0.80*****
Gold	**0.18**	−0.02	**0.22**	**0.50*****	**0.39*****	**0.33*****		**0.36*****	**0.73****	**0.42**	**0.50**	**0.56*****
Natural	−1.06	**−0.78***	0.05	**−2.64***	2.02	**−0.89*****	−0.10		0.08	0.15	−1.90	**−1.32*****
Silver	**0.52*****	**0.28**	**0.33**	**0.23**	**0.54**	−0.22***	−0.16	0.01		**0.61**	**1.74**	**0.82*****
Soybean	0.01	**0.18**	**0.09**	**0.53***	**0.16****	**0.19**	**0.25****	**0.49**	−0.05*		**0.10**	**0.49****
Sugar	−0.01	**0.09****	−0.09***	−0.02	−0.05**	−0.05***	−0.11**	**0.15*****	**0.17***	**0.08**		−1.34***
Equity	−5.74	−1.77	0.05	−4.81	−6.26**	**0.54*****	−8.10	−0.77***	−1.01***	**0.48**	−0.41*	

Panel C - Distress

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.34***	**0.76**	**1.12****	−0.27	−0.21	−1.38*	−0.71	**0.62**	**0.12**	−1.72	−1.16
Coffee	**0.52***		−0.31	**1.07**	**2.50**	**2.24*****	**0.69**	−0.21	−0.48	**0.08**	**0.26***	−0.19
Copper	0.15	**0.12****		−0.08	0.55	0.21	1.13	0.02	0.69	−0.09	1.48	0.54
Corn	**1.15***	**1.23*****	1.12		0.25	1.37	1.66	**3.00****	−1.26	**0.50*****	0.34	0.56
Cotton	**0.05**	**0.70***	**0.37**	**0.54****		**0.55**	**0.56**	**0.52**	**0.06**	**0.61**	**1.03***	**0.34**
Crude	−0.11	**0.05***	**0.70****	**1.84****	**1.16***		**0.67**	**0.55*****	**0.97**	**0.20***	**0.08**	−0.66***
Gold	**0.36**	**0.09**	**0.27**	**0.30**	**0.35**	**0.26**		**1.63**	**1.67**	**0.37**	**0.49****	**0.33****
Natural	−0.14	−0.26	**0.31**	**3.28**	**4.48**	0.04	−0.38		−0.30	−4.16	**0.25****	−0.30*
Silver	**0.46**	**0.83***	**0.23**	**0.15**	**0.13**	**0.46****	**1.06****	**0.58**		−0.08	**1.11**	**1.39*****
Soybean	**0.19**	**0.55**	**0.43**	**0.84****	**0.17**	**0.53***	**0.45**	**0.30**	0.04		**0.61**	**0.60**
Sugar	**0.83**	−0.48	−2.74	**0.32**	**1.70**	**0.38**	−1.96***	**0.15**	**0.69**	**0.17**		−1.62
Equity	−3.99***	−1.94	−2.16	−6.16	−2.43	−1.92	−3.56	−2.07	**0.85**	**0.17**	−4.64**	

Table A5: Spillovers Between Different Markets – Curvature Factor

This table presents in-sample and out-of-sample results for spillover tests for the curvature of the volatility term structure. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = 0$ ($H_0 : \gamma_u^2 = 0$, $H_0 : \gamma_u^3 = 0$) for normal (tranquil, distressed) periods. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,**,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Normal

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		$\mathbf{0.09}^{***}$	**0.85**	$\mathbf{0.70}^{***}$	-0.37^{*}	$\mathbf{0.09}^{**}$	**0.24**	-0.12^{***}	**1.79**	**0.56**	$\mathbf{1.93}^{***}$	$\mathbf{1.00}^{***}$
Coffee	$\mathbf{0.19}^{***}$		**0.34**	-0.09^{*}	0.02	**1.13**	**0.54**	$\mathbf{1.99}^{**}$	**1.00**	0.06	-0.17^{***}	**0.06**
Copper	$\mathbf{0.56}^{*}$	**0.07**		$\mathbf{0.36}^{***}$	$\mathbf{0.47}^{**}$	**0.19**	$\mathbf{0.50}^{*}$	**0.07**	**0.41**	**0.38**	**0.34**	**0.17**
Corn	-0.01^{**}	**1.67**	**0.15**		$\mathbf{1.32}^{**}$	**0.31**	0.05	$\mathbf{1.49}^{***}$	−0.65	**2.17**	$\mathbf{0.82}^{**}$	**0.22**
Cotton	−0.06	$\mathbf{0.36}^{*}$	**0.06**	0.04		**0.12**	$\mathbf{0.19}^{***}$	**0.28**	**0.36**	**0.08**	$\mathbf{0.37}^{***}$	0.05
Crude	$\mathbf{0.14}^{*}$	**1.48**	**0.18**	**1.36**	**0.50**		**0.59**	−0.00	−0.47	0.02	**0.07**	−0.35
Gold	−0.10	0.01	−0.01	**0.15**	−0.09	$\mathbf{0.38}^{**}$		$\mathbf{0.36}^{*}$	-0.21^{*}	−0.16	**0.39**	**0.14**
Natural	$\mathbf{1.38}^{***}$	**0.16**	−0.59	$\mathbf{1.03}^{***}$	-0.27^{**}	−0.46	-0.24^{**}		$\mathbf{0.22}^{*}$	−0.12	−0.82	-0.13^{***}
Silver	**0.22**	-0.29^{***}	**0.65**	0.03^{**}	−1.10	−0.11	0.06	**0.30**		$\mathbf{0.35}^{**}$	0.03	**0.07**
Soybean	−0.09	−0.04	**0.50**	$\mathbf{0.54}^{**}$	**0.18**	-0.12^{*}	**0.62**	0.05	0.02		0.01	−0.10
Sugar	$\mathbf{0.52}^{***}$	**0.08**	−2.80	$\mathbf{0.51}^{***}$	**2.00**	**1.05**	−3.94	$\mathbf{0.11}^{***}$	$\mathbf{0.12}^{**}$	-2.34^{**}		−1.63
Equity	-1.93^{**}	−7.34	−2.81	−1.59	−0.58	−1.76	-2.82^{***}	-1.22^{*}	−0.01	0.02^{***}	-2.82^{***}	

Panel B - Tranquil

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		$\mathbf{0.58}^{**}$	-0.13^{***}	$\mathbf{0.25}^{*}$	**0.19**	-0.07^{*}	0.04	−0.00	**0.10**	-0.19^{**}	0.03	$\mathbf{0.42}^{***}$
Coffee	0.05		**0.26**	−0.12	−0.27	**0.14**	**0.12**	$\mathbf{0.07}^{***}$	**0.27**	0.00^{***}	-0.11^{***}	$\mathbf{0.05}^{***}$
Copper	$\mathbf{0.06}^{***}$	$\mathbf{0.21}^{**}$		-0.01^{***}	$\mathbf{0.27}^{*}$	0.01	-0.30^{***}	-0.00^{**}	−0.38	−0.18	$\mathbf{0.43}^{***}$	$\mathbf{0.25}^{**}$
Corn	$\mathbf{0.52}^{*}$	−0.20	-0.00^{***}		−0.01	−0.06	**0.26**	−0.02	−0.05	−0.28	-1.68^{***}	$\mathbf{0.39}^{***}$
Cotton	**0.44**	$\mathbf{0.17}^{**}$	$\mathbf{0.29}^{***}$	$\mathbf{0.19}^{*}$		**0.49**	**0.08**	**0.40**	$\mathbf{0.91}^{*}$	$\mathbf{0.42}^{**}$	$\mathbf{1.09}^{**}$	$\mathbf{0.06}^{**}$
Crude	**0.64**	**0.12**	0.05^{***}	**0.18**	$\mathbf{0.20}^{*}$		**0.34**	−0.66	-0.00^{*}	0.02	−0.01	-0.48^{*}
Gold	**0.08**	0.01	0.04^{*}	**0.12**	−0.20	-0.04^{**}		$\mathbf{0.10}^{**}$	$\mathbf{0.14}^{*}$	$\mathbf{0.89}^{**}$	**0.06**	$\mathbf{0.09}^{***}$
Natural	-0.71^{***}	**1.41**	−0.44	$\mathbf{2.19}^{*}$	−1.30	−0.28	−1.75		**0.18**	$\mathbf{1.73}^{***}$	**0.58**	$\mathbf{1.82}^{***}$
Silver	−0.24	$\mathbf{0.25}^{*}$	**0.48**	$\mathbf{0.40}^{**}$	$\mathbf{0.29}^{***}$	$\mathbf{0.17}^{***}$	$\mathbf{0.37}^{***}$	**0.74**		−0.65	−0.14	$\mathbf{0.14}^{*}$
Soybean	-0.01^{**}	0.05	$\mathbf{0.08}^{***}$	$\mathbf{0.18}^{**}$	**0.09**	0.03	−0.01	**0.27**	$\mathbf{0.16}^{***}$		**0.10**	$\mathbf{0.27}^{*}$
Sugar	-0.04^{***}	**0.07**	$\mathbf{0.10}^{***}$	-0.02^{***}	−0.02	-0.18^{**}	0.04	−0.04	$\mathbf{0.34}^{*}$	**0.14**		$\mathbf{0.11}^{**}$
Equity	-4.60^{**}	**0.79**	-0.20^{***}	−2.85	−3.68	0.01	−2.68	-0.58^{*}	-0.02^{**}	−1.90	-0.09^{***}	

Panel C - Distress

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		-0.80^{***}	**0.94**	$\mathbf{0.76}^{***}$	-0.39^{**}	**0.68**	**0.22**	-0.05^{***}	$\mathbf{0.47}^{**}$	**0.61**	$\mathbf{2.02}^{***}$	$\mathbf{0.30}^{**}$
Coffee	**0.32**		**0.18**	**0.61**	**1.80**	**2.03**	**0.19**	$\mathbf{1.56}^{**}$	$\mathbf{1.38}^{***}$	−0.08	**0.09**	−0.51
Copper	**0.46**	0.01		**0.65**	**0.56**	$\mathbf{0.27}^{*}$	**0.50**	**0.09**	**0.38**	**0.74**	**0.94**	**0.49**
Corn	$\mathbf{1.97}^{*}$	**1.48**	**0.74**		$\mathbf{3.59}^{**}$	**0.49**	**1.00**	$\mathbf{2.14}^{**}$	**0.82**	−0.65	$\mathbf{0.45}^{***}$	$\mathbf{0.94}^{**}$
Cotton	**0.72**	$\mathbf{0.64}^{*}$	$\mathbf{0.40}^{**}$	0.04		**0.62**	**0.35**	**0.33**	$\mathbf{1.33}^{*}$	**0.82**	**0.76**	**0.37**
Crude	**0.48**	**0.18**	**0.09**	**1.73**	**0.36**		−0.52	$\mathbf{0.28}^{**}$	−0.53	−0.06	**0.99**	−0.65
Gold	**0.01**	**0.31**	0.04	**0.44**	**0.69**	**0.11**		**0.45**	$\mathbf{1.40}^{*}$	−0.07	$\mathbf{0.15}^{**}$	$\mathbf{0.20}^{**}$
Natural	**1.46**	**0.91**	$\mathbf{0.49}^{**}$	$\mathbf{1.65}^{*}$	$\mathbf{0.87}^{*}$	**0.55**	**0.99**		**0.22**	$\mathbf{0.20}^{*}$	**0.38**	**0.94**
Silver	−0.10	-0.30^{***}	**0.23**	0.05	−1.25	**0.16**	−0.08	**0.57**		**0.23**	−0.67	**0.44**
Soybean	**0.53**	**0.24**	**0.64**	$\mathbf{0.93}^{***}$	$\mathbf{1.69}^{*}$	$\mathbf{0.45}^{*}$	−0.04	**1.08**	**0.94**		0.08	−0.26
Sugar	**0.45**	−0.55	−12.08	$\mathbf{0.95}^{**}$	**4.24**	$\mathbf{1.70}^{***}$	−13.89	**0.25**	-0.57^{*}	$\mathbf{0.98}^{***}$		−10.35
Equity	−2.69	−1.52	−2.57	−2.69	−0.44	−2.80	-2.07^{*}	−1.23	−0.13	−0.29	−2.02	

Table A6: State-Dependent Spillovers – Pre-Financialization

This table presents in-sample and out-of-sample results for spillover tests for the different components of the volatility term structure, for the pre-financialization period. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = \gamma_u^2 = \gamma_u^3 = 0$. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,**,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Level

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.68**	**1.51**	**1.78**	**0.99**	**0.62**	**0.26**	**0.87**	**5.61*****	**7.82**	**1.61*****	**0.38****
Coffee	**3.08**		**2.11**	**0.78**	**2.83**	**1.22***	**3.19**	**2.75**	−0.15	**2.28***	**3.25**	**1.54**
Copper	**2.28*****	**3.40**		**4.95**	**6.08****	**2.50**	**4.43****	**5.46*****	**2.44*****	**1.55**	**3.14**	**1.65***
Corn	**0.89**	**1.72***	**2.39*****		**2.51**	**1.56**	**2.39**	**1.37**	**2.56**	**6.66****	**3.17****	**1.19**
Cotton	**1.74**	**6.32**	**2.63**	**1.82**		**1.09**	**2.01****	**5.81**	**2.72**	0.31	**1.71**	**1.83**
Crude	**1.03**	**1.54**	**2.09****	**1.30**	**3.87***		**1.42**	**1.73****	**3.39****	**2.86**	**1.55***	**2.26**
Gold	**1.44*****	**2.77***	**1.01**	**1.10**	**2.29**	**0.53**		**1.28**	**5.14****	**2.95**	**0.75**	**1.56**
Natural	**3.94**	**3.52**	0.07	**2.91**	**7.24**	**3.92**	−1.79		**3.16**	**2.43**	**3.03**	**3.22*****
Silver	**2.03**	0.10**	**0.45**	**1.20****	**2.60**	**0.69**	**2.34*****	**1.72*****		**3.91*****	−1.17*	**3.45*****
Soybean	**8.22*****	**7.80**	**3.80**	**1.78**	−2.63	**6.43*****	**5.46**	**4.66***	**1.44***		**4.59*****	**2.70**
Sugar	0.13	0.10***	**0.40**	**1.36**	−3.23	−0.58	−0.39***	**9.96**	**4.65*****	**10.43**		**2.00*****
Equity	−0.25	−0.34**	−0.30	**1.35**	−0.07	**0.51*****	−0.68*	0.11	**0.82****	**2.86**	**1.93**	

Panel B - Slope

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**2.53****	**1.67**	**3.55****	**1.41**	−0.43	**0.49*****	−1.76***	−3.40	0.25	−1.30***	−0.46
Coffee	**2.02**		**2.34*****	**1.69**	**0.84**	**1.38**	**0.90**	**4.66*****	**6.57***	**2.94**	**2.08**	**0.51**
Copper	0.16***	**1.26**		**4.05***	**2.19***	**1.95**	−0.59	**3.77**	**2.59**	**2.14**	**3.41****	**0.63*****
Corn	**2.56****	**6.01*****	**1.88**		**1.97**	**1.58**	**3.36*****	**4.62***	**4.74*****	**5.73*****	**2.60**	**0.83**
Cotton	**1.59**	**3.38**	**1.56**	**3.17*****		**4.00**	**1.92**	**5.28*****	**2.40****	**3.48*****	**2.90**	**2.36**
Crude	**1.61**	**0.96**	**2.00*****	**1.06*****	**2.04*****		**4.01*****	**0.54*****	−0.52	**2.71**	**1.37***	**1.75**
Gold	**1.33****	**3.07*****	**2.33*****	**1.71*****	**0.68**	**1.15*****		**2.66*****	**3.63**	**2.99*****	**2.38*****	**0.55**
Natural	**1.36**	**0.44**	0.14	**0.91*****	**5.01**	−0.54	**3.55**		**0.78*****	**2.82**	−0.00	−1.42***
Silver	**0.84*****	**3.05*****	**1.32**	−0.04***	−1.23***	**0.52****	**2.91*****	**2.79*****		**3.21**	**3.57*****	**1.31*****
Soybean	**0.94****	**2.89*****	−0.29	**3.36****	0.25	**0.68**	**1.87**	0.11	−1.67		**4.70***	**1.26**
Sugar	−3.53	−0.97	0.06	−0.88**	−11.77	−0.04	−2.46**	−0.03*	**4.87****	**5.50**		**0.51**
Equity	−4.21***	−4.09	−3.51***	−6.54	−2.68	−0.58***	−9.08***	−14.56	0.21	−2.74	−1.78	

Panel C - Curvature

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		0.04***	**2.06*****	**3.58*****	**2.82***	**1.73***	**1.74*****	**2.03*****	−1.73	**3.55*****	**3.84*****	**0.40*****
Coffee	**2.02****		**0.53**	**0.77**	**0.37**	**0.38**	**1.94**	**2.09**	**2.87**	−1.00	**0.47**	−0.18
Copper	**2.24**	**1.14**		**4.75*****	**2.26***	**0.91**	**1.73**	**2.12*****	**2.95**	**3.79*****	**2.62*****	**0.62****
Corn	**3.49**	**4.34****	**2.37**		**5.12****	**4.99**	**2.71**	**6.10*****	−1.08	**3.77*****	**4.18*****	**1.94**
Cotton	**1.68**	**3.17****	**2.45**	**1.50**		**3.82**	**0.67*****	**3.97**	**3.47**	−0.05	**4.64*****	**1.77**
Crude	**0.51***	−1.10	**0.96**	**0.40**	−0.08		0.08	**0.35****	**0.69**	**1.91**	**1.71**	**0.39***
Gold	**0.16****	**1.01*****	−0.02	**1.07**	−0.40	**0.44****		**0.72***	**0.76**	0.22	−0.17	**0.30*****
Natural	0.08	**2.96**	**4.20**	**3.02**	**2.90**	**0.29**	**0.86**		**3.29**	0.35*	**1.09**	**1.47*****
Silver	**3.48*****	−1.03***	**1.68**	**3.77*****	−1.32**	**1.67**	**2.02**	**1.55*****		**3.34*****	**4.49*****	**2.79*****
Soybean	**0.96***	**0.77**	**0.57**	**1.45**	**0.84*****	**0.76**	**1.50**	**1.94*****	**5.69*****		**4.48**	**0.86**
Sugar	−9.83*	**0.37**	−6.93	**4.20*****	−9.55**	**2.36*****	−11.60	**1.27*****	**4.44*****	**9.48****		0.13
Equity	−4.47	−3.15	−6.61	−6.76	−8.87	−8.73	−7.26	−9.32**	−1.69	**0.97**	−8.74**	

Table A7: State-Dependent Spillovers – Post-Financialization

This table presents in-sample and out-of-sample results for spillover tests for the different components of the volatility term structure, for the post-financialization period. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = \gamma_u^2 = \gamma_u^3 = 0$. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,**,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Level	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**1.47**	**0.84*****	**3.28*****	**2.93*****	**1.61**	**1.84****	**1.78*****	**0.82**	**3.26*****	**3.08*****	**2.33*****
Coffee	**1.70****		**1.83**	**2.57****	**1.69**	**2.06*****	**1.86*****	**2.47****	**0.64****	**1.06**	**2.26*****	**1.71*****
Copper	**2.14*****	**0.77*****		**2.01*****	**1.83*****	**1.69*****	**2.29*****	**1.50*****	**1.88***	**0.59*****	**1.13****	**2.27*****
Corn	**0.97**	**1.60*****	**0.81*****		**2.19*****	**2.11***	**1.47***	**0.93*****	**1.28**	**2.41*****	**1.30*****	**1.48**
Cotton	**1.18**	**1.18**	**1.06****	**2.50*****		**3.10*****	**1.97**	**0.51****	**2.19**	**0.64***	**2.84*****	**1.73*****
Crude	**3.21*****	**2.16*****	**2.37****	**0.97****	**2.74*****		**2.81*****	**1.21**	**3.06*****	**2.45*****	**2.40*****	**2.32*****
Gold	**2.14*****	**1.94****	**2.52*****	**2.27*****	**1.77*****	**3.22*****		**1.43****	**2.01*****	**1.98*****	**2.01***	**2.81*****
Natural	**0.96*****	**2.71****	**0.94*****	**3.27**	**1.38****	**1.11*****	**1.70**		**2.15****	**1.57*****	**1.53**	**1.09***
Silver	**1.27****	**1.86**	**1.69*****	**1.55*****	**1.69*****	**2.49*****	**3.93*****	**0.88*****		**0.68**	**2.74****	**2.43*****
Soybean	**0.95*****	**0.55**	**1.94***	**1.50*****	**1.19**	**1.70**	**1.10*****	**0.63***	**0.80**		**1.75****	**0.93**
Sugar	**1.82*****	**1.88**	**3.16**	**4.71*****	**1.32*****	**1.95*****	**2.03*****	**1.87*****	**1.86**	**2.44**		**1.80*****
Equity	**0.67**	**0.52****	**1.64**	**0.34**	**0.50*****	**1.51****	**1.91***	-0.56^{*}	**0.44*****	**0.70**	**1.51**	
Panel B - Slope	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.48*****	**0.92***	**0.01***	**0.84****	**1.63*****	**1.14*****	**1.02***	**0.37**	**1.02**	**2.04*****	**0.75*****
Coffee	**2.13*****		**1.83*****	**2.57**	**0.88*****	**2.50*****	**2.06*****	**3.06*****	**2.70*****	**1.30**	**2.82*****	**1.25*****
Copper	**0.94****	**0.33**		**0.86***	**0.73**	**1.66****	**2.41**	**0.98***	**0.53****	**2.12***	**−0.13**	**1.52*****
Corn	**0.52*****	**2.18*****	**0.29*****		**0.56*****	**2.10*****	**0.84*****	-0.06^{*}	**1.54*****	**2.12*****	**2.26*****	**1.17*****
Cotton	**0.98****	**1.09**	**1.03****	**1.51****		**2.36*****	**2.95*****	**0.89**	**2.62**	**0.93**	**1.99*****	**1.44*****
Crude	**0.96**	**1.77**	**0.79**	**1.06*****	**0.72****		**1.79***	**0.70*****	**1.83*****	**0.97**	**1.06**	**1.41*****
Gold	**0.72***	**0.44***	**0.54**	**1.34***	**0.60****	**2.46*****		**0.61**	**1.64**	**0.20**	**1.76*****	**2.95*****
Natural	**1.61****	**0.71****	**0.34****	**1.78*****	**0.75****	**2.71*****	-0.00^{***}		**2.59*****	**1.09*****	-0.26^{***}	**0.58*****
Silver	**0.71**	**0.77***	**1.45**	**1.35*****	**1.77***	**2.43*****	**2.19****	**1.01**		0.08	**1.50*****	**2.19*****
Soybean	**1.41**	**1.48*****	**1.48*****	**1.41*****	**0.93**	**1.28*****	**2.88*****	**1.29**	**1.27**		**1.61****	**2.37*****
Sugar	**0.86**	**2.06****	**4.40****	-0.52^{***}	**2.14**	**6.05*****	**6.66**	**0.74*****	**7.32*****	**0.83**		**4.65**
Equity	**1.08**	-0.57	-2.19^{**}	-0.47	-0.66^{***}	**0.34*****	0.07^{***}	-1.55	-3.33	-0.89	**0.60****	
Panel C - Curvature	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**1.40*****	**0.61*****	**1.61*****	**1.04****	**1.66*****	**0.42**	**1.93*****	**2.86*****	**1.28*****	**2.02*****	0.09^{***}
Coffee	**0.22**		**0.84*****	**0.60*****	**2.04*****	**0.64****	**0.79****	**0.79****	**1.31*****	**1.24*****	**0.58*****	**1.24*****
Copper	**2.43***	**0.58*****		**1.41****	**2.12****	**0.92***	-0.31	**0.25**	-0.01^{**}	**3.88**	**2.41**	**0.43****
Corn	**4.03*****	**0.82*****	**1.22*****		**1.69*****	**1.96*****	**1.22**	**1.65****	0.03^{***}	-0.06^{***}	**4.99*****	**1.56*****
Cotton	**0.92**	**1.34*****	**0.82*****	**0.85*****		**0.69****	**1.18*****	**0.48**	**1.00*****	**1.67*****	**1.75*****	**0.70*****
Crude	**0.62**	0.06	**0.55**	**1.05****	**0.68**		**1.04*****	**0.50**	**0.25*****	**0.68*****	**0.85**	-0.13^{***}
Gold	**0.66****	**0.37**	**0.83*****	**0.38**	**1.69**	**0.39*****		**0.95**	**1.98*****	**0.76***	**1.40*****	**3.59*****
Natural	**2.65*****	**0.84*****	**0.83****	**2.18***	**0.09**	**1.47*****	**1.00**		**2.54**	**1.61*****	**1.91*****	**0.86*****
Silver	**0.73**	**0.70**	**1.30**	**0.69*****	**0.50****	**1.95*****	**0.64**	**1.11**		**1.13*****	**1.46***	**1.99*****
Soybean	-0.04	-0.00	**0.91*****	**0.33*****	**0.34***	**1.61*****	**2.74****	-0.27	**1.57**		**1.94****	-0.76^{***}
Sugar	**2.52*****	**1.20****	**1.26****	**1.02*****	**1.35**	**1.96*****	**2.68*****	**0.93*****	**2.68*****	**0.37*****		**1.32*****
Equity	-2.03^{***}	-2.14	-1.50	-0.31^{**}	-1.79	-0.96^{***}	-1.32^{***}	-0.80	-3.63^{***}	-1.96^{***}	-1.72^{***}	

Table A8: Macroeconomic News Announcements

This table presents the percentage overlap between news announcement dates of different macroeconomic series. We use the abbreviations in the horizontal that are defined in the first column of the table.

	E	CC	CPI	D	FO	FFR	GDP	H	IP	IJC	IT	ISM-M	ISM-N-M	RS	M
Employment (E)	100	0	0	0	15	0	1	0	0	0	4	9	12	1	11
Consumer Confidence (CC)	0	100	1	14	0	4	3	14	0	0	0	0	0	0	0
CPI	0	1	100	0	0	6	2	22	33	8	6	0	0	13	17
Durable (D)	0	14	0	100	0	4	5	38	0	11	0	0	0	0	12
Factory Orders (FO)	16	0	0	0	100	3	3	0	0	8	1	1	30	0	7
Federal Funds Rate (FFR)	0	5	8	5	4	100	8	18	3	1	6	3	5	6	1
GDP	1	3	1	5	3	5	100	9	1	13	0	2	2	0	31
Housing (H)	0	7	11	19	0	7	5	100	11	6	0	0	1	3	10
Industrial Production (IP)	0	0	33	0	0	2	1	21	100	3	2	0	0	15	30
Initial Jobless Claims (IJC)	0	0	6	8	6	1	10	8	2	100	9	3	5	5	3
International Trade (IT)	4	0	6	0	1	5	0	1	2	13	100	0	5	4	14
ISM Manufacturing PMI (ISM-M)	9	0	0	0	1	2	2	0	0	5	0	100	0	0	9
ISM-N-Mfg PMI (ISM N-M)	12	0	0	0	30	4	2	1	0	8	5	0	100	0	1
Retail Sales (RS)	1	0	13	0	0	5	0	6	15	7	4	0	0	100	24
Michigan Consumer Sentiment (M)	6	0	8	6	3	0	18	10	15	2	7	4	1	12	100
Obs.	239	240	240	238	236	190	279	477	240	346	238	240	240	239	479
In % of the sample	4.78	4.80	4.80	4.76	4.72	3.80	5.58	9.55	4.80	6.93	4.76	4.80	4.80	4.78	9.59

Table A9: Summary Statistics SVIX Term Structure

This table presents the summary statistics for the SVIX option-implied volatility term structure. It shows the annualized model-free estimate of option-implied volatility for the commodity market for monthly and annual volatilities. The SVIX is seasonally adjusted via a trigonometric function. The sample starts from 1996 through 2015. Vol_1 is the one-month volatility, Vol_{12} is the twelve-month volatility. The column sd presents the standard deviation, 10%, 15% and 90% denote the respective percentiles of the distribution. Finally $AR(1)$ reports the first-order AR coefficient (in percentage points).

		mean	*sd*	10%	50%	90%	$AR(1)$
Cocoa	Vol_1	0.34	0.10	0.21	0.33	0.46	95.05
	Vol_{12}	0.31	0.08	0.22	0.30	0.41	98.58
Coffee	Vol_1	0.43	0.15	0.27	0.41	0.63	96.33
	Vol_{12}	0.41	0.11	0.29	0.40	0.56	98.56
Copper	Vol_1	0.31	0.11	0.19	0.30	0.43	95.55
	Vol_{12}	0.28	0.11	0.18	0.24	0.41	99.23
Corn	Vol_1	0.29	0.12	0.16	0.28	0.43	91.76
	Vol_{12}	0.27	0.07	0.19	0.26	0.38	96.57
Cotton	Vol_1	0.27	0.10	0.18	0.25	0.40	97.28
	Vol_{12}	0.24	0.07	0.16	0.22	0.34	99.10
Crude Oil	Vol_1	0.36	0.14	0.22	0.34	0.49	97.95
	Vol_{12}	0.29	0.09	0.18	0.28	0.38	96.99
Gold	Vol_1	0.18	0.07	0.10	0.17	0.26	97.80
	Vol_{12}	0.19	0.07	0.10	0.18	0.29	99.77
Natural Gas	Vol_1	0.51	0.17	0.32	0.49	0.73	97.48
	Vol_{12}	0.38	0.11	0.26	0.37	0.50	93.58
Silver	Vol_1	0.31	0.12	0.19	0.29	0.44	97.82
	Vol_{12}	0.31	0.12	0.19	0.31	0.46	99.75
Soybeans	Vol_1	0.24	0.09	0.15	0.23	0.36	95.92
	Vol_{12}	0.25	0.08	0.18	0.23	0.38	97.77
Sugar	Vol_1	0.37	0.13	0.23	0.36	0.54	96.48
	Vol_{12}	0.28	0.08	0.19	0.27	0.39	98.58
Equity	Vol_1	0.21	0.08	0.12	0.19	0.31	92.58
	Vol_{12}	0.21	0.05	0.15	0.20	0.27	99.40

Table A10: State-Dependent Out-Of-Sample R^2 SVIX

This table presents in-sample and out-of-sample results for spillover tests for the different components of the SVIX term structure. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = \gamma_u^2 = \gamma_u^3 = 0$. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,**,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Level

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.63**	**2.32**	**2.09**	**3.08*****	**2.77*****	**5.58*****	−0.92	**1.97*****	**1.01**	**2.19*****	**2.57*****
Coffee	**1.74**		**0.70*****	**1.78***	**3.21**	**3.53*****	0.04***	**3.38***	**1.78***	**0.90**	**0.77****	**0.98*****
Copper	**1.61*****	**0.60**		**1.17****	**0.88*****	**1.84*****	**2.66*****	**0.44**	**2.90*****	**1.49***	**1.48****	**2.72*****
Corn	**1.98****	**1.57**	**0.67*****		−0.26**	**1.64*****	**2.05****	**1.77****	**2.35*****	**1.88****	**1.71**	**1.36**
Cotton	**0.85**	**0.96**	**1.09**	**1.23**		**1.13****	**0.65**	**1.63**	**2.53**	**2.37*****	**1.49***	**0.64**
Crude	**0.89***	**1.10*****	**2.17*****	**1.45***	**2.23*****		**2.34*****	**0.23**	**1.89*****	**2.07*****	**2.14****	**2.70*****
Gold	**1.35*****	**0.86**	**1.38*****	**1.54***	**1.87*****	**2.70*****		**2.17**	**4.12*****	**1.33****	**1.38*****	**2.28*****
Natural	**0.99*****	**2.59****	**0.68***	**2.51****	**6.94*****	**1.39****	**2.33*****		**1.22*****	**2.39**	**0.34*****	**2.11*****
Silver	**1.55****	**1.13**	**2.22*****	**1.87****	**1.00*****	**2.69*****	**3.11*****	**1.40*****		0.05	**1.65**	**2.91*****
Soybean	**1.09*****	**0.72*****	**2.77*****	**1.42****	**1.20***	**1.97****	**1.51*****	**3.20****	**0.60*****		**0.51*****	**1.22**
Sugar	**0.95**	**0.41*****	**0.30**	**1.42*****	**1.76*****	**5.60*****	**0.25**	**0.37*****	**1.18*****	**0.17**		−0.06***
Equity	**0.73*****	**0.81*****	**1.77*****	**1.04**	**0.88*****	**1.61*****	**0.72*****	**0.96*****	**2.93*****	**0.17**	**0.94*****	

Panel B - Slope

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		−0.72*	**4.07*****	**0.78*****	−1.54	**1.31*****	**2.97**	−0.01***	**3.00**	**1.12*****	−1.24	**1.14*****
Coffee	**0.25*****		−0.31*	**1.29*****	**3.19**	**3.87*****	**1.21**	**0.69*****	**1.97**	**0.68**	**0.48***	**0.52*****
Copper	**0.81*****	**0.47***		−0.05	**0.62**	**0.19*****	**1.95*****	0.05***	**0.50*****	**1.20***	**1.99**	**1.82*****
Corn	−0.32***	**2.15*****	**1.05**		**0.79****	**1.25*****	**1.02**	**4.00*****	−2.47	**0.70*****	−0.86	**0.54**
Cotton	**0.98**	**1.09**	**0.54*****	**1.25*****		**0.52*****	**0.84**	**0.78*****	**1.51**	**1.85***	**2.84****	**0.39**
Crude	**0.99***	**0.65***	**1.47**	**2.18*****	**0.91**		**2.54**	**0.53*****	**2.01**	**0.81***	−0.26	**0.44*****
Gold	**1.30*****	**0.31**	**1.06**	**0.42*****	**0.72*****	**1.99*****		**2.27*****	**3.58*****	**2.09***	**1.16**	**0.76****
Natural	−0.99	**0.14**	**0.72**	**0.63*****	**1.61**	**1.83***	**1.91**		**0.42***	−2.12	−0.34*	−1.64
Silver	**0.11****	**1.05****	−0.48	**0.91***	−1.08	**0.22*****	**0.93*****	**0.32*****		−0.40***	**1.15*****	**2.14*****
Soybean	**1.23**	**1.38*****	**1.35**	**1.10*****	**1.17**	**1.85*****	**1.81*****	**1.45*****	**0.14**		**0.67*****	**0.60**
Sugar	**1.39****	−0.02	−3.32***	−0.25***	**2.14*****	**0.45*****	−0.13***	**0.28*****	**1.26****	**0.37**		−0.93**
Equity	−3.79***	−1.37	−1.23***	−0.48**	−1.56***	**0.72*****	−3.01***	−0.47***	**0.34*****	−6.29	−1.14	

Panel C - Curvature

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		−0.42***	**1.56*****	**1.74*****	−0.94**	**1.73*****	**1.09**	−0.46***	**1.07**	−0.33***	**2.93*****	**1.87*****
Coffee	**1.20**		−0.28***	−0.24**	**2.34****	**1.82**	**0.58**	**0.36*****	**4.36***	**2.37*****	−0.60**	−0.04***
Copper	**1.22*****	**0.33*****		**0.60*****	**1.06****	**0.62*****	**0.98*****	**0.16**	**0.19***	**0.22*****	**1.81*****	**1.08**
Corn	**2.57*****	**2.39****	**2.30*****		**2.44****	**0.95*****	**0.24**	**3.91*****	**3.37**	**1.11*****	**1.53*****	**1.15***
Cotton	**1.33**	**0.82***	**0.59*****	**0.36**		**0.95*****	**1.08****	**0.84**	**2.12***	**2.86*****	**2.52***	**0.30**
Crude	**1.41**	**1.44**	**0.39*****	**2.30**	**1.16**		−0.44	**0.35**	−0.18*	−0.12***	−0.10**	−1.65***
Gold	0.04	**0.64**	−0.14	**0.60**	**0.38**	**0.07*****		**0.48*****	**0.24**	**3.11*****	**1.03***	**0.26**
Natural	**1.24***	**2.39**	−0.34***	**4.69*****	**5.83**	**1.32**	**0.65**		**0.75**	**3.26*****	**0.41**	**1.84**
Silver	−0.48	−0.55***	**0.92**	**0.11****	−2.26**	−0.71***	**0.51*****	**0.98*****		0.07	−0.09	0.01
Soybean	**3.23**	**2.15**	**3.10*****	**1.87*****	**3.79**	**1.31****	**2.50**	**2.69***	**0.80**		0.03**	**1.69**
Sugar	−0.71***	−0.38	−17.28***	**0.05*****	**7.18**	**2.46**	−22.43	−0.11***	**0.21***	−1.84***		−14.89
Equity	−3.00	−1.35**	−2.03***	−0.89**	−0.32	−4.38***	−4.11***	−1.28	−0.34***	−9.43***	−3.67*	

Table A11: State-Dependent Out-Of-Sample R^2 Parametric

This table presents in-sample and out-of-sample results for spillover tests for the different components of the implied volatility term structure. We define the implied volatility term structure with a parametric definition, the level $VIX_{1,\ldots,12}$, the slope $VIX_1 - VIX_{12}$ and the curvature $-VIX_1 + 2VIX_6 - VIX_{12}$. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = \gamma_u^2 = \gamma_u^3 = 0$. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,**,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Level

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**1.21****	**0.98**	**2.31***	**2.92*****	**2.66*****	**3.75*****	**0.39*****	**1.99*****	**0.99**	**1.70*****	**1.63*****
Coffee	**1.52**		**0.62**	**1.87***	**3.68**	**3.12***	**0.39****	**3.04***	**1.20*****	**0.90**	**0.91**	**0.72**
Copper	**1.44*****	**0.43**		**1.43***	**0.75**	**1.89*****	**2.58*****	**0.45**	**3.60*****	**1.35***	**1.74****	**2.12*****
Corn	**2.14**	**1.51**	**0.87****		**0.28**	**1.80*****	**1.83****	**1.85**	**1.92*****	**1.58*****	**0.47*****	**1.40***
Cotton	**0.82**	**0.97**	**1.36**	**1.21**		**1.41***	**0.98**	**1.92**	**2.58**	**2.00*****	**2.45****	**0.56**
Crude	**0.97****	**1.26*****	**2.14*****	**1.42**	**2.40****		**2.12*****	**0.40**	**2.03*****	**2.47*****	**1.95***	**2.83*****
Gold	**1.25*****	**1.00*****	**2.60*****	**1.65****	**2.06*****	**2.07*****		**3.37**	**3.26*****	**1.35****	**1.30*****	**1.54*****
Natural	**0.82**	**2.86***	**0.37*****	**2.95*****	**6.99*****	**1.34*****	**1.09**		**1.29*****	**1.91****	**0.39***	**1.31*****
Silver	**1.46***	**1.47**	**2.20*****	**2.69****	**1.27*****	**3.84*****	**2.68*****	**1.30*****		**0.14**	**1.69**	**2.81*****
Soybean	**0.93*****	**0.58*****	**2.98*****	**1.28***	**1.13***	**2.41*****	**1.24****	**3.61****	**0.59*****		**0.61*****	**0.28***
Sugar	**1.30**	**0.43*****	**0.96**	**3.02****	**1.34*****	**4.17*****	**0.84****	**0.37*****	**1.43*****	**0.23**		**0.62**
Equity	−1.14***	−0.77***	**1.61*****	−0.03	−0.70***	**1.95*****	−0.36***	**0.99*****	**2.79*****	0.03	−0.14***	

Panel B - Slope

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		−0.14**	**1.42**	**1.01*****	**0.74****	−1.61***	−1.68	−1.36	**1.17**	−0.26	−2.95	−2.35***
Coffee	**0.94****		−0.23	**1.62**	**2.23**	**3.97*****	**1.03**	**1.27*****	**0.60**	**0.60**	**0.73*****	−0.21***
Copper	**0.67****	**0.13*****		−0.07	**0.42****	**0.77*****	**1.56****	**0.29**	**0.83*****	**0.30***	**1.62**	**1.08**
Corn	**0.92***	**2.69*****	0.04		**1.06***	**1.23*****	**1.02**	**4.24****	−0.73**	**1.42*****	−0.12***	**0.50*****
Cotton	**0.97*****	**0.28*****	**0.61*****	**1.54*****		**0.51**	**0.88***	**0.33**	**1.65**	**0.84**	**2.81*****	**0.80*****
Crude	**0.63*****	**0.66**	**1.37*****	**0.59*****	**1.18**		**1.00*****	**0.22***	**2.56*****	**0.43**	**0.40**	**1.37*****
Gold	**0.75*****	**0.34***	**0.87**	**0.96*****	**1.01****	**2.02*****		**2.79***	**2.32*****	**2.28**	**1.25*****	**1.05*****
Natural	**0.17**	**0.97**	**0.54**	**2.54**	**3.73**	**0.78**	**1.16**		**0.10**	−0.58	**0.38*****	−0.17***
Silver	**1.44**	**1.25**	**0.68**	**0.86**	**1.46**	**1.47*****	**1.38****	**0.37*****		−0.63	**2.57***	**2.13*****
Soybean	**0.40**	**0.97***	**1.39**	**1.45****	**0.69**	**0.92****	**0.91***	**1.98**	**0.27**		**0.47**	**0.53****
Sugar	**0.38**	**0.20*****	−0.21***	**1.45***	**1.90*****	**2.07*****	**0.59*****	**0.21*****	**2.13*****	**0.33**		**0.18**
Equity	−7.76***	−5.94	−2.57***	−4.68	−5.04*	−3.09***	−13.22***	−2.90***	**0.73*****	−1.74	−5.57***	

Panel C - Curvature

	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**1.15*****	**0.22*****	**0.19*****	−0.12	**0.06*****	−0.29	**1.57*****	**1.44****	**0.65***	−1.26**	−0.77***
Coffee	**0.56**		**0.45****	**0.82*****	**0.62*****	**2.06**	**1.10***	**3.74*****	**1.04**	**1.60****	**0.44***	**0.38*****
Copper	**1.24**	**0.32*****		**0.22****	**0.45*****	**0.28*****	**0.86*****	**0.22****	**0.95*****	**0.89***	**1.28**	**0.71**
Corn	**0.66**	**2.56*****	−0.11		**0.24*****	−0.59	**0.65*****	**2.51*****	−0.52***	**2.48****	−0.54	**0.58*****
Cotton	**0.87**	**0.86**	**1.09****	**1.34***		**0.66**	**0.63**	**0.94*****	**1.52****	**2.22****	**1.74**	**0.62*****
Crude	**0.95**	**0.49*****	**1.69*****	**2.62*****	**0.78**		−0.07	**1.45*****	**2.79*****	**1.58**	**0.96**	**0.42*****
Gold	**0.14**	**0.21**	**0.28*****	**0.11****	**0.52*****	**0.21*****		**1.69*****	**3.22*****	**2.25**	**0.44***	**0.36*****
Natural	**0.24**	**1.08**	−0.88***	**1.61*****	**3.15**	**0.86****	**0.14**		**0.95**	**0.33**	**0.53*****	**3.23*****
Silver	**0.39***	**0.15****	**0.85*****	−0.64**	−0.60***	**0.35*****	**0.69****	**0.13*****		**0.76****	**1.56*****	**1.45*****
Soybean	**0.47**	**0.56**	**2.26****	**1.18****	**1.64**	**1.02*****	**0.65**	**2.27****	**0.61*****		**0.39*****	**0.49**
Sugar	**1.14***	**0.76*****	−1.65***	**2.03*****	**1.28****	**2.08**	−0.83	**0.28**	**1.82*****	**0.53**		−0.42*
Equity	−7.97	−7.93	−4.71***	−3.10	−6.01	−5.62***	−7.95***	−3.24***	**0.36*****	−2.25	−7.67	

Table A12: State-Dependent out-of-sample R^2 1% VaR

This table presents in-sample and out-of-sample results for spillover tests for the different components of the implied volatility term structure. To construct the dummy variables, we use the 1%-VaR. We run the following regression:

$$PC_{i,t} = \sum_{k=1}^{p} \beta_k^1 PC_{i,t-k} \cdot I_N + \sum_{k=1}^{p} \beta_k^2 PC_{i,t-k} \cdot I_T + \sum_{k=1}^{p} \beta_k^3 PC_{i,t-k} \cdot I_D +$$
$$\sum_{u=1}^{p} \gamma_u^1 PC_{j,t-u} \cdot I_N + \sum_{u=1}^{p} \gamma_u^2 PC_{j,t-u} \cdot I_T + \sum_{u=1}^{p} \gamma_u^3 PC_{j,t-u} \cdot I_D + VRP_t + PCE_t + \epsilon_t.$$

Commodity i (which is affected by the spillovers) is presented in the first column, commodity j (from which the spillovers originate) is presented in the first row. We test the null hypothesis, $H_0 : \gamma_u^1 = \gamma_u^2 = \gamma_u^3 = 0$. For in-sample significance, we use a Wald test of the H_0 using Newey and West (1986) standard errors with 10 lags. *,**,***, respectively indicate significance for the 10%, 5% and 1% level, respectively. For out-of-sample tests, we use an expanding window, initialized by 100 observations. We present the out-of-sample R^2 ($R^2 = 1 - \frac{MSE_{\text{un}}}{MSE_{\text{re}}}$) in the body of the tables. Significant R^2s based on McCracken (2007) test statistics are printed in **bold**.

Panel A - Level												
	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.73*****	**1.43**	**1.60*****	**3.95*****	**2.56*****	**3.36*****	**1.77**	**0.48*****	**0.86****	**1.90*****	**2.06*****
Coffee	**1.68*****		**1.60*****	**1.63*****	**4.58*****	**2.60*****	**0.20*****	**3.74*****	**0.90*****	**0.64***	**1.29*****	**1.59*****
Copper	**1.54*****	**0.67**		**1.60**	**0.42*****	**2.14*****	**2.79*****	**0.68*****	**1.82*****	**1.02*****	**1.75*****	**1.95*****
Corn	**1.70**	**1.58**	**0.87****		**0.95*****	**1.68****	**2.41**	**2.13*****	**0.81**	**1.84*****	−0.16***	**0.84***
Cotton	**0.43****	**0.85**	**1.16**	**1.13**		**1.81*****	**0.92**	**1.85*****	**0.57**	**2.23*****	**1.42****	**0.50****
Crude	**0.92*****	**1.26*****	**2.04*****	**1.40***	**2.43*****		**1.73*****	**0.79**	**0.81*****	**1.94*****	**1.94***	**1.76*****
Gold	**1.22*****	**1.06***	**1.49*****	**1.18*****	**2.07*****	**2.35*****		**3.53**	**2.26*****	**0.40*****	**1.22*****	**1.60*****
Natural	**0.62*****	**2.24**	**0.26***	**1.92*****	**7.52*****	**0.27*****	**1.38*****		**1.05*****	**1.94*****	**0.23**	**0.64*****
Silver	**1.61*****	**1.31**	**1.87*****	**1.89**	**2.02*****	**2.43*****	**3.01*****	**1.07*****		**1.44**	**1.53**	**2.23*****
Soybean	**0.28*****	**0.53**	**2.63**	**1.52**	**0.88*****	**1.36*****	**0.39*****	**2.68**	**0.75**		**0.48**	**0.77***
Sugar	**1.42***	**0.40*****	−0.07	**2.12**	**0.82**	**4.31*****	**0.79**	**0.33*****	**0.17****	**0.21***		**0.20*****
Equity	−0.68***	−0.45**	**1.35*****	**0.26**	−0.36***	**1.74*****	**0.19*****	**1.02****	0.04	−0.09***	**0.25*****	
Panel B - Slope												
	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.20*****	**0.91***	−0.46***	−0.96*	−1.52*	−0.92	−1.29***	−0.14	−0.12***	−2.11	−1.76***
Coffee	**0.67***		−0.49	**1.05*****	**2.23****	**1.01*****	**0.83***	**1.03*****	**0.73**	**0.23***	**0.60****	**0.21*****
Copper	**0.70**	**0.41***		−0.23	**0.56****	**0.86*****	**1.64*****	**0.19****	**0.71*****	**0.35****	**1.81*****	**1.20**
Corn	**1.79*****	**3.11*****	−0.02		**1.03****	**1.00*****	**1.39***	**0.39*****	−0.01*	**2.64*****	−0.59**	**0.88*****
Cotton	−0.74	**0.82**	**1.50*****	**1.36*****		**0.32****	**1.41**	**0.78****	**0.97**	**0.89**	**1.89*****	**0.63*****
Crude	**1.09**	**1.08**	**1.42***	**1.29*****	**1.51**		**1.34**	**0.25*****	**0.30**	**0.58**	−0.37	**0.32*****
Gold	**0.84*****	**0.43****	**1.09**	**0.91*****	**1.17**	**1.73*****		**2.58*****	**1.14*****	**2.33**	**1.43*****	**0.97*****
Natural	−1.35	**0.37**	**0.28**	**2.23*****	**1.57**	−0.65	**3.01**		**0.34**	−1.39	−1.90*	−1.73***
Silver	**0.27***	**0.28****	**1.48*****	**1.44*****	**1.77***	0.05**	**1.36*****	**1.21*****		−0.19	**1.73**	**0.22*****
Soybean	**0.73***	**1.97*****	**1.62**	**1.73***	**0.59**	**0.40****	**0.47****	**1.66*****	**0.16*****		**0.90*****	**0.71****
Sugar	**1.31**	−0.37**	−1.77***	**0.44****	**2.25*****	**1.37*****	−1.17***	**0.27*****	**0.39*****	**0.18**		−1.67
Equity	−10.41	−2.64	−3.17***	−4.60	−4.27**	−1.74***	−9.59***	−2.71***	0.04***	−0.68	−5.07**	
Panel C - Curvature												
	Cocoa	Coffee	Copper	Corn	Cotton	Crude	Gold	Natural	Silver	Soybean	Sugar	Equity
Cocoa		**0.21*****	**0.92*****	**1.90*****	−0.25	**1.70*****	**1.22****	**0.81*****	**1.39*****	**1.10**	**3.77*****	**1.53*****
Coffee	**0.72*****		**1.06**	**1.50****	**1.46**	**1.13**	**0.80**	**1.99*****	**0.50*****	**1.18**	−0.14***	−0.66***
Copper	**1.24*****	**0.37**		**1.23*****	**0.20*****	**0.50**	**0.83****	**0.24*****	**0.30*****	−0.18	**1.85*****	**0.85**
Corn	**2.47*****	**2.18**	**1.70*****		**2.55****	**1.62*****	−0.04	**2.51*****	**0.65*****	**1.36****	**0.43*****	**1.71*****
Cotton	**1.00**	**1.19****	**0.66*****	−0.09*		**1.40*****	**0.55**	**1.03**	**1.53*****	**2.04****	**2.44****	**0.37*****
Crude	**1.02**	**0.98***	**0.21*****	**2.12**	**1.68***		−0.99	−0.13***	0.04**	−0.40**	**0.45**	−0.67***
Gold	**0.24***	**0.68**	−0.03	**0.39**	**0.29*****	**0.36***		**0.64*****	**0.30****	−0.23***	**0.65***	**0.54*****
Natural	**1.97*****	**0.56***	−0.93**	**3.75*****	**2.31****	−0.29***	**0.87**		**0.46**	**4.30***	−0.32	**2.39*****
Silver	**1.00****	**0.10*****	**0.64**	**1.00*****	**1.36*****	**0.41*****	**0.27*****	**0.85*****		**1.03***	**1.28**	**0.64*****
Soybean	0.02	**0.55**	**1.62*****	**1.28*****	**1.56**	**1.04***	−0.21***	**3.16*****	**1.16****		**0.18**	0.03**
Sugar	**0.78*****	−0.37	−12.05***	**1.26*****	**6.91**	**1.66**	−13.64	**0.17*****	**0.02*****	−0.28		−9.63
Equity	−4.24**	−5.27***	−4.23***	−4.02	−1.23	−3.12	−2.43***	−0.24**	−0.67**	−1.78	−1.52***	

Chapter 3

Measuring Tail Risk*

3.1 Introduction

Tail risk can be defined as the risk of ending up in an exceptionally bad state of the world. That is, one in which a low-probability, high-impact, i.e., high-marginal-utility event occurs. In asset pricing, such a (left-)tail event is typically associated with high (extreme) negative market returns. Several anecdotal and empirical observations suggest that investors are concerned with such tail risk. First, previous studies find that the prices of out-of-the-money put options, instruments that provide a positive payoff in case of a left tail event, are substantially higher than suggested by theory (Jackwerth, 2000; Bondarenko, 2014). Thus, investors seem to be willing to pay more than advocated by standard models to receive crash insurance. Second, The Economist describes "low-probability, high-impact events" as "a fact

*This chapter is based on the Working Paper "Measuring Tail Risk" authored by Maik Dierkes, Fabian Hollstein, Marcel Prokopczuk, and Christoph Matthias Würsig, 2021.

of life".[1] Investment practitioners and politicians worry about "fail[ure] to capture [...] the extreme negative tail" (Alan Greenspan) and see one of their main objectives to "remove [...] tail risks, and the perception of tail risks" (Olivier Blanchard).[2,3]

The apparent interest of investors in tail events has sparked a large literature on different tail risk measures. Such measures come in a variety of fashions from highly parameterized models to non-parametric approaches. The underlying data vary from option prices, over historical index and stock returns, to macroeconomic time series. Some measures capture tail risk under the physical, while others rely on the risk-neutral probability distribution. In short, both investors and politicians face a difficult choice between different measures with potentially conflicting predictions.

In this paper, we seek to provide some guidance as to how best to measure tail risk. Our main contribution is a systematic, coherent, and comprehensive evaluation of the tail risk measures proposed in the literature. Knowing how to measure tail risk is very important for academics, investment practitioners, and politicians. Decisions based on an inaccurate measure could lead to vast investment and welfare losses. Furthermore, under the assumption that tail risk is a relevant risk factor, for academics and investors it is essential to accurately ascribe portfolio performance to tail risk exposures. There is thus a great need to identify good tail risk measures.

We analyze a large set of 15 potential tail risk measures. Because they are partially based on very different concepts, theories, assumptions, and underlying data, the different tail risk measures likely measure different things. Indeed, we find that the first two principal components (PCs) of the tail risk measures can only explain 49% of their variation. The

[1]Lead article "The next catastrophe" in the Economist Issue June 25th 2020.

[2]The first quote is from a speech of Alan Greenspan in 1999: `https://www.federalreserve.gov/boarddocs/speeches/1999/19991014.htm`. The second is from an interview with Olivier Blanchard, then chief economist at the IMF, for The Economist, January 31, 2009.

[3]In addition, the Chicago Board Options Exchange (CBOE) introduced the VIX Tail Hedge Index (VXTH), designed to cope with extreme downward movements in the stock index.

correlations between the different measures are moderate at best. In some instances, we even observe negative correlations. Thus, the decision to use a specific measure is non-trivial, with potentially important consequences. The tail risk measures should not be treated as interchangeable.

As a preview, Figure 3.1 illustrates the vast heterogeneity across the measures. It displays the average levels of the tail risk measures (each standardized to have a mean of zero and standard deviation of one) one day before tail events, as well as one day before placebo (non-tail) events. Some of them have high values (as they should) while others are close to or even below their average before a tail event. Similarly, some measures on average indicate that a tail event is likely to happen when, in fact, no such event is subsequently realized.

After having documented significant heterogeneity between the measures, we continue by defining the desirable criteria a tail risk measure should possess: it should matter both statistically and economically. That is, on the one hand, the tail risk measure should be able to capture both the risk of jumps and deliver an indication about the expected magnitude and quadratic variation caused by tail events. On the other, several studies show that tail risk also matters for investors (e.g., Rietz, 1988; Barro, 2006; Gourio, 2012; Muir, 2017; Dew-Becker, Giglio, and Kelly, 2021). Hence, a tail risk measure should be priced in the market. We thus require a tail risk measure to predict both risk and risk premia.[4]

We devise three main tests. The first two are statistical in nature with (i) a probit predictive regression, predicting two-sigma events and (ii) a prediction of the future left tail variation. With the first test, we examine whether the measures can forecast future tail events, while with the second test we additionally account for the contribution of tail events

[4] Of course, a tail risk measure can also be useful if it only predicts either risk or risk premia. In that case, it could still be used for the tasks it performs well for. Our main goal, however, is to identify measures that can be used for all applications.

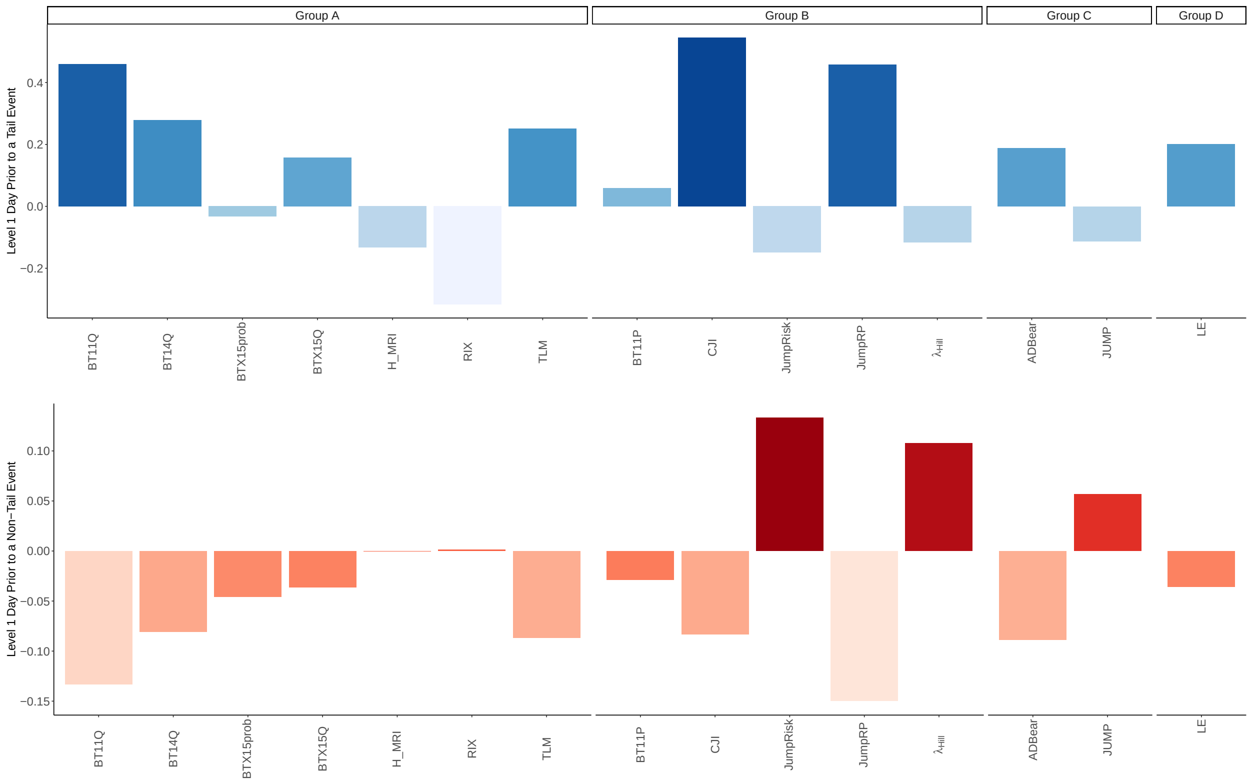


Figure 3.1: Tail Risk before Crash Event

The upper panel of this figure displays the average levels of different tail risk measures one day before (two-sigma or more) left tail events. In the lower panel, we display a simple placebo test that shows the average level of the tail risk measures ahead of (absolute return of 0.02 sigma or less) non-tail events. All tail risk measures are standardized to have a mean of zero and a volatility of one. We separate the tail risk measures into four groups: Option-Implied (Group A), Stock-Return-Based (Group B), Option-Return Based (Group C), and Macroeconomic Measures (Group D). The colors indicate the intensity of the tail risk measures ahead of the events. The definitions of the tail risk measure acronyms are in Table 3.1.

to the quadratic variation. The final test (iii) is of an economic nature: we examine whether the measures can forecast future market excess returns.

Our analysis produces a clear winner: The Bollerslev and Todorov (2011b) option-implied left tail measure ($BT11Q$) performs best overall. It works well in forecasting the occurrence of and, in particular, the variation associated with future tail events up to one week ahead. More importantly, it is able to forecast future market excess returns up to one year ahead. $BT11Q$ is among the best measures for each of the individual tasks, and it is the only one that consistently performs well across all tests. On top of that, it is also fairly simple to implement compared to other tail risk measures. It only requires observed deep out-of-the-money put index option prices.

We document that $BT11Q$ can also predict the magnitude, not only the occurrence, of future tail events. Furthermore, it performs well in predicting stock returns in the cross-section. It also predicts real economic activity: $BT11Q$ is a strong negative predictor of the growth of industrial production during the next month. We perform several further tests that underline the robustness of our results. Among others, we show that the results are qualitatively similar across subsample periods, for different multiple regression selection procedures, when predicting the number of jumps, when varying the tail event thresholds, for left tail variation with and without overnight returns, and for different bootstrap approaches to determine the statistical significance. For all tests, the $BT11Q$ measure is amongst the best.

Why does the $BT11Q$ measure perform so well? It appears to combine several desirable properties for a tail risk measure. On the one hand, it uses forward-looking information from options markets. Apart from being forward-looking, options markets have also been shown to contain information about future returns that is not readily found in physical risk measures (Andersen, Fusari, and Todorov, 2015).[5] Most stock-return-based and macroeconomic tail risk measures fail in particular for the return forecasting exercises. In addition, the $BT11Q$ measure has the advantage of being entirely non-paramteric, requiring no estimation of structural parameters. Thereby, it appears to contain substantially less noise than measures which require a parametric optimization or which rely on high-frequency or options returns. While this noise does not seem to affect the return predictability exercises that strongly ($BT11Q$ still performs substantially better than all other measures for these), it seems to have a large impact on the statistical tests. None of the other option-implied measures

[5] Indeed, David Einhorn refers to the traditional Value-at-Risk (VaR) approach based on historical return data as “an airbag that works all the time, except when you have a car accident” (`https://www.valuewalk.com/wp-content/uploads/2014/05/Grants-Conference-04-08-2008.pdf`).

performs nearly as good as $BT11Q$ for predicting future tail events and left tail variation.

The literature contains studies that compare different risk measures in several areas. For example, there is a large literature comparing the ability of different approaches to forecast future volatility (e.g., Andersen and Bollerslev, 1998; Hansen and Lunde, 2005; Jiang and Tian, 2005; Brownlees and Gallo, 2010). There are also studies concerned with how to best forecast covariances (e.g., Symitsi, Symeonidis, Kourtis, and Markellos, 2018) and beta (e.g., Faff, Hillier, and Hillier, 2000; Hollstein and Prokopczuk, 2016; Hollstein et al., 2019b). Surprisingly, however, to the best of our knowledge, to date no such study exists about tail risk. Given the plethora of different measures that have been proposed over the last decade, we feel there is an urgent need for such a study. Our main contributions are, thus, to (i) define the criteria a good tail risk measure should fulfill and (ii) comprehensively analyze the measures proposed in previous studies based on these criteria. Importantly, we use the same methodology to analyze and evaluate all measures.

The remainder of the paper is organized as follows: In Section 3.2, we present the tail risk measures considered. Section 3.3 outlines our evaluation methodology and the data employed. In Section 3.4, we present the results of our main analysis and in Section 3.5 we perform further tests and analyze the robustness of our results. Section 3.6 concludes.

3.2 Tail Risk Measures

Our aim is to analyze the most comprehensive set of tail risk measures possible. The measure selection is based on two main criteria: (i) relevance/importance and (ii) (public) availability of the underlying data on the measure. Based on these criteria, we have compiled the ensuing list.[6]

[6] Further relevant measures include Andersen et al. (2015); Andersen, Fusari, and Todorov (2017), Agarwal, Ruenzi, and Weigert (2017), Seo and Wachter (2018) and Weller (2018). We refrain from using the measure of Andersen et al. (2015) because the model is highly parameterized, making the estimation computationally very intensive. For Andersen et al. (2017) the weekly options are only available for a limited

In the following, we introduce the main tail risk measures analyzed in this study. To keep the paper focused, in this section we describe only the main mechanisms of the different measures. *The technical details are in Section B1.1 of the Appendix.* We categorize the measures into four main groups, mainly based on their underlying data: (i) option-implied measures, (ii) stock-return-based measures, (iii) option-return-based measures, and (iv) tail risk measures based on macroeconomic data.

In Table 3.1, we summarize the measure acronyms and provide brief descriptions, further information about how the different measures can be interpreted, as well as the estimation frequency. Whenever possible, we define the tail risk measure acronyms in accordance with those in the original studies. For cases in which this would lead to names that could not be uniquely identified, we rely on bibliographic information about the study to generate generic acronyms based on the author names, years, and the probability measure under which they are estimated. All measures are estimated such that an investor could have observed these in real time. Thus, whenever estimation of parameters is necessary, it is based on data available at the time.

3.2.1 Option-Implied Measures

$\boldsymbol{BT11Q}$ (Bollerslev and Todorov, 2011b) is a left tail measure under the risk-neutral probability distribution, which is based on the theoretical framework developed in Bollerslev and Todorov (2011a). Using close-to-maturity deep out-of-the-money put options with constant moneyness, the authors approximate the tail behavior. Intuitively, it is based on the idea that the options will not end up in-the-money at expiration unless a tail event occurs. This results in an expected-shortfall-like measure. We rely on the approximation of Bollerslev and Todorov (2011b).

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time period starting in 2011, making a meaningful empirical evaluation infeasible. Finally, we do not have access to the data underlying the measures in Agarwal et al. (2017), Seo and Wachter (2018), and Weller (2018).

BT14Q and ***BTX15Q*** (Bollerslev and Todorov, 2014; Bollerslev et al., 2015) are extensions of the $BT11Q$ left tail measure. For $BT14Q$, the shape of the tail is allowed to be time-varying. Furthermore, instead of using an approximation, we rely on the fully parameterized model, pooling the options and re-estimating parameters on a weekly basis. For $BT14Q$, Bollerslev and Todorov (2014) only impose a structure on the jump intensity, not on the level shift, smoothing the shift parameter estimates. ***BTX15prob*** (Bollerslev et al., 2015) is defined as the probability of a daily loss of 10% or more. The $BTX15Q$ and $BTX15prob$ measures are based on the non-parametric estimation of Lin and Todorov (2019), using the median level and shift parameters computed from different options.[7] Both $BTX15Q$ and $BTX15prob$ are estimated daily.

H_MRI (Gormsen and Jensen, 2020) is a measure of higher-moment risk. It is defined as the first principal component (PC) of the four moments: skewness, kurtosis, hyperskewness, and hyperkurtosis. The moments are calculated using out-of-the-money put options and the inference techniques of Breeden and Litzenberger (1978) and Martin (2017). To obtain a constant time to maturity, Gormsen and Jensen (2020) interpolate between times to maturity.[8]

RIX (Gao, Lu, and Song, 2019; Gao, Gao, and Song, 2018) is a left tail volatility index. The measure is constructed as the difference between a downside volatility index that, compared to the construction of the VIX, overweights deep out-of-the money put prices and a downside VIX.

TLM (Vilkov and Xiao, 2015) is a parameterized expected shortfall measure. To infer the tail parameters, the authors optimize over the difference between the theoretical (using Extreme Value Theory, EVT) and observed prices of deep out-of-the-money put options.

[7] See also the approach used for the website `https://tailindex.com/` created by Andersen, Todorov, and Fusari.

[8] The authors also show that the first PC loads positively on the kurtosis measures and negatively on the skewness measures. The measure is negatively correlated with volatility. Thus, it tends to be low during volatile periods.

The resulting density can be used to calculate the expected shortfall.

3.2.2 Stock-Return-Based Measures

BT*11*P (Bollerslev and Todorov, 2011b) is a left tail measure under the objective probability measure. Based on intraday high-frequency returns that exceed a certain threshold, the authors estimate the shape and the level of the tail, while adjusting for the time-of-day factor that accounts for intraday variation. Finally, Bollerslev and Todorov (2011b) estimate the tail risk factor based on a time-varying cutoff value.[9]

CJI (Christoffersen, Jacobs, and Ornthanalai, 2012) is the jump intensity from a parametric dynamic volatility model with separate dynamic jumps (DVSDJ). The model is estimated with daily return data. To obtain the unobservable measures, Christoffersen et al. (2012) use a filtering technique. We estimate the model using an expanding window and annual reestimation of the coefficients.[10]

JumpRisk and ***JumpRP*** (Maheu, McCurdy, and Zhao, 2013) are the conditional jump intensity and the conditional equity premium due to jumps, respectively. Both measures are derived from a parametric Generalized Autoregressive Conditional Heteroskedastic (GARCH)-jump mixture model. The jump risk premium is calculated as the first derivative of the equity risk premium with respect to the jump intensity. Since they argue that risk premia in the model behave oppositely to the current state of volatility and jump risk, we define *JumpRP* as the inverse of the corresponding Maheu et al. (2013) measure. Like for the Christoffersen et al. (2012) model, we also use an expanding window with annual coefficient reestimation.

$\boldsymbol{\lambda_{Hill}}$ (Kelly and Jiang, 2014) is an expected-shortfall-like measure, derived from the

[9]See Section B1.1 of the Appendix for further details.

[10]The estimated coefficients are then used to calculate the observations for next years jump intensity over the next year. This procedure ensures that the measure is entirely out-of sample, and thus comparable to the other measures used in this study.

cross-sectional distribution of individual stock returns. The tail threshold is defined as the fifth percentile of all daily unsystematic returns in the cross-section during the past month. The measure is computed using the Hill (1975) power law estimator. Unsystematic returns are defined as the residuals from a regression of the excess returns on the common return factors of Fama and French (1993).

3.2.3 Option-Return-Based Measures

ADBear (Lu and Murray, 2019) is the excess return of a bear spread portfolio of S&P 500 options. The bear spread portfolio is designed to pay \$1 if the S&P 500's excess return is below a threshold K_2. To generate this payoff, they go long a put option with strike price K_1 and short a put option with strike K_2, with $K_1 > K_2$, and scale by $K_1 - K_2$. The resulting portfolio pays off \$0 above K_1 and \$1 below K_2. They set K_2 and K_1 to be 1.5 and 1 standard deviations below zero, respectively, and hold the portfolio for five days.

JUMP (Cremers, Halling, and Weinbaum, 2015) is the return of a vega-neutral and gamma-positive portfolio created from market-neutral straddles written on the S&P 500. We use the daily returns resulting from a strategy with daily rebalancing.

3.2.4 Macroeconomic Measures

LE (Adrian, Boyarchenko, and Giannone, 2019) is a measure of the left entropy of the expected gross domestic product (GDP) growth distribution. The authors model the conditional GDP growth distribution using interpolated quantile regressions with the the National Financial Conditions Index (NFCI) as the explanatory variable.

Table 3.1: Description of Tail Risk Measures

This table presents the main tail risk measures used in this study. The column "Source" provides the original paper, "Description" delivers a brief sketch of the approach. "Acronym" defines the symbol used in this paper to refer to the measure. "Interpretation" characterizes the main concepts underlying the measure. We allocate the measures to the different categories to which they most naturally (but rather broadly defined) belong. "Estimation" characterizes how the parameters are estimated: "OS" and "IS" denote the characterization as an out-of-sample (available in real-time) or an in-sample (parameters optimized using forward-looking data) measure, respectively. Finally, "Freq" denotes the frequency at which the different measures are available. "D" indicates that we observe a measure every trading day. "W", "M" and "Q" denote weekly, monthly and quarterly observation frequencies, respectively.

Source	Description	Acronym	Interpretation	Estimation	Freq
Group A - Option-Implied Measures					
Bollerslev and Todorov (2011b)	Left tail approximation measure under $\mathbb{Q}$	BT11Q	Expected Shortfall	OS	D
Bollerslev and Todorov (2014)	Weekly parametric estimate of time-varying left tail measure	BT14Q	Expected Shortfall	OS	W
Bollerslev et al. (2015)	Probability of a daily loss of 10% or more	BTX15prob	Tail Probability	OS	D
Bollerslev et al. (2015)	Daily non-parametric estimate of time-varying left tail measure	BTX15Q	Expected Shortfall	OS	D
Gormsen and Jensen (2020)	First PC of risk-neutral higher moments	H_MRI	Higher Moment Risk	OS	D
Gao et al. (2018) and Gao et al. (2019)	Left tail volatility as the difference in two volatility indexes	RIX	Left Tail Volatility	OS	M
Vilkov and Xiao (2015)	Expected shortfall inferred from parametrised tail distribution	TLM	Expected Shortfall	OS	D
Group B - Stock-Return-Based Measures					
Bollerslev and Todorov (2011b)	Left-tail approximation measure under $\mathbb{P}$	BT11P	Expected Shortfall	OS	D
Christoffersen et al. (2012)	Parametric model-implied jump intensity	CJI	Jump Intensity	OS	D
Maheu et al. (2013)	Parametric model-implied jump intensity	JumpRisk	Jump Intensity	OS	D
Maheu et al. (2013)	Parametric model-implied jump risk premium	JumpRP	Jump Risk Premium	OS	D
Kelly and Jiang (2014)	Left tail of the cross-section of stock returns	λ_{Hill}	Expected Shortfall	OS	M
Group C - Option-Return-Based Measures					
Lu and Murray (2019)	Return of bear spread put option positions	ADBear	Jump Risk Premium	OS	D
Cremers et al. (2015)	Return of vega-neutral, gamma-positive option portfolio	JUMP	Jump Risk Premium	OS	D
Group D - Macroeconomic Measures					
Adrian et al. (2019)	Left entropy of expected GDP growth	LE	Left Entropy	OS	Q

3.3 Data and Methodology

3.3.1 Data

Previous studies rely on several different data sources for estimating tail risk. Following the characterization performed in the previous section, we obtain options as well as stock return data from various sources. First, we obtain data on S&P 500 option prices as well as the corresponding Greeks and the risk-free interest rate and dividend yield from OptionMetrics. To clean the options data, we follow the steps outlined in Carr and Wu (2003, 2009). First, we remove strike prices that are duplicated per day, retaining the one with higher open interest. Second, the bid prices are required to be strictly positive and ask prices cannot be lower than bid prices. Some measures impose a cutoff level for short-maturity options. To be consistent we follow Carr and Wu (2003, 2009) and choose 8 days.

Second, we use the 1-minute prices of the S&P 500 from Thomson Reuters Tick History (TRTH). We follow the steps advocated by Barndorff-Nielsen, Hansen, Lunde, and Shephard (2009) to clean the data. First, we use only data with a time stamp falling during the exchange trading hours, i.e., between 9:30 AM and 4:00 PM EST. Second, we remove recording errors in prices. To be more specific, we filter out prices that differ by more than 10 mean absolute deviations from a rolling centered median of 50 observations. Afterwards, we use the nearest previous entry to assign prices to every 1-minute interval.

Third, we obtain prices of all stocks traded on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotations (NASDAQ) that are classified as ordinary common shares (CRSP share codes 10 or 11) from the Center for Research in Security Prices (CRSP). In addition, we obtain data on the S&P 500 index from the same source. We use the total return on the S&P 500 as the market return, subtracting the 1-month Treasury Bill rate from Kenneth

French to obtain excess returns.[11]

Finally, we obtain data on the National Financial Conditions Index (NFCI) from the Chicago Federal Reserve and on the GDP from the Bureau of Economic Analysis (BEA). We collect further data from Amit Goyal's webpage (10-year, 3-month, and 1-month Government Bond yields), the St. Louis FRED (AAA and BAA rated corporate bond yields, industrial production), and Martin Lettau's webpage (CAY).[12]

Our sample period extends from 1996 to 2017.[13] Because the aim of this study is, to compare different tail risk measures, we restrict our attention to this period, also for those measures for which data would be available for longer time series.

3.3.2 Empirical Test Design

What characterizes a good tail risk measure? Obviously, it should be good at predicting future tail events. To test this property, we devise two statistical tests to gauge the measure's ability to forecast future tail events. Moreover, a good tail risk measure should also matter economically. That is, it should command a risk premium, i.e., be priced by investors (Rietz, 1988; Barro, 2006). To analyze the economic content, we test the measure's ability to forecast future aggregate market returns. In the following sections we describe the corresponding tests in more detail.

Statistical Tests

The first test we use is a simple forecast analysis of realized tail events. To do so, we use a binary probit model (Vilkov and Xiao, 2015). We define the threshold based on the VIX.

[11] The website is `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[12] Amit Goyal's webpage can be reached as `http://www.hec.unil.ch/agoyal/`. Martin Lettau's webpage is `https://sites.google.com/view/martinlettau/datawebpage`.

[13] The starting date, 1996, is dictated by the fact that both the OptionMetrics and TRTH databases do not start before that date. The ending date of our sample period is restricted by the data availability when we started this project.

The binary dummy variable is defined as follows:

$$D_{t+\Delta t} = \begin{cases} 1 & \text{if } R_{t+\Delta t} \leq -2\sigma_t, \\ \\ 0 & \text{if otherwise,} \end{cases} \tag{3.1}$$

where $R_{t+\Delta t}$ is the market excess return over the period from t until $t+\Delta t$, with Δt measured in trading days. $\sigma_t = \widehat{VIX}_t/100\sqrt{\Delta t/252}$ is the conditional volatility. VIX_t is the level of the VIX at the end of day t.

To test if the tail risk measure can capture the realization of a 2-sigma tail event, we conduct the following regression:

$$D_{t+\Delta t} = a + b \cdot TRM_t + \epsilon_{t+\Delta t}, \tag{3.2}$$

where TRM_t is the observation of the tail risk measure at time t.

While the probit model captures the occurrence of tail events, it does not account for by how much the observed returns exceed the specified threshold and how much quadratic variation they account for. Forecasting the quadratic variation due to left tail events might thus be even more important for investors. Hence, for a second test, we examine the measures' abilities to forecast the future realized left tail variation. This measure yields particularly high values if the magnitude of (ex-post) tail realizations are very large (or if there are many tail events over the examined period). Based on Mancini (2001), Bollerslev and Todorov (2011b) propose the following left tail variation measure, which is a special case of the truncated variance:[14]

$$\begin{aligned} LTV_t^{\mathbb{P}} &= \sum_{i=1}^{n-1} r_i^2 \cdot 1_{r_i<(-\alpha_{t,i}\Psi^{0.49})} \\ LTV_{t+\Delta t}^{\mathbb{P}} &= \sum_{i=t}^{t+\Delta t} LTV_i^{\mathbb{P}}, \end{aligned} \tag{3.3}$$

where r_i denotes an intraday log-return. Following Mancini (2001) and Bollerslev and Todorov (2011b) we include intraday returns only. In Section 3.5.9, we show that the results are qualitatively similar when also including overnight returns in the analysis. Ψ is the length, as a fraction of a day, of each intraday sampling interval. We use market excess returns during $n = 390$ 1-minute intervals every day to estimate Equation (3.3). $1_{r_i<(-\alpha_{t,i}\Psi_n^{0.49})}$ describes a dummy variable that is 1 if the realized intraday return r_i is below $-\alpha_{t,i}\Psi_n^{0.49}$. $\alpha_{t,i}$ is a time-varying threshold adjusted by a time-of-day (TOD) factor, which accounts for the predictable variation of the intraday returns:

$$\alpha_{t,i} = 4\sqrt{BV_t \wedge RV_t} \cdot TOD_i \cdot \Psi^{0.49}. \tag{3.4}$$

BV_t and RV_t are the bi-power and realized variation, respectively. To test if the tail risk measure can capture the future left tail variation we run the following regression:

$$LTV_{t+\Delta t}^{\mathbb{P}} = a + b \cdot TRM_t + c \cdot LTV_t^{\mathbb{P}} + d \cdot VIX_t + \epsilon_{t+\Delta t}. \tag{3.5}$$

We control both for the lagged left tail variation $LTV_t^{\mathbb{P}}$ as well as the current conditional volatility, measured by VIX_t. We do so to see whether the tail risk measures contribute to predicting the left tail variation beyond its own lag and the VIX.

[14]The left tail variation measure is based on a decomposition of the realized variation into continuous and jump variation first proposed by Mancini (2001), which Bollerslev and Todorov (2011b) use to separate the jump variation further into left and right jump variation.

Economic Tests

For our main economic test, we examine the ability of the different tail risk measures to forecast future market excess returns. If tail risk is a relevant risk-factor in the market, the equity risk premium should include compensation for tail risk. Thus, if tail risk is large, the equity risk premium should be higher than during calm times of low tail risk. Hence, a tail risk measure that is priced in the market should be able to positively forecast future market excess returns.

We use the following regression model to test if the tail risk measures can predict returns:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}. \tag{3.6}$$

Since there are several variables that have been previously documented to predict future stock returns, we follow Bollerslev et al. (2009) and use several control variables in the vector $Controls_t$: the variance risk premium (VRP), the log dividend price ratio (log(D/P)), the default spread (DFSP), the term spread (TMSP), and the stochastically detrended risk-free rate (RREL).

Further Methodological Details

Throughout this paper, we report partial rather than "full" R^2s. We do so to emphasize the marginal contribution of each tail risk measure to the explanatory power of a model that may contain several variables.[15] For the probit regressions we calculate the partial R^2 via dominance analysis. We retrieve the average contribution from the dominance analysis following Azen and Budescu (2003). A predictor is dominant if it contributes more to the prediction than another one. We report the measure for general dominance, which is the

[15]This is particularly important since most of our analyses also contain control variables. In addition, for the analyses with multiple tail risk measures we can gauge the contribution of each individual variable.

mean of the average additional contribution on each level. For all other tests we use the partial R^2 of Lindeman et al. (1980). This measure uses a simple unweighted average of the average contributions of different models of different sizes. It sums up to the unadjusted R^2.

For statistical inference, we rely on the wild bootstrap procedure of Rapach, Strauss, and Zhou (2013), which we describe in more detail in the Appendix. The bootstrap preserves the contemporaneous correlation structure in the data, controls for the Stambaugh (1999) bias, and allows or conditional heteroskedasticity in stock returns. To account for autocorrelation, we base all t-statistics in the original and the bootstrap samples on robust Newey and West (1987) standard errors with 29 lags (252 lags for annual horizons). For a robustness test, in Section 3.5.10 we also present the results when using a block bootstrap. These are qualitatively similar.

Finally, to reduce the dimensionality in multiple regressions, we follow Bekaert, Harvey, Lundblad, and Siegel (2011) and use the general-to-specific PcGets search algorithm. In multiple steps, this algorithm eliminates insignificant predictor variables. For a robustness test, in Section 3.5.5 we alternatively also present the results for the jackknife procedure (Bekaert et al., 2011). We outline both methods in Section B1.3 of the Appendix.

3.4 Main Analysis

3.4.1 Summary Statistics

In Table 3.2, we present the summary statistics of the 15 different tail risk measures. We find that the main characteristics of the measures in our sample match those documented in the literature. The measures are vastly heterogeneous in their means and standard deviations. To account for that and to make the results comparable across measures, we standardize all measures to have a mean of zero and a standard deviation of one for the ensuing tests.

Importantly, all but two measures have positive skewness and all measures but one have substantial excess kurtosis. This observation is consistent with the measures' interpretation as capturing the risk of low-probability high-impact events. Once these events become increasingly likely, a tail risk measure should experience a distinct peak. This initial intuition already calls into question the usefulness of those tail risk measures that have negative skewness and/or little to no excess kurtosis, notably λ_{Hill}, $JumpRisk$, and $JumpRP$.

Table 3.2: Summary Statistics

This table displays the summary statistics of the tail risk measures considered. The definitions of the tail risk measure acronyms are given in Table 3.1. We sort the tail risk measures into different categories based on their underlying data. We present several time-series statistics. "$Mean$" denotes the time-series average, "SD" is the standard deviation. For the remainder of the paper, we standardize the tail risk measures to have a mean of zero and a standard deviation of one. "$Median$", "Min" and "Max" denote the median, the lowest and the highest values, respectively, attained by the measures. "$Skewness$" and "$Kurtosis$" denote the skewness and kurtosis of the measures' distributions. Finally, "$AR(1)$" denotes the first-order autocorrelation of the measures. All measures except for RIX, $BT14Q$, λ_{Hill} and LE are available at the daily frequency. $BT14Q$ is weekly, λ_{Hill} and RIX are monthly, and LE is quarterly. $BT11P$ is scaled by 100.

	$Mean$	SD	$Median$	Min	Max	$Skewness$	$Kurtosis$	$AR(1)$
Group A - Option-Implied Measures								
$BT11Q$	0.3962	0.6099	0.2144	0.0060	10.4551	5.2393	45.0622	0.9280
$BT14Q$	0.0086	0.0046	0.0076	0.0023	0.0579	3.4557	28.2029	0.6107
$BTX15prob$	0.8299	0.5640	0.6490	0.0000	4.5502	1.5709	6.1317	0.9973
$BTX15Q$	0.0789	0.0359	0.0703	0.0021	0.3985	2.4158	13.4343	0.9320
H_MRI	0.0000	1.9152	−0.4398	−2.3253	17.5014	3.5753	21.2163	0.9730
RIX	0.1572	0.0205	0.1545	0.1230	0.2402	1.3616	5.7250	0.8154
TLM	0.0437	0.0146	0.0403	0.0218	0.1628	1.8851	9.4089	0.9770
Group B - Stock-Return-Based Measures								
$BT11P$	0.0058	0.0072	0.0038	0.0000	0.0864	2.6368	15.7063	0.0490
CJI	0.0152	0.0228	0.0095	−0.0194	0.1727	2.9916	15.0090	0.9823
$JumpRisk$	0.1596	0.0272	0.1651	0.0885	0.2089	−0.5478	2.4405	0.9988
$JumpRP$	0.7400	0.3102	0.6585	0.3556	1.9788	0.8626	2.9707	0.9646
λ_{Hill}	0.4426	0.0275	0.4450	0.3447	0.5054	−0.5789	3.8619	0.7538
Group C - Option-Return-Based Measures								
$ADBear$	−0.0963	0.7638	−0.3089	−0.9950	10.1970	2.8190	18.9207	0.6775
$JUMP$	−0.0019	0.0518	−0.0083	−0.8375	1.2189	4.6072	99.0955	−0.0401
Group D - Macroeconomic Measures								
LE	0.0885	0.1690	0.0331	−0.0266	1.0478	3.5552	17.7338	0.7904

An important feature to distinguish between the different tail risk measures is their persistence. The (daily) first-order autocorrelation exceeds 0.99 for $BTX15prob$, and $JumpRisk$. It is further above 0.90 for $BT11Q$, $BTX15Q$, CJI, H_MRI, and $JumpRP$.[16] The high autocorrelations imply that the tail risk measured by these variables is highly persistent and changes little on a day-by-day basis. On the other hand, there are also two measures with near-zero autocorrelations: $BT11P$ and $JUMP$. The low autocorrelations of these two measures would imply that tail risk changes heavily even over short windows. In part, this is surely caused by large noise in the estimation of these measures. For $JUMP$, the construction of the measure as a daily return likely also plays a role. It appears to be more akin to the first difference in tail risk. The first-order autocorrelations of the remaining measures all exceed 0.60, indicating that according to most measures tail risk is quite persistent.[17] The question, though, whether low, medium, or high persistence is a desirable property of a good tail risk measure is an empirical one, which we seek to answer in this section.

Figures 3.2, 3.3, and 3.4 display the time-series of the standardized tail risk measures. For a better visualization, we further average all daily observations of the tail risk measures during a month. For most measures, we observe distinct peaks during October 2008, the peak of the financial crisis right after the Lehman bankruptcy. In particular, all Bollerslev–Todorov measures show this peak. However, for part of the other measures, we do not observe it. E.g., for λ_{Hill} there is rather a trough than a peak in the time-series at that time. In addition, even among the Bollerslev–Todorov measures we observe substantially different behavior in the time series, with large peaks in some measures that seem to be mostly absent in others. This visual inspection of the tail risk measures suggests that they may not be very strongly correlated among each other and thus contain quite different information.

[16] The autocorrelation of the λ_{Hill} measure in our sample is somewhat lower than that reported by Kelly and Jiang (2014) (0.75 vs. 0.93). However, this seems to be dependent on the sample period. For their full sample period (1963–2010), we also obtain an autocorrelation of 0.93.

[17] In statistical tests, we use bootstrap procedures (described in the Appendix) to ensure that the inference is robust to this persistence in the explanatory variables.

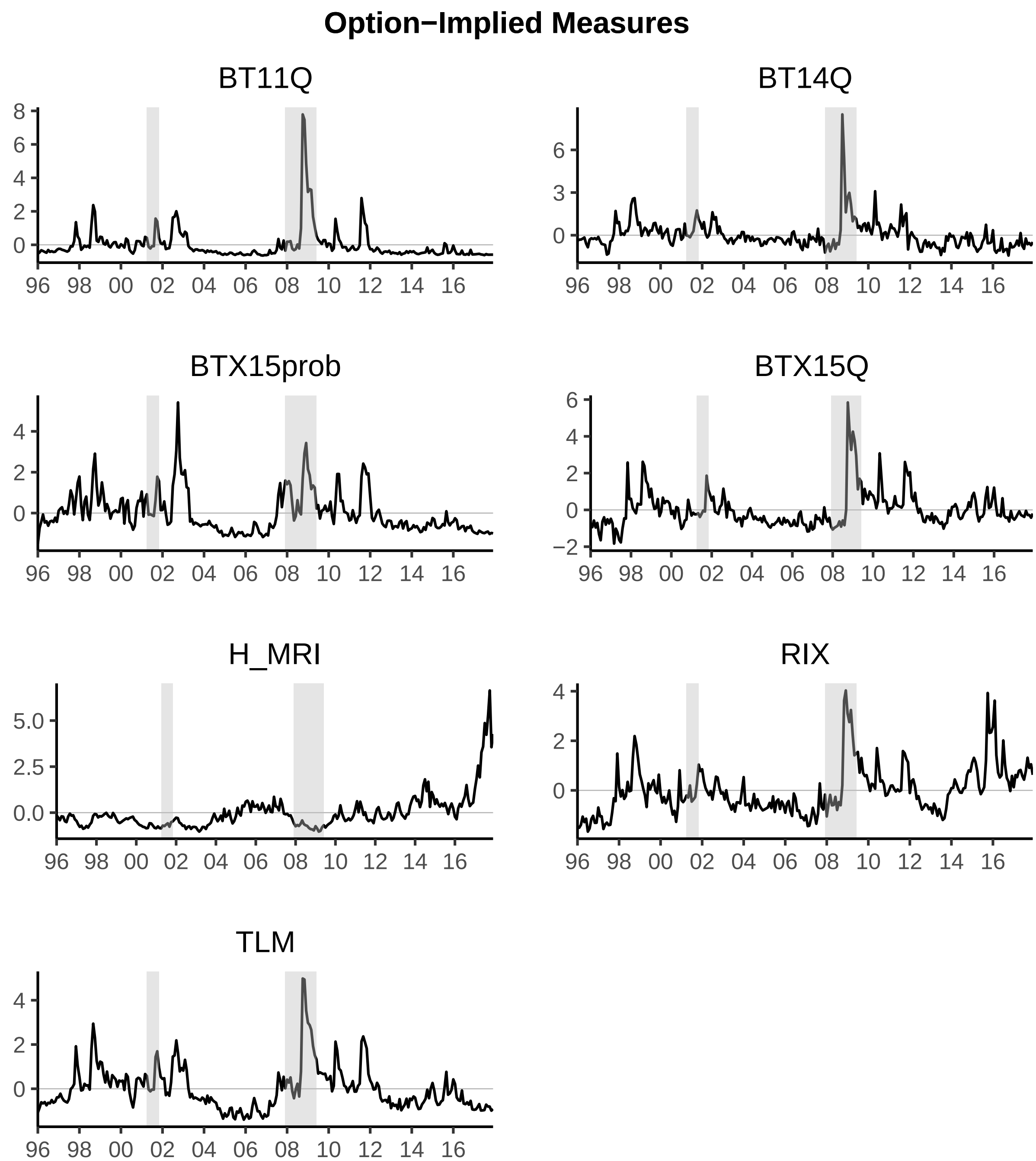


Figure 3.2: Tail Risk Measures: Option-Implied Measures

This figure displays the time-series of the standardized (mean of zero and standard deviation of one) option-implied tail risk measures. For a better visualization, we average all daily observations of the tail risk measures during a month. The shaded areas indicate business cycle contractions as identified by the NBER. The definitions of the tail risk measure acronyms are given in Table 3.1.

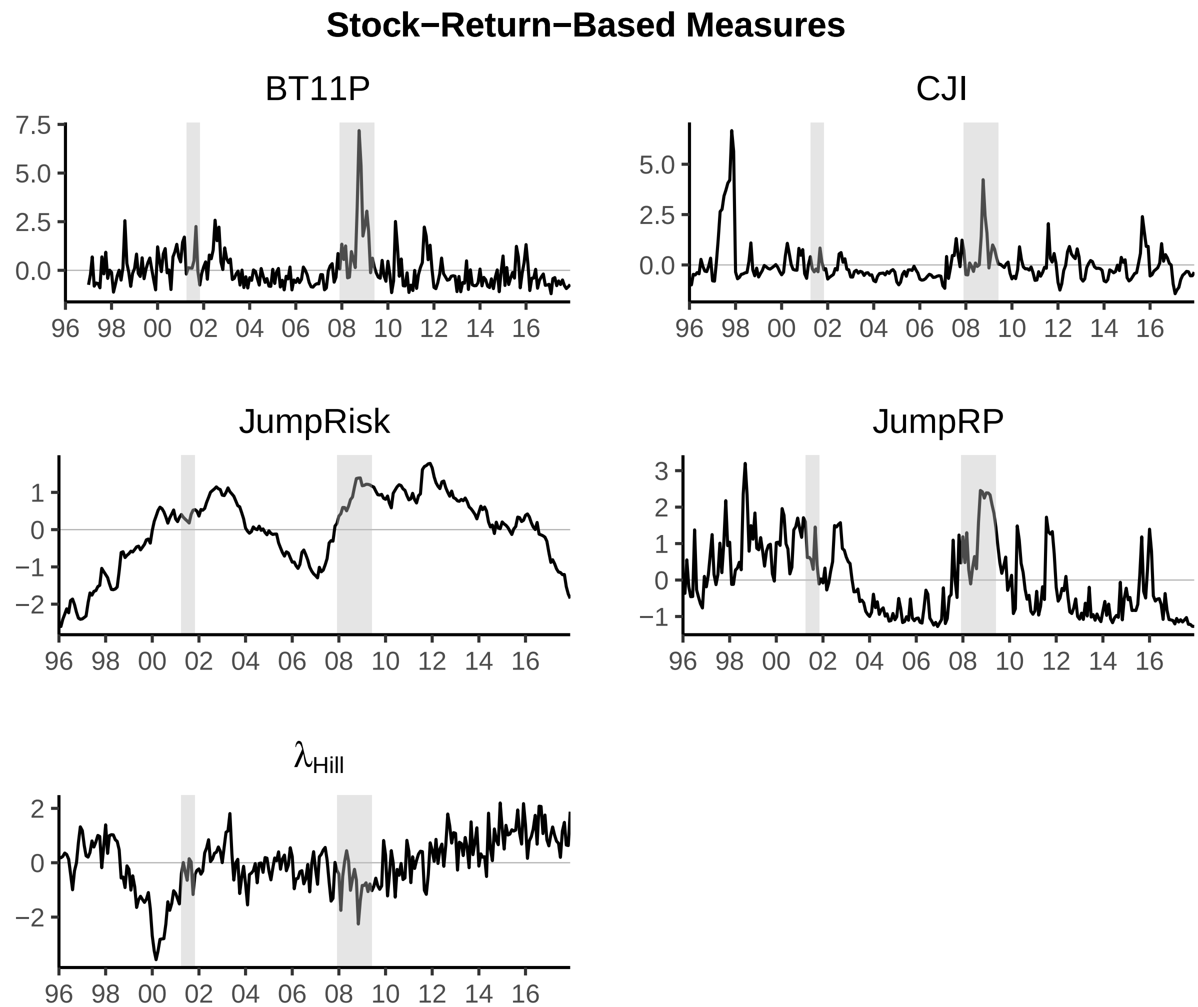


Figure 3.3: Tail Risk Measures: Stock Return Based Measures

This figure displays the time-series of the standardized (mean of zero and standard deviation of one) stock-return-based tail risk measures. For a better visualization, we average all daily observations of the tail risk measures during a month. The shaded areas indicate business cycle contractions as identified by the NBER. The definitions of the tail risk measure acronyms are given in Table 3.1.

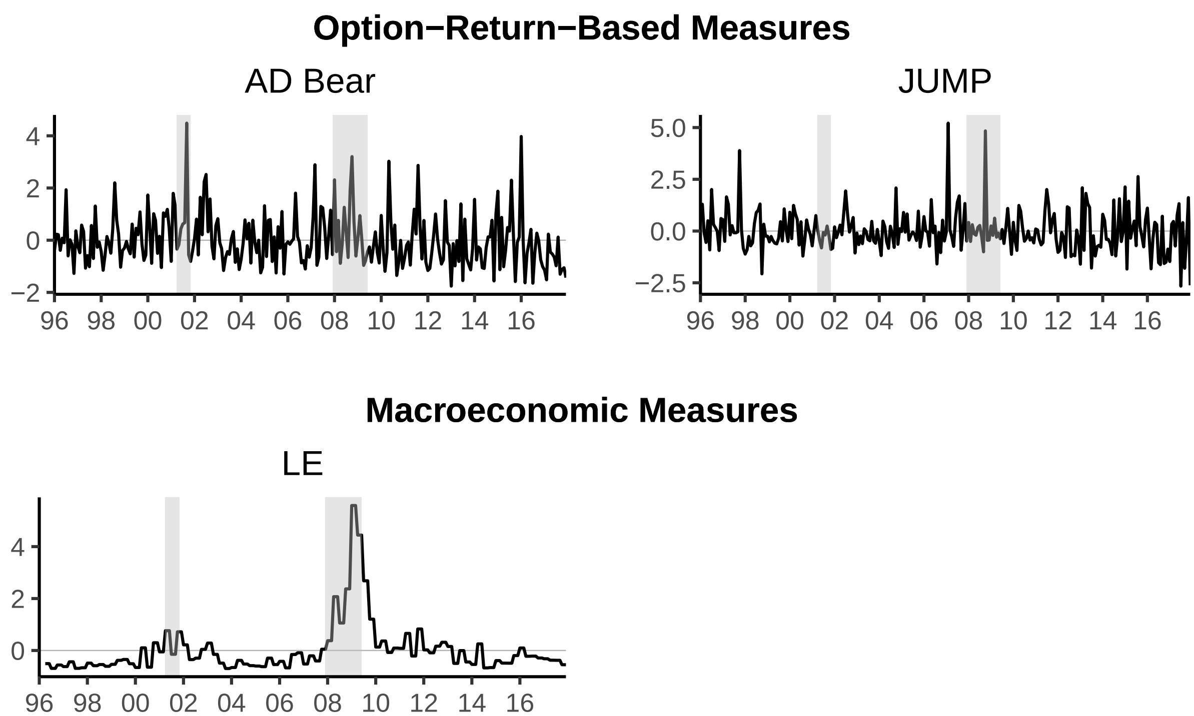


Figure 3.4: Tail Risk Measures: Option Return Based and Macroeconomic Measures

This figure displays the time-series of the standardized (mean of zero and standard deviation of one) option-return-based- and macroeconomic tail risk measures. For a better visualization, we average all daily observations of the tail risk measures during a month. The shaded areas indicate business cycle contractions as identified by the NBER. The definitions of the tail risk measure acronyms are given in Table 3.1.

Table 3.3 displays the correlations of the tail risk measures. Consistent with the time-series plots, we find that the correlations are indeed much lower than what one would expect from different measures that are broadly designed to capture essentially the same underlying risk. In particular, the correlation between measures across different groups is typically low.

Among the option-implied measures, we generally observe the highest correlations. E.g., $BT11Q$ and $BTX15prob$ have correlations of 0.87 and 0.79 with TLM, respectively. On the other hand, H_MRI is negatively correlated with all but one of the other option-implied measures.[18] Among the stock-return-based measures, the correlations are generally lower. Interestingly, the correlations of $JumpRP$ with most option-implied measures are also relatively high. On the other hand, the correlation of $BT11Q$ with $BT11P$, which are related measures, is relatively low, with 0.37.[19] The correlations of the option-return-based measures with all the others are rather low. Interestingly, the only macroeconomic measure in our dataset, although measured at low-frequency and based on non-financial data, is rather strongly correlated with several of the other measures. E.g., the correlation between LE and TLM is as high as 0.51.

Table 3.3 also presents the correlations of the tail risk measures with the VIX, a simple measure of the current conditional volatility. Finding that there is some correlation of tail risk with volatility would be natural. However, the tail risk measures should capture the risk of ending up in particularly bad states of the world on top of "normal" day-to-day variation. We find that many tail risk measures have high correlations with the VIX, e.g., $BT11Q$ (0.89), $BTX15prob$ (0.80), TLM (0.96), and $JumpRP$ (0.85). These high correlations imply that the tail risk measures may allow only little additional insights about tail risk beyond what is captured by the VIX. To account for this, we control for volatility in our empirical tests.

[18] This is consistent with Gormsen and Jensen (2020), who show hat H_MRI tends to be low when volatility is high.

[19] λ_{Hill} has negative correlations with almost all other measures, apart from H_MRI. The latter observation is consistent with Kelly and Jiang (2014), who show that λ_{Hill} loads negatively on skewness and positively on kurtosis, as does (by construction) H_MRI.

In Table 3.4 we present a principal component (PC) analysis of the tail risk measures. We calculate the first two PCs among all measures, as well as the respective first two PCs within each group of measures. Consistent with our previous results in this section, commonality among the different measures is rather low. The first PC of all measures can only explain 38% of the variation. Together with the second PC, the share rises to only 49%. Thus, it is difficult to capture the information contained in the different tail risk measures with just few PCs.

The largest loadings of the first PC are on $BT11Q$ (0.37), TLM (0.40), and $JumpRP$ (0.35). Thus, these measures appear to be most representative of the common variation in the tail risk measures. Within the subgroups, the degree of commonality is somewhat larger. The first two PCs in each subgroup capture at least 59% of the variation in the tail risk measures. The highest loadings of the first PC among the option-implied measures are on $BT11Q$ (0.44) and TLM (0.48). Among the stock-return-based measures, the highest PC loadings are on $BT11P$ and $JumpRP$. However, being able to capture common variation in the tail risk measures may be a misguided objective for the selection of a certain measure. We should rather judge the measures based on their ability to forecast future tail events and capture risk premia.

Table 3.3: Correlations

This table displays the time-series correlations among the tail risk measures considered. The definitions of the tail risk measure acronyms are given in Table 3.1. In order to compare the correlations, we use a daily sample with constant extrapolation. The last line shows the correlation with the VIX.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Group A - Option-Implied Measures															
(1) $BT11Q$		0.66	0.64	0.70	−0.28	0.39	0.87	0.37	0.38	0.33	0.61	−0.26	0.25	0.09	0.49
(2) $BT14Q$			0.42	0.62	−0.12	0.30	0.67	0.17	0.26	0.19	0.47	−0.22	0.14	0.03	0.33
(3) $BTX15prob$				0.44	−0.44	0.33	0.79	0.16	0.28	0.37	0.63	−0.28	0.05	0.02	0.36
(4) $BTX15Q$					−0.05	0.56	0.77	0.22	0.25	0.33	0.48	−0.12	0.14	0.05	0.45
(5) H_MRI						0.14	−0.36	−0.13	−0.07	−0.41	−0.30	0.40	−0.16	−0.11	−0.25
(6) RIX							0.49	0.07	0.09	0.32	0.29	0.04	−0.04	−0.03	0.44
(7) TLM								0.32	0.37	0.43	0.74	−0.30	0.24	0.09	0.51
Group B - Stock-Return-Based Measures															
(8) $BT11P$									0.08	0.12	0.34	−0.09	0.44	0.33	0.13
(9) CJI										−0.02	0.47	0.04	0.08	0.01	0.09
(10) $JumpRisk$											0.19	−0.22	0.07	0.03	0.47
(11) $JumpRP$												−0.35	0.32	0.12	0.36
(12) λ_{Hill}													−0.05	−0.03	−0.22
Group C - Option-Return-Based Measures															
(13) $ADBear$														0.23	0.01
(14) $JUMP$															0.01
Group D - Macroeconomic Measures															
(15)LE															
ρ_{VIX}	0.89	0.64	0.80	0.69	−0.49	0.41	0.96	0.36	0.44	0.38	0.85	−0.35	0.26	0.08	0.53

Table 3.4: Principal Components

This table presents the results of a principal component analysis (PCA) of the standardized tail risk measures. The definitions of the tail risk measure acronyms are given in Table 3.1. We use a daily sample of the tail risk measures, with constant extrapolation. We display the first two PCs among all measures and within the different subgroups. The column "*CumVar*" displays the cumulative variance explained by the PCs. The last column displays the correlation of each PC with the VIX.

	BT11Q	*BT14Q*	*BTX15prob*	*BTX15Q*	*H_MRI*	*RIX*	*TLM*	*BT11P*	*CJI*	*JumpRisk*	*JumpRP*	λ_{Hill}	*ADBear*	*JUMP*	*LE*	*CumVar*	ρ_{VIX}
Full Sample																	
PC1	0.37	0.30	0.32	0.32	−0.19	0.21	0.40	0.16	0.18	0.20	0.35	−0.15	0.12	0.05	0.25	0.38	0.96
PC2	−0.01	−0.08	−0.06	−0.18	−0.25	−0.40	−0.04	0.44	0.10	−0.14	0.17	−0.12	0.49	0.41	−0.25	0.49	0.05
Group A - Option-Implied Measures																	
PC1	0.44	0.38	0.38	0.41	−0.17	0.29	0.48									0.58	0.94
PC2	−0.03	0.05	−0.27	0.26	0.76	0.52	−0.06									0.76	-0.23
Group B - Stock-Return-Based Measures																	
PC1								0.41	0.38	0.31	0.66	−0.40				0.37	0.84
PC2								−0.03	−0.69	0.56	−0.12	−0.45				0.59	-0.04
Group C - Option-Return-Based Measures																	
PC1													0.71	0.71		0.61	0.21
PC2													−0.71	0.71		1.00	-0.14

3.4.2 Statistical Tests

We start with the statistical tests. We use three different forecast horizons: (i) one day ($Daily$), (ii) one week ($Weekly$), and (iii) one month ($Monthly$).[20] We do not look at longer horizons for this analysis because being able to predict realized tail events or variation in the far future appears unrealistic. Beginning with the probit model, we examine how well the tail risk measures perform in forecasting future tail events. For each measure and forecast horizon we conduct separate regressions of the (horizon-specific) dummy variables on the lagged standardized tail risk measures.

First, in Figure B1 of the Appendix, we illustrate the timing of realized left tail events. We separately depict these for the daily, weekly, and monthly horizons. There is some clustering of realized left tail events during specific crisis periods such as the burst of the dot-com bubble and the recent financial crisis. Interestingly, we find that not all daily left tail realizations lead to weekly or monthly left tail observations. Similarly, part of the weekly and monthly tail events occur without being driven by single or multiple daily tail observations.

The probit regression results are presented in Table 3.5. At the daily level, we find that many of the tail risk measures have some predictive power for future tail events. The 3 measures that show the highest R^2s and that are statistically significant are, in order, $JumpRP$, CJI, and $BT11Q$. Figures B2 to B4 of the Appendix plot the fitted values of the regressions at the daily frequency along with the realized tail events. These fitted values visualize the time-varying probabilities of a crash implied by the regression model. While many measures are largely useless for predicting future left tail events at the daily horizon, it becomes apparent why $JumpRP$, CJI, and $BT11Q$ perform best. They often yield their most pronounced peak implied tail event probabilities around actual tail event realizations. For all measures, periods in which the models suggest high probabilities of a

[20]Four of the measures are not available on a daily frequency. In the case of these measures, we constantly extrapolate the last weekly, monthly, or quarterly observation until new information becomes available.

tail event without one actually occurring do not appear to be all that common.

At the weekly and monthly horizons, the overall performance of the measures becomes much weaker. None of the three tail risk measures that perform best at the daily horizon yields a significant positive predictive coefficient. At the weekly horizon, $ADBear$ yields a weakly significant positive predictive coefficient. At the monthly horizon, $JumpRisk$ and $JUMP$ are able to predict future tail events. No tail risk measure can predict future left tail events for more than one horizon.

It is important to mention that we require the tail risk measures to be positively related to future tail events. That is, a high tail risk measure should be associated with a higher probability of a future tail event. At the monthly horizons, for example, $BTX15prob$ and RIX even yield slope coefficients that are significantly negative. Such results are surely inconsistent with being a good tail risk measure.

Beside the individual tail risk measures, we also repeat the probit regressions with the first PC of all measures and among the different subgroups. We find that the first PC of all measures and that only using stock-return-based measures significantly predict tail events at the daily frequency. At the weekly and monthly horizons none of the PCs significantly predicts future tail events.

We further report the results of multiple probit regressions in Table 3.6. For each horizon, we select the measures with PcGets. For the daily forecast horizon, the selected measures that have significant positive coefficients are $BT11Q$ and CJI. For the weekly horizon, only $BT14Q$ is selected and yields a significant positive coefficient. At the monthly horizon, we cannot detect any significant positive coefficient.

Table 3.5: Prediction of Tail Events

This table presents the coefficients from the predictive probit regressions. We perform single probit regressions of a dummy variable on each lagged tail risk measure:

$$D_{t+\Delta t} = a + b \cdot TRM_t + \epsilon_{t+\Delta t}.$$

$D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the end of the previous day. TRM_t is the current observation of a tail risk measure. We use three different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), and (iii) one-month (*Monthly*). In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. The columns R^2 present the McFadden R^2s, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2
Group A - Option-Implied Measures						
BT11Q	0.09***	1.22	0.08	0.68	0.03	0.08
	(0.021)		(0.048)		(0.046)	
BT14Q	0.07	0.53	0.08	0.56	0.08**	0.68
	(0.042)		(0.048)		(0.041)	
BTX15prob	0.00	0.01	−0.04	0.08	−0.12***	0.60
	(0.060)		(0.079)		(0.040)	
BTX15Q	0.04	0.17	0.04	0.12	0.00	0.01
	(0.072)		(0.073)		(0.055)	
H_MRI	−0.24	1.46	−0.12	0.49	−0.28	1.76
	(0.183)		(0.092)		(0.271)	
RIX	−0.14	1.08	−0.09	0.55	−0.16**	1.13
	(0.132)		(0.106)		(0.076)	
TLM	0.08	0.55	0.06	0.28	0.04	0.14
	(0.058)		(0.084)		(0.054)	
Group B - Stock-Return-Based Measures						
BT11P	0.02	11.37	0.02	0.83	0.05	1.05
	(0.072)		(0.055)		(0.049)	
CJI	0.12***	1.75	0.09	0.81	0.08	0.49
	(0.044)		(0.088)		(0.074)	
JumpRisk	−0.03	0.07	0.02	0.03	0.35**	4.82
	(0.107)		(0.102)		(0.144)	
JumpRP	0.16**	2.06	0.05	0.20	0.11	0.92
	(0.070)		(0.100)		(0.121)	
λ_{Hill}	−0.05	0.24	−0.04	0.18	0.08	0.39
	(0.070)		(0.081)		(0.073)	
Group C - Option-Return-Based Measures						
ADBear	0.06	0.32	0.11**	1.15	0.05	0.22
	(0.049)		(0.053)		(0.061)	
JUMP	−0.04	0.11	−0.03	0.06	0.05**	0.27
	(0.055)		(0.040)		(0.027)	
Group D - Macroeconomic Measures						
LE	0.06	4.05	−0.01	0.20	0.07	0.63
	(0.055)		(0.092)		(0.069)	
PCOneAll	0.12**	12.57	0.05	1.01	0.06	1.09
	(0.047)		(0.092)		(0.063)	
PCOneOption	0.06	0.43	0.05	0.27	0.02	0.08
	(0.057)		(0.076)		(0.044)	
PCOneStReturn	0.15**	13.17	0.06	1.12	0.12	1.87
	(0.064)		(0.110)		(0.111)	
PCOneOpReturn	0.02	0.05	0.06	0.36	0.06	0.38
	(0.046)		(0.042)		(0.043)	

Table 3.6: Multiple Prediction of Tail Events

This table presents the coefficients from the predictive probit regressions. We perform multiple probit regressions of a dummy variable on lagged tail risk measures:

$$D_{t+\Delta t} = a + b \cdot TRM_t + \epsilon_{t+\Delta t}.$$

$D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the end of the previous day. TRM_t is a vector of the current observations of the tail risk measures. We use four different forecast horizons Δt: (i) one-day ($Daily$), (ii) one-week ($Weekly$), and (iii) one-month ($Monthly$). For each forecast horizon, we first perform variable selection based on the PcGets algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. The columns R^2 present the partial McFadden R^2s, obtained by dominance analysis, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$Daily$	R^2	$Weekly$	R^2	$Monthly$	R^2
Group A - Option-Implied Measures						
$BT11Q$	0.06**	1.09				
	(0.027)					
$BT14Q$			0.12**	0.78	0.02	0.68
			(0.054)		(0.121)	
$BTX15prob$			−0.07	0.19	−0.45***	1.77
			(0.088)		(0.144)	
$BTX15Q$						
H_MRI						
RIX			−0.14	0.90	−0.27*	1.99
			(0.140)		(0.138)	
TLM					0.35	1.07
					(0.217)	
Group B - Stock-Return-Based Measures						
$BT11P$						
CJI	0.11**	1.72				
	(0.047)					
$JumpRisk$						
$JumpRP$						
λ_{Hill}						
Group C - Option-Return-Based Measures						
$ADBear$						
$JUMP$						
Group D - Macroeconomic Measures						
LE						
$Controls$	Yes		Yes		Yes	

Next, we move from a left-hand-side variable that only indicates whether there is a tail event or not to one that also includes information about the magnitude of the tail event and, correspondingly, the variation it causes. That is, we predict the realized left tail variation (also standardized to have a mean of zero and a standard deviation of one). We present the results in Table 3.7. We study the same horizons as before (daily, weekly, and monthly) and control for the lagged left tail variation measure and the VIX.

Starting with the daily frequency, we find that $BT11Q$ turns out to be the best predictor. It yields the largest slope coefficient and highest partial R^2. The slope coefficient of 0.19 indicates that, all else equal, an increase in $BT11Q$ by one standard deviation increases the left tail variation by 0.19 standard deviations. The measures $BT14Q$, $BTX15Q$, H_MRI, $JumpRisk$, and $JUMP$ are also significant positive predictors of future left tail variation at the daily frequency. At the weekly horizon, only $BT11Q$ and $JumpRisk$ yield a significant positive slope coefficient. At the monthly forecast horizon, $BT11P$, $JUMP$, and LE are significant predictors of the future left tail variation.

Turning to the PCs, we find that only the first PC of all measures has predictive power for future left tail variation at all horizons. The first PC of the option-return-based measures further has predictive power at the monthly horizon.

We present the results for the multiple regressions to predict the future left tail variation in Table 3.8. $BT11Q$ turns out as the best predictor of realized left tail variation for the daily horizon. It has by far the largest slope coefficient and partial R^2. At the weekly and monthly horizon, on the other hand, LE performs performs best.

Thus, overall, the statistical analysis places $BT11Q$ in pole position in the tail risk measure horse race. It performs well not only for predicting future tail events, but seems to also accurately capture the future left tail variation over short horizons. For predicting tail events and left tail variation over longer horizons, other measures perform well, most notably $BT14Q$ and $JumpRisk$ for tail events and LE for left tail variation.

Table 3.7: Predictability of Left Tail Variation

This table presents the coefficients from a predictive regression for future left tail variation. We perform single regressions of the standardized realized left tail variation on each lagged tail risk measure:

$$LTV^{\mathbb{P}}_{t+\Delta t} = a + b \cdot TRM_t + c \cdot LTV^{\mathbb{P}}_t + d \cdot VIX_t + \epsilon_{t+\Delta t}.$$

TRM_t is the current observation of a tail risk measure. We control for the lagged left tail variation $LTV^{\mathbb{P}}_t$ and the current level of the VIX (VIX_t). We use three different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), and (iii) one-month (*Monthly*). In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2
Group A - Option-Implied Measures						
BT11Q	0.19**	2.88	0.30**	8.52	0.14	9.27
	(0.098)		(0.173)		(0.140)	
BT14Q	0.10*	2.18	0.18*	6.67	0.09	6.05
	(0.070)		(0.133)		(0.083)	
BTX15prob	−0.12**	0.96	−0.23*	2.99	−0.23**	3.40
	(0.057)		(0.152)		(0.183)	
BTX15Q	0.09**	1.95	0.13	5.42	0.02	4.77
	(0.053)		(0.111)		(0.093)	
H_MRI	0.03*	0.31	0.05	0.97	−0.01	1.35
	(0.020)		(0.050)		(0.041)	
RIX	−0.03	0.19	−0.06	0.60	−0.06	0.86
	(0.028)		(0.062)		(0.081)	
TLM	0.05	1.99	0.14	6.39	−0.07	6.73
	(0.088)		(0.219)		(0.271)	
Group B - Stock-Return-Based Measures						
BT11P	−0.01	0.23	0.04	1.30	0.06**	1.91
	(0.046)		(0.029)		(0.034)	
CJI	0.02	0.62	0.04	1.84	0.03	2.30
	(0.030)		(0.053)		(0.055)	
JumpRisk	0.03**	0.63	0.06**	1.95	0.09**	3.50
	(0.014)		(0.030)		(0.076)	
JumpRP	−0.09*	1.18	−0.15	3.64	−0.03	4.18
	(0.053)		(0.164)		(0.134)	
λ_{Hill}	0.01	0.21	0.01	0.68	0.00	1.03
	(0.018)		(0.037)		(0.050)	
Group C - Option-Return-Based Measures						
ADBear	0.01	0.22	0.02	0.64	0.06**	1.02
	(0.026)		(0.038)		(0.049)	
JUMP	0.04*	0.24	0.02	0.10	0.03***	0.16
	(0.031)		(0.014)		(0.021)	
Group D - Macroeconomic Measures						
LE	0.03	0.89	0.06*	2.81	0.14***	5.83
	(0.024)		(0.041)		(0.063)	
PCOneAll	0.20**	2.30	0.32**	7.12	0.29**	8.47
	(0.099)		(0.145)		(0.191)	
PCOneOption	0.14	2.27	0.19	6.78	−0.05	7.08
	(0.114)		(0.223)		(0.301)	
PCOneStReturn	−0.02	1.37	0.02	4.66	0.13	6.47
	(0.064)		(0.111)		(0.119)	
PCOneOpReturn	0.04	0.35	0.02	0.51	0.06**	0.81
	(0.031)		(0.032)		(0.040)	
Controls	*Yes*		*Yes*		*Yes*	

Table 3.8: Multiple Predictability of Left Tail Variation

This table presents the coefficients from a predictive regression for future left tail variation. We perform multiple regressions of the realized left tail variation on the lagged tail risk measures:

$$LTV^{\mathbb{P}}_{t+\Delta t} = a + b \cdot TRM_t + c \cdot LTV^{\mathbb{P}}_t + d \cdot VIX_t + \epsilon_{t+\Delta t}.$$

TRM_t is a vector of the current observations of the tail risk measures. We control for the lagged left tail variation $LTV^{\mathbb{P}}_t$ and the current level of the VIX (VIX_t). We use three different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), and (iii) one-month (*Monthly*). For each forecast horizon, we first perform variable selection based on the PcGets algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2
Group A - Option-Implied Measures						
$BT11Q$	0.19***	4.15			−0.02**	10.27
	(0.046)				(0.008)	
$BT14Q$						
$BTX15prob$						
$BTX15Q$						
H_MRI						
RIX						
TLM						
Group B - Stock-Return-Based Measures						
$BT11P$						
CJI						
$JumpRisk$	0.04***	0.65				
	(0.015)					
$JumpRP$						
λ_{Hill}						
Group C - Option-Return-Based Measures						
$ADBear$						
$JUMP$						
Group D - Macroeconomic Measures						
LE			0.04***	3.12	0.01***	4.76
			(0.010)		(0.004)	
Controls	*Yes*		*Yes*		*Yes*	

3.4.3 Economic Tests

Finally, we turn to the question of whether tail risk is priced in the market. While part of the tail risk measures are developed for slightly differing purposes, the majority of studies appear to argue that their tail risk measure is priced. Hence, this analysis is equitable. We examine whether the tail risk measures have predictive power for future market excess returns over various horizons. For this analysis, we include an annual forecast period in addition to the daily, weekly, and monthly horizons. We do so for two reasons. First, it is common in the return predictability literature to also consider longer horizons. Second, long-horizon returns can be also be influenced by tail risk expectations, while for the statistical tests we would need to observe actual tail event realizations, which are exceedingly rare at long horizons. In the analysis we are interested in the marginal effect of the tail risk measures, controlling for several other predictor variables (see the details in Section 3.3.2). We present the results in Table 3.9. As in Kelly and Jiang (2014), we use annualized returns in percentage points.

As for the previous analyses, we find that $BT11Q$ again performs very well. It is the only measure that significantly predicts future market excess returns at the daily, weekly, monthly, and annual horizons. For each of the horizons, the size of the predictive coefficient and/or the partial R^2 are among the top 3. At the daily and weekly horizon, the slope coefficient is even the largest among all models. For example, at the daily frequency, a one-standard-deviation increase in $BT11Q$, all else equal, implies that the annualized market excess return increases by 35.96 percentage points. The partial R^2 is 0.52%.

$BTX15prob$, TLM, $BT11P$, and $ADBear$ also have predictive power at the daily horizon, but their impact on market excess returns is somewhat smaller. Out of these, only $BT11P$, and $ADBear$ also have predictive ability at both the weekly and monthly horizons. None of these variables can predict excess returns one year ahead. On the other hand, the predictive power of λ_{Hill} seems to start only at the annual forecast horizon. With a partial

R^2 of 9.38%, though, the measure's long-term predictive ability is very strong.[21]

The PCs also perform quite well for predicting future market excess returns. All yield significant coefficients for the daily horizon. Furthermore, all PCs except that from only option-implied measures significantly predict future returns at both the weekly and monthly horizons.

The results for the multiple return predictions are in Table 3.10. Confirming our previous results, the PcGets selection procedure selects $BT11Q$ for the daily, monthly, and annual horizons. For each of these horizons, the measure yields a statistically significant slope coefficient. $BT11P$ is selected and yields a significant positive slope coefficient at the daily and weekly horizons, making it suitable for predicting returns over short horizons.

[21] Kelly and Jiang (2014) also report a good performance of λ_{Hill} for the 3- and 5-year forecast horizons in their 1963–2010 sample period.

Table 3.9: Return Predictability

This table presents the coefficients from a return predictability regression. We perform single regressions of the market excess returns on each lagged tail risk measure:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is the current observation of a tail risk measure. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), (iii) one-month (*Monthly*), and (iv) one-year (*Annually*). In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
BT11Q	35.96***	0.52	15.21**	0.51	6.64*	0.48	2.85*	2.17
	(7.350)		(5.613)		(4.504)		(1.915)	
BT14Q	5.15	0.02	0.70	0.02	−4.18*	0.34	0.71	0.56
	(6.213)		(4.386)		(2.742)		(1.713)	
BTX15prob	11.67**	0.07	7.40	0.24	8.41**	1.18	−2.13	0.49
	(6.121)		(5.518)		(4.242)		(3.193)	
BTX15Q	1.50	0.01	−3.19	0.03	−3.37	0.14	1.14	1.61
	(5.816)		(5.227)		(3.141)		(2.337)	
H_MRI	−7.23**	0.02	−2.98	0.04	−0.65	0.09	3.10	1.01
	(4.028)		(3.313)		(2.917)		(2.620)	
RIX	2.48	0.02	3.16	0.13	3.35	0.61	0.25	1.32
	(5.927)		(5.402)		(4.528)		(3.315)	
TLM	26.51***	0.26	13.48**	0.50	4.11	0.50	−0.73	0.77
	(8.577)		(6.277)		(4.563)		(2.825)	
Group B - Stock-Return-Based Measures								
BT11P	25.95***	0.63	13.89***	0.96	3.91***	0.29	0.58	0.10
	(5.859)		(2.855)		(1.383)		(0.394)	
CJI	3.75	0.01	1.49	0.03	−0.03	0.05	1.22	0.70
	(4.335)		(4.330)		(2.941)		(1.285)	
JumpRisk	−5.67	0.01	−7.73*	0.05	−10.91**	0.55	−15.36***	12.30
	(5.754)		(5.798)		(5.197)		(2.654)	
JumpRP	15.94***	0.11	11.29**	0.38	4.72	0.52	−2.14	0.46
	(5.360)		(4.721)		(3.997)		(2.319)	
λ_{Hill}	−0.42	0.00	1.36	0.05	0.04	0.08	6.25***	9.38
	(4.057)		(4.015)		(3.469)		(1.610)	
Group C - Option-Return-Based Measures								
ADBear	19.16***	0.39	13.31***	1.07	3.30**	0.30	−0.10	0.01
	(4.820)		(3.073)		(1.565)		(0.381)	
JUMP	2.83	0.01	5.80***	0.20	1.14*	0.03	0.20	0.01
	(6.084)		(1.585)		(0.703)		(0.141)	
Group D - Macroeconomic Measures								
LE	2.20	0.01	0.45	0.03	3.14	0.09	−2.27	0.49
	(7.517)		(7.774)		(5.657)		(2.816)	
PCOneAll	34.45***	0.29	18.66***	0.54	8.19*	0.68	1.18	1.38
	(8.736)		(6.265)		(4.955)		(2.975)	
PCOneOption	22.46***	0.18	9.16*	0.26	2.74	0.33	0.52	1.21
	(8.518)		(6.161)		(4.788)		(3.112)	
PCOneStReturn	24.42***	0.25	14.23***	0.49	5.39*	0.41	−2.27	0.79
	(5.310)		(4.605)		(3.644)		(1.983)	
PCOneOpReturn	14.06***	0.21	12.22***	0.89	2.84**	0.22	0.06	0.00
	(5.477)		(2.523)		(1.294)		(0.271)	
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

Table 3.10: Multiple Return Predictability

This table presents the coefficients from a return predictability regression. We perform multiple regressions of the market excess returns on lagged tail risk measures:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is a vector of the current observations of the tail risk measures. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), (iii) one-month (*Monthly*), and (iv) one-year (*Annually*). For each forecast horizon, we first perform variable selection based on the PcGets selection algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
$BT11Q$	47.61^{***}	0.53			10.47^{*}	0.57	6.35^{***}	6.42
	(10.620)				(5.865)		(0.831)	
$BT14Q$					-6.45^{**}	0.63		
					(2.499)			
$BTX15prob$					8.32^{**}	1.31		
					(4.793)			
$BTX15Q$	-21.81^{***}	0.12	-21.65^{***}	0.44	-8.22^{***}	0.36		
	(8.673)		(6.785)		(3.136)			
H_MRI								
RIX								
TLM			22.23^{***}	0.53				
			(7.645)					
Group B - Stock-Return-Based Measures								
$BT11P$	17.39^{***}	0.46	7.35^{***}	0.51				
	(5.906)		(2.697)					
CJI								
$JumpRisk$							-13.26^{***}	7.93
							(3.057)	
$JumpRP$								
λ_{Hill}								
Group C - Option-Return-Based Measures								
$ADBear$			8.78^{***}	0.70				
			(3.063)					
$JUMP$								
Group D - Macroeconomic Measures								
LE								
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

3.5 Further Analyses and Robustness Tests

3.5.1 Tail Event Return Predictability

In the main analysis, we have separately analyzed the statistical and economic value of the tail risk measures. Next, we perform a joint analysis that also enables us to analyze whether the size of the tail event is predictable. That is, in the absence of a tail event the tail risk premium should be larger the larger the tail risk. If the tail risk is realized in a sudden market event, on the other hand, the exact opposite relationship should hold: the tail event (negative market excess return) should be larger the higher the previous tail risk.

To analyze these subtleties, we perform an alternative return predictability regression. We use the dummy variable defined in Equation (3.1) to isolate periods with tail events from those without and run the following regression:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot D_{t+\Delta t} \cdot TRM_t + d \cdot D_{t+\Delta t} + e \cdot Controls_t + \epsilon_{t+\Delta t}. \qquad (3.7)$$

As before, we expect a good tail risk measure to have a positive b coefficient. The c coefficient on the interaction of the tail risk measure with the dummy variable, on the other hand, should be very low. To understand that, remember from Equation (3.1) that the dummy variable $D_{t+\Delta t}$ indicates that we are in a tail state. Thus, the higher the level of the tail risk measure, the lower should be the future (negative) realized tail-state return. Hence, with this specification we essentially jointly analyze both the tail risk measures' risk premia and whether they can predict the size of future tail events.

Table 3.11: Tail Return Predictability

This table presents the coefficients from a return predictability regression. We perform single regressions of the market excess returns on each lagged tail risk measure, while separating crash and non-crash periods:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot TRM_t \cdot D_{t+\Delta t} + d \cdot D_{t+\Delta t} + e \cdot Controls_t + \epsilon_{t+\Delta t},$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is the current observation of a tail risk measure. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use three different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), and (iii) one-month (*Monthly*). In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily				Weekly				Monthly			
	b	c	$R^2(b)$	$R^2(c)$	b	c	$R^2(b)$	$R^2(c)$	b	c	$R^2(b)$	$R^2(c)$
Group A - Option-Implied Measures												
BT11Q	40.39***	−338.62***	0.64	2.25	17.20***	−136.04***	0.63	2.29	6.04	−77.01***	0.44	1.11
	(7.059)	(45.081)			(5.126)	(13.557)			(4.437)	(10.087)		
BT14Q	8.79*	−277.34***	0.05	1.37	2.01	−109.26***	0.03	1.30	-3.57	−20.61**	0.27	0.93
	(5.773)	(46.027)			(3.863)	(39.328)			(2.680)	(10.689)		
BTX15prob	9.52*	−487.18***	0.07	0.91	6.61	−166.08***	0.23	0.38	6.80*	−153.63***	0.98	2.29
	(5.791)	(90.487)			(5.175)	(46.441)			(3.909)	(49.487)		
BTX15Q	4.46	−324.63***	0.02	1.34	-2.62	−139.01***	0.03	1.14	-3.52	-19.10	0.15	0.05
	(5.797)	(31.139)			(4.776)	(43.157)			(2.949)	(18.197)		
H_MRI	−10.09**	460.77***	0.03	1.74	-4.22	223.13**	0.06	1.86	-1.61	83.69***	0.10	3.36
	(4.396)	(143.909)			(3.209)	(93.710)			(2.699)	(17.492)		
RIX	-1.09	−251.02***	0.01	0.20	0.88	-53.51	0.11	0.14	2.01	76.79*	0.48	3.42
	(5.435)	(39.112)			(4.735)	(60.278)			(3.811)	(48.160)		
TLM	29.90***	−380.12***	0.32	1.95	14.76***	−148.76***	0.57	1.69	4.05	−76.75***	0.49	1.31
	(8.310)	(29.557)			(5.744)	(26.982)			(4.352)	(5.684)		
Group B - Stock-Return-Based Measures												
BT11P	26.24***	−152.49*	0.64	0.14	14.32***	−74.21**	1.01	0.32	4.16***	−14.01***	0.33	0.27
	(5.347)	(86.166)			(2.740)	(32.716)			(1.296)	(2.929)		
CJI	8.37*	−313.94***	0.05	2.15	3.69	−93.70***	0.07	1.68	0.68	−47.02***	0.06	1.47
	(3.834)	(40.887)			(3.338)	(14.757)			(2.700)	(5.383)		
JumpRisk	-2.24	−206.95**	0.00	0.25	-5.31	−122.78***	0.03	0.77	−8.43**	−51.40**	0.36	4.28
	(5.583)	(69.684)			(5.252)	(44.655)			(4.594)	(26.137)		
JumpRP	20.69***	−374.10***	0.17	2.36	12.05***	−150.32***	0.43	1.57	6.01	−54.31***	0.62	2.19
	(5.216)	(51.523)			(4.521)	(24.816)			(3.621)	(5.942)		
λ_{Hill}	-1.75	110.82	0.00	0.23	1.59	2.86	0.04	0.06	0.27	35.16	0.09	0.27
	(3.840)	(67.286)			(3.779)	(30.153)			(3.317)	(29.537)		
Group C - Option-Return-Based Measures												
ADBear	20.89***	−201.24***	0.44	0.51	15.51***	−109.58***	1.30	1.78	3.66***	−22.52***	0.35	0.39
	(4.947)	(78.491)			(3.055)	(32.255)			(1.484)	(7.778)		
JUMP	2.63	−298.81**	0.01	0.08	5.47***	45.19*	0.19	0.15	1.55**	−26.06***	0.05	0.67
	(5.852)	(137.860)			(1.551)	(28.837)			(0.651)	(5.660)		
Group D - Macroeconomic Measures												
LE	0.34	−283.63*	0.00	0.86	-1.81	−170.44***	0.02	0.76	2.41	−61.01***	0.07	1.81
	(7.734)	(126.200)			(7.326)	(23.943)			(5.515)	(15.042)		
PCOneAll	38.39***	−383.62***	0.36	2.27	19.36***	−152.37***	0.60	1.79	7.68*	−77.29***	0.65	1.76
	(8.253)	(25.363)			(5.879)	(16.306)			(4.770)	(6.328)		
PCOneOption	25.56***	−350.24***	0.23	1.71	9.85*	−163.89***	0.29	1.70	2.33	−69.30***	0.31	0.59
	(8.048)	(24.938)			(5.506)	(26.526)			(4.512)	(11.117)		
PCOneStReturn	28.90***	−365.28***	0.33	2.26	15.59***	−127.52***	0.58	1.67	6.22**	−46.68***	0.49	2.06
	(5.493)	(49.459)			(4.042)	(17.046)			(3.229)	(4.089)		
PCOneOpReturn	15.01***	−337.43***	0.23	0.44	13.40***	−87.56**	1.01	0.80	3.34***	−26.93***	0.28	0.70
	(5.502)	(117.600)			(2.612)	(45.750)			(1.184)	(8.059)		
Controls	Yes				Yes				Yes			

Table 3.12: Multiple Tail Return Predictability

This table presents the coefficients from a return predictability regression. We perform multiple regressions of the market excess returns on lagged tail risk measures, while separating crash and non-crash periods:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot TRM_t \cdot D_{t+\Delta t} + d \cdot D_{t+\Delta t} + e \cdot Controls_t + \epsilon_{t+\Delta t},$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is a vector of the current observations of the tail risk measures. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use three different forecast horizons Δt: (i) one-day ($Daily$), (ii) one-week ($Weekly$), and (iii) one-month ($Monthly$). For each forecast horizon, we first perform variable selection based on the PcGets algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily				Weekly				Monthly			
	b	c	$R^2(b)$	$R^2(c)$	b	c	$R^2(b)$	$R^2(c)$	b	c	$R^2(b)$	$R^2(c)$
Group A - Option-Implied Measures												
$BT11Q$	49.53***		0.62		11.53	−104***	0.24	1.06	9.04*	80***	0.38	0.27
	(11.241)				(8.244)	(24.364)			(5.658)	(17.896)		
$BT14Q$						−50***		0.47	−7.31***		0.65	
						(13.879)			(2.550)			
$BTX15prob$		854***		0.55					5.46		0.78	
		(111.802)							(5.004)			
$BTX15Q$	−23.25***		0.13		−22.65***	61**	0.53	0.32	−9.54***		0.54	
	(8.856)				(6.522)	(26.000)			(3.522)			
H_MRI	−7.38**	547***	0.03	1.01		−131**		1.06		35*		1.52
	(3.633)	(109.927)				(52.794)				(19.635)		
RIX		−346***		0.22						−34		2.00
		(55.323)								(20.823)		
TLM		−717***		1.46	14.15*		0.38		6.95	−22	0.55	0.29
		(49.652)			(9.038)				(6.627)	(13.952)		
Group B - Stock-Return-Based Measures												
$BT11P$	15.99***		0.43		5.63**	−55***	0.46	0.14				
	(5.518)				(2.633)	(12.993)						
CJI										−45***		0.44
										(9.402)		
$JumpRisk$		99***		0.13		−47***		0.11		−4.00		1.88
		(28.341)				(10.078)				(9.405)		
$JumpRP$						−102***		0.48		−54***		0.82
						(23.582)				(11.273)		
λ_{Hill}										−31**		0.63
										(10.169)		
Group C - Option-Return-Based Measures												
$ADBear$					11.18***		0.88					
					(3.052)							
$JUMP$		−208**		0.09		115***		0.21		−7.00		0.21
		(74.195)				(17.097)				(5.171)		
Group D - Macroeconomic Measures												
LE		163***		0.38		58**		0.30				
		(23.176)				(23.597)						
Controls	Yes				Yes				Yes			

We present the results in Table 3.11.[22] We find that $BT11Q$ also performs well for all horizons in this more granular analysis. For all forecast horizons except monthly, the b coefficient is significantly positive and the c coefficient is significant and negative, as it should be. $BTX15prob$, TLM, $BT11P$, $JumpRP$, $ADBear$, and the first PCs also work well.

In Table 3.12, we present the corresponding multiple regression analysis. Consistent with the previous results, $BT11Q$ performs well. The measure yields the largest b coefficients at the daily and monthly horizons. In addition, the c coefficient at the weekly horizons is significantly negative with the highest partial R^2. Other measures' b and c coefficients are sometimes selected and yield more significant results, but none of them consistently performs similarly well to $BT11Q$.

3.5.2 Tail Risk and the Cross-Section of Stock Returns

Next, we analyze the impact of the tail risk measures on the cross-section of stock returns. That is, we conduct a cross-sectional return prediction test to analyze whether stocks with higher tail risk loadings exhibit larger expected returns.

For this analysis, as Kelly and Jiang (2014), we use the same design as for the predictive regressions. We first estimate the stocks' sensitivities to tail risk using a rolling historical window. We use a window length of one month for all measures available at the daily frequency.[23] At the end of each month, the factor loadings are then estimated by the following predictive regression:

$$R^i_{t+\Delta t} = a^i + b^i \cdot TRM_t + \epsilon^i_t, \tag{3.8}$$

[22]Note that, as before, we skip the annual horizon due to lack of sufficient observations for the tail dummy variable.

[23]For all other frequencies, the rolling window length is defined based on a mechanical rule: we require at least 22 non-overlapping observations. Thus, the window for weekly, monthly, and quarterly variables is six months, two years, and six years, respectively.

where $R^i_{t+\Delta t}$ denotes the excess return of stock i during the period t until $t + \Delta t$. We focus on a Δt of 1 day. TRM_t is the tail risk measure at time t. We sort the stock based on the estimated b^i and hold the portfolio for one month. Afterwards, we repeat the entire procedure.

Stocks that perform comparably better following high-tail-risk observations are very desirable for investors. These stocks essentially insure high-marginal-utility states. Thus, investors likely have a strong demand for those stocks that yield high b^is in Equation (3.8). This increased demand leads to high prices and, hence, low unconditional average returns. These low average returns are akin to an insurance premium paid by investors. On the other hand, those stocks that perform poorly following an observation of high tail risk are undesirable for investors. Hence, they have to pay a higher return in order to induce investors to hold them.

We present the results for value-weighted portfolios in Table 3.13. We find that for $BT11Q$ the portfolio with the lowest tail risk loadings has an average annualized excess return of 11.01%. Thus, stocks that perform poorly after a high-tail-risk observation have high returns. On the other hand, the stocks in the portfolio with the highest tail risk loadings only yield an average annualized excess return of only 1.53%. Thus, stocks that do well following a high-tail-risk observation perform less well on average. The difference between the high and low portfolios is -9.48% per year on average. These results are consistent with the intuition described above. Stocks that do well following the observation of high tail risk appear to be very desirable for investors and trade at a premium.

Table 3.13: Cross-Sectional Return Predictability (Value-Weighted)

This table presents the average annualized percentage excess returns of quintile portfolios sorted on the stock loadings on the different tail risk measures. Each month, we estimate the tail risk loadings (b^i) for each stock based on a rolling historical window:

$$R^i_{t+\Delta t} = a^i + b^i \cdot TRM_t + \epsilon^i_t,$$

$R^i_{t+\Delta t}$ is the excess return of stock i over the period between t and Δt. TRM_t is the current observation of a tail risk measure. We forecast stock returns at the daily frequency and use a window length of one month for all measures available at the daily frequency, and accordingly longer windows for measures available on lower frequencies. Based on their current b^i we then sort the stocks into quintile portfolios and obtain the value-weighted portfolio excess return over the next month. We repeat the entire procedure in the next month. The $High - Low$ portfolio simultaneously buys the stocks in the portfolio with the highest b^i and sells those in the portfolio with the lowest b^i. In parentheses, we report robust Newey and West (1987) standard errors using 22 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Low	(2)	(3)	(4)	*High*	*High−Low*
Group A - Option-Implied Measures						
$BT11Q$	11.01***	10.01***	9.49***	6.33*	1.53	−9.48***
	(3.305)	(3.260)	(3.021)	(3.584)	(5.806)	(3.445)
$BT14Q$	5.41	6.98	6.98*	7.73**	6.78*	1.37
	(5.131)	(4.230)	(3.900)	(3.618)	(4.079)	(2.887)
$BTX15prob$	9.51**	8.16**	7.69**	6.71	3.18	−6.33*
	(4.753)	(3.516)	(3.021)	(4.123)	(5.083)	(3.249)
$BTX15Q$	4.60	8.27**	9.34***	7.08*	6.95	2.35
	(4.685)	(3.303)	(3.189)	(3.745)	(5.186)	(3.390)
H_MRI	8.99**	8.19**	7.23**	6.74	5.32	−3.68
	(4.536)	(3.905)	(3.610)	(4.120)	(4.869)	(2.586)
RIX	9.04***	7.02**	6.87**	6.63	6.31	−2.73
	(3.466)	(3.535)	(3.182)	(4.158)	(6.253)	(3.796)
TLM	9.16**	9.30***	7.83**	7.62**	2.66	−6.51*
	(3.973)	(3.111)	(3.350)	(3.683)	(5.725)	(3.338)
Group B - Stock-Return-Based Measures						
$BT11P$	9.52**	10.00***	7.34**	5.76	4.14	−5.38*
	(4.577)	(3.080)	(3.431)	(3.917)	(5.672)	(2.773)
CJI	4.01	8.76**	8.39***	8.16**	5.54	1.53
	(4.768)	(3.885)	(3.023)	(3.416)	(4.892)	(2.282)
$JumpRisk$	8.71**	9.66***	8.38***	6.04	3.54	−5.17*
	(3.837)	(3.097)	(3.007)	(3.956)	(5.782)	(2.999)
$JumpRP$	9.74***	8.42**	7.35**	7.30*	4.34	−5.39
	(3.538)	(3.458)	(3.119)	(3.756)	(5.669)	(3.397)
λ_{Hill}	11.88**	7.30**	7.44**	6.52*	4.93	−6.95
	(5.390)	(3.625)	(3.586)	(3.902)	(5.084)	(4.726)
Group C - Option-Return-Based Measures						
$ADBear$	7.56*	8.80**	8.12**	7.85**	3.39	−4.17
	(4.500)	(3.468)	(3.201)	(3.477)	(5.135)	(2.680)
$JUMP$	7.88**	9.14***	8.29***	8.30**	2.98	−4.90
	(3.902)	(3.073)	(3.110)	(3.475)	(6.521)	(4.157)
Group D - Macroeconomic Measures						
LE	6.63	7.40*	8.33**	7.13*	6.65	0.03
	(4.988)	(3.777)	(3.325)	(3.680)	(4.126)	(2.056)

While the results for $BT11Q$ are clear and consistent with economic theory, we find that the vast majority of the other tail risk measures do not yield significant negative high–low portfolio excess returns. Thus, these measures do not seem to be priced in the cross-section of stock returns. Exceptions include $BTX15prob$, TLM, $BT11P$, and $JumpRisk$. The cross-sectional tail risk premia implied by these measures, however, are substantially smaller than that of $BT11Q$.

In Table B1 of the Appendix, we also present the results for equally weighted portfolios. These are qualitatively similar. Finally, in Table B2 of the Appendix, we report the value-weighted Fama and French (2015) five-factor model alphas instead of raw excess returns. These are also qualitatively very similar. Thus, the pricing of tail risk appears to be distinct from that of market risk as well as the other factors in this model.

3.5.3 Tail Risk and Real Economic Activity

Facing high tail risk, new investments in the real economy may be delayed and hiring of new staff paused (Kelly and Jiang, 2014; Gormsen and Jensen, 2020). Thus, if tail risk affects real economic activity, it should have an impact on growth in industrial production. Therefore, we also run predictive regressions of log industrial production growth on the different tail risk measures. We use the following regression model:

$$IND_{t+\Delta t} = a + b \cdot \overline{TRM}_t + \epsilon_{t+\Delta t}, \tag{3.9}$$

where $IND_{t+\Delta t}$ is the log change in industrial production over the period Δt. Since industrial production is only available on a monthly level, we focus on monthly and annual prediction windows. Therefore, $\overline{TRM}_t$ is the current observation of a tail risk measure, computed as the average of all observations during month t.

Table 3.14: Industrial Production

This table presents the coefficients from a predictive regression for industrial production growth. We perform single regressions of the log growth rate in industrial production (in percentage points) on each tail risk measure, averaged over the previous month:

$$IND_{t+\Delta t} = a + b \cdot \overline{TRM}_t + \epsilon_{t+\Delta t},$$

$IND_{\Delta t}$ is the log change in industrial production over the period Δt. $\overline{TRM}_t$ is the current observation of a tail risk measure, computed as the average of all observations during month t. We use two different forecast horizons Δt: (i) one month ($Monthly$) and (ii) one year ($Annually$). In parentheses, we present robust Newey and West (1987) standard errors with 14 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the R^2s multiplied with 100. "*PCOneAll*", "$PCOnePortfolio$", "*PCOneOption*", and "*PCOneReturn*" denote the first principal components of all measures, the option-implied, stock-return-based and option-return-based tail risk measures, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Monthly	R^2	*Annually*	R^2
Group A - Option-Implied Measures				
$BT11Q$	-0.24^{**}	15.75	-0.60^{**}	12.09
	(0.063)		(0.423)	
$BT14Q$	-0.12	6.36	0.11	10.44
	(0.090)		(0.810)	
$BTX15prob$	-0.15^{*}	8.09	-0.72	12.84
	(0.100)		(1.421)	
$BTX15Q$	-0.16^{*}	8.80	0.06	10.40
	(0.084)		(1.168)	
H_MRI	0.07	4.20	0.55	11.83
	(0.061)		(1.818)	
RIX	-0.18^{**}	10.30	-0.09	10.42
	(0.072)		(1.007)	
TLM	-0.19^{*}	10.99	-0.54	11.74
	(0.095)		(0.932)	
Group A - Option-Implied Measures				
$BT11P$	-0.22^{***}	12.61	-1.28^{***}	15.70
	(0.064)		(0.534)	
CJI	-0.04	3.53	-0.34	10.94
	(0.118)		(1.065)	
JumpRisk	-0.18^{**}	9.74	-1.42^{***}	19.92
	(0.070)		(1.576)	
JumpRP	-0.14^{*}	7.65	-0.78	13.23
	(0.090)		(1.705)	
λ_{Hill}	0.07	4.16	0.80^{*}	13.43
	(0.082)		(1.132)	
Group A - Option-Implied Measures				
$ADBear$	-0.06^{**}	3.93	-0.88^{***}	14.04
	(0.026)		(0.370)	
$JUMP$	0.02	3.24	-0.30^{*}	10.81
	(0.030)		(0.264)	
Group A - Option-Implied Measures				
LE	-0.21^{**}	12.03	-0.61	11.43
	(0.085)		(3.385)	
PCOneAll	-0.21^{**}	11.33	-0.65^{*}	9.55
	(0.087)		(1.125)	
PCOneOption	-0.20^{**}	11.99	-0.39	11.09
	(0.088)		(0.434)	
PCOneStReturn	-0.19^{**}	10.23	-1.21^{**}	14.76
	(0.094)		(1.330)	
PCOneOpReturn	0.02	3.22	0.68^{***}	12.58
	(0.028)		(0.339)	

We present the results in Table 3.14. Indeed, we find that tail risk has an impact on the growth in industrial production. For example, at the monthly frequency, a one-standard-deviation increase in $BT11Q$ decreases the log industrial production growth by 0.24 percentage points. The economic impact is the largest among all tail risk measures. At the annual frequency, only $BT11Q$, $BT11P$, and $ADBear$ are significant negative predictors of future industrial production growth.

3.5.4 Subsample Analysis

Next, we analyze the robustness of the tail risk measures' return predictability for two distinct subsamples. For that purpose, we divide our total sample period in two roughly equal halves: one ending in 2007, before the Financial Crisis, and the other starting from 2008 until the end of our sample period. The extreme returns around the peak of the Financial Crisis may be influential and drive part of the overall predictability results. By running the main economic test separately for both subsamples, we can therefore assess how stable the predictability is.

The results for the pre-2008 period are in Tables B3 and B4 of the Appendix. We find that $BT11Q$ significantly predicts returns at the daily, weekly, and monthly horizons. Other measures that perform well include $BT11P$, $ADBear$, and $JUMP$. The model selection algorithm picks $BT11Q$ for three out of four horizons, for which it also yields significantly positive coefficients. Thus, our results for the first half of the sample period are consistent with those for the full period.

Next, we examine the post-2008 period. The corresponding results are in Tables B5 and B6 of the Appendix. We find that $BT11Q$ significantly predicts future market excess returns at the daily, weekly, and annual horizons. $BT11P$ and $ADBear$ also perform well for the second half of the sample period. Importantly, the predictive ability of the best measures thus appears to be rather stable over time.

3.5.5 Jackknife Model Selection

In a next step, we analyze the robustness of our main results to the model selection algorithm in the multiple regression analysis. That is, instead of the PcGets algorithm, we alternatively employ a jackknife procedure, which we describe in detail in Appendix B1.3.

We present the results in Tables B7, B8, and B9 of the Appendix. These are overall qualitatively similar to those for the PcGets selection algorithm. Although the two approaches select different measures in some instances, the big picture remains the same. While $BT11Q$ is not selected for the tail event prediction, it is instead selected for all horizons and yields statistically significant coefficients for predicting left tail variation. For the return predictability, $BT11Q$ also turns out to be the best model under the jackknife selection.

3.5.6 The Number of Jumps

We also devise an alternative statistical test to evaluate the tail risk measures: the number of jumps. That is, for each forecast window, we simply count the number of realized jumps (NLJ) based on the jump test implicit in Equation (3.3).[24] Analogously to the test for the left tail variation, we then perform univariate regressions of the standardized realized number of negative jumps on each lagged tail risk measure:

$$NLJ_{t+\Delta t} = a + b \cdot TRM_t + c \cdot NLJ_t + d \cdot VIX_t + \epsilon_{t+\Delta t},$$

where all variables are as previously defined.

We present the results in Table B11 of the Appendix. $BT11Q$ performs well also for this test. For all forecast horizons, it yields the highest slope coefficient, which is also statistically significant in every case.

[24] Technically, we estimate Equation (3.3) without multiplying the jump-imposed dummy variable with the squared returns. Thus, we simply count by summing up ones if there are jumps.

3.5.7 Tail Threshold

In Figures B5 – B7 of the Appendix we vary the threshold to define the tail events for the probit regressions. We display the t-statistics of the b coefficient in Equation (3.2) for tail thresholds varying between -0.2 and -2 times the conditional volatility (in steps of 0.1). The results for common thresholds are qualitatively similar to those of Table 3.5. At the daily forecast horizon, $BT11Q$ and $JumpRP$ can predict future tail events for all analyzed tail thresholds. At the weekly and monthly horizons, the performance is typically more dependent on the tail threshold. Some measures succeed for certain thresholds. On the other hand, part of the measures only perform well for extreme thresholds; e.g., $ADBear$ at the weekly horizon and $JumpRisk$ and $JUMP$ at the monthly horizon.

3.5.8 The Impact of Future Tail Events on Tail Risk

Additionally, we investigate a specification that essentially reverses the direction of the probit regression and thereby examines the robustness of Figure 3.1:

$$TRM_t = a + b \cdot D_{t+\Delta t} + \epsilon_{t+\Delta t}.$$

We display the b coefficient estimates along with their 90% confidence intervals based on robust Newey and West (1987) standard errors in Figures B8 to B10 of the Appendix. A good measure should have a positive and statistically significant b coefficient. The results are qualitatively very similar to those of the tail event predictability analysis.

3.5.9 Left Tail Variation With Overnight Returns

We also examine the robustness of our results for the predictability of future realized left tail variation to also including overnight returns. We present these results in Tables B12 of the Appendix. The results are qualitatively similar to those without including overnight returns. If anything, they are even more favorable for $BT11Q$, which performs best for all forecast horizons.

3.5.10 Block Bootstrap

Finally, we examine the robustness of our results to the bootstrap method to determine the statistical inference. For that purpose, we conduct a block-bootstrap. As advised by Lahiri (1999), we use overlapping blocks. The block length is $n^{1/3}$ or the number of overlapping observations, whichever is larger (Hall, Horowitz, and Jing, 1995). The block bootstrap places more emphasis on the dependence structure in the residuals and is a reality check mainly for the long-term predictive performance of the tail risk measures.

We present the results for the predictability of left tail variation in Tables B13 and B14 of the Appendix. These are very similar to those for the wild bootstrap. For return predictability, we present the results in Tables B15 and B16 of the Appendix. While the long-term return predictability is indeed somewhat more modest, overall the results are also very similar for the return predictability when using a block bootstrap.

3.6 Conclusion

We contribute to the literature by conducting a comprehensive empirical analysis of a wide range of tail risk measures that have been proposed over the recent decade. We detect a large heterogeneity across different tail risk measures measures. The first two principal components explain only 49% of their total variation, while some tail risk measures are even negatively correlated. This finding sends a clear warning to researchers and practitioners not to treat different tail risk measures as interchangeable.

We find that the option-implied measure of Bollerslev and Todorov (2011b), $BT11Q$, performs best. Further refinements of the Bollerslev and Todorov (2011b) measures by the same authors appear to be of limited practical value. $BT11Q$ performs well for all tests: It can predict the occurrence and the magnitude of future tail events as well as the variation caused by them. The measure also predicts market excess returns at horizons up to one year. In addition, it is priced in the cross-section of stock returns and affects real economic activity. Other measures only perform well at most for part of the tasks (while most consistently underperform the winning measure).

B1 Appendix

B1.1 Tail Risk Measures

In this section, we describe the tail risk measures in more detail. For further information, we refer the reader to the original papers.

Option-Implied Measures

Unless explicitly stated otherwise, for all option-implied measures we follow Bollerslev and Todorov (2011b) and use the options with the shortest maturity available, but with at least 8 days to expiration.

BT*11*Q Bollerslev and Todorov (2011b) construct a measure of tail risk perceived by investors that is based on close-to-maturity deep out-of-the-money options. They use the insights of the quadratic variation to decompose the volatility into two separate parts in a model-free fashion. To isolate extreme tail risks, they use only deep out-of-the-money options. Only a rare event will be large enough to affect the prices of these derivatives significantly. Bollerslev and Todorov (2011b) use the following definition of the price of a call and put ($C_t(K)$, $P_t(K)$):

$$e^{r_{(t,T]}} P_t(K) \approx \int_t^T \mathbb{E}_t^{\mathbb{Q}} \Big(\int_{\mathbb{R}} 1_{F_{s-}>K} max(0, K - F_{s-}e^x) v_S^{\mathbb{Q}}(dx) \Big) ds,$$

to construct the model-free risk-neutral jump tail measures:

$$LT_t^{\mathbb{Q}}(k) \equiv \frac{1}{T-t} \int_t^T \int_{\mathbb{R}} max(0, e^k - e^x) \mathbb{E}_t^{\mathbb{Q}}(v_S^{\mathbb{Q}}(dx)) ds \approx \frac{e^{r_{(t,T]}} P_t(K)}{(T-t)F_{t-}}. \tag{B1}$$

We use the approximation above for the calculation of our tail risk measure. The log-moneyness is $k = log(K/F_{t-})$. K is the option's strike price and F_{t-} is the futures price for the aggregate market portfolio. $T - t$ denotes the time-to-maturity as a fraction of a year. As in Bollerslev and Todorov (2011b), we interpolate the option price to the desired moneyness levels, here 0.9, using Black and Scholes (1973) implied volatilities.

BT14Q, ***BTX15Q***, and ***BTX15prob*** Bollerslev and Todorov (2014) and Bollerslev et al. (2015) construct a tail risk estimate using the information from the entire panel of available short-maturity options. The option price is $O_{t,\tau}(k)$ at time t with time-to-maturity τ, price X_t and the log-moneyness is $k = log(K/F_{t-,\tau})$. Bollerslev and Todorov (2011a) show that the jump intensity can be formulated in the following way, with a time-varying shape parameter α^-:

$$\frac{e^{r_{t,\tau}} O_{t,\tau}(k)}{F_{t-,\tau}} \approx \frac{\tau \phi_t^+ e^{k(1-\alpha_t^-)}}{\alpha_t^-(\alpha_t^- - 1)}, \text{ if } k < 0,$$

for the risk-free rate $e^{r_{t,\tau}}$ over period $[t,t + \tau]$. In combination with the extreme-value approximation, Bollerslev and Todorov (2014) follow that the level shift parameter $\phi_t^\pm$ can be purged from the ratio of logarithmic prices, if options with the same time-to-maturity, but different levels of moneyness ($k_1 < k_2$), are considered:

$$\hat{\alpha_t}^- = \underset{\alpha_t^-}{\operatorname{argmin}} \frac{1}{N_t^-} \sum_{i=2}^{N_t^-} g \left(\frac{log\left(\frac{O_{t,\tau_t}(k_{t,i})}{O_{t,\tau}(k_{t,i-1})}\right)}{k_{t,i} - k_{t,i-1}} - (1 + \alpha_t^-) \right).$$

Thus, Bollerslev and Todorov (2014) conclude that the tail shape α^- can be estimated from an increasing span of options over either an increasing range of strikes or an increasing sample span. This method imposes only a parametric structure on the jump intensity, not on the level shift estimates (ϕ^-). Because option data is not continuously available, Bollerslev and Todorov (2014) pool the parameters and obtain weekly, monthly, or annual tail shape parameter estimates.

Because of the noise of the parameters α_t^- Bollerslev and Todorov (2014) propose the following parametric model, to smooth the estimates:

$$\alpha_j^- = \beta_0^- + \beta_1^- \alpha_{j-1}^- + \beta_2^- log(1 + QV_{\tau_{j-1},\tau_j}^c) + \beta_3^- log(1 + QV_{\tau_{j-1},\tau_t}^d) + \epsilon_j^- \tag{B2}$$

where $j = 1, ..., J$ refers to the weeks in the sample and QV to the quadratic variation of the series (the variation that includes both jumps and continuous variation). QV^c refers to the continuous variation in the sample and QV^d to the discontinuous portion of the total variation. Bollerslev and Todorov (2014) then subsequently estimate the model using the function:

$$\hat{\beta}^- = \underset{\beta^-}{\text{argmin}} \sum_{j=1}^{J} \sum_{t=\tau_{j-1}}^{\tau_j} \frac{1}{N_t^-} \sum_{i=2}^{N_t^-}$$
$$g\left(\frac{log(\frac{O_{t,\tau_t}(k_{t,i})}{O_{t,\tau}(k_{t,i-1})})}{k_{t,i} - k_{t,i-1}} - \left(1 - \beta_0^- - \beta_1^- \hat{\alpha}_{j-1}^- - \beta_2^- log(1 + QV_{(\tau_{j-1},\tau_j]}^c) - \beta_3^- log(1 + QV_{(\tau_{j-1},\tau_j]}^d)\right)\right),$$

and omit all variables that are insignificant at the 5% level. QV is calculated using 5-minute prices. To estimate the tail of the distribution, not only the tail shape $\alpha_t^\pm$ needs to be estimated, but also the level shift $\phi_t^\pm$. After the estimation of $\alpha_t^\pm$, $\phi_t^\pm$ can be estimated in a second step:

$$\hat{\phi}_t^- = \underset{\phi_t^-}{\text{argmin}} = \frac{1}{N_t^-} \sum_{i=1}^{N_t^-} \left| log\left(\frac{e^{r_{t,\tau}} O_{t,\tau}(k_{t,i})}{\tau F_{t,\tau}}\right) - (1 + \hat{\alpha}_t^-)k_{t,i} + log(\hat{\alpha}_t^- + 1) + log(\hat{\alpha}_t^-) - log(\phi^-) \right|.$$

In turn, the jump intensity process is characterized by: $v_t^{\mathbb{Q}} = (\phi_t^+ e^{-\alpha_t^+ x} 1_{x>0} + \phi^- e^{-\alpha_t^- |x|} 1_{x<0})$, and can be estimated via:

$$LJV_{t,t+\tau}^{\mathbb{Q}} = \frac{\tau \phi_t^- e^{-\alpha_t^- |k_t|}(\alpha_t^- k_t(\alpha_t^- k_t + 2) + 2)}{(\alpha_t^-)^3}. \tag{B3}$$

k_t is a threshold that serves as a cutoff point at each tail, we define it as: $k_t = 10\sigma_{ATM,30d}\sqrt{5/252}$,

$\sigma_{ATM,30d}$ is the at-the money 30-day volatility of the interpolated option surface obtained from Option Metrics.

Alternatively, Bollerslev et al. (2015) obtain the estimates for $\hat{\alpha}_t^-$ and $\hat{\phi}_t^-$ with a non-parametric estimation:

$$\begin{aligned}\hat{\alpha}_t^- &= median\left|1 - \frac{log\frac{O_{t,\tau}(k_{t,i})}{O_{t,\tau}(k_{t,i-1})}}{k_{t,i} - k_{t,i-1}}\right|,\\ \hat{\phi}_t^- &= median\left|log\left(\frac{e^{r_{t,\tau}O_{t,\tau}(k_{t,i})}}{\tau F_{t,\tau}}\right) - (1-\hat{\alpha}_t^-)k_{t,i} + log(\hat{\alpha}_t^- + 1) + log(\hat{\alpha}_t^-)\right|.\end{aligned} \tag{B4}$$

The current tail estimates are measures of return variation expected by the market in the left or the right tail of the distribution. The threshold depends on the current volatility. It might also be useful to consider a constant threshold and obtain the probability, similar to the commonly used Value-at-Risk (VaR). For a probability measure that captures the probability of a 10% crash over the next week, the equation can be rearranged in the following way:

$$LeftProb_t = 100\hat{\phi}_t^- \frac{e^{-\hat{\alpha}_t^-|k_t|}}{\hat{\alpha}_t^-}. \tag{B5}$$

In our analysis we will use the probability measure and the left tail risk measure, estimated non-parametrically and the parametrically smoothed and estimated left tail risk measure, both of which have a correlation of just 75%.

H_MRI Gormsen and Jensen (2020) develop a measure of higher-moment risk, based on the out-of the money put and call options. They use the inference techniques developed by Breeden and Litzenberger (1978) and Bakshi, Kapadia, and Madan (2003) to infer the ex-ante moments. The moments are estimated from out-of the money put and call options, using the following representation:

$$
\begin{aligned}
E_t[R_{t,T}^n] &= \frac{(R_{t,T}^f)^{n+\gamma} + R_{t,T}^f \left[\sum_{i=1}^N \frac{(\gamma+n)(\gamma+n-1)}{S^{\gamma+n}} (S_t R_{t,T}^f - F_{t,T} + K_i)^{n+\gamma-2} \Omega_{t,T}(K_i) \Delta K_i\right]}{(R_{t,T}^f)^{\gamma} + R_{t,T}^{\gamma} \left[\sum_{i=1}^N \frac{\gamma(\gamma-1)}{S^{\gamma}} (S_t R_{t,T}^f - R_{t,T} + K_i)^{\gamma-2} \Omega_{t,T}(K_i) \Delta K_i\right]}, \\
\Omega_{t,T} &= \begin{cases} call_{t,T}(K) & \text{if } K \geq F_{t,T}, \\ put_{t,T}(K) & \text{if } K < F_{t,T}, \end{cases} \\
\Delta K_i &= \begin{cases} K_{i+1} - K_i & \text{if } i = 1, \\ K_i - K_{i-1} & \text{if } i = N, \\ \frac{K_{i+1} - K_{i-1}}{2} & \text{else.} \end{cases}
\end{aligned}
\tag{B6}
$$

Strike prices K_1, ..., K_N of the N out-of-the money options are in ascending order. The moments are then calculated using the following calculations:

$$
\begin{aligned}
Skewness_{t,T} &= \frac{E_t[R_{t,T}^3] - 3E_t[R_{t,T}]E_t[R_{t,T}^2] + 2E_t[R_{t,T}]^3}{(E_t[R_{t,T}^2] - E_t[R_{t,T}]^2)^{(3/2)}}, \\
Kurtosis_{t,T} &= \frac{E_t[R_{t,T}^4] - 3E_t[R_{t,T}]^4 + 6E_t[R_{t,T}]^2 E_t[R_{t,T}^2] - 4E_t[R_{t,T}]E_t[R_{t,T}^3]}{(E_t[R_{t,T}^2] - E_t[R_{t,T}]^2)^2}, \\
Hyperskewness_{t,T} &= \frac{E_t[R_{t,T}^5] + 4E_t[R_{t,T}]^5 + 10E_t[R_{t,T}]^2 E_t[R_{t,T}^3]}{(E_t[R_{t,T}^2] - E_t[R_{t,T}]^2)^{(5/2)}} + \\
&\quad \frac{-10E_t[R_{t,T}]^3 E_t[R_{t,T}^2] - 5E_t[R_{t,T}]E_t[R_{t,T}^4]}{(E_t[R_{t,T}^2] - E_t[R_{t,T}]^2)^{(5/2)}}, \\
Hyperkurtosis_{t,T} &= \frac{E_t[R_{t,T}^6] - 5E_t[R_{t,T}]^6 + 15E_t[R_{t,T}]^4 E_t[R_{t,T}^2]}{(E_t[R_{t,T}^2] - E_t[R_{t,T}]^2)^3} + \\
&\quad \frac{-20E_t[R_{t,T}]^3 E_t[R_{t,T}^3] + 15E_t[R_{t,T}]^2 E_t[R_{t,T}^4] - 6E_t[R_{t,T}]E_t[R_{t,T}^5]}{(E_t[R_{t,T}^2] - E_t[R_{t,T}]^2)^3}.
\end{aligned}
$$

We linearly interpolate between the times-to-maturity to generate the moments with constant 30-day time-to-maturity. To obtain the higher-moments risk index, we use the first PC of the four measures. The first PC loads positively on the kurtosis measures and negatively on the skewness measures.

RIX Gao et al. (2018) and Gao et al. (2019) construct an index for tail risk concern (RIX). They use two option portfolios to model the expected downside movement of the market. The two portfolios have the following design:

$$\begin{aligned} IV^{-} &\equiv \frac{2e^{r\tau}}{\tau} \int_{K<X_t} \frac{1}{K^2} P(X_t; K, \tau) dK, \\ V^{-} &\equiv \frac{2e^{r\tau}}{\tau} \int_{K<X_t} \frac{1 - log(K/X_t)}{K^2} P(X_t; K, \tau) dK. \end{aligned} \tag{B7}$$

Both portfolios differ on how they assign weight to out-of-the money put option prices, V^- assigns relatively larger weight to deeper out-of-the money options. The resulting index is constructed by going long in the portfolio with higher exposure to deep out-of-the money options (V^-) and short the portfolio with a lower exposure (IV^-), resulting in a positive exposure of the portfolio towards jump risk, while being relatively immune to volatility risk. In order to estimate both portfolios, we interpolate the implied volatility of the options with a cubic spline along the moneyness, following Gao et al. (2018). This way, we generate 2,000 artificial options in a strike range between zero and three times the price of the underlying. For artificial options outside the observed strike range, we constantly extrapolate the implied volatilities. The resulting portfolio can be constructed with the following weights (Gao et al., 2018):

$$RIX^{-} \equiv V^{-} - IV^{-} = \frac{2e^{r\tau}}{\tau} \int_{K<X_t} \frac{log(X_t/K)}{K^2} P(X_t; K, \tau) dK, \tag{B8}$$

where r is the constant risk-free rate and P is the price of the out-of-the money put option with maturity τ and strike price K. We use a trapezoidal rule to approximate the integrals. Finally, we linearly interpolate between the two times-to-maturity closest to (above and below) 30 days to generate the RIX^- with a constant 30-day time-to-maturity.

TLM Vilkov and Xiao (2015) build on Extreme Value Theory (EVT) to estimate the measure of tail risk implied from option prices under the risk-neutral measure. According to

EVT, the price $P_t(K)$ of an out-of-the-money put option can be calculated using the rules of conditional volatilities.

Combining the equations of the EVT, Vilkov and Xiao (2015) rewrite the price of a further out-of-the money option as a function of an option that is closer at-the-money.

$$P_t(K_1) = P_t(K)\left(1 + \xi \times \frac{K - K_1}{\beta(K)}\right)^{1-1/\xi}. \tag{B9}$$

Vilkov and Xiao (2015) use the above equation to price deep out-of-the-money puts relative to a boundary put. Then, they compare the theoretically obtained price with the empirical price and infer the parameters $\beta(K)$ and ξ by minimizing the pricing errors. Finally, Vilkov and Xiao (2015) estimate the tail loss measure on a given threshold via $TLM = \frac{\beta(K)}{1-\xi}$, which they estimate as follows:

$$\begin{aligned}
K_{0,\tau} &= S_t\left(1 - 2\frac{\widehat{VIX}_t/100}{\sqrt{12}}\right), \\
\widehat{VIX}_t &= \frac{1}{63}\sum_{i=0}^{62} VIX_{t-i}, \\
P^*_{i,t} &= P^*_{0,t}\left[\frac{\xi_t}{\beta_t}(K_{0,t} - K_{i,t}) + 1\right]^{1-1/\xi_t}, \\
\{\xi_t, \beta_t\} &= \operatorname{argmin}\sum_{i=0}^{n-1}\left|\frac{P_{i,t} - P^*_{i,t}}{P^*_{i,t}}\right|, \\
TLM &= \frac{\beta_t}{1-\xi_t}.
\end{aligned}$$

Stock-Return-Based Measures

BT*11*P Bollerslev and Todorov (2011a) use a threshold estimator. To identify the presence of jumps, they use the bipower variation (BV_t) proposed by Barndorff-Nielsen and Shephard (2004, 2006) and the realized variation (RV_t). The bipower measures should only identify the continuous part of the variation and an exceedance should clearly indicate the jumps, Bollerslev and Todorov (2011a) use for the threshold:

$$\alpha_t = 4\sqrt{BV_t \wedge RV_t}.$$

To avoid false positives, Bollerslev and Todorov (2011a) use a time-of-day factor (TOD), to adjust alpha for the intraday pattern of volatility. Bollerslev and Todorov (2011b) say any $\alpha > 0$ and $\omega \in (0, 0.5)$ would work, but they fix ω to 0.49. α, however, is chosen as displayed above. They define the TOD factor in the following way:

$$\begin{aligned} TOD_i =& NOI_i \frac{\sum_{t=1}^{N} (p_{t-1+\pi_t+i\Delta_{n,t}} - p_{t-1+\pi_t+(i-1)\Delta_{n,t}})^2 1_{|p_{t-1+\pi_t+i\Delta_{n,t}} - p_{t-1+\pi_t+(i-1)\Delta_{n,t}}| \leq \bar{\alpha}\Delta_n^{0.49}}}{\sum_{t=1}^{N}\sum_{i=1}^{M} (p_{t-1+\pi_t+i\Delta_{n,t}} - p_{t-1+\pi_t+(i-1)\Delta_{n,t}})^2}, \text{ where} \\ NOI_i =& \frac{\sum_{t=1}^{N}\sum_{i=1}^{n-1} 1_{|p_{t-1+\pi_t+i\Delta_{n,t}} - p_{t-1+\pi_t+(i-1)\Delta_{n,t}}| \leq \bar{\alpha}\Delta_n^{0.49}}}{\sum_{t=1}^{N} 1_{|p_{t-1+\pi_t+i\Delta_{n,t}} - p_{t-1+\pi_t+(i-1)\Delta_{n,t}}| \leq \bar{\alpha}\Delta_n^{0.49}}}, \text{ and} \\ \bar{\alpha} =& 4\sqrt{\frac{\pi}{2}}\sqrt{\frac{1}{N}\sum_{t=1}^{N}\sum_{i=2}^{n-1} |p_{t-1+\pi_t+i\Delta_{n,t}} - p_{t-1+\pi_t+(i-1)\Delta_{n,t}}||p_{t-1+\pi_t+(i-1)\Delta_{n,t}} - p_{t-1+\pi_t+(i-2)\Delta_{n,t}}|}. \end{aligned}$$

Thus, the intraday α is:

$$\alpha_{t,i} = 4\sqrt{BV_t \wedge RV_t} \times TOD_i \times \Delta_n^{0.49}. \tag{B10}$$

Bollerslev and Todorov (2011a) define the following parameter vector that can be estimated: $\theta \equiv (\sigma^-, \xi^-, k_0^- \bar{v}_\psi^-(\varrho_T), k_1^- \bar{v}_\psi^-(\varrho_T))$. The estimation is based on the scores associated with the log-likelihood function of the generalized Pareto distribution. Specifically Bollerslev and Todorov (2011a) estimate the following equations:

$$\frac{1}{N}\sum_{t=1}^{N}\sum_{j=1}^{n-1}\phi_i^-(\psi^-(\Delta_j^{n,t}p)-tr^-)1_{\psi^-(\Delta_j^{n,t}p)>tr^-}=0,$$

$$\frac{1}{N}\sum_{t=1}^{N}\sum_{j=1}^{n-1}1_{\psi^-(\Delta_j^{n,t}p)>tr^-}-(1-\phi)k_0^-\overline{v}_\psi^-(\varrho_T)-k_1^-\overline{v}_\psi^-(\varrho_T))CV_t=0,$$

$$\frac{1}{N}\sum_{t=2}^{N}\left(\sum_{j=1}^{n-1}1_{\psi^-(\Delta_j^{n,t}p)>tr^-}-(1-\phi)k_0^-\overline{v}_\psi^-(\varrho_T)-k_1^-\overline{v}_\psi^-(\varrho_T))CV_t\right)CV_{t-1}=0,$$

$$\text{and } (1-\phi)\frac{1}{N}\sum_{t=1}^{N}(p_{t+\phi_t}-p_t)^2-\phi\frac{1}{N}\sum_{t=1}^{N}RV_t=0.$$

$n=\frac{1}{\Delta_n}$ is the number of high-frequency price observations over one day. $\Delta_i^{n,t}p := p_{t+i\delta_n} - p_{t+(i-1)\Delta_n}$ refers to the corresponding price increments over one day. Furthermore Bollerslev and Todorov (2011a) define the tail parameter as tr^-, such that it corresponds in log-prices of 0.6%. For tr^- this implied $e^{0.006}\approx 1.006$ for the left tails, respectively.

CJI Christoffersen et al. (2012) fit a parametric model. To investigate the tail risk dynamics using daily returns, the authors propose four nested models; we present the most general and best performing model, the DVSDJ model (dynamic volatility with separate dynamic jumps). The model can be estimated using only return data, or both option and return data. They propose the following model specifications:

$$\begin{aligned} h_{z,t+1} &= w_z + b_z h_{z,t} + \frac{a_z}{h_{z,t}}(z_t - c_z h_{z,t})^2 + d_z(y_t - e_z)^2, \\ h_{y,t+1} &= w_y + b_y h_{y,t} + \frac{a_y}{h_{z,t}}(z_t - c_y h_{z,t})^2 + d_y(y_t - e_y)^2. \end{aligned} \tag{B11}$$

$h_{z,t+1}$ is the return innovation for the market price of risk of the normal component, while $h_{y,t+1}$ is the return innovation for the market price of risk of the jump component. In order to obtain the unobservable measures, Christoffersen et al. (2012) propose a filtering technique for the returns to obtain the number of jumps (n_t), the normal component of the return (z_t) and the jump component of the return (y_t). Then, the variance of the normal, and the jump component can be determined. First, Christoffersen et al. (2012) use Bayes' rule to filter the density:

$$Pr_t(n_t = j) \equiv Pr_{t-1}(n_t = j|x_t) = \frac{f_{t-1}(x_t|n_t = j)Pr_{t-1}(n_t = j)}{f_{t-1}(x_t)}, \tag{B12}$$

where

$$\begin{aligned} f_t(x_{t+1}|n_{t+1} = j) &= \frac{1}{\sqrt{2\pi(h_{z,t+1} + j\delta^2)}} exp\left(-\frac{(x_{t+1} - \mu_{t+1} - j\theta)^2}{2(h_{z,t+1} + j\delta^2)}\right), \\ Pr_t(n_{t+1} = j) &= \frac{(h_{y,t+1})^j}{j!} exp(-h_{y,t+1}), \\ f_t(x_{t+1}) &= \sum_{j=0}^{\infty} f_t(x_{t+1}|n_{t+1} = j)Pr_t(n_{t+1} = j). \end{aligned}$$

$Pr_t(n_t = j)$ is the ex-post inference on n_t. Multiplying the density function by the amount of jumps results in the filtered number of jumps: $\tilde{n}_t = \sum_{j=0}^{\infty} jPr_t(n_t = j)$. To solve the ex-post filtration on the normal component, Christoffersen et al. (2012) filter the expectation of z_t. If the return and the number of jumps are known, Christoffersen et al. (2012) define z_t in the following way:

$$z_t(x_t, n_t = j) = \sqrt{\frac{\tilde{h}_{z,t}}{\tilde{h}_{z,t} + j\delta^2}}(x_t - \mu_t - j\theta). \tag{B13}$$

$\tilde{h}_{z,t}$ is the filtered $h_{z,t}$, μ_t is the first conditional return moment; Christoffersen et al. (2012) define it as follows: $\mu_t = r + (\lambda_z - 0.5)h_{z,t} + (\lambda_y - \xi)$. The expectation can be solved via the following summation: $\tilde{z}_t = E_t[z_t] = \sum_{j=0}^{\infty} z_t(x_t, n_t = j)Pr_t(z_t, n_t = j)$, where $Pr_t(z_t, n_t = j) \equiv Pr_{t-1}(z_t, n_t = j|x_t) \propto Pr_{t-1}(z_t|x_t, n_t = j)Pr_t(n_t = j)$.

$Pr_{t-1}(z_t|x_t, n_t = j) = Pr_{t-1}(x_t, n_t = j|x_t, n_t = j)\sqrt{\frac{\tilde{h}_{z,t}}{\tilde{h}_{z,t}+j\delta^2}}$, the first term on the right-hand-side of this equation is one, using this equation, and Equation (B13) to be:

$$\begin{aligned}\tilde{z}_t &= \sum_{j=0}^{\infty} z_t(x_t, n_t = j) Pr_{t-1}(z_t | x_t, n_t = j) Pr_t(n_t = j) \\ &= \sum_{j=0}^{\infty} \frac{\tilde{h}_{z,t}}{\tilde{h}_{z,t} + j\delta^2}(x_t - \mu_t - j\theta) Pr_t(n_t = j).\end{aligned} \tag{B14}$$

From $\tilde{z}_t$ Christoffersen et al. (2012) can directly infer the filtered jump innovation $\tilde{y}_t$. It is given by $\tilde{y}_t = x_t - \mu_t - \tilde{z}_t$. With the two variables, the filtered variance and the jump intensity for the next period can be computed:

$$\begin{aligned}\tilde{h}_{z,t+1} &= w_z + b_z \tilde{h}_{z,t} + \frac{a_z}{\tilde{h}_{z,t}}(\tilde{z}_t - c_z \tilde{h}_{z,t})^2 + d_z(\tilde{y}_t - e_z)^2, \\ \tilde{h}_{y,t+1} &= w_y + b_y \tilde{h}_{y,t} + \frac{a_y}{\tilde{h}_{z,t}}(\tilde{z}_t - c_y \tilde{h}_{z,t})^2 + d_y(\tilde{y}_t - e_y)^2.\end{aligned} \tag{B15}$$

For the likelihood at time t=0, Christoffersen et al. (2012) assume that the time-series is equal to the mean of the filtered time-series from the prior iteration. With the filtered data, Christoffersen et al. (2012) conduct the following optimization via maximum likelihood:

$$L_{returns} = \sum_{t=1}^{\tau-1} log(f_t(x_{t+1})) = \sum_{t=1}^{\tau-1} log\left(\sum_{j=0}^{\infty} f_t(x_{t+1|n_{t+1}=j}) Pr_t(n_{t+1} = j)\right), \tag{B16}$$

with

$$\begin{aligned}f_t(x_{t+1}|n_{t+1} = j) &= \frac{1}{\sqrt{2\pi(\tilde{h}_{z,t+1} + j\delta^2)}} exp\left(-\frac{(x_{t+1} - \mu_{t+1} - j\theta)^2}{2(\tilde{h}_{z,t+1} + j\delta^2)}\right), \\ Pr_t(n_{t+1} = j) &= \frac{(\tilde{h}_{y,t+1})^j}{j!} exp(-\tilde{h}_{y,t+1}).\end{aligned}$$

JumpRisk and ***JumpRP*** Maheu et al. (2013) estimate a stochastic jump model to calculate the time-varying jump risk from the daily returns of a time-series. They use a utility-based framework to achieve this. Maheu et al. (2013) assume that the innovation in the return process stems from two stochastic processes, $\epsilon_{1,t} = \sigma_t * N(0,1)$ and $\epsilon_{2,t} = \sum_{K=1}^{n+1} N(\theta, \delta^2) - \theta\lambda_t$. To obtain the measure Maheu et al. (2013) estimate the following system of equations:

$$P(n_t = j|\Phi_{t-1}) = \frac{e^{\lambda_t}\lambda_t^j}{j!},\ j = 0,1,2,...,$$

$$\lambda_t = E[n_t|\Phi_{t-1}] = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi_{t-1},$$

$$\xi_{t-1} = \sum_{j=0}^{\infty} jP(n_{t-1} = j|\Phi_{t-1}) - \lambda_{t-1},$$

$$E[\lambda_t] = \frac{\lambda_0}{1-\rho},$$

$$E[\lambda_{t+i}|\Phi_{t-1}] = \begin{cases} \lambda_t & i = 0. \\ \lambda_0(1+p+...+p^{i-1}) + p\lambda_t & i \geq 1. \end{cases}$$

$$\lambda_t = \lambda_0 + (\rho - \gamma)\lambda_{t-1} + \gamma E[n_{t-1}|\Phi_{t-1}].$$

As a start value for λ_t Maheu et al. (2013) use $E[\lambda_t]$, for ξ_1 we choose 0. Maheu et al. (2013) calculate first the following result:

$$P(n_{t+1} = j|\Phi_{t+1}, \theta) = \frac{f(r_{t+1}|n_{t+1} = j, \Phi_t, \theta)P(n_{t+1} = j|\Phi_t, \theta)}{f(r_{t+1}|\Phi_t, \theta)}, \tag{B17}$$

$$f(r_{t+1}|n_{t+1} = j, \Phi_t, \theta) = \frac{1}{\sqrt{2\pi(\sigma_t^2 + j\delta^2)}} e^{-0.5\frac{(r_{t+1} - m_t - \rho_1(r_t - m_{t-1}) - \rho_2(r_{t-1} - m_{t-2}) - (j - \lambda_t)\theta)^2}{\sigma_t^2 + j\delta^2}},$$

$$P(n_{t+1} = j|\Phi_t, \theta) = \frac{e^{-\lambda_{t-1}^j}\lambda_{t-1}^j}{j!},\ j = 0,1,2,...,$$

$$f(r_{t+1}|\Phi_t, \theta) = \sum_{j=0}^{\infty} f(r_{t+1}|n_{t+1} = j, \Phi_t)P(n_{t+1} = j|\Phi_t),$$

$$\lambda_t = \lambda_0 + \rho\lambda_{t-1} + \gamma\xi t - 1,$$

$$E[\lambda_t] = \frac{\lambda_0}{1-\rho}.$$

As Maheu et al. (2013) state, risk premia in their model behave opposite to the current state of volatility and jump risk. This often leads to low estimations in crisis periods. Thus, we conduct the regressions with inverse jump risk premia. We use two measures from this estimation. We use the risk of a jump (λ_t) and we use the jump risk premium, which is calculated using the first derivative of the equity risk premium (m_t) with respect to λ_t.

$\boldsymbol{\lambda_{Hill}}$ Kelly and Jiang (2014) assume that returns obey the dynamic power law structure for equity returns. In their specification, the tail distribution obeys a potentially time-varying power law. In order to improve upon a main obstacle, the low sample size for individual returns, Kelly and Jiang (2014) exploit the information in the cross-section of stock returns. Thus, they assume that all individual assets have tail risks that are governed by a single process. Kelly and Jiang (2014) apply the power law of Hill (1975). The estimator is defined for a pooled cross-section as follows:

$$\lambda_t^{Hill} = \frac{1}{E_t} \sum_{k=1}^{E_t} log\left(\frac{X_{k,t}}{u_t}\right). \tag{B18}$$

u_t is the extreme-value threshold in month t. E_t is the total number of exceedances of u_t in a month, all cross-sectional returns in this month are considered; this is without loss of generality, because this estimator does not consider any differences in the tails for each company. u_t is chosen by the econometrician to define where the tail of the distribution begins. Kelly and Jiang (2014) define the threshold as the fifth percentile of the cross-section in the sample. The estimator only considers exceedances of u_t for the power law. Kelly and Jiang (2014) refer to this exponent as tail risk. To remove dependencies in the returns of the observed returns, Kelly and Jiang (2014) use the residuals from a regression with the common return factors of Fama and French (1993).

Option-Return-Based Measures

ADBear Lu and Murray (2019) construct another measure that uses option portfolios. They create a portfolio that yields a positive payoff of \$1 when the S&P 500 is below a certain threshold K_2. To create a tradeable position of this portfolio, they take a short position in a put option with strike price $K_1 > K_2$ and a short position in a put option with strike price K_2. Then they scale the positions by $K_1 - K_2$ to achieve the desired payoff. This generates a payoff that is \$1 below K_2 and is linearly decreasing between K_2 and K_1. The price of the portfolio is then the following:

$$P_{\text{AD Bear}} = \frac{P(K_1) - P(K_2)}{K_1 - K_2} \ . \tag{B19}$$

Lu and Murray (2019) define K_2 to be 1.5 standard deviations below the S&P 500 index forward price. This threshold is chosen based with the objective of capturing the pricing of the extreme left tails of the index, while avoiding the noise of the extreme tails. K_1 is chosen to be 0.5 standard deviations above K_2. The standard deviation is the level of the VIX index divided by 100, multiplied by the square root of the time to maturity. In order to create a price for the desired out-of-the-money put option, Lu and Murray (2019) calculate the price to be the volume weighted average price of the put options within a 0.25 standard deviation range of the desired targeted strike price. This leads to the following specification:

$$\begin{aligned} P(K_1) &= \sum_{K \in [Fe^{-1.25 \frac{VIX}{100}\sqrt{\tau}}, Fe^{-0.75 \frac{VIX}{100}\sqrt{\tau}}]} P(K)w(K), \\ P(K_2) &= \sum_{K \in [Fe^{-1.75 \frac{VIX}{100}\sqrt{\tau}}, Fe^{-1.25 \frac{VIX}{100}\sqrt{\tau}}]} P(K)w(K). \end{aligned} \tag{B20}$$

For liquidity reasons, Lu and Murray (2019) consider only one-month options, which are options that expire in the next month. The portfolio is held for the next five trading days, but the portfolio is constructed daily. In addition, they subtract the five-day risk-free rate from the returns. As a result Lu and Murray (2019) have five-day overlapping $ADBear$ portfolio excess returns, which we use as our jump risk measure.

JUMP Cremers et al. (2015) construct factors for volatility and jump risk with delta-neutral at-the-money straddles. They construct delta-neutral at-the-money straddles to create portfolios that mimic volatility or jump risk. The straddles have large vegas as well as high gammas.[1] Cremers et al. (2015) create two portfolios, one with exposure to vega and another that is only exposed to gamma risk. These portfolios capture exclusively volatility or jump risk. To create gamma or vega neutral straddles, Cremers et al. (2015) use the fact that the gamma of an option is decreasing with increasing time to maturity, while vega is increasing with increasing time to maturity. They are able to create both strategies with long/short portfolios involving market-neutral straddles with different maturities.

They construct a zero-beta straddle:

$$x_{MN} = \theta x_c + (1-\theta)x_p,$$
$$0 = \theta\beta_c + (1-\theta)\beta_p.$$

x_{MN} is the return of a market-neutral straddle , x_c is the return of a call, x_p is the return of a put. β_c and β_p are the market betas of the call and put options. To calculate the sensitivities Cremers et al. (2015) use the Black and Scholes (1973) option pricing formula.

Cremers et al. (2015) create the following two portfolios: A jump risk factor-mimicking portfolio (JUMP) is a market-neutral, vega-neutral, and gamma-positive strategy, where the time-to maturity $T_2 > T_1$. Thus, they use (i) a long position in one market-neutral at-the-money straddle with maturity T_1 and (ii) a short position in y market-neutral at-the-money straddles with maturity T_2. y is chosen to create a vega-neutral portfolio. To construct the short-dated straddles Cremers et al. (2015) use the option pair that is being closest at-the-

[1] Thus, a high sensitivity towards volatility and jumps, respectively.

money. For short-dated straddles they choose the options that expire in the next calendar month, for long-dated options they choose options that expire in the calendar month that follows the next month. The strategy is re-balanced daily. For our analysis, we use the returns of the gamma-positive, vega- and market-neutral $JUMP$ strategy.

Macroeconomic Measures

LE Adrian et al. (2019) develop a measure that infers tail risk for GDP growth from an index of financial conditions. For this purpose, they use the National Financial Conditions Index (NFCI) from Brave and Butters (2012) provided by the Chicago FED.[2] They use quantile regressions to empirically estimate the quantiles of the distribution. They use this to fit a skewed t-distribution, to infer the entire distribution. The authors minimize the squared error between the estimation from the quantile distribution, based on the parameters of the t-distribution and the skewed t-distribution every quarter. They argue that financial conditions can account for a proportion of GDP growth; especially in the left tail, tightening financial conditions leads to downside risks in GDP growth. Adrian et al. (2019) fit the following quantile regression:

$$\hat{Q}_{y_{t+\tau}|x_t}(\tau|x_t) = x_t\hat{\beta}_\tau. \tag{B21}$$

They use the estimates, to create a quantile function (the inverse cumulative distribution function) and fit the quantile function to the skewed t-distribution to recover a probability density function:

$$f(y;\mu,\sigma,\alpha,v) = \frac{2}{\sigma}t\left(\frac{y-\mu}{\sigma};v\right)T\left(\alpha\frac{y-\mu}{\sigma}\sqrt{\frac{v+1}{v+\left(\frac{y-\mu}{\sigma}\right)^2}};v+1\right), \tag{B22}$$

where $t(\bullet)$ is the probability density function (PDF) of the Student t-distribution and $T(\bullet)$ is the cumulative distribution function (CDF) of the Student t-distribution. μ is the loca-

[2] `https://www.chicagofed.org/`.

tion, σ is the scale, v is the fatness, and α is the shape. For each quarter, following Adrian et al. (2019), the four parameters are chosen to minimize the distance between the estimated quantile function $\hat{Q}_{y_{t+\tau}|x_t}(\tau|x_t)$ and the quantile function of the skewed t-distribution $F^{-1}(\tau; \mu, \sigma, \alpha, v)$ at the 5, 25, 75, and 95 quantiles:

$$\{\hat{\mu}_{t+\tau}, \hat{\sigma}_{t+\tau}, \hat{\alpha}_{t+\tau}, \hat{v}_{t+\tau}\} = \underset{\mu,\sigma,\alpha,v}{\operatorname{argmin}} \sum_{\tau} (\hat{Q}_{y_{t+\tau}|x_t}(\tau|x_t) - F^{-1}(\tau; \mu, \sigma, \alpha, v))^2. \tag{B23}$$

We retain two measures from this estimation for each tail: the expected shortfall and the left entropy. While the expected shortfall is the expectation of the worst outcomes of economic growth, the left entropy describes the left-skewedness of the distribution.

B1.2 Wild Bootstrap Procedure

For statistical inference, we generally rely on the multivariate wild bootstrap of Rapach et al. (2013). For example, with the predictive regression in Equation (3.6), the wild bootstrap procedure retains the residuals from the main estimation procedure and the residuals of a $VAR(1)$ from all RHS variables, the parameters are estimated with a reduced-bias VAR estimate by iterating on the Nicholls and Pope (1988) expression for the analytical bias of the OLS estimates. The coefficients and residuals of these estimations are used to build pseudo-samples for all RHS variables. In each pseudo-sample, the LHS returns are constructed under the null of no predictability. The RHS variables in each pseudo-sample rely on the reduced-bias $VAR(1)$ parameter estimates from the original residuals, multiplied with standard normal random variables. This procedure preserves the contemporaneous correlation of the variables and captures conditional heteroskedasticity. Using the pseudo-samples, one can calculate the t-statistics for the usual regression. With this distribution of t-statistics, one can obtain the p-values based on the location of the sample t-statistic in this distribution.

For example, in a return predictability regression, assuming we have only one control variable (to keep the notation short we only use the VRP; the extension to multiple control variables is straightforward), we estimate the following set of regressions:

$$R_{t+\Delta t} = a + b \cdot TRM_t + VRP_t + \epsilon_{t+\Delta t}$$

$$TRM_{t+1} = \rho_{d,0} + \rho_{d,1} TRM_t + \rho_{d,2} VRP_t + \nu_{d,t+1}$$

$$VRP_{t+1} = \rho_{b,0} + \rho_{b,1} VRP_t + \rho_{b,2} TRM_t + \nu_{b,t+1}.$$

We retain the estimated coefficients: $(\hat{\rho}_{d,0}, \hat{\rho}_{d,1}, \hat{\rho}_{d,2})$, $(\hat{\rho}_{b,0}, \hat{\rho}_{b,1}, \hat{\rho}_{b,2})$ as well as the residuals $\hat{\epsilon}_{t+\Delta t}$, $\hat{\nu}_{d,t+1}$ and $\hat{\nu}_{b,t+1}$. Using these estimates and residuals, we build the pseudo-samples under the null:

$$R^*_{t+\Delta t} = \bar{R} + \hat{\epsilon}_{t+\Delta t} w_{t+1}$$

$$TRM^*_{t+1} = \hat{\rho}_{d,0} + \hat{\rho}_{d,1} TRM^*_t + \hat{\rho}_{d,2} VRP^*_t + \hat{\nu}_{d,t+1} w_{t+1}$$

$$VRP^*_{t+1} = \hat{\rho}_{b,0} + \hat{\rho}_{b,1} VRP^*_t + \hat{\rho}_{b,2} TRM^*_t + \hat{\nu}_{b,t+1} w_{t+1},$$

where w_{t+1} is a standard normally distributed variable to produce the pseudo-sample. We repeat this procedure 1,000 times. The p-value represents the percentage of times the t-statistics of the pseudo-sample are greater (for positive coefficients) or smaller (for negative coefficients) than the t-statistic of the original sample. To account for autocorrelation, we base all t-statistics in the original and the bootstrap samples on robust Newey and West (1987) standard errors with 29 lags (252 lags for annual horizons).

B1.3 Multiple Regression Selection Procedures

PcGets Procedure

For the multiple regression analysis, we use the general-to-specific search algorithm of Hendry (1995) and Hendry and Krolzig (2001). We follow the detailed implementation as described by Bekaert et al. (2011) in their Appendix Table 4. For convenience, we provide the steps here:

1 Estimate a general model (G1) including all variables.

  a If all coefficients are individually significant at a level of 0.025, G1 is the final model (*t-test*).

  b If an F-test cannot reject the null hypothesis at a level of 0.500 that all coefficients are zero, or all coefficients but the constant are zero, the null not rejected constitutes the final model (*F-test*).

2 Pre-search tests

  a Top-down tests: We test an expanding list of coefficients (from smallest to largest t-statistic). If an F-test does not reject the null hypothesis at a level of 0.500 when we add a coefficient, we remove the corresponding explanatory variable. The resulting reduced model is the new general model G2 (*F-test*).

  b Estimate G2 and repeat (a) with the new model at a level of 0.250 for the null hypothesis (*F-test*).

  c Bottom-up tests: We test a decreasing list of coefficients (from largest to smallest t-statistic). If the F-test does not reject at a level of significance of 0.025, remove the additional variables. The reduced model is the new general model (G3) (*F-test*).

3 Multiple-path tests

  a Estimate G3. If all coefficient estimates are individually significant at a significance level of 0.025, G3 is the final model (*t-test*).

  b Initiate search paths, re-estimate the model after removing all variables with p-values above (0.90, 0.70, 0.50, 0.25, 0.10, 0.05, 0.01, 0.001). This leaves 8 paths.

Additionally start a path for each variable that is insignificant at the 0.025 level. Proceed with these paths in (c).

c As long as insignificant estimates survive at a level of 0.025, drop the least significant one and re-estimate (*t-test*). A search path is abandoned if no coefficients are significant. A path arrives at a terminal model if all coefficient estimates are significant.

4 Encompassing

If all search paths are abandoned, G3 is the final model.

If there is only one terminal model, it is the final model.

If there are multiple terminal models, test each model against the union of all models with an F-test with a significance level of 0.025 (F-*test*).

If all models are rejected, the union is the final model.

If only one model is not rejected, it is the final model.

If multiple models are not rejected, they are tested against their union (after removing any rejected models).

If only one model is not rejected, it is the final model.

If all models are rejected, the union is the final model.

If no model is rejected, their union is the new general model (G4).

5 Repeat steps 3 and 4 for the new general model (G4)

If there is only one terminal model, it is the final model.

If there are multiple terminal models, they are tested against their union:

If only one model is not rejected, it is the final model.

If all models are rejected and their union equals G4, then G4 is the final model.

If several models are not rejected and their union does not equal G4, their union is the new general model (G5) and steps 3 and 4 are repeated.

If several models are not rejected and their union equals G4, the model with the smallest Schwarz criterion is the final model.

Jackknife Procedure

Alternatively, we follow Bekaert et al. (2011) and also consider a jackknife procedure. It entails the following steps. First, for each tail risk measure (the candidate variable), we perform a regression with a selection of the other variables and the candidate variable. First, we randomly select the number of variables to be used. We require at least 30% of all variables to be included in the selection procedure, which amounts to 9 variables for the return predictability regression. Second, we randomly select the chosen number of variables from all available variables without replacement. We then run a regression with all these variables. Third, we eliminate all variables with t-statistics whose magnitudes are below one (except for the candidate variable). Then, we run another regression with the remaining variables. In the last step, the coefficient of the candidate variable is retained. This procedure is repeated one thousand times for each candidate variable, calculating 90% confidence intervals. All candidate variables whose confidence intervals exclude zero are retained for the final multiple regression.

B1.4 Additional Figures

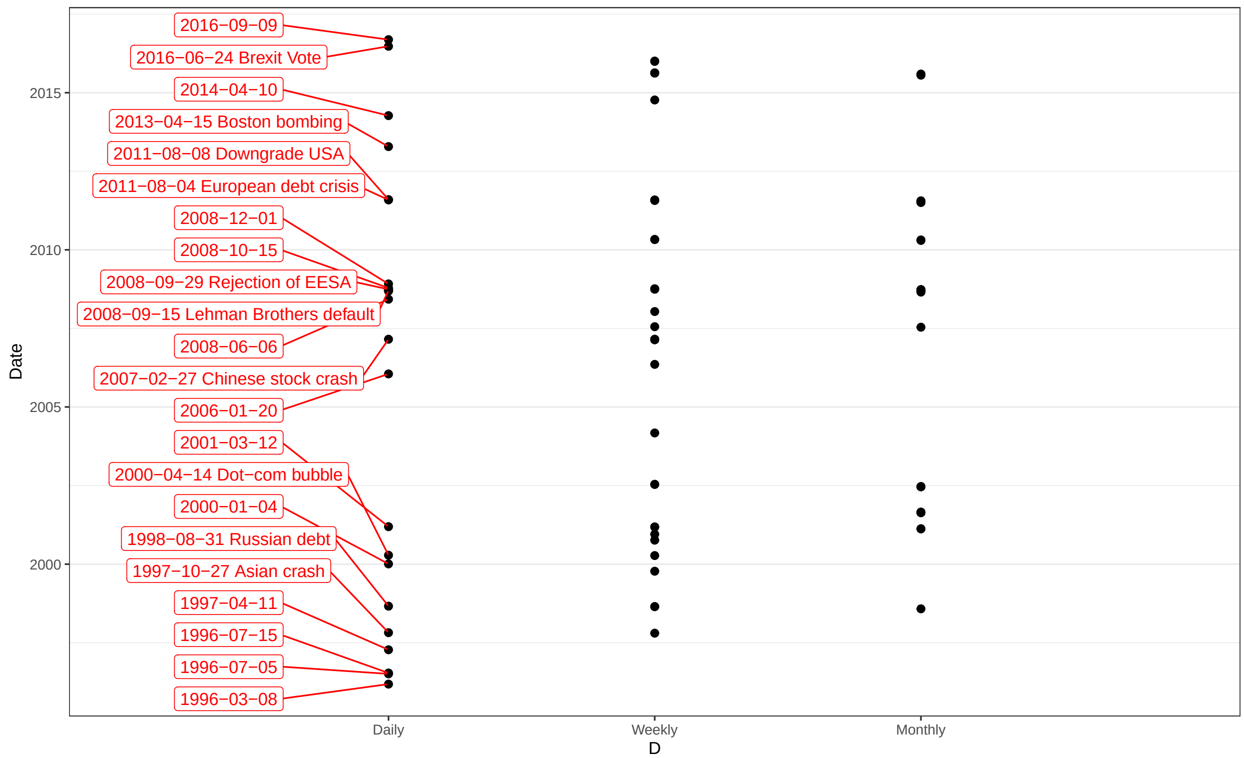


Figure B1: Realized Tail Events

This figure displays the realized tail events ($D_{t+\Delta t}$). The points illustrate the times of the tail event realizations at the daily, weekly, and monthly horizons. For the daily frequency, in red we display the exact dates and, in cased where the events are clearly linked to certain events, we also indicate these events. The numbers of observed left-tail events are 24 at the daily horizon, 37 at the weekly horizon, and 46 at the monthly horizon. Weekly and monthly tail events are clustered due to the use of overlapping return windows.

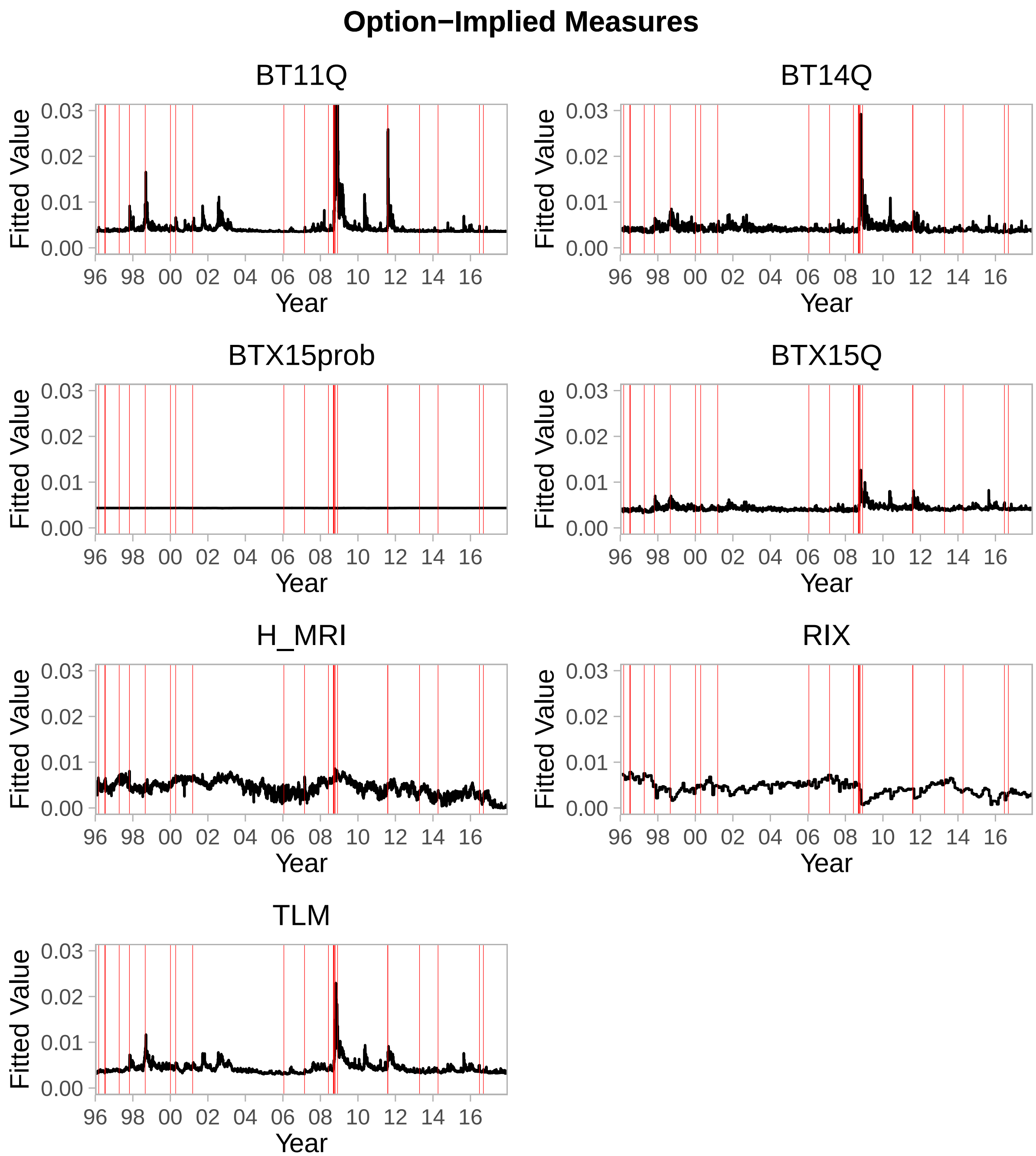


Figure B2: Fitted Crash Risk: Option-Implied Measures

This figure displays the fitted values ($b \cdot TRM_t$) from the probit regression: $D_{t+\Delta t} = a + b \cdot TRM_t + \epsilon_{t+\Delta t}$, executed at the daily frequency. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the end of the previous day. TRM_t is the current observation of a tail risk measure. We indicate the actual crash realizations ($D_{t+\Delta t} = 1$) by vertical red lines. For $BT11Q$, the figure truncates values between October and December 2008. The largest peak occurs on October 13th, 2008, reaching 0.139.

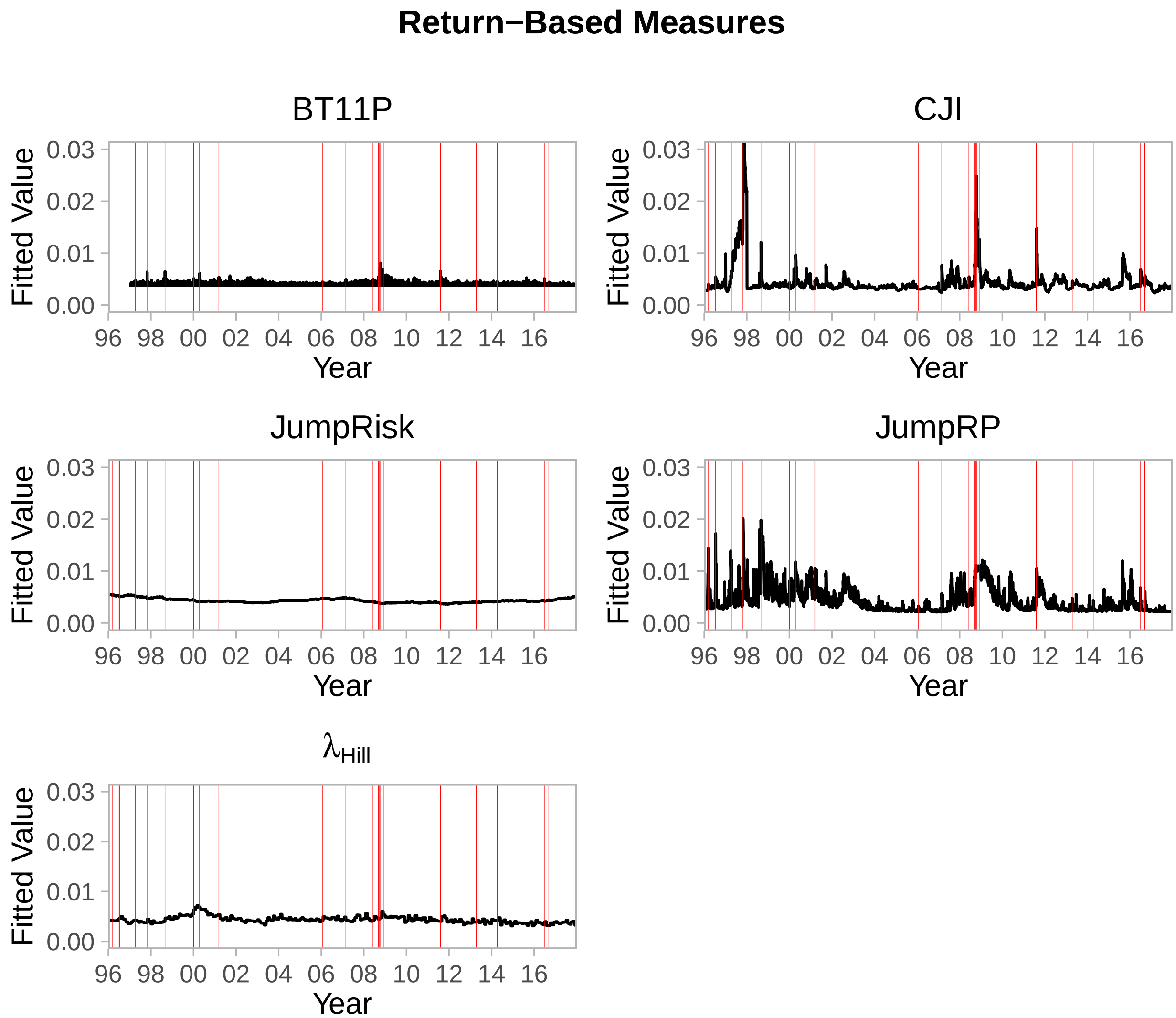


Figure B3: Fitted Crash Risk: Stock Return Based Measures

This figure displays the fitted values ($b \cdot TRM_t$) from the probit regression: $D_{t+\Delta t} = a + b \cdot TRM_t + \epsilon_{t+\Delta t}$, executed at the daily frequency. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the end of the previous day. TRM_t is the current observation of a tail risk measure. We indicate the actual crash realizations ($D_{t+\Delta t} = 1$) by vertical red lines. For CJI, the figure truncates values between October and November 1997. The largest peak occurs on October 30th, 1997, reaching 0.036.

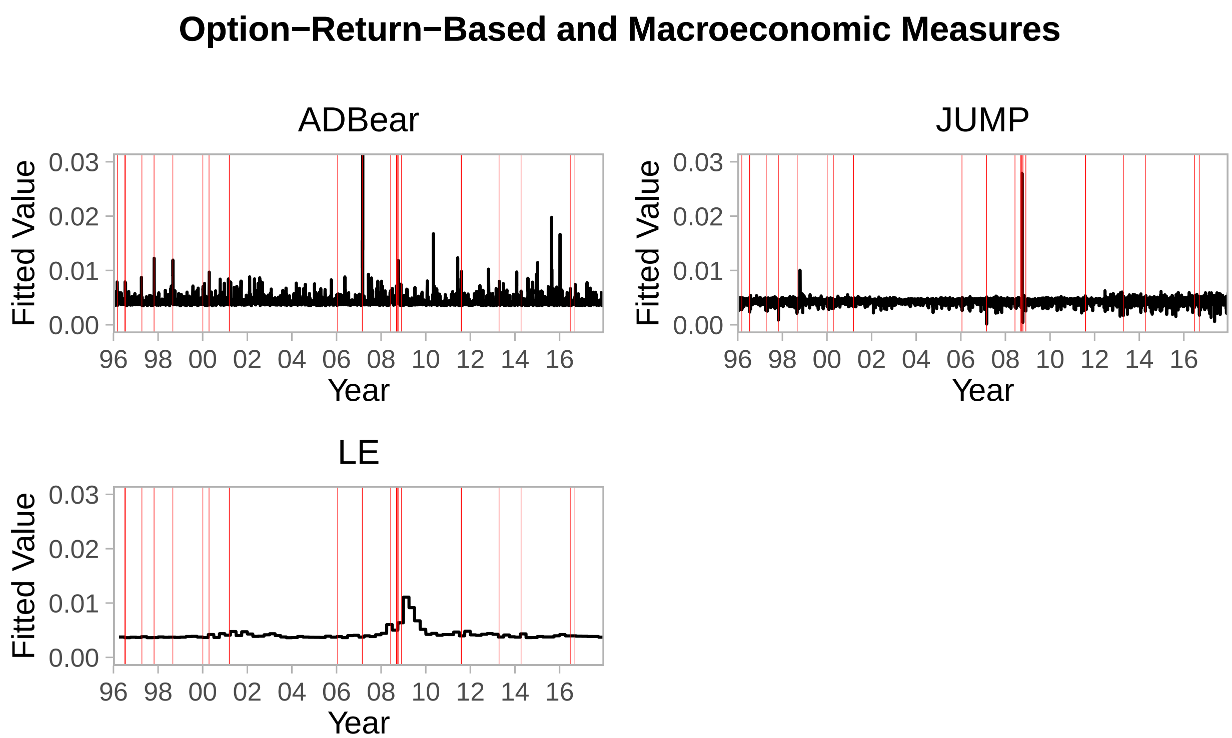


Figure B4: Fitted Crash Risk: Option Return Based Measures

This figure displays the fitted values ($b \cdot TRM_t$) from the probit regression: $D_{t+\Delta t} = a + b \cdot TRM_t + \epsilon_{t+\Delta t}$, executed at the daily frequency. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the end of the previous day. TRM_t is the current observation of a tail risk measure. We indicate the actual crash realizations ($D_{t+\Delta t} = 1$) by vertical red lines.

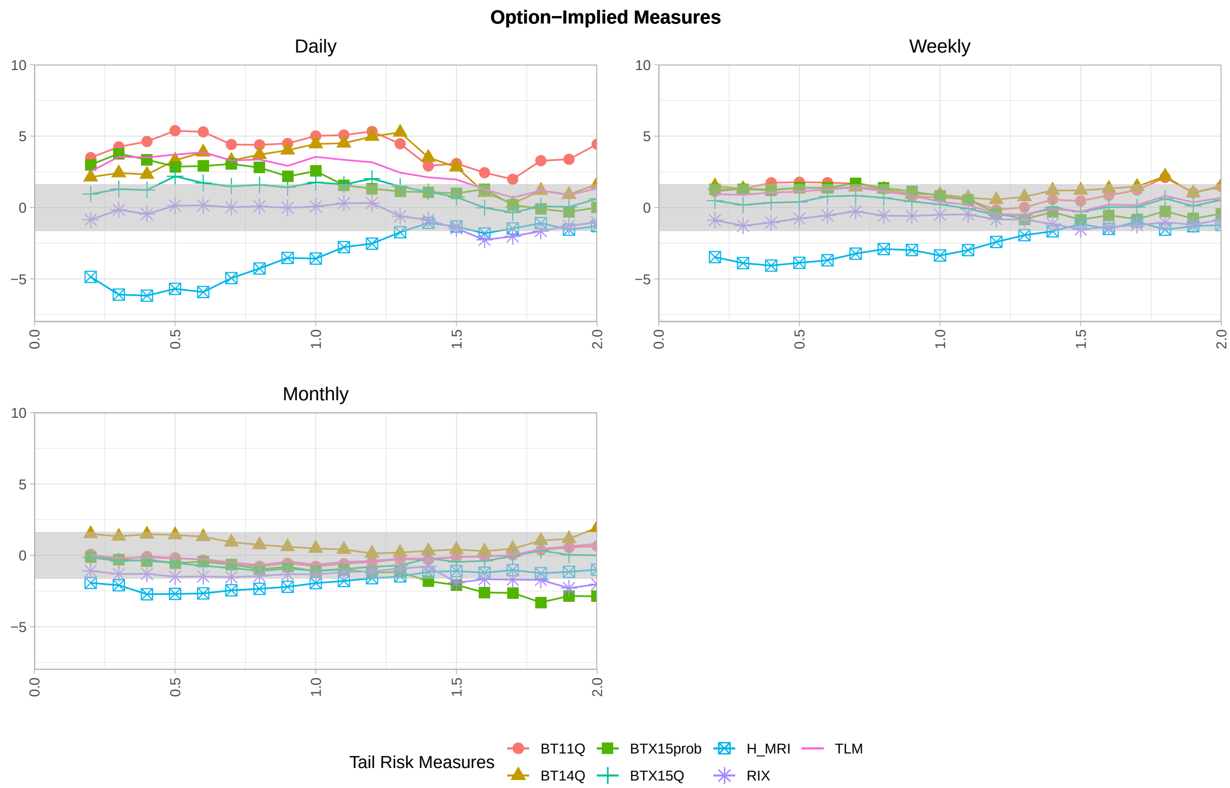


Figure B5: Crash Thresholds Robustness: Option-Implied Measures

This figure presents the z-statistics from predictive probit regressions for different tail thresholds for option-implied tail risk measures. We perform the regression over different time intervals, from daily (top left) to annually (bottom). We perform single regressions of a dummy variable on each lagged tail risk measure. The dummy variable is 1 if the realized market excess return falls below the threshold defined by minus x times the current conditional volatility, with x shown on the horizontal axis ($x \in [0.2; 2]$). The conditional volatility is defined as the VIX at the end of the previous day. The gray shaded area denotes statistical insignificance at the 5% level. Different colors and point shapes indicate the different tail risk measures. The definitions of the tail risk measure acronyms are given in Table 3.1.

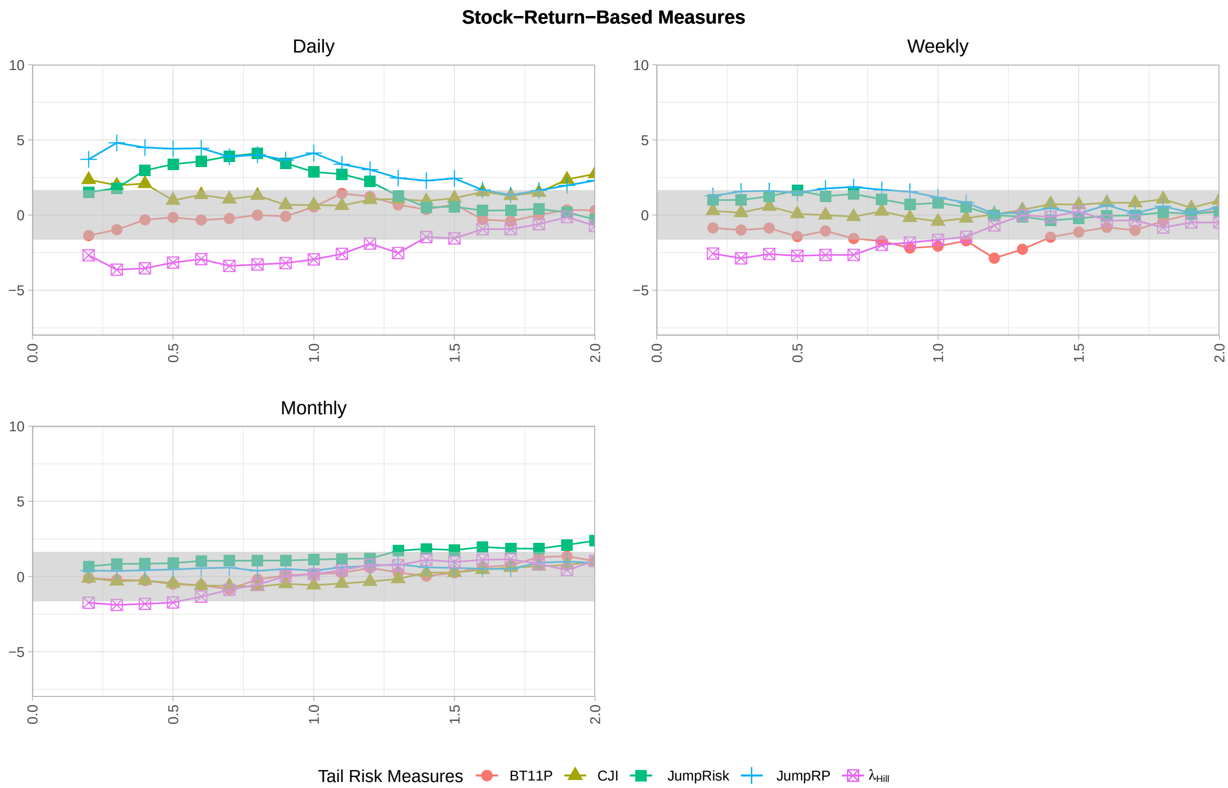


Figure B6: Crash Thresholds Robustness: Stock Return Based Measures

This figure presents the z-statistics from predictive probit regressions for different tail thresholds for return-based tail risk measures. We perform the regression over different time intervals, from daily (top left) to annually (bottom). We perform single regressions of a dummy variable on each lagged tail risk measure. The dummy variable is 1 if the realized market excess return falls below the threshold defined by minus x times the current conditional volatility, with x shown on the horizontal axis ($x \in [0.2; 2]$). The conditional volatility is defined as the VIX at the end of the previous day. The gray shaded area denotes statistical insignificance at the 5% level. Different colors and point shapes indicate the different tail risk measures. The definitions of the tail risk measure acronyms are given in Table 3.1.

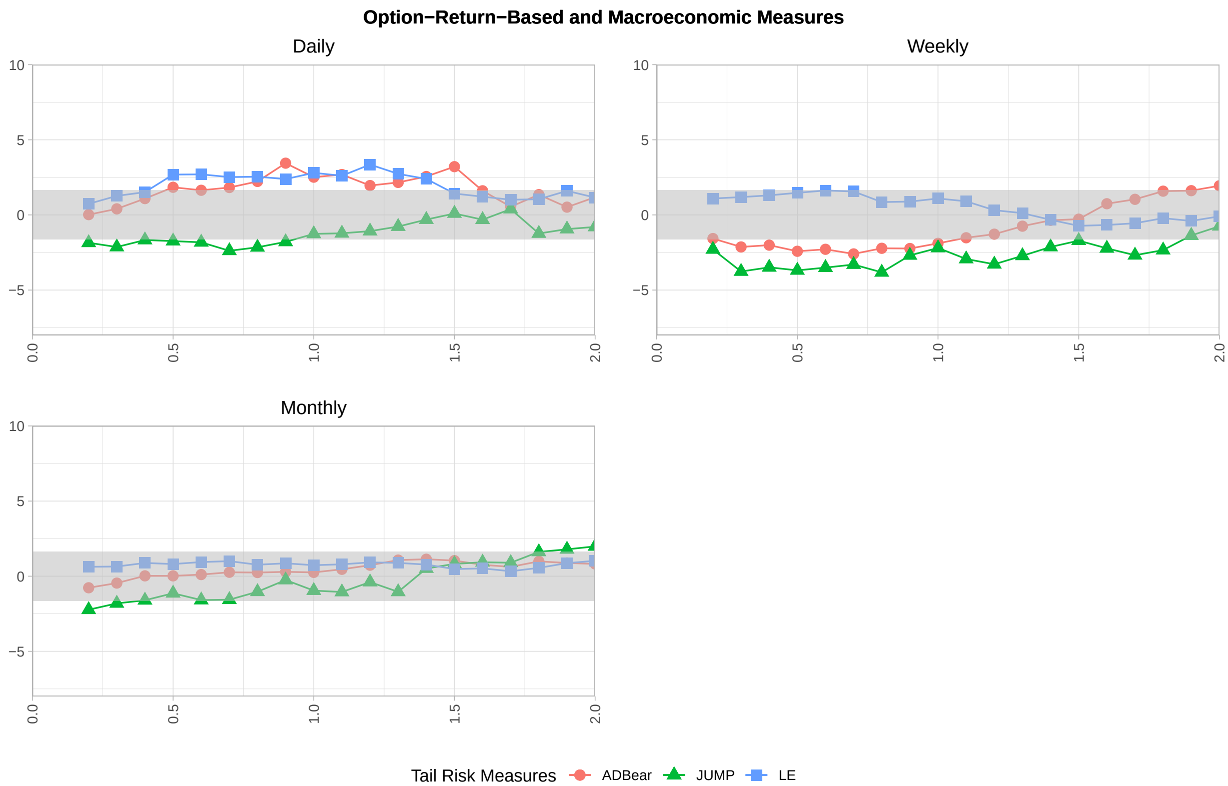


Figure B7: Crash Thresholds Robustness: Option Return Based Measures

This figure presents the z-statistics from predictive probit regressions for different tail thresholds for option-return-based and macroeconomic tail risk measures. We perform the regression over different time intervals, from daily (top left) to annually (bottom). We perform single regressions of a dummy variable on each lagged tail risk measure. The dummy variable is 1 if the realized market excess return falls below the threshold defined by minus x times the current conditional volatility, with x shown on the horizontal axis ($x \in [0.2; 2]$). The conditional volatility is defined as the VIX at the end of the previous day. The gray shaded area denotes statistical insignificance at the 5% level. Different colors and point shapes indicate the different tail risk measures. The definitions of the tail risk measure acronyms are in Table 3.1.

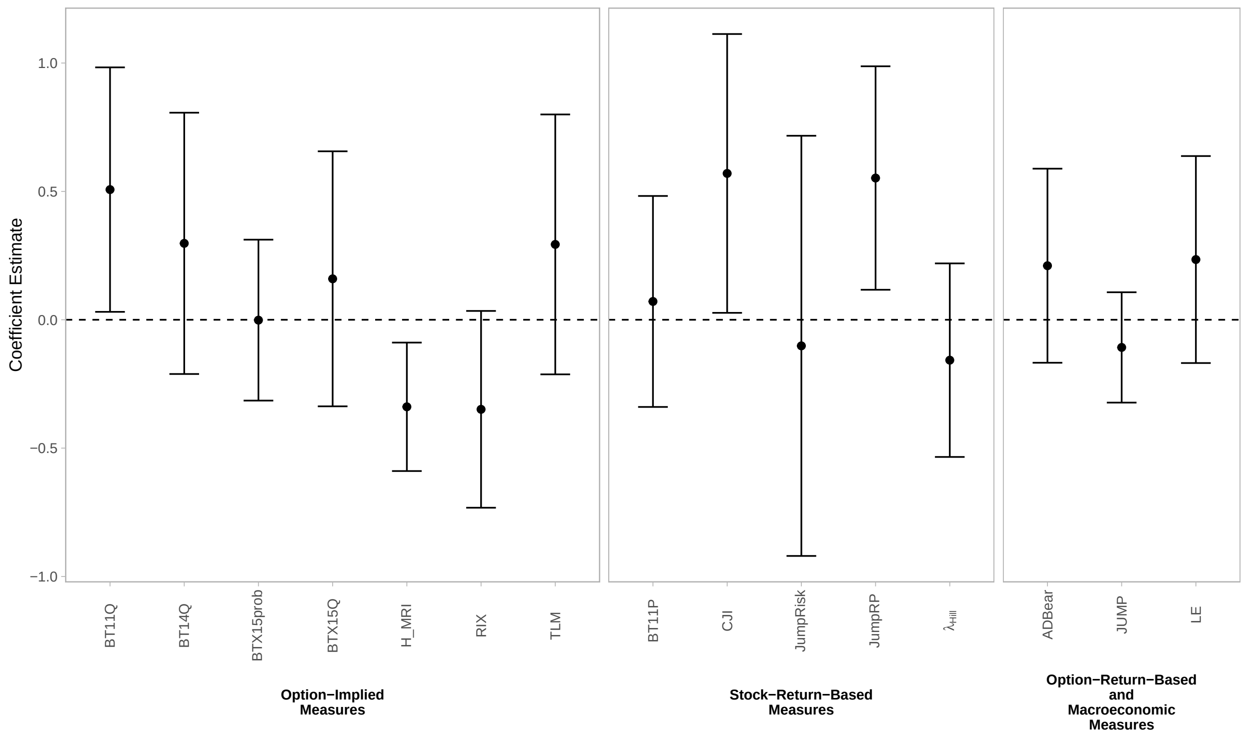


Figure B8: Crash Predictability: Daily

For the daily forecast horizon, this figure displays the coefficient estimate b from the regression: $TRM_t = a + b \cdot D_{t+\Delta t} + \epsilon_{t+\Delta t}$. TRM_t is the current observation of a tail risk measure. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the end of the previous day. We indicate the point estimate with a point. The 90% confidence interval around the point estimate is displayed by the vertical line. The confidence interval is based on Newey and West (1987) standard errors with 29 lags.

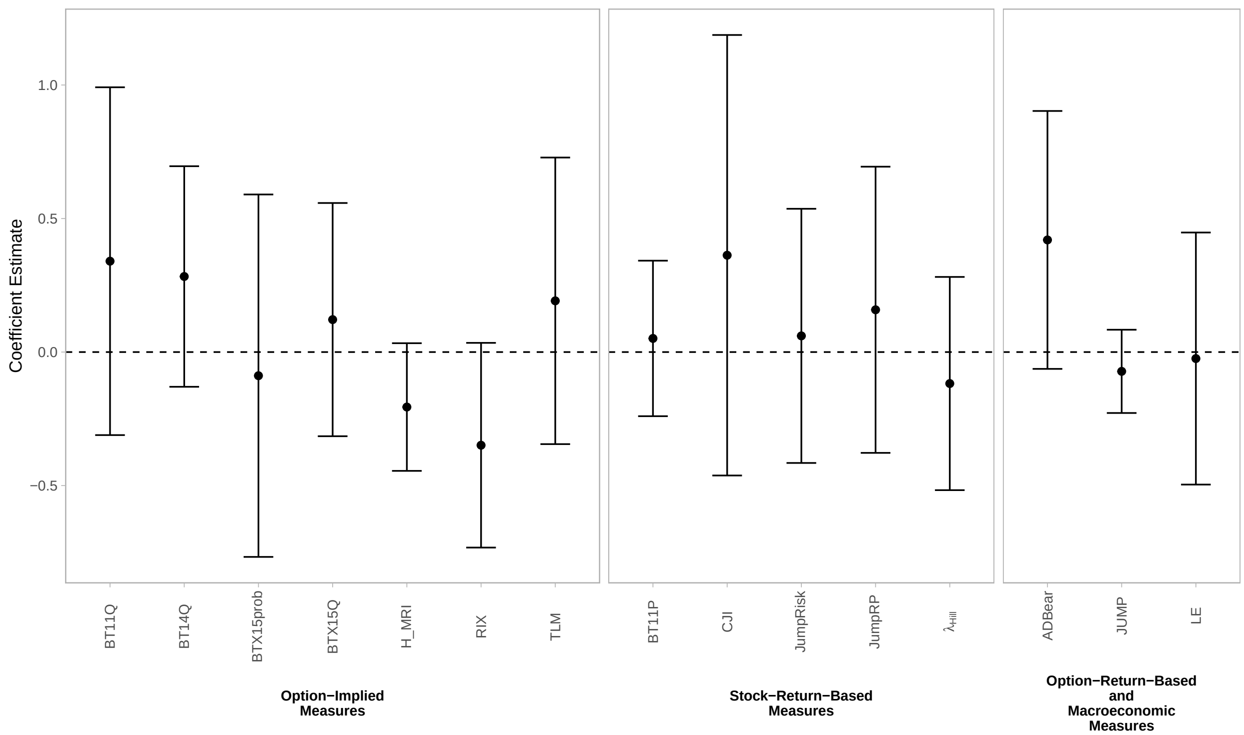


Figure B9: Crash Predictability: Weekly

For the weekly forecast horizon, this figure displays the coefficient estimate b from the regression: $TRM_t = a + b \cdot D_{t+\Delta t} + \epsilon_{t+\Delta t}$. TRM_t is the current observation of a tail risk measure. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the end of the previous day. We indicate the point estimate with a point. The 90% confidence interval around the point estimate is displayed by the vertical line. The confidence interval is based on Newey and West (1987) standard errors with 29 lags.

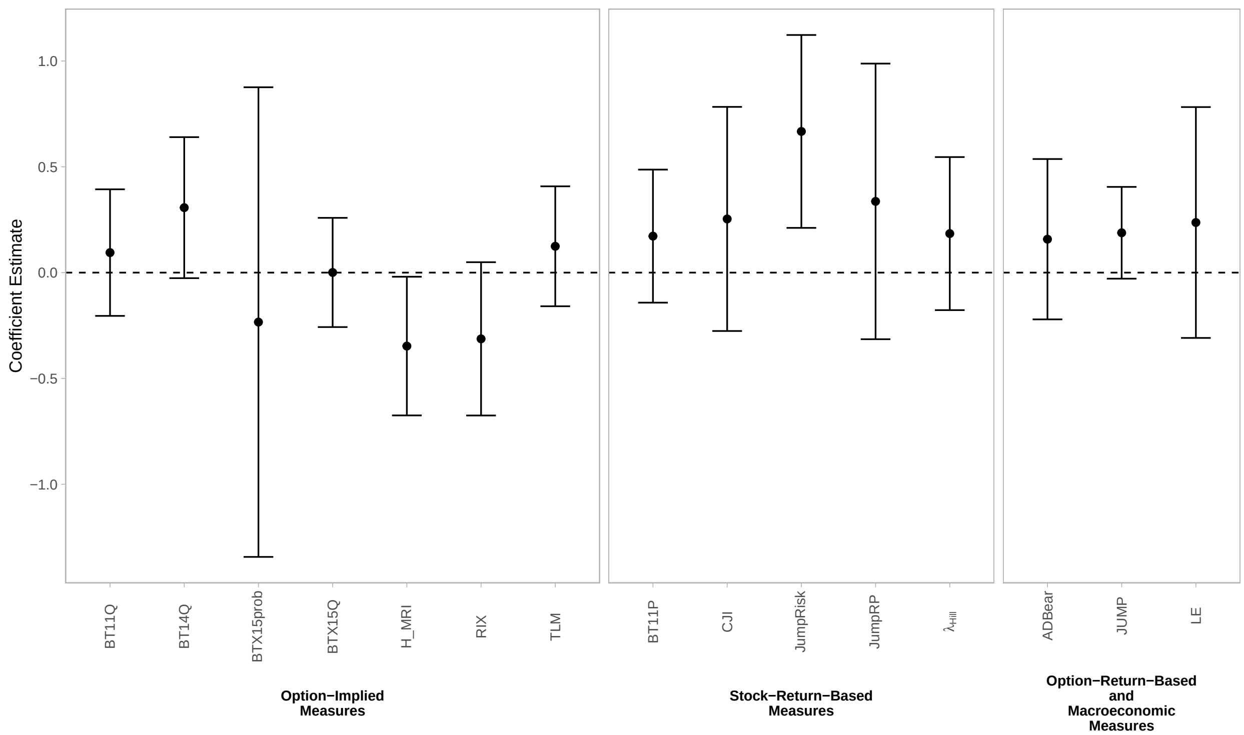


Figure B10: Crash Predictability: Monthly

For the monthly forecast horizon, this figure displays the coefficient estimate b from the regression: $TRM_t = a + b \cdot D_{t+\Delta t} + \epsilon_{t+\Delta t}$. TRM_t is the current observation of a tail risk measure. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the end of the previous day. We indicate the point estimate with a point. The 90% confidence interval around the point estimate is displayed by the vertical line. The confidence interval is based on Newey and West (1987) standard errors with 29 lags.

B1.5 Additional Tables

Table B1: Cross-Sectional Return Predictability (Equally-Weighted)

This table presents the average annualized percentage excess returns of quintile portfolios sorted on the stock loadings on the different tail risk measures. Each month, we estimate the tail risk loadings (b^i) for each stock based on a rolling historical window:

$$R^i_{t+\Delta t} = a^i + b^i \cdot TRM_t + \epsilon^i_t,$$

$R^i_{t+\Delta t}$ is the excess return of stock i over the period between t and Δt. TRM_t is the current observation of a tail risk measure. We forecast stock returns at the daily frequency and use a window length of one month for all measures available at the daily frequency, and accordingly longer windows for measures available on lower frequencies. Based on their current b^i we then sort the stocks into quintile portfolios and obtain the equally-weighted portfolio excess return over the next month. We repeat the entire procedure in the next month. The $High - Low$ portfolio simultaneously buys the stocks in the portfolio with the highest b^i and sells those in the portfolio with the lowest b^i. In parentheses, we report robust Newey and West (1987) standard errors using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Low	(2)	(3)	(4)	*High*	*High−Low*
Group A - Option-Implied Measures						
$BT11Q$	10.97**	10.43***	9.76***	8.59**	5.46	−5.51***
	(4.548)	(3.226)	(3.088)	(3.703)	(5.341)	(1.906)
$BT14Q$	10.97**	9.30**	9.04***	9.36***	5.45	−5.52**
	(5.177)	(3.817)	(3.406)	(3.465)	(4.991)	(2.387)
$BTX15prob$	11.57**	9.91***	9.43***	8.79**	5.02	−6.56
	(5.019)	(3.352)	(3.207)	(3.813)	(5.492)	(4.247)
$BTX15Q$	6.82	8.94***	9.33***	10.14***	9.97*	3.15
	(4.837)	(3.226)	(3.235)	(3.613)	(5.354)	(2.774)
H_MRI	13.77**	10.16**	10.64**	9.74**	10.18	−3.59
	(5.989)	(4.324)	(4.157)	(4.720)	(6.201)	(2.816)
RIX	12.05**	10.13***	8.79**	8.65**	9.36	−2.68
	(4.740)	(3.596)	(3.493)	(4.162)	(6.210)	(2.811)
TLM	10.64**	10.52***	9.03***	9.37**	5.66	−4.98**
	(4.587)	(3.244)	(3.295)	(3.801)	(5.222)	(2.407)
Group B - Stock-Return-Based Measures						
$BT11P$	9.50*	10.51***	8.71***	8.31**	6.79	−2.70
	(5.106)	(3.437)	(3.299)	(3.827)	(5.274)	(1.881)
CJI	7.82*	9.28***	9.63***	9.93***	8.56	0.74
	(4.422)	(3.318)	(3.196)	(3.617)	(5.333)	(1.908)
$JumpRisk$	11.18***	10.11***	9.60***	8.72**	5.59	−5.59**
	(4.267)	(3.101)	(3.364)	(3.793)	(5.605)	(2.759)
$JumpRP$	10.67**	9.63***	9.24***	8.97**	6.70	−3.97*
	(4.468)	(3.230)	(3.231)	(3.791)	(5.293)	(2.277)
λ_{Hill}	12.73**	10.08**	8.89**	8.69**	8.66	−4.07
	(5.984)	(4.021)	(3.597)	(3.665)	(5.305)	(3.460)
Group C - Option-Return-Based Measures						
$ADBear$	10.15**	10.67***	9.27***	8.89**	6.25	−3.90*
	(4.884)	(3.234)	(3.219)	(3.732)	(5.006)	(2.108)
$JUMP$	10.15**	10.03***	8.93***	8.82**	7.28	−2.87
	(4.664)	(3.225)	(3.102)	(3.644)	(5.308)	(2.117)
Group D - Macroeconomic Measures						
LE	7.74	9.21**	8.85***	9.86***	9.54**	1.80
	(5.247)	(3.553)	(3.192)	(3.213)	(4.595)	(1.378)

Table B2: Cross-Sectional Return Predictability (Value-Weighted FF-5 Alphas)

This table presents the annualized percentage Fama and French (2015) 5-factor alphas of quintile portfolios sorted on the stock loadings on the different tail risk measures. Each month, we estimate the tail risk loadings (b^i) for each stock based on a rolling historical window:

$$R^i_{t+\Delta t} = a^i + b^i \cdot TRM_t + \epsilon^i_t,$$

$R^i_{t+\Delta t}$ is the excess return of stock i over the period between t and Δt. TRM_t is the current observation of a tail risk measure. We forecast stock returns at the daily frequency and use a window length of one month for all measures available at the daily frequency, and accordingly longer windows for measures available on lower frequencies. Based on their current b^i we then sort the stocks into quintile portfolios and obtain the value-weighted portfolio excess return over the next month. We repeat the entire procedure in the next month. The $High - Low$ portfolio simultaneously buys the stocks in the portfolio with the highest b^i and sells those in the portfolio with the lowest b^i. In parentheses, we report robust Newey and West (1987) standard errors using 22 lags. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Low	(2)	(3)	(4)	*High*	*High−Low*
Group A - Option-Implied Measures						
$BT11Q$	6.59**	3.49**	1.85	−0.32	−3.32	−9.91***
	(2.931)	(1.639)	(1.285)	(1.365)	(2.470)	(2.049)
$BT14Q$	5.69*	2.02	1.21	1.76	−2.77	−8.46***
	(3.416)	(1.983)	(1.621)	(1.475)	(2.416)	(3.129)
$BTX15prob$	6.61*	2.94*	1.57	0.31	−3.26	−9.87**
	(3.757)	(1.685)	(1.510)	(1.714)	(2.995)	(4.875)
$BTX15Q$	0.86	1.65	1.21	1.81	2.76	1.90
	(2.456)	(1.701)	(1.493)	(1.513)	(3.162)	(3.056)
H_MRI	4.94	1.89	2.44**	1.77	0.52	−4.42
	(3.268)	(1.299)	(1.097)	(1.651)	(2.258)	(2.759)
RIX	3.40	2.20	1.77	1.70	3.80	0.40
	(2.468)	(1.638)	(1.644)	(1.847)	(3.242)	(1.912)
TLM	6.17**	3.43**	0.87	0.63	−2.81	−8.97***
	(3.011)	(1.700)	(1.404)	(1.370)	(2.501)	(2.428)
Group B - Stock-Return-Based Measures						
$BT11P$	4.34	3.61*	1.21	0.17	−0.83	−5.18***
	(2.903)	(1.887)	(1.475)	(1.521)	(2.317)	(1.991)
CJI	2.31	1.90	1.81	1.50	0.77	−1.53
	(2.659)	(1.524)	(1.485)	(1.435)	(2.731)	(2.390)
$JumpRisk$	6.06*	3.14*	1.66	0.01	−2.58	−8.64***
	(3.162)	(1.784)	(1.613)	(1.283)	(2.137)	(2.572)
$JumpRP$	5.89*	2.29	1.42	0.28	−1.59	−7.48***
	(3.149)	(1.682)	(1.429)	(1.324)	(2.172)	(2.300)
λ_{Hill}	6.84**	2.97*	1.80	0.88	0.55	−6.29**
	(3.462)	(1.769)	(1.712)	(1.527)	(2.943)	(2.957)
Group C - Option-Return-Based Measures						
$ADBear$	5.35*	3.67*	1.21	0.17	−2.09	−7.44***
	(2.972)	(1.909)	(1.401)	(1.291)	(2.235)	(2.078)
$JUMP$	3.81	2.00	0.80	0.97	0.71	−3.10
	(2.902)	(1.522)	(1.364)	(1.388)	(2.377)	(1.926)
Group D - Macroeconomic Measures						
LE	1.82	1.28	0.81	1.92	2.45	0.63
	(2.533)	(1.577)	(1.440)	(1.355)	(2.531)	(1.275)

Table B3: Return Predictability: Pre−2008

This table presents the coefficients from a return predictability regression for the period from 1996 to 2007. We perform single regressions of the market excess returns on each lagged tail risk measure:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is the current observation of a tail risk measure. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), (iii) one-month (*Monthly*), and (iv) one-year (*Annually*). In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
BT11Q	18.07**	0.24	18.56**	1.27	10.19**	2.68	−0.63	0.38
	(8.136)		(7.838)		(4.758)		(2.199)	
BT14Q	−3.07	0.01	−1.45	0.03	−1.73	0.19	−1.92*	0.69
	(7.754)		(6.436)		(3.356)		(1.208)	
BTX15prob	11.01	0.09	10.82*	0.44	9.66**	1.95	−0.59	0.43
	(8.350)		(7.470)		(5.408)		(3.645)	
BTX15Q	1.83	0.03	−5.69	0.07	−6.39*	0.43	−3.41**	1.89
	(7.282)		(6.888)		(3.740)		(1.605)	
H_MRI	−5.08	0.02	−1.94	0.02	0.01	0.06	5.63**	4.42
	(4.913)		(4.493)		(3.623)		(2.845)	
RIX	−0.89	0.02	−2.63	0.08	−8.12*	0.52	−6.36**	4.34
	(6.144)		(6.275)		(4.829)		(2.818)	
TLM	16.21*	0.16	13.60*	0.65	2.07	0.97	−5.30*	2.48
	(8.962)		(9.443)		(5.497)		(3.300)	
Group B - Stock-Return-Based Measures								
BT11P	15.60***	0.28	12.93***	1.03	4.46***	0.57	0.08	0.01
	(6.366)		(2.417)		(1.265)		(0.534)	
CJI	5.94	0.05	6.52*	0.31	2.82	0.52	−0.63	0.14
	(4.676)		(4.573)		(3.542)		(1.490)	
JumpRisk	−7.81	0.03	−8.78*	0.16	−12.32***	1.48	−15.63***	27.33
	(6.282)		(5.969)		(5.014)		(2.055)	
JumpRP	16.27**	0.18	13.67**	0.72	3.92	0.89	−4.41*	2.47
	(6.744)		(5.615)		(4.538)		(2.579)	
λ_{Hill}	3.61	0.01	6.54	0.17	7.57**	0.92	9.41***	21.83
	(5.214)		(5.115)		(4.287)		(1.809)	
Group C - Option-Return-Based Measures								
ADBear	18.45***	0.43	15.47***	1.59	4.71***	0.72	−0.04	0.01
	(5.148)		(3.943)		(1.850)		(0.452)	
JUMP	9.83**	0.12	4.89**	0.15	2.37***	0.17	0.41**	0.03
	(6.150)		(2.508)		(0.879)		(0.236)	
Group D - Macroeconomic Measures								
LE	−2.62	0.01	−2.43	0.06	−4.48	0.73	−8.55***	18.35
	(5.192)		(5.234)		(4.090)		(1.721)	
PCOneAll	24.07***	0.27	19.57**	1.01	7.84	1.73	−5.47	2.49
	(9.069)		(9.206)		(6.056)		(3.558)	
PCOneOption	12.92	0.12	9.23	0.40	1.08	0.92	−6.30*	2.89
	(10.030)		(10.138)		(6.024)		(3.506)	
PCOneStReturn	15.66***	0.20	12.11**	0.67	2.88	0.36	−6.06***	8.54
	(5.916)		(4.921)		(3.733)		(1.961)	
PCOneOpReturn	17.83***	0.40	12.85***	1.09	4.47***	0.64	0.23	0.01
	(5.993)		(3.718)		(1.565)		(0.320)	
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

Table B4: Multiple Return Predictability: Pre−2008

This table presents the coefficients from a return predictability regression for the period from 1996 to 2007. We perform multiple regressions of the market excess returns on lagged tail risk measures:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is a vector of the current observations of the tail risk measures. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), (iii) one-month (*Monthly*), and (iv) one-year (*Annually*). For each forecast horizon, we first perform variable selection based on the PcGets algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
$BT11Q$			17.74**	1.44	18.01***	2.44	6.01***	4.41
			(6.789)		(6.427)		(1.122)	
$BT14Q$					−1.53	0.13		
					(2.384)			
$BTX15prob$					13.42**	1.72		
					(6.468)			
$BTX15Q$					−5.18*	0.51	−2.49**	0.62
					(3.427)		(1.103)	
H_MRI					−4.44	0.32		
					(3.598)			
RIX					−0.22	0.17		
					(4.655)			
TLM	12.33**	0.15			−12.69*	0.79		
	(5.096)				(8.570)			
Group B - Stock-Return-Based Measures								
$BT11P$					1.42	0.17		
					(1.202)			
CJI					3.43	0.32		
					(4.034)			
$JumpRisk$					−9.03	0.94	−5.98**	9.05
					(9.147)		(2.629)	
$JumpRP$					3.86	0.48		
					(8.952)			
λ_{Hill}					5.00	0.62	6.30***	16.36
					(6.394)		(1.691)	
Group C - Option-Return-Based Measures								
$ADBear$			11.54***	1.26	1.28	0.20		
			(4.109)		(1.880)			
$JUMP$					−0.52	0.03		
					(0.923)			
Group D - Macroeconomic Measures								
LE					2.53	0.45	−3.19	9.80
					(4.585)		(1.792)	
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

Table B5: Return Predictability: Post−2008

This table presents the coefficients from a return predictability regression for the period from 2008 to 2017. We perform single regressions of the market excess returns on each lagged tail risk measure:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is the current observation of a tail risk measure. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), (iii) one-month (*Monthly*), and (iv) one-year (*Annually*). In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
BT11Q	64.68***	0.98	24.49**	0.64	8.83	0.39	4.96***	6.38
	(14.971)		(9.276)		(6.878)		(1.314)	
BT14Q	15.72*	0.09	6.35	0.07	−5.54*	1.10	3.07**	3.95
	(10.345)		(6.456)		(3.870)		(1.089)	
BTX15prob	26.53***	0.13	17.20**	0.34	15.33**	1.34	1.31	1.55
	(11.021)		(9.209)		(7.874)		(1.882)	
BTX15Q	2.57	0.00	2.17	0.03	−0.41	0.14	3.13**	7.88
	(11.498)		(9.171)		(4.422)		(1.491)	
H_MRI	−7.85	0.03	−2.57	0.05	0.63	0.10	4.65**	2.06
	(5.962)		(4.966)		(4.494)		(1.457)	
RIX	8.22	0.02	13.18*	0.30	13.46**	1.71	0.00	5.01
	(9.907)		(8.315)		(5.806)		(1.712)	
TLM	55.75***	0.56	29.54***	0.87	11.09*	0.57	4.08**	5.00
	(18.324)		(11.359)		(6.902)		(2.013)	
Group B - Stock-Return-Based Measures								
BT11P	37.03***	1.07	15.49***	1.00	3.57*	0.17	1.09**	0.56
	(8.989)		(5.357)		(2.181)		(0.366)	
CJI	−0.03	0.00	−6.90	0.27	−7.50	1.38	0.49	1.69
	(10.334)		(9.809)		(5.857)		(1.227)	
JumpRisk	11.23	0.03	5.77	0.13	−3.97	0.34	−4.25	3.73
	(13.992)		(15.032)		(13.690)		(3.347)	
JumpRP	26.29***	0.12	18.29**	0.37	9.84*	0.50	1.24	1.81
	(8.508)		(7.541)		(6.172)		(1.492)	
λ_{Hill}	−14.14**	0.03	−16.11***	0.24	−21.01***	2.51	−3.51**	1.38
	(6.849)		(6.142)		(5.378)		(1.403)	
Group C - Option-Return-Based Measures								
ADBear	20.27**	0.37	11.19**	0.67	2.12	0.09	0.64	0.10
	(8.588)		(4.838)		(2.349)		(0.479)	
JUMP	−3.56	0.01	6.58***	0.24	0.03	0.00	0.04	0.00
	(9.473)		(1.944)		(1.017)		(0.095)	
Group D - Macroeconomic Measures								
LE	7.19	0.01	4.64	0.07	13.95	0.72	2.52	2.93
	(15.163)		(15.484)		(10.704)		(2.627)	
PCOneAll	−62.98***	0.42	−32.17***	0.62	−13.49*	0.57	−4.72**	4.91
	(18.664)		(11.067)		(8.141)		(2.107)	
PCOneOption	48.25**	0.36	24.29**	0.49	8.80	0.35	4.23*	6.04
	(18.070)		(10.266)		(7.642)		(2.089)	
PCOneStReturn	−42.56***	0.26	−20.61*	0.35	−9.37	0.45	−2.30	2.37
	(11.598)		(12.301)		(8.930)		(1.782)	
PCOneOpReturn	10.78	0.10	11.48***	0.71	1.39	0.03	0.44	0.05
	(9.165)		(3.575)		(1.909)		(0.375)	
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

Table B6: Multiple Return Predictability: Post−2008

This table presents the coefficients from a return predictability regression for the period from 2008 to 2017. We perform multiple regressions of the market excess returns on lagged tail risk measures:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is a vector of the current observations of the tail risk measures. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week ($Weekly$), (iii) one-month ($Monthly$), and (iv) one-year (*Annually*). For each forecast horizon, we first perform variable selection based on the PcGets algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
$BT11Q$	53.43*	0.59					3.43**	3.79
	(26.057)						(1.322)	
$BT14Q$							0.83	2.00
							(0.705)	
$BTX15prob$								
$BTX15Q$	−83.25***	0.68	−36.89***	0.70				
	(22.970)		(12.843)					
H_MRI							4.39***	2.90
							(1.092)	
RIX								
TLM	79.31*	0.43	46.30***	0.95				
	(40.381)		(14.624)					
Group B - Stock-Return-Based Measures								
$BT11P$	22.67**	0.68					0.38	0.26
	(8.962)						(0.283)	
CJI								
$JumpRisk$								
$JumpRP$								
λ_{Hill}								
Group C - Option-Return-Based Measures								
$ADBear$								
$JUMP$			6.22***	0.23				
			(1.956)					
Group D - Macroeconomic Measures								
LE								
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

Table B7: Multiple Prediction of Tail Events: Jackknife Procedure

This table presents the coefficients from the predictive probit regressions. We perform multiple probit regressions of a dummy variable on lagged tail risk measures:

$$D_{t+\Delta t} = a + b \cdot TRM_t + \epsilon_{t+\Delta t}.$$

$D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. The conditional volatility is defined as the level of the VIX at the previous day. TRM_t is a vector of the current observations of the tail risk measures. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), and (iii) one-month (*Monthly*). For each forecast horizon, we first perform variable selection based on a jackknife procedure. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the partial McFadden R^2s, obtained by dominance analysis, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2
Group A - Option-Implied Measures						
$BT11Q$						
$BT14Q$	0.13^{**}	1.87			0.12	0.73
	(0.050)				(0.075)	
$BTX15prob$	-0.23	0.74	-0.13	0.39	-0.71^{**}	3.47
	(0.147)		(0.129)		(0.279)	
$BTX15Q$						
H_MRI	-0.10	0.70	-0.11	0.37		
	(0.134)		(0.070)			
RIX	-0.16	0.98	-0.08	0.62	-0.37^{**}	2.57
	(0.151)		(0.139)		(0.154)	
TLM						
Group B - Stock-Return-Based Measures						
$BT11P$			0.09^{**}	0.82		
			(0.044)			
CJI			0.08	0.49		
			(0.092)			
$JumpRisk$					0.51^{**}	5.88
					(0.205)	
$JumpRP$	0.15	1.42			0.44^{*}	2.54
	(0.151)				(0.254)	
λ_{Hill}					0.21^{***}	0.96
					(0.063)	
Group C - Option-Return-Based Measures						
$ADBear$	0.03	1.02	0.06	0.56		
	(0.084)		(0.067)			
$JUMP$	0.10^{**}	3.45	-0.13^{***}	1.26	0.00	0.22
	(0.042)		(0.041)		(0.033)	
Group D - Macroeconomic Measures						
LE	0.08	0.43	-0.04	0.09		
	(0.101)		(0.109)			

Table B8: Multiple Predictability of Left Tail Variation: Jackknife Procedure

This table presents the coefficients from a predictive regression for future left tail variation. We perform multiple regressions of the realized left tail variation on the lagged tail risk measures:

$$LTV^{\mathbb{P}}_{t+\Delta t} = a + b \cdot TRM_t + c \cdot LTV^{\mathbb{P}}_t + d \cdot VIX_t + \epsilon_{t+\Delta t}.$$

TRM_t is a vector of the current observations of the tail risk measures. We control for the lagged left tail variation $LTV^{\mathbb{P}}_t$ and the current level of the VIX (VIX_t). We use three different forecast horizons Δt: (i) one-day ($Daily$), (ii) one-week ($Weekly$), and (iii) one-month ($Monthly$). For each forecast horizon, we first perform variable selection based on a jackknife procedure. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	$Daily$	R^2	$Weekly$	R^2	$Monthly$	R^2
Group A - Option-Implied Measures						
$BT11Q$	0.13^{**}	1.78	0.20^{**}	5.16	0.15^{**}	6.89
	(0.051)		(0.073)		(0.064)	
$BT14Q$	0.06^{***}	1.28	0.16^{**}	4.17	0.10^{**}	4.07
	(0.028)		(0.086)		(0.054)	
$BTX15prob$	-0.11^{*}	0.48	-0.07	0.91	-0.10^{*}	1.34
	(0.069)		(0.058)		(0.069)	
$BTX15Q$			0.06	2.47		
			(0.067)			
H_MRI						
RIX	-0.08^{**}	0.30	-0.12^{**}	0.70	-0.12^{**}	0.81
	(0.038)		(0.059)		(0.054)	
TLM	0.14^{*}	1.36				
	(0.090)					
Group B - Stock-Return-Based Measures						
$BT11P$	-0.05	0.13	0.04^{**}	0.83	0.06^{**}	1.34
	(0.034)		(0.024)		(0.028)	
CJI	0.03	0.36	0.07	1.21	0.08^{*}	1.82
	(0.029)		(0.051)		(0.055)	
$JumpRisk$	0.05^{***}	0.36	0.09^{***}	1.30	0.11^{**}	2.65
	(0.021)		(0.040)		(0.053)	
$JumpRP$						
λ_{Hill}						
Group C - Option-Return-Based Measures						
$ADBear$						
$JUMP$	-0.01	0.01				
	(0.010)					
Group D - Macroeconomic Measures						
LE	0.03	0.41	0.07^{**}	1.58	0.16^{***}	4.41
	(0.024)		(0.038)		(0.057)	
$Controls$	Yes		Yes		Yes	

Table B9: Multiple Return Predictability: Jackknife Procedure

This table presents the coefficients from a return predictability regression. We perform multiple regressions of the market excess returns on lagged tail risk measures:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is a vector of the current observations of the tail risk measures. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), (iii) one-month (*Monthly*), and (iv) one-year (*Annually*). For each forecast horizon, we first perform variable selection based on a jackknife procedure. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
$BT11Q$	36.50***	0.25					4.83**	4.14
	(9.343)						(1.631)	
$BT14Q$	−9.15	0.04			−3.03	0.36		
	(7.750)				(2.532)			
$BTX15prob$					13.49***	1.89		
					(4.676)			
$BTX15Q$	−21.46***	0.10	−8.60*	0.14	−4.06*	0.20	0.40	2.98
	(7.587)		(5.801)		(2.475)		(2.096)	
H_MRI								
RIX			5.35	0.22	1.04	0.75		
			(5.495)		(3.808)			
TLM								
Group B - Stock-Return-Based Measures								
$BT11P$	10.81	0.14	5.82*	0.22				
	(9.500)		(3.292)					
CJI								
$JumpRisk$					−2.13	0.19	−6.13**	2.92
					(4.402)		(3.024)	
$JumpRP$								
λ_{Hill}							2.21*	7.70
							(1.519)	
Group C - Option-Return-Based Measures								
$ADBear$	6.68	0.09	6.63**	0.29				
	(6.313)		(3.101)					
$JUMP$	−13.78**	0.14	2.68	0.10	1.53***	0.05		
	(6.561)		(3.067)		(0.639)			
Group D - Macroeconomic Measures								
LE								
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

Table B10: Multiple Tail Return Predictability: Jackknife Procedure

This table presents the coefficients from a return predictability regression. We perform multiple regressions of the market excess returns on lagged tail risk measures, while separating crash and non-crash periods:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot TRM_t \cdot D_{t+\Delta t} + d \cdot D_{t+\Delta t} + e \cdot Controls_t + \epsilon_{t+\Delta t},$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is a vector of the current observations of the tail risk measures. $D_{t+\Delta t}$ is 1 if the realized market excess return falls below the threshold defined by minus two times the current conditional volatility. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use three different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), and (iii) one-month (*Monthly*). For each forecast horizon, we first perform variable selection based on the jackknife algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	c	$R^2(b)$	$R^2(c)$	Weekly	c	$R^2(b)$	$R^2(c)$	Monthly	c	$R^2(b)$	$R^2(c)$
Group A - Option-Implied Measures												
$BT11Q$	32.47***	73	0.20	0.30		−119***		1.61				
	(9.417)	(66.251)				(15.350)						
$BT14Q$	-9.43	−123***	0.05	0.14					-2.65		0.31	
	(7.893)	(47.453)							(2.473)			
$BTX15prob$									11.57***		1.65	
									(4.292)			
$BTX15Q$	−22.85***		0.11		-6.96		0.08		−4.68**		0.18	
	(7.753)				(4.812)				(2.535)			
H_MRI												
RIX	8.05		0.06									
	(7.275)											
TLM												
Group B - Stock-Return-Based Measures												
$BT11P$	12.15		0.15		5.17*		0.21					
	(9.684)				(3.278)							
CJI		191***		0.51								
		(38.943)										
$JumpRisk$										−61***		4.01
										(22.157)		
$JumpRP$		211***		0.55								
		(62.152)										
λ_{Hill}												
Group C - Option-Return-Based Measures												
$ADBear$	6.53		0.09		8.39***		0.37		3.41**		0.21	
	(6.551)				(2.866)				(1.506)			
$JUMP$	−14.13**		0.14		2.10	18	0.09	0.05	1.16*		0.04	
	(6.531)				(2.836)	(41.763)			(0.689)			
Group D - Macroeconomic Measures												
LE												
Controls	Yes				Yes				Yes			

Table B11: Prediction of Tail Events (Number of Jumps)

This table presents the coefficients from a predictive regression for the number of future negative jumps. We perform single regressions of the realized number of negative jumps (NLJ) on each lagged tail risk measure:

$$NLJ_{t+\Delta t} = a + b \cdot TRM_t + c \cdot NLJ_t + d \cdot VIX_t + \epsilon_{t+\Delta t}.$$

TRM_t is the current observation of a tail risk measure. We control for the lagged number of negative jumps NLJ_t and the current level of the VIX (VIX_t). We use three different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), and (iii) one-month (*Monthly*). In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2
Group A - Option-Implied Measures						
$BT11Q$	0.16***	1.39	0.78***	3.63	1.69***	5.41
	(0.040)		(0.173)		(0.700)	
$BT14Q$	0.07***	0.56	0.27***	1.51	0.08	2.69
	(0.025)		(0.106)		(0.294)	
$BTX15prob$	−0.01	1.48	−0.12	4.34	0.08	7.05
	(0.040)		(0.169)		(0.618)	
$BTX15Q$	0.05**	0.76	0.27**	1.88	0.14	3.28
	(0.029)		(0.115)		(0.405)	
H_MRI	0.00	0.48	0.00	1.35	0.02	2.27
	(0.023)		(0.091)		(0.349)	
RIX	−0.03	0.60	−0.12	1.66	−0.13	2.54
	(0.030)		(0.121)		(0.487)	
TLM	−0.04	2.04	−0.06	5.38	−1.20	8.50
	(0.078)		(0.320)		(1.253)	
Group A - Option-Implied Measures						
$BT11P$	−0.10***	1.16	−0.28***	1.92	−0.57***	1.58
	(0.018)		(0.053)		(0.126)	
CJI	0.04**	0.25	0.20**	0.60	0.38	0.93
	(0.025)		(0.096)		(0.378)	
$JumpRisk$	−0.11***	1.52	−0.38***	3.71	−0.96**	5.56
	(0.027)		(0.110)		(0.484)	
$JumpRP$	−0.23***	3.14	−0.72***	7.20	−1.81***	9.91
	(0.043)		(0.198)		(0.677)	
λ_{Hill}	0.03	0.46	0.10	1.20	0.39	2.39
	(0.031)		(0.128)		(0.482)	
Group A - Option-Implied Measures						
$ADBear$	−0.10***	1.09	−0.42***	2.37	−1.10***	1.72
	(0.017)		(0.062)		(0.186)	
$JUMP$	−0.04***	0.20	−0.15***	0.30	−0.16*	0.07
	(0.016)		(0.044)		(0.095)	
Group A - Option-Implied Measures						
LE	0.02	0.47	0.09	1.25	0.59*	1.95
	(0.024)		(0.095)		(0.382)	
$PCOneAll$	−0.19**	2.34	−0.50*	5.94	−1.61	9.12
	(0.091)		(0.355)		(1.296)	
$PCOneOption$	0.14**	1.70	0.61**	4.52	0.55	7.32
	(0.071)		(0.285)		(1.060)	
$PCOneStReturn$	−0.26***	3.50	−0.83***	7.88	−2.24***	10.97
	(0.040)		(0.154)		(0.519)	
$PCOneOpReturn$	−0.09***	0.90	−0.36***	1.82	−0.80***	1.01
	(0.017)		(0.054)		(0.166)	
Controls	*Yes*		*Yes*		*Yes*	

Table B12: Predictability of Left Tail Variation (Including Overnight Returns)

This table presents the coefficients from a predictive regression for future left tail variation, including the overnight variation. We perform single regressions of the standardized realized left tail variation on each lagged tail risk measure:

$$LTV^{\mathbb{P}}_{t+\Delta t} = a + b \cdot TRM_t + c \cdot LTV^{\mathbb{P}}_t + d \cdot VIX_t + \epsilon_{t+\Delta t}.$$

TRM_t is the current observation of a tail risk measure. We control for the lagged left tail variation $LTV^{\mathbb{P}}_t$ and the current level of the VIX (VIX_t). We use three different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), and (iii) one-month (*Monthly*). In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the wild bootstrap of Rapach et al. (2013). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2
Group A - Option-Implied Measures						
BT11Q	0.44***	9.62	0.41***	17.31	0.26*	15.18
	(0.120)		(0.098)		(0.152)	
BT14Q	0.13**	4.86	0.13**	9.67	0.04	7.34
	(0.071)		(0.060)		(0.036)	
BTX15prob	−0.19**	2.80	−0.20*	5.43	−0.24**	5.62
	(0.099)		(0.099)		(0.138)	
BTX15Q	0.12**	4.78	0.11**	9.36	0.03	7.74
	(0.053)		(0.054)		(0.056)	
H_MRI	0.07**	0.83	0.06***	1.64	0.01	1.79
	(0.033)		(0.025)		(0.022)	
RIX	−0.01	0.81	−0.02	1.69	−0.08	1.94
	(0.037)		(0.041)		(0.069)	
TLM	0.04	5.56	−0.05	11.15	−0.14	10.62
	(0.089)		(0.123)		(0.219)	
Group B - Stock-Return-Based Measures						
BT11P	0.02	1.01	0.06**	2.85	0.08**	2.89
	(0.042)		(0.029)		(0.043)	
CJI	0.05	1.79	0.03	3.29	0.04	3.31
	(0.053)		(0.054)		(0.075)	
JumpRisk	0.07***	1.97	0.08***	4.24	0.11***	5.78
	(0.017)		(0.025)		(0.034)	
JumpRP	−0.15**	3.36	−0.17**	6.71	−0.01	6.72
	(0.084)		(0.072)		(0.081)	
λ_{Hill}	0.03	0.45	0.02	0.97	0.02	1.08
	(0.024)		(0.021)		(0.027)	
Group C - Option-Return-Based Measures						
ADBear	0.01	0.47	−0.01	0.93	0.08***	1.45
	(0.017)		(0.019)		(0.040)	
JUMP	0.00	0.04	0.01*	0.15	0.02	0.10
	(0.017)		(0.009)		(0.017)	
Group D - Macroeconomic Measures						
LE	0.07**	2.76	0.10**	6.25	0.12**	7.58
	(0.034)		(0.040)		(0.057)	
PCOneAll	0.35***	6.67	0.36***	13.53	0.26**	12.91
	(0.112)		(0.106)		(0.145)	
PCOneOption	0.24***	6.49	0.19**	12.74	−0.10	11.32
	(0.111)		(0.100)		(0.205)	
PCOneStReturn	0.00	4.07	0.04	8.76	0.15*	9.64
	(0.051)		(0.048)		(0.106)	
PCOneOpReturn	0.01	0.32	0.00	0.73	0.06***	0.94
	(0.020)		(0.015)		(0.026)	
Controls	*Yes*		*Yes*		*Yes*	

Table B13: Predictability of Left Tail Variation: Block Bootstrap

This table presents the coefficients from a predictive regression for future left tail variation. We perform single regressions of the standardized realized left tail variation on each lagged tail risk measure:

$$LTV^{\mathbb{P}}_{t+\Delta t} = a + b \cdot TRM_t + c \cdot LTV^{\mathbb{P}}_t + d \cdot VIX_t + \epsilon_{t+\Delta t}.$$

TRM_t is the current observation of a tail risk measure. We control for the lagged left tail variation $LTV^{\mathbb{P}}_t$ and the current level of the VIX (VIX_t). We use three different forecast horizons Δt: (i) one-day ($Daily$), (ii) one-week ($Weekly$), and (iii) one-month ($Monthly$). In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the block bootstrap of Lahiri (1999). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2
Group A - Option-Implied Measures						
BT11Q	0.19**	2.88	0.30**	8.52	0.14	9.27
	(0.098)		(0.173)		(0.140)	
BT14Q	0.10*	2.18	0.18*	6.67	0.09	6.05
	(0.070)		(0.133)		(0.083)	
BTX15prob	−0.12**	0.96	−0.23*	2.99	−0.23*	3.40
	(0.057)		(0.152)		(0.183)	
BTX15Q	0.09*	1.95	0.13	5.42	0.02	4.77
	(0.053)		(0.111)		(0.093)	
H_MRI	0.03**	0.31	0.05*	0.97	−0.01	1.35
	(0.020)		(0.050)		(0.041)	
RIX	−0.03	0.19	−0.06	0.60	−0.06	0.86
	(0.028)		(0.062)		(0.081)	
TLM	0.05	1.99	0.14	6.39	−0.07	6.73
	(0.088)		(0.219)		(0.271)	
Group B - Stock-Return-Based Measures						
BT11P	−0.01	0.23	0.04*	1.30	0.06**	1.91
	(0.046)		(0.029)		(0.034)	
CJI	0.02	0.62	0.04	1.84	0.03	2.30
	(0.030)		(0.053)		(0.055)	
JumpRisk	0.03**	0.63	0.06**	1.95	0.09**	3.50
	(0.014)		(0.030)		(0.076)	
JumpRP	−0.09*	1.18	−0.15	3.64	−0.03	4.18
	(0.053)		(0.164)		(0.134)	
λ_{Hill}	0.01	0.21	0.01	0.68	0.00	1.03
	(0.018)		(0.037)		(0.050)	
Group C - Option-Return-Based Measures						
ADBear	0.01	0.22	0.02	0.64	0.06**	1.02
	(0.026)		(0.038)		(0.049)	
JUMP	0.04**	0.24	0.02*	0.10	0.03***	0.16
	(0.031)		(0.014)		(0.021)	
Group D - Macroeconomic Measures						
LE	0.03*	0.89	0.06**	2.81	0.14***	5.83
	(0.024)		(0.041)		(0.063)	
PCOneAll	0.20**	2.30	0.32**	7.12	0.29**	8.47
	(0.099)		(0.145)		(0.191)	
PCOneOption	0.14	2.27	0.19	6.78	−0.05	7.08
	(0.114)		(0.223)		(0.301)	
PCOneStReturn	−0.02	1.37	0.02	4.66	0.13	6.47
	(0.064)		(0.111)		(0.119)	
PCOneOpReturn	0.04*	0.35	0.02	0.51	0.06**	0.81
	(0.031)		(0.032)		(0.040)	
Controls	*Yes*		*Yes*		*Yes*	

Table B14: Multiple Predictability of Left Tail Variation: Block Bootstrap

This table presents the coefficients from a predictive regression for future left tail variation. We perform multiple regressions of the realized left tail variation on the lagged tail risk measures:

$$LTV^{\mathbb{P}}_{t+\Delta t} = a + b \cdot TRM_t + c \cdot LTV^{\mathbb{P}}_t + d \cdot VIX_t + \epsilon_{t+\Delta t}.$$

TRM_t is a vector of the current observations of the tail risk measures. We control for the lagged left tail variation $LTV^{\mathbb{P}}_t$ and the current level of the VIX (VIX_t). We use three different forecast horizons Δt: (i) one-day ($Daily$), (ii) one-week ($Weekly$), and (iii) one-month ($Monthly$). For each forecast horizon, we first perform variable selection based on the PcGets algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with 29 lags. Statistical inference is based on the block bootstrap of Lahiri (1999). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2
Group A - Option-Implied Measures						
$BT11Q$	0.19***	4.15			−0.02***	10.27
	(0.046)				(0.008)	
$BT14Q$						
$BTX15prob$						
$BTX15Q$						
H_MRI						
RIX						
TLM						
Group B - Stock-Return-Based Measures						
$BT11P$						
CJI						
$JumpRisk$	0.04***	0.65				
	(0.015)					
$JumpRP$						
λ_{Hill}						
Group C - Option-Return-Based Measures						
$ADBear$						
$JUMP$						
Group D - Macroeconomic Measures						
LE			0.04***	3.12	0.01***	4.76
			(0.010)		(0.004)	
Controls	*Yes*		*Yes*		*Yes*	

Table B15: Return Predictability: Block Bootstrap

This table presents the coefficients from a return predictability regression. We perform single regressions of the market excess returns on each lagged tail risk measure:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is the current observation of a tail risk measure. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), (iii) one-month (*Monthly*), and (iv) one-year (*Annually*). In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the block bootstrap of Lahiri (1999). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. "*PCOneAll*", "*PCOneOption*", "*PCOneStReturn*", and "*PCOneOpReturn*" denote the first PCs of all measures, option-implied, stock-return-based, and option-return-based tail risk measures, respectively. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
BT11Q	35.96***	0.52	15.21**	0.51	6.64*	0.48	2.85	2.17
	(7.350)		(5.613)		(4.504)		(1.915)	
BT14Q	5.15	0.02	0.70	0.02	−4.18	0.34	0.71	0.56
	(6.213)		(4.386)		(2.742)		(1.713)	
BTX15prob	11.67**	0.07	7.40	0.24	8.41*	1.18	−2.13	0.49
	(6.121)		(5.518)		(4.242)		(3.193)	
BTX15Q	1.50	0.01	−3.19	0.03	−3.37	0.14	1.14	1.61
	(5.816)		(5.227)		(3.141)		(2.337)	
H_MRI	−7.23**	0.02	−2.98	0.04	−0.65	0.09	3.10	1.01
	(4.028)		(3.313)		(2.917)		(2.620)	
RIX	2.48	0.02	3.16	0.13	3.35	0.61	0.25	1.32
	(5.927)		(5.402)		(4.528)		(3.315)	
TLM	26.51***	0.26	13.48**	0.50	4.11	0.50	−0.73	0.77
	(8.577)		(6.277)		(4.563)		(2.825)	
Group B - Stock-Return-Based Measures								
BT11P	25.95***	0.63	13.89***	0.96	3.91***	0.29	0.58	0.10
	(5.859)		(2.855)		(1.383)		(0.394)	
CJI	3.75	0.01	1.49	0.03	−0.03	0.05	1.22	0.70
	(4.335)		(4.330)		(2.941)		(1.285)	
JumpRisk	−5.67	0.01	−7.73*	0.05	−10.91**	0.55	−15.36***	12.30
	(5.754)		(5.798)		(5.197)		(2.654)	
JumpRP	15.94***	0.11	11.29***	0.38	4.72	0.52	−2.14	0.46
	(5.360)		(4.721)		(3.997)		(2.319)	
λ_{Hill}	−0.42	0.00	1.36	0.05	0.04	0.08	6.25***	9.38
	(4.057)		(4.015)		(3.469)		(1.610)	
Group C - Option-Return-Based Measures								
ADBear	19.16***	0.39	13.31***	1.07	3.30**	0.30	−0.10	0.01
	(4.820)		(3.073)		(1.565)		(0.381)	
JUMP	2.83	0.01	5.80***	0.20	1.14*	0.03	0.20	0.01
	(6.084)		(1.585)		(0.703)		(0.141)	
Group D - Macroeconomic Measures								
LE	2.20	0.01	0.45	0.03	3.14	0.09	−2.27	0.49
	(7.517)		(7.774)		(5.657)		(2.816)	
PCOneAll	34.45***	0.29	18.66***	0.54	8.19	0.68	1.18	1.38
	(8.736)		(6.265)		(4.955)		(2.975)	
PCOneOption	22.46**	0.18	9.16	0.26	2.74	0.33	0.52	1.21
	(8.518)		(6.161)		(4.788)		(3.112)	
PCOneStReturn	24.42***	0.25	14.23***	0.49	5.39*	0.41	−2.27	0.79
	(5.310)		(4.605)		(3.644)		(1.983)	
PCOneOpReturn	14.06***	0.21	12.22***	0.89	2.84**	0.22	0.06	0.00
	(5.477)		(2.523)		(1.294)		(0.271)	
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

Table B16: Multiple Return Predictability: Block Bootstrap

This table presents the coefficients from a return predictability regression. We perform multiple regressions of the market excess returns on lagged tail risk measures:

$$R_{t+\Delta t} = a + b \cdot TRM_t + c \cdot Controls_t + \epsilon_{t+\Delta t}.$$

$R_{t+\Delta t}$ is the excess return over the period Δt. TRM_t is a vector of the current observations of the tail risk measures. We use the following control variables (in $Controls_t$): variance risk premium, log dividend-price ratio, stochastically detrended risk free rate, consumption–wealth ratio, default spread, and term spread. We use four different forecast horizons Δt: (i) one-day (*Daily*), (ii) one-week (*Weekly*), (iii) one-month (*Monthly*), and (iv) one-year (*Annually*). For each forecast horizon, we first perform variable selection based on the PcGets selection algorithm. Space left blank implies that a measure has not been chosen. In parentheses, we present robust Newey and West (1987) standard errors with lag length chosen to be the maximum of 29 and the number of overlapping observations. Statistical inference is based on the block bootstrap of Lahiri (1999). The columns R^2 present the Lindeman et al. (1980) partial R^2 of each tail risk measure, multiplied by 100. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Daily	R^2	*Weekly*	R^2	*Monthly*	R^2	*Annually*	R^2
Group A - Option-Implied Measures								
$BT11Q$	47.61***	0.53			10.47*	0.57	6.35***	6.42
	(10.620)				(5.865)		(0.831)	
$BT14Q$					−6.45***	0.63		
					(2.499)			
$BTX15prob$					8.32*	1.31		
					(4.793)			
$BTX15Q$	−21.81***	0.12	−21.65***	0.44	−8.22***	0.36		
	(8.673)		(6.785)		(3.136)			
H_MRI								
RIX								
TLM			22.23***	0.53				
			(7.645)					
Group B - Stock-Return-Based Measures								
$BT11P$	17.39***	0.46	7.35***	0.51				
	(5.906)		(2.697)					
CJI								
$JumpRisk$							−13.26***	7.93
							(3.057)	
$JumpRP$								
λ_{Hill}								
Group C - Option-Return-Based Measures								
$ADBear$			8.78***	0.70				
			(3.063)					
$JUMP$								
Group D - Macroeconomic Measures								
LE								
Controls	*Yes*		*Yes*		*Yes*		*Yes*	

Chapter 4

Commodity Tail Risk*

4.1 Introduction

Commodity markets exhibit regularly reoccurring “supercycles” and “busts”.[1] These cycles are generally accompanied by sharp increases or declines in prices due to various events, such as supply disruptions, demand shocks, political instabilities, or natural catastrophes. For market participants these risk are very crucial, because they represent high marginal utility events. Moreover, commodities are important for the real economy as production and consumption goods. Hence studying these events and understanding their dynamics constitutes an important analysis.

Whereas concerns regarding left tail risk dominate in equity markets, left and right tail risks play an equally important role in commodity markets. For commodity producers,

*This chapter is based on the Working Paper ”Commodity Tail Risk” authored by Manuel Ammann, Mathis Moerke, Marcel Prokopczuk, and Christoph Matthias Würsig, 2021.

[1]The Economist – Commodity prices are surging Jan 12 2021

negative price jumps (left tail risk) might have devastating consequences, akin to the role of left tail risks for market participants in stock markets. For commodity consumers though, e.g., companies that process commodities, right tail risks matter more. This is especially true when they need to fulfill long term contracts with a lack of future market supply of raw materials. Tail risks in commodity markets are also important for countries whose exports mainly rely on commodities. Moreover, commodity markets, and especially tail events, have a large influence on inflation and consumer spending (Garratt and Petrella, 2019). Thus an understanding of tail risks in commodity markets is crucial to understanding movements in the cross-section of commodity market returns and overall extreme risks in the market.

The contribution of our paper is twofold: First, we seek to identify the determinants of tail risk in commodity markets. We consider left and right tail risk for a wide cross-section of 19 commodities. In doing do, we control for past tail risk in order to account for the autocorrelation in time series. We posit multiple possible factors that may influence the tail risk in commodity markets and order them into the following groups: commodity specific factors, commodity market factors, and equity market factors.

Second, we analyse whether tail risk is priced in the cross-section of the commodity market. We find that it is. Tail risk carries a statistically significant risk premium for both, the right and left tail of the return distribution. The effect is stronger for right tail risk, than for left tail risk, with a return of the long-short portfolio of 10.60% p.a. for the right tail risk and 8.50% p.a. for the left tail risk, which indicates that there are different risk premia for commodity producers and consumers to hedge tail risks.

The commodity specific factors we identify are: basis, speculation, and the variance risk premium. The basis is the slope of the futures term structure and is, as such, related to the supply and inventory of commodity markets. The inventory of commodities might influence the tail risk of commodity markets because speculators and insurance providers face limited risk capacity and financing constraints (Bianchi, 2018). Tail risk might also be related to speculation. Excessive speculation might lead to tail risk if investors face liquidity or short selling constraints. Option-implied tail risk is part of the variance under the risk-neutral measure. Therefore we also investigate links to the variance risk premium (Prokopczuk et al., 2017).

We also identify commodity market factors: the average return of the commodity market, the return on a commodity momentum strategy, and the return on a commodity carry strategy. These factors are motivated by Bakshi et al. (2017), who find that the average return of the commodity market, the momentum return, and the carry return can explain up to 71% of the variation in commodity futures returns.

Some authors argue that commodity markets are increasingly integrated with equity markets due to the financialization of commodities and the following influx of retail investors (Henderson, Pearson, and Wang, 2014). Hence, we include equity market factors that might capture links between the equity market volatility, equity market tail risk, and tail risks in commodity markets. In particular, we consider the VIX, the left or right tail risk of the S&P 500, and the market return of the S&P 500 index.

We find that commodity specific factors have the largest influence on left, right, total, and asymmetry tail risk. Different commodity specific factors seem to influence the left and the right tail. First, we find that the variance risk premium is closely linked to both left and right tail risk, as the corresponding coefficient is significant for most commodities in our sample. Furthermore, we find that speculation is negatively linked to left tail risk and to right tail risk, for the agricultural market. Left tail risk of the S&P 500 seems to be positively linked for most commodities in the case of the left tail and for some cases of the right tail. This effect is more significant and at least twice as larger for right tail risk. For the right tail the VIX seems to matter more than the right tail risk of the equity market. Commodity market factors only matter for the right tail and indicate a link to the average return of the overall commodity market. We find that both right and left tail risk seem to be influenced by equity market factors, and this mainly for the agricultural sector. This link is positive and statistically significant, which indicates that a higher tail risk in the equity market indicates a higher tail risk for agricultural commodities. The VIX is only linked to right tail risk for the agricultural market.

We also include total tail risk and asymmetry in our study, computed as the sum of right and left tail risk and the difference between left and right tail risk, both divided by implied volatility. For asymmetry, most of the links from the variance risk premium persist while these links do not persist for total tail risk. We find that speculation in the agricultural and energy market is negatively linked to total tail risk, which indicates that tail risk is large in periods where there is little speculation. For asymmetry this link is positive and present for agricultural and metal markets. This implies that the impact of speculation is mostly influential for the left tail risk, which indicates that speculative activity dampens left tail risk more, than right tail risk. Overall, speculation in general seems to reduce tail risk, rather than increase it by providing liquidity. The S&P 500 return is mostly linked to total tail risk. Which, indicates that the S&P 500 is equally influenced by left and right tail risk.

Our paper is related to various strands of the literature. First, it contributes to the growing literature on option-implied tail risks in financial markets. Bollerslev et al. (2015) analyse the importance of tail risks for predicting the aggregate stock market return. Kelly and Jiang (2014) find that U.S. single stocks with high loadings on an aggregated market tail risk factor outperform stocks with low tail risk loadings. Gao et al. (2019) consider the cross-sectional pricing of tail risk in a global setting. They find that a global option-based tail risk index drives the cross-sectional return variation across different asset classes. Moreover, the authors do not include commodities in their analysis. Fan, Londono, and Xiao (2021) document that an ex-ante U.S. equity tail risk factor is priced in the cross-section of currency returns. Ex-ante tail risks in commodity markets have been mainly studied for single commodities in isolation. Using the approach of Bollerslev et al. (2015), Ellwanger

(2015) and Ebrahimi and Pirrong (2020) investigate the predictive power of tail risks in the WTI crude oil market. A notable exception is Gao (2017), who includes ex-ante tail risk as a control in her analysis of the pricing of implied volatility in the cross-section of commodities. Gao (2017) also finds that left tail risk is priced, but the analysis does not extend beyond this fact. By studying ex-ante tail risks, we also complement the literature on price jumps in commodity prices (e.g., Nguyen and Prokopczuk, 2018; van Oordt, Stork, and de Vries, 2021).

Second, our paper contributes to the literature on identifying priced factors in the cross-section of commodity returns (e.g., Bakshi et al., 2017), especially to the pricing of higher implied moments in commodity markets. Chabi-Yo, Doshi, and Zurita (2020) introduce the concept of entropy risk in commodity markets. The authors find that the difference of entropy under the physical and risk-neutral measures has predictive power for the cross-section of commodity returns.

Finally, our paper also relates to the literature analysing drivers of commodity returns and volatility, such as Büyükşahin and Robe (2014) and Kim (2015), who investigate the links between speculation and volatility. Additionally, Symeonidis, Prokopczuk, Brooks, and Lazar (2012) and Szymanowska et al. (2014) link returns and volatilites to the commodity futures basis. Finally, there are a number of papers that investigate possible links between the equity market, various macroeconomic variables, and commodity markets (e.g. Christoffersen et al., 2019; Hollstein, Prokopczuk, and Würsig, 2020).

The remainder of the paper is organized as follows: in Section 4.2 we present the data and methodology. In Section 4.3, we discuss the empirical results. We conclude in Section 4.4.

4.2 Data and Methodology

4.2.1 Data

We obtain data on commodity futures and options from the Commodity Research Bureau (CRB). Our data cover 19 commodities: soybean oil, corn, oats, soybeans, soybean meal, wheat, cocoa, cotton, orange juice, coffee, sugar, milk, feeder cattle, livestock, gold, copper, silver, crude oil, and natural gas; These are grouped in 5 sectors: agricultural, softs, livestock, metal, and the energy sector. The selected commodities are in line with the literature on commodities and dictated by the availability and liquidity of options data. In order to construct the tail risk measures, we use options on futures prices. Since the options on commodity futures prices are American type options, we approximate the early exercise premium and calculate the implied volatility following Barone-Adesi and Whaley (1987). We use this implied volatility to convert all in-the-money options into out-of-the money options using the model of Black (1976). CRB records strike prices by means of four digits. In case there is space left, CRB fills them with zeros on the right hand side, i.e., a strike price of 10 is recorded as 1000. In order to infer the correct strike price, we follow the procedure described by Hollstein et al. (2021).[2] Next, we apply several data filters to our option sample. First, we keep only options with a time to maturity of at maximum 365 days. Second, we remove options with prices lower than four times the minimum tick size. Third, we discard options violating simple no-arbitrage restrictions. Our data covers the period from January 1996 to April 2020. Table 4.1 lists the selected commodities with their respective sector, maturity months, and the number of available options.

Throughout the analyses, 3-month T-Bills are taken as the risk-free asset. Furthermore, we source options data on the S&P 500 index from OptionMetrics, data on the futures and

[2]Details are presented in the Appendix in Section C1.1.

options positions of various market participants (Commitments of Traders report) from the Commodity Futures Trading Commission (CFTC), and the VIX index from the CBOE.

4.2.2 Tail Risk

To measure tail risk, we use the approach proposed by Bollerslev and Todorov (2011b). Bollerslev and Todorov (2011b) construct a measure of tail risk perceived by investors that is based on close-to-maturity deep out-of-the-money options. Dierkes, Hollstein, Prokopczuk, and Würsig (2021) show that this measure outperforms other tail measures proposed in the literature. This approach uses insights of the quadratic variation to decompose the volatility into two separate parts in a model-free way. To isolate tail risks, only deep out-of-the-money options are used, since only a large event will affect the prices of these options significantly. Specifically, let F_t denote the commodities futures price. We assume a quite general form for the dynamics of F_t, given as

$$\frac{dF_t}{F_t} = \alpha_t dt + \sigma_t dW_t + \int_{\mathbb{R}} (e^x - 1)\, \tilde{\mu}(dt, dx), \tag{4.1}$$

where α_t and σ_t are locally bounded drift and instantaneous volatility processes and W_t is a standard Brownian motion. The last term in Equation 4.1 accounts for jumps by means of the compensated jump measure $\tilde{\mu}(dt, dx) = \mu(dt, dx) - \nu_t^{\mathbb{P}} dt$ with $\mu(dt, dx)$ being a counting measure for the jumps and $\nu_t^{\mathbb{P}} dt$ denoting the compensator of the jumps under the physical measure $\mathbb{P}$. We require that $\nu_t^{\mathbb{P}} dt$ is predictable and $\int_{\mathbb{R}} (x^2 \wedge 1)\, \nu_t^{\mathbb{P}} dt$ is locally integrable. To move from $\mathbb{P}$ to $\mathbb{Q}$, we denote by $\nu_t^{\mathbb{Q}}(dx)dt$ the compensator for the jumps under $\mathbb{Q}$ and let λ_t denote the change of drift that turns W_t in a Brownian motion under $\mathbb{Q}$, i.e., $W_t^{\mathbb{Q}} = W_t + \int_0^t \lambda_s ds$. Subsequently, the total, expected quadratic variation of F_t under $\mathbb{Q}$ is

$$QV_t^{\mathbb{Q}} = \frac{1}{T-t} \mathbb{E}_t^{\mathbb{Q}} \left(\int_t^T \sigma_s^2 ds \right) + \frac{1}{T-t} \mathbb{E}_t^{\mathbb{Q}} \left(\int_t^T \int_{\mathbb{R}} x^2 \mu(ds, dx) \right). \tag{4.2}$$

As Equation 4.2 shows, the expected quadratic variation can be decomposed into diffusive and discontinuous price moves, the latter being of interest for tail risks. As Bollerslev and Todorov (2011b) show, if $T \downarrow t$ and $K > F_{t-} = \lim_{s \uparrow t} F_s$, then the price of a call with strike price K can be approximated by

$$e^{r^f_{(t,T]}} C_t(K) \approx \int_t^T \mathbb{E}_t^{\mathbb{Q}} \Big(\int_{\mathbb{R}} 1_{F_{s-}<K} max(0, F_{s-}e^x - K) v_S^{\mathbb{Q}}(dx) \Big) ds, \tag{4.3}$$

while for a put with strike price $K < F_{t-}$ it holds that

$$e^{r^f_{(t,T]}} P_t(K) \approx \int_t^T \mathbb{E}_t^{\mathbb{Q}} \Big(\int_{\mathbb{R}} 1_{F_{s-}>K} max(0, K - F_{s-}e^x) v_S^{\mathbb{Q}}(dx) \Big) ds. \tag{4.4}$$

Based on Equations 4.3 and 4.4, Bollerslev and Todorov (2011b) define the model-free risk-neutral left and right jump tail measures as

$$LT_t^{\mathbb{Q}}(k) \equiv \frac{1}{T-t} \int_t^T \int_{\mathbb{R}} max(0, e^k - e^x) \mathbb{E}_t^{\mathbb{Q}}(v_S^{\mathbb{Q}}(dx)) ds \approx \frac{e^{r^f_{(t,T]}} P_t(K)}{(T-t)F_{t-}},$$

and

$$RT_t^{\mathbb{Q}}(k) \equiv \frac{1}{T-t} \int_t^T \int_{\mathbb{R}} max(0, e^x - e^k) \mathbb{E}_t^{\mathbb{Q}}(v_S^{\mathbb{Q}}(dx)) ds \approx \frac{e^{r^f_{(t,T]}} C_t(K)}{(T-t)F_{t-}},$$

where $k = log(K/F_{t-,\tau})$ denotes the log-moneyness.

For the estimation, Bollerslev and Todorov (2011b) use options with at least 8 days to expiration and interpolate the option price to the desired moneyness levels. Bollerslev and Todorov (2011b) set k equal to 0.9 for the left tail and 1.1 for the right tail. Most commodity options have no regular monthly expiration cycle, thus we set the limits further, to ensure we consider mostly jump days. We set the limits for k equal to 0.8 for the left tail and 1.2 for the right tail. This threshold is exceeded only 3% of the time within 30 days. Therefore this seems to be a reasonable value.[3] To obtain tail risks with a time to maturity of 30

[3]But we will estimate these certainly with more noise, compared to the equity indices.

days, we linearly interpolate or extrapolate the tail risk measures from the adjacent time to maturities. We calculate total tail risk as the sum of both tail risk measure. The asymmetry of the tails is captured as the difference between left and right tail risk, standardized by the implied volatility.

4.2.3 Futures Returns

We use futures returns of the first nearby contract throughout our analyses. To construct them, we roll futures contracts at the end of the month that is one month prior to maturity. We hold futures contracts with fixed maturity date, that is, we do not calculate returns of hypothetical futures contracts with constant time to maturity. By regularly rolling the first nearby contract, our returns entail only futures spot premia, not term premia (Szymanowska et al., 2014).

Let $F_{t,T}$ denote the price of the first-nearby futures contract at time t and expiration at T. The simple return on a fully collateralized futures position is then

$$r_{t+1} = \frac{F_{t+1,T} - F_{t,T}}{F_{t,T}} + r_t^f, \tag{4.5}$$

where r_t^f denotes the risk-free rate. Consequently, the corresponding excess return on a fully collateralized futures position is given as

$$xr_{t+1} = r_{t+1} - r_t^f. \tag{4.6}$$

As apparent from Equation 4.5, returns are always computed by comparing prices from the same contract at different time periods. This is especially important when rolling futures contracts from one expiration month into the following expiration month. Hence, our returns are always constructed in a way that they are investable.

4.2.4 Explanatory Variables

Commodity Specific Factors

Commodity Basis For this measure we follow Gorton et al. (2012). The basis is associated with inventory, where low inventory months are associated with above average basis and vice versa. Gorton et al. (2012) calculate the basis with the following formula

$$\left(\frac{F_{1,t}}{F_{2,t-1}} - 1\right) \times \frac{365}{(D_{2,t} - D_{1,t})}, \tag{4.7}$$

where $F_{1,t}$ is the nearest futures contract with at least 30 days time to maturity. $F_{2,t}$ is the next nearest futures contract. $D_{2,t}$ and $D_{1,t}$ represent the number of trading days until the expiration of the underlying futures contract.

Speculation We employ Working's T following Working (1960)

$$WorkingT = \begin{cases} 1 + \frac{SS_t}{HL_t + HS_t} & , SS_t > HL_t \\ 1 + \frac{SL_t}{HL_t + HS_t} & , otherwise, \end{cases} \tag{4.8}$$

where HS_t is the open interest of commercials that are short, HL_t is the open interest of commercials which are long, SS_t is the open interest of noncommercials which are short, and SL_t is the open interest of noncommercials which are long. We use this measure for the total tail risk and asymmetry. Because we assume that speculation matters only in one direction for the left tail risk, we use $\frac{SS_t}{TP_t}$, where TP_t are the total open interest (long and short) at time t. For the right tail risk, we use: $\frac{SL_t}{TP_t}$ (Bakshi et al., 2017). This measure is only available at the monthly frequency, so we extrapolate the last month's observation over the subsequent month to facilitate our daily analysis.

Variance Risk Premium We follow Carr and Wu (2009) and Prokopczuk et al. (2017)

to create synthetic 30-day overlapping variance swap rates. Then we subtract the variance swap rates over 30 days from the realized variance to obtain an estimate for the variance risk premium

$$VRP_{t,T} = RV_{t,T} - E_t^{\mathbb{Q}}(V_{t,T}),$$

$$E_t^{\mathbb{Q}}(V_{t,T}) = MFIV_{t,T} = \frac{2e^{r_t(T-t)}}{T-t}\left[\int_0^{F_{t,T}} \frac{P(t,K,T)}{K^2}dK + \int_{F_{t,T}}^{\infty} \frac{C(t,K,T)}{K^2}dK\right], \qquad (4.9)$$

where $RV_{t,T}$ is the realized variance, computed as the sum of daily squared returns over the next month. $MFIV_{t,T}$ refers to the model-free implied variance between t and T. The annualized risk-free rate is denoted r_t. $F_{t,T}$ denotes the futures contract observed at time t and expires at time T. We truncate the first and second integrals at $F_{t,T} * e^{-10\sigma T}$ and $F_{t,T} \times e^{10\sigma T}$. σ is the average implied volatility of all out-of-the-money options. For each maturity we linearly interpolate the available Black (1976) implied volatilities across moneyness. We create a grid of 1,000 equidistant implied volatilities between the truncation threshold. We convert the implied volatilities with the Black (1976) option formula and calculate Equation (4.9). We linearly interpolate between the two swap rates, to obtain the 30-day swap rates.

Commodity Market Factors

Average For this factor, we calculate the return of the equally weighted commodity portfolio for every day.

Carry For this factor, we calculate the slope of the two nearest maturity futures for each commodity. The carry factor is $log(\frac{nearest}{secondnearest})$, where *nearest* is the next time to maturity, which cannot have the first notice day in the next month and *secondnearest* is the contract after this one. To ensure for commodities in contango (backwardation) a downward (upward) sloping curve, we require that the log differences is above (below) zero. Each day, we construct four portfolios, two contango and two backwardation portfolios. The daily return of the carry portfolio is the portfolio in which we go long in the equally weighted portfolio that is most in backwardation and short in the equally weighted contango portfolio.

Momentum To construct this factor, we invest in an equally weighted portfolio going long the five past winners over the last 12 months and shorting the portfolio with the past five losers over the same period. We re-balance the portfolio daily.

Equity Market Factors

VIX Is the volatility index of the S&P 500.

Tail Variation of the S&P 500 For the tail risk of the S&P 500, we follow the same methodology as outlined in Section 4.2.2.

Figure 4.1: This figure displays the time series of left and right tail risk of all commodities, ordered by sector. We smooth the daily left and right tail risk with the moving average over one week.

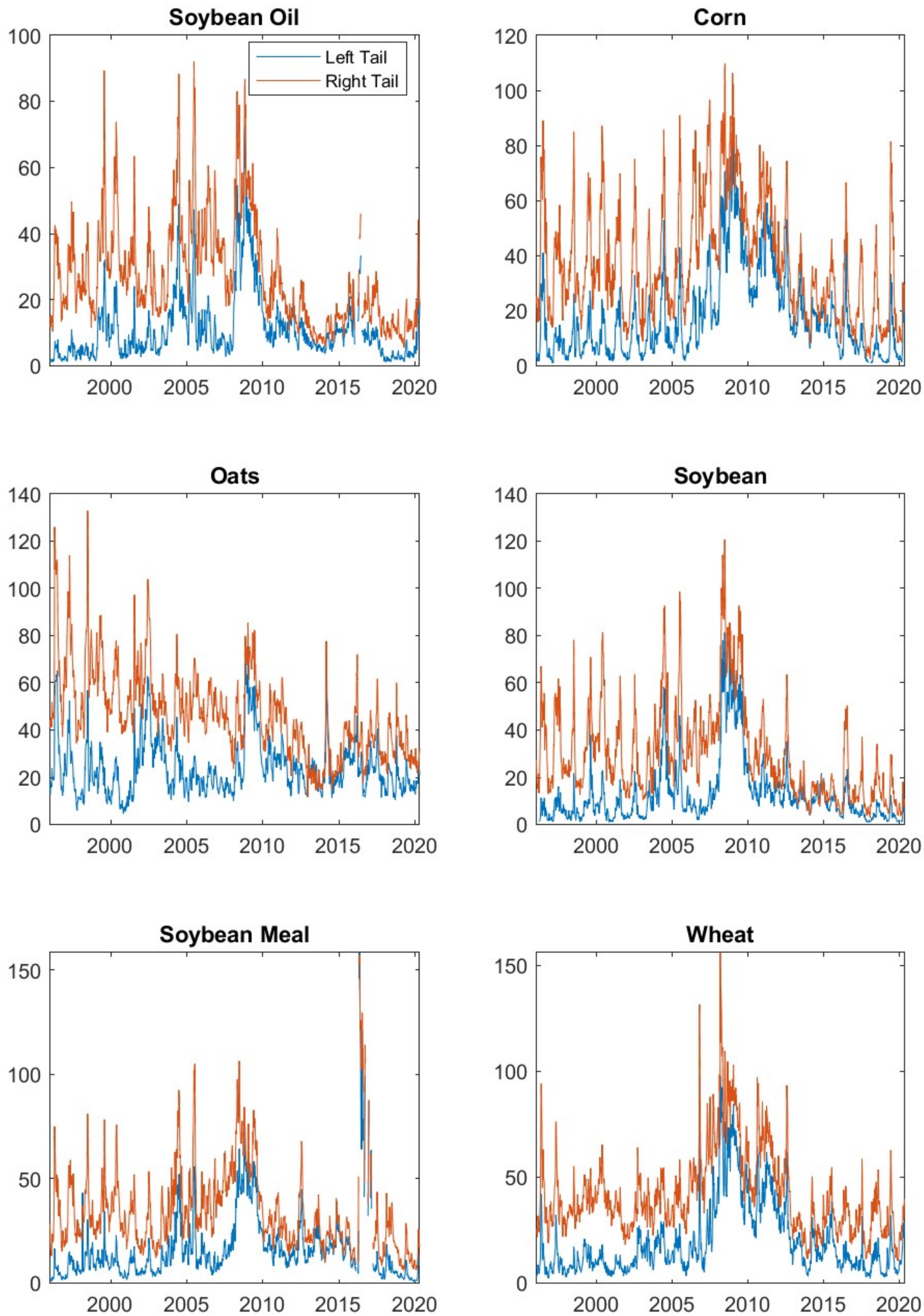


Figure 1 (continued)

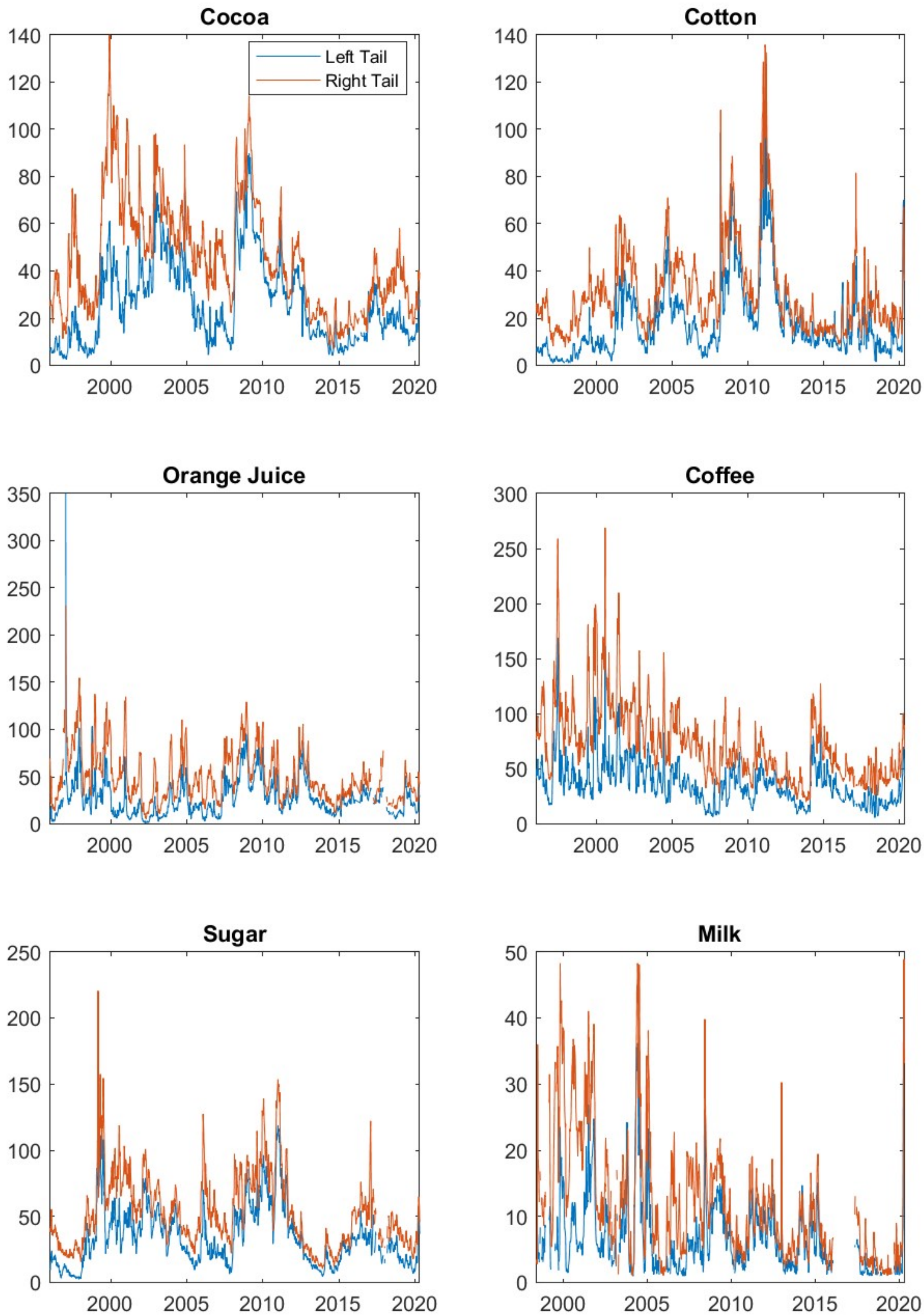


Figure 1 (continued)

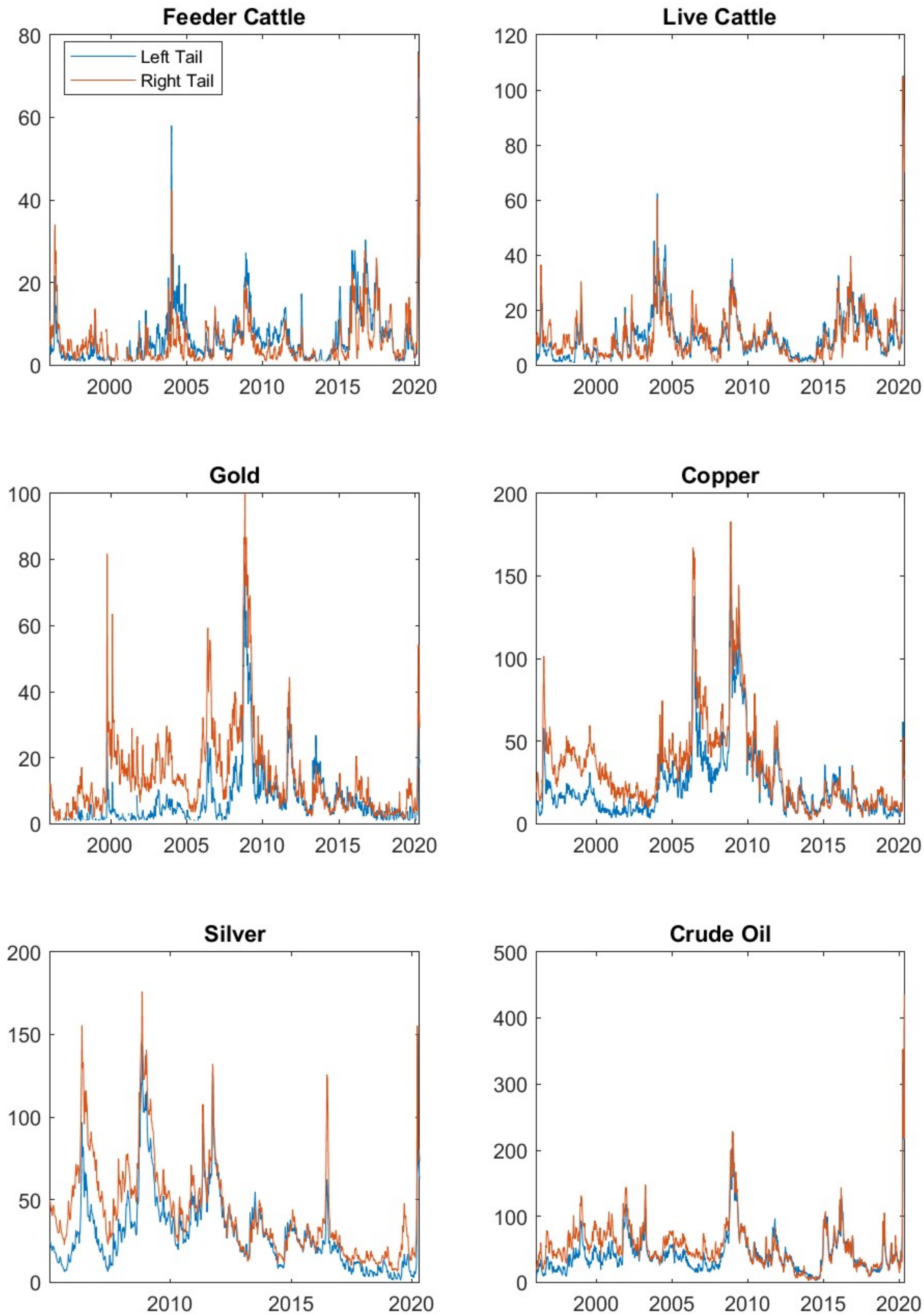
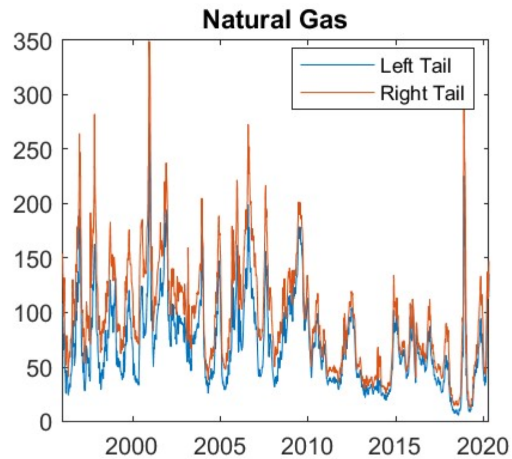


Figure 1 (continued)



4.3 Empirical Results

4.3.1 Summary Statistics

Table 4.2 shows the summary statistics for daily left and right tail risk measures, while Figure 4.1 depicts their weekly time series.[4]

There are several noteworthy aspects. First, right tail risk is for most commodities larger than left tail risk. This contrasts findings for the equity index market. Bollerslev et al. (2015) show that right tail risk is negligible compared to left tail risk. However, our findings are more line with tail risk in single stock options, where left and right tail risk exhibit the same order of magnitude (Lin and Todorov, 2019). Second, right tail risk is not higher all of the time. As seen for example for livestocks, left and right tail risk might alternate. Third, the skewness for most tail risk measures is positive, which indicates that the distribution is left skewed. Fourth, the kurtosis is considerably larger for left than for right tail risk, indicating that crashes are larger and more immediate than booms in commodity markets.

Moreover, the level of tail risks varies across commodities. Livestocks show comparably low readings of tail risk, contrary to energy commodities, with natural gas exhibiting the highest tail risk. For the softs market we observe higher levels, whereas agriculture and precious metals tend to exhibit lower degrees of tail risks.

[4]As not all commodities have the same range of strike prices in their corresponding option market, we observe for very few occasions missing data for some commodities. In these occasions, there have not been enough options to yield a robust estimate for our tail risk measures.

Table 4.1: Data Overview

This table lists the 19 commodities contained in our sample. It provides the identifier (*Mnemonic*), names (*Name*), sectors (*Sector*), time period (*Period*), and the number of observations (*# Obs*) in our sample.

Mnemonic	*Name*	*Sector*	*Period*	*# Obs*
BO	Soybean Oil	Agricultural	Jan 1996 - Apr 2020	1,778,463
C-	Corn	Agricultural	Jan 1996 - Apr 2020	1,538,713
O-	Oats	Agricultural	Jan 1996 - Apr 2020	678,336
S-	Soybean	Agricultural	Jan 1996 - Apr 2020	2,686,906
SM	Soybean Meal	Agricultural	Jan 1996 - Apr 2020	1,830,590
W-	Wheat	Agricultural	Jan 1996 - Apr 2020	1,619,442
CC	Cocoa	Softs	Jan 1996 - Apr 2020	2,506,768
CT	Cotton	Softs	Jan 1996 - Apr 2020	3,476,720
JO	Orange Juice	Softs	Jan 1996 - Apr 2020	1,783,598
KC	Coffee	Softs	Jan 1996 - Apr 2020	4,242,466
SB	Sugar	Softs	Jan 1996 - Apr 2020	3,033,164
DE	Milk	Livestock	Jan 1996 - Apr 2020	2,679,425
FC	Feeder Cattle	Livestock	Jan 1996 - Apr 2020	1,927,744
LC	Live Cattle	Livestock	Jan 1996 - Apr 2020	1,236,194
GC	Gold	Metal	Jan 1996 - Apr 2020	6,849,366
HG	Copper	Metal	Jan 1996 - Apr 2020	4,682,776
SI	Silver	Metal	Jan 2005 - Apr 2020	5,908,771
CL	Crude Oil	Energy	Jan 1996 - Apr 2020	5,654,093
NG	Natural Gas	Energy	Jan 1996 - Apr 2020	2,878,146

The crash in commodity prices after 2008 is mirrored in tail risks for most commodities as they exhibit a build-up of tail risk until 2009. This effect is especially pronounced for commodities which are more influenced by the business cycle, e.g., WTI crude oil and copper. Additionally, though there seem to exist events affecting commodities at the same time, most of the time-series dynamics of tail risk appear to be commodity specific. Finally, and related to that, tail risks exhibit seasonality, presumably caused by the seasonal production/consumption cycle present in many commodity markets.

In Table 4.3, we present correlations of the left and right tail risk measures. We highlight in grey correlations within each sector. The correlations within the agricultural and metal sector are the highest, around 0.60 for left and right tail risk. Within the softs, livestock, and energy sector there seems to be substantially lower within sector correlations, they are around 0.30 in most cases. Cocoa, cotton, and orange juice seem to share a higher correlation with the agricultural market than within their own sector. Correlations for most tail risk measures across sectors seem to be moderately high. Gold and copper seem to have the largest correlations with the entire sector, which highlights their importance as economic predictors.

Table 4.2: Left and Right Tail Risk

This table shows the summary statistics of the left tail risk on the left hand side and right tail risk on the right hand side. We order the commodities by sector. First, we have the agricultural sector, with soybean oil (BO), corn ($C-$), oats ($O-$), soybeans ($S-$), soybean meal (SM), and wheat ($W-$). Second, we have the softs sector, with cocoa (CC), cotton (CT), orange juice (JO), coffee (KC), and sugar (SB). Third, we have livestock, with milk (DE), feeder cattle (FC), and live cattle (LC). Fourth, we have metals, with gold (GC), copper (HG), and silver (SI). Finally, we have the energy sector, with WTI crude oil (CL) and natural gas (NG). We present the mean ($Mean$), the median ($Median$), the standard deviation (Std), the skewness ($Skew$), and the excess kurtosis ($Kurtosis$).

	Left Tail					**Right Tail**				
	Mean	*Median*	*Std*	*Skew*	*Kurtosis*	*Mean*	*Median*	*Std*	*Skew*	*Kurtosis*
Soybean Oil	11.17	8.24	10.20	2.32	6.95	27.29	23.33	15.78	1.19	1.52
Corn	17.84	13.09	15.68	1.46	1.96	37.63	33.47	21.11	0.77	0.09
Oats	23.95	21.35	11.63	1.46	2.65	46.76	44.29	18.48	1.09	3.04
Soybeans	12.90	8.98	13.44	2.46	6.7	29.87	24.64	20.07	1.33	2.01
Soybean Meal	16.36	11.99	16.68	3.46	18.89	34.21	28.93	20.30	1.81	5.05
Wheat	19.69	13.66	16.89	1.75	3.06	41.98	36.76	20.05	1.44	3.12
Cocoa	26.53	21.86	17.80	0.97	0.61	45.85	42.08	23.45	0.82	0.384
Cotton	18.59	12.55	16.99	2.62	13.43	31.14	26.25	19.05	2.10	6.72
Orange Juice	27.50	22.85	20.58	3.58	40.53	49.77	43.08	27.13	1.20	1.83
Coffee	36.92	33.92	19.98	1.65	5.53	73.05	66.28	34.70	1.50	3.60
Sugar	34.31	29.95	22.38	1.21	2.26	53.21	47.93	28.30	1.26	3.15
Milk	7.29	5.75	6.12	2.57	11.55	12.37	10.05	9.71	1.57	3.40
Feeder Cattle	7.26	5.12	7.60	5.21	56.51	6.03	4.17	6.29	4.92	45.95
Live Cattle	10.96	8.72	10.06	4.36	38.25	10.97	8.79	9.37	4.29	35.25
Gold	8.26	5.46	9.52	3.42	14.91	14.41	10.74	13.44	2.57	8.86
Copper	23.90	17.36	22.33	2.59	8.27	34.02	27.06	27.56	2.08	5.90
Silver	30.22	25.12	23.42	1.75	4.26	42.75	34.69	28.82	1.51	2.55
Crude	43.41	36.41	33.61	4.15	34.15	54.23	47.94	36.82	3.44	27.65
Natural Gas	71.04	63.78	39.28	1.11	2.18	97.14	88.54	51.50	1.08	2.24

Table 4.3: Correlation of Tail Risk across Commodities

This table shows the correlation between multiple commodities. The left tail risk is on the lower half of the table and right tail risk on the upper half. We order the commodities by sector. First, we have the agricultural sector, with soybean oil (BO), corn ($C-$), oats ($O-$), soybeans ($S-$), soybean meal (SM), and wheat ($W-$). Second, we have the softs sector, with cocoa (CC), cotton (CT), orange juice (JO), coffee (KC), and sugar (SB). Third, we have livestock, with milk (DE), feeder cattle (FC), and live cattle (LC). Fourth, we have metals, with gold (GC), copper (HG), and silver (SI). Finally, we have the energy sector, with WTI crude oil (CL) and natural gas (NG). We present the correlation within a sector shaded in grey.

	BO	$C-$	$O-$	$S-$	SM	$W-$	CC	CT	JO	KC	SB	DE	FC	LC	GC	HG	SI	CL	NG
BO		0.51	0.49	0.77	0.70	0.33	0.37	0.22	0.12	0.25	0.18	0.21	0.08	0.09	0.26	0.33	0.50	0.13	0.06
$C-$	0.58		0.38	0.64	0.55	0.64	0.23	0.45	0.10	0.16	0.27	0.07	0.04	0.01	0.33	0.49	0.57	0.09	0.06
$O-$	0.26	0.33		0.46	0.34	0.24	0.29	0.15	0.11	0.34	0.18	0.24	−0.01	−0.04	0.10	0.24	0.36	0.12	0.20
$S-$	0.66	0.73	0.25		0.77	0.46	0.31	0.29	0.13	0.22	0.18	0.18	0.04	0.02	0.22	0.33	0.39	0.05	0.02
SM	0.47	0.33	0.12	0.41		0.43	0.17	0.22	0.13	0.17	0.12	0.17	0.11	0.06	0.19	0.28	0.33	0.05	0.01
$W-$	0.48	0.75	0.22	0.65	0.26		0.18	0.44	0.18	0.06	0.31	0.04	0.07	0.05	0.38	0.41	0.47	0.15	0.05
CC	0.29	0.24	0.20	0.25	0.07	0.21		0.13	0.25	0.36	0.25	0.35	−0.07	−0.02	0.38	0.20	0.49	0.23	0.19
CT	0.30	0.51	0.13	0.31	0.18	0.38	0.11		0.03	0.07	0.35	0.01	0.08	0.12	0.29	0.29	0.40	0.15	0.02
JO	0.13	0.15	0.01	0.17	0.11	0.11	0.08	0.04		0.15	0.11	0.21	−0.00	0.03	0.20	0.21	0.33	0.18	0.36
KC	0.00	−0.09	0.09	−0.07	−0.08	−0.07	0.22	−0.03	0.03		0.08	0.32	0.01	0.02	0.12	0.00	0.13	0.03	0.14
SB	0.19	0.36	0.18	0.21	0.09	0.27	0.34	0.35	0.06	0.01		0.13	−0.01	0.02	0.19	0.21	0.36	0.11	0.08
DE	0.02	−0.04	0.02	0.01	0.00	−0.02	0.11	0.03	0.12	0.15	0.09		0.06	0.10	0.07	0.03	0.08	0.08	0.09
FC	0.12	0.09	0.03	0.09	0.07	0.07	0.02	0.21	−0.01	−0.01	0.09	0.30		0.77	0.16	0.06	0.19	0.42	0.00
LC	0.17	0.07	0.00	0.09	0.07	0.06	0.00	0.19	0.00	0.01	0.05	0.28	0.59		0.20	0.08	0.26	0.53	0.06
GC	0.53	0.54	0.20	0.47	0.32	0.43	0.11	0.35	0.12	−0.03	0.15	0.12	0.31	0.34		0.58	0.80	0.45	0.23
HG	0.46	0.58	0.28	0.48	0.22	0.43	0.12	0.27	0.11	−0.09	0.14	0.00	0.16	0.13	0.51		0.75	0.28	0.30
SI	0.50	0.58	0.28	0.41	0.17	0.40	0.37	0.39	0.25	0.23	0.36	0.08	0.23	0.34	0.72	0.52		0.50	0.37
CL	0.33	0.35	0.22	0.26	0.14	0.27	0.21	0.27	0.08	0.03	0.19	0.22	0.48	0.59	0.55	0.32	0.54		0.25
NG	0.05	0.07	0.12	0.06	0.02	0.04	0.12	0.01	0.13	0.06	0.10	0.06	0.10	0.11	0.06	0.24	0.20	0.27	

The correlation between the economically important commodities in the metal market and crude oil are quite sizable at around 0.50. This might indicate that there are commodity-wide events that influence the risk of the entire market. Especially for the left tail, we also see correlations around 0.20 with crude oil.

4.3.2 Determinants of Tail Risk

In order to investigate the determinants of tail risk, we conduct regressions, that include commodity specific, commodity market, and equity market variables. As commodity specific variables we use: the basis to proxy for inventory risk, Workings T or the number of speculative long/short trading relative to the total trading to proxy for speculation, and the variance risk premium as proxy for the return on variance risk which should also be captured by tail risk. These variables are commonly used proxies for idiosyncratic behaviour of commodities.

As commodity market variables, we use the factors suggested by Bakshi et al. (2017): the average return of a commodity portfolio, the momentum return, and the return from a commodity carry strategy. These variables should capture any common variation between the tail risk measures in the overall commodity market. Lastly, we consider equity market specific variables, which are the volatility index, the tail risk of the S&P 500, and the overall market return.

With these variables, we estimate the following regression

$$TR_{j,t} = a + \gamma CS_{j,t} + \theta CM_t + \Omega EM_t + \beta TR_{j,t-1} + \sum_{k=1}^{11} \zeta_k S^D_{k,t} + \epsilon_{j,t}, \tag{4.10}$$

where $TR_{j,t}$ is the left or right tail risk of commodity j at time t, CS, CM, and EM are vectors of the commodity specific, commodity market, and equity market variables. $S^D_{k,t}$ represents a seasonal dummy variable, that is one if the observation is in month k and zero otherwise.

In Tables 4.4 to C5 we present the results, for the left tail risk, for right tail risk, and asymmetry (left minus right tail risk scaled by implied volatility).[5]

Overall, we find that commodity specific factors and the volatility of the equity market influence tail risk for all commodities or for particular sectors. Moreover, there seem to be some commodity market factors that influence specific commodities, but there does not seem to be a pattern across different commodity markets. For all tail risk measures, we see that the variance risk premium plays the by far most significant role to explain tail risks.

Focusing on left tail risk, in Table 4.4, we can observe that the coefficient estimates for the variance risk premium are between -0.19 and -3.89. This implies that a 1% increase in the variance risk premium can decrease the left tail risk by up to 3.89%. For the right tail risk, we see in Table 4.5 that the coefficient estimates range between -0.14 and -3.42, which implies that if the variance risk premium changes by 1%, we observe an decrease in the right tail risk of up to 3.42%. We see that the coefficient of the right tail risk has more links to the variance risk premium. While left tail risk has no link between the livestock market and the variance risk premium, right tail risk is statistically significant for all markets and almost all commodities. This implies that tail risks are a significant part of the variance risk premium of commodity markets, which indicates that higher tail risk is associated with a significantly lower variance risk premium. Right tail risk is associated with higher coefficients for the variance risk premium, compared to left tail risk.

[5]Total tail risk, i.e., the sum of left and right tail risk and tail asymmetry is the difference between left and right tail risk.

Table 4.4: Determinants of Left Tail Risks

This table reports the results for the following regression

$$LT_{j,t} = a + \gamma CS_{j,t} + \theta CM_t + \Omega EM_t + \beta LT_{j,t-1} + \sum_{k=1}^{11} \zeta_k S^D_{k,t} + \epsilon_{j,t},$$

where CS is a vector of the commodity specific variables (basis, speculation, and variance risk premium). CM is a vector of commodity market factors (average portfolio return, return of a momentum portfolio, and return of a carry portfolio). EM is a vector for equity market factors (volatility index, left tail variation of the S&P 500, and the return of the S&P 500). Additionally we include the own lagged tail variation and seasonal dummies ($S^D_{k,t}$). We will not report the dummies for brevity. We scale the left tail variation to have a mean of zero and standard deviation of 1. We use Newey and West (1987) standard errors, the coefficient estimates in **bold** indicate a significance level of 5%. The t-statistic is indicated in brackets below the estimates.

	Agricultural						**Softs**				
	BO	*C−*	*O−*	*S−*	*SM*	*W−*	*CC*	*CT*	*JO*	*KC*	*SB*
Commodity Specific Factors											
Basis	0.22	**0.08**	**0.17**	0.04	0.03	0.17	0.14	**0.74**	**−0.45**	**0.75**	0.20
	(0.96)	(2.75)	(4.90)	(0.52)	(1.06)	(0.79)	(0.70)	(2.48)	(−2.42)	(3.98)	(1.49)
Spec	**−0.43**	**−0.81**	**0.34**	**−0.70**	−0.30	**−0.41**	0.35	0.10	−0.36	−0.27	−0.25
	(−2.16)	(−5.21)	(2.73)	(−2.77)	(−1.77)	(−2.28)	(1.00)	(0.26)	(−1.45)	(−1.31)	(−1.00)
VRP	−0.70	**−1.62**	**−0.24**	**−3.39**	−0.08	**−2.00**	**−1.06**	**−3.02**	**−3.83**	**−1.67**	−2.26
	(−0.86)	(−6.00)	(−4.05)	(−4.72)	(−1.04)	(−3.51)	(−2.61)	(−2.99)	(−2.91)	(−4.36)	(−1.63)
Commodity Market Factors											
Average	0.06	**2.71**	−0.61	1.81	0.97	**3.57**	−1.75	**5.22**	0.55	0.82	1.02
	(0.03)	(2.05)	(−0.66)	(0.82)	(0.59)	(2.23)	(−1.46)	(2.21)	(0.42)	(0.82)	(0.59)
Momentum	**1.99**	0.55	0.41	0.74	0.72	1.38	0.44	1.34	0.34	0.72	−0.05
	(2.11)	(1.39)	(0.85)	(1.20)	(1.24)	(1.84)	(0.70)	(1.38)	(0.67)	(1.41)	(−0.09)
Carry	**−2.03**	−0.24	0.18	−0.63	−1.44	−0.81	0.47	0.05	0.72	**−1.02**	0.08
	(−2.11)	(−0.42)	(0.29)	(−0.73)	(−1.48)	(−0.89)	(0.67)	(0.03)	(0.52)	(−2.24)	(0.17)
Equity Market Factors											
VIX	**−0.01**	0.00	**0.00**	0.00	**−0.01**	0.00	**0.02**	0.01	**0.01**	**0.01**	0.01
	(−2.25)	(0.59)	(2.07)	(−0.68)	(−2.14)	(−0.30)	(4.07)	(1.48)	(3.01)	(2.13)	(1.31)
LTSP	**3.95**	**0.88**	0.46	**2.45**	**1.86**	**1.76**	−0.23	**2.24**	−0.37	−0.47	−0.52
	(4.94)	(2.50)	(1.84)	(2.02)	(2.82)	(2.99)	(−0.61)	(4.17)	(−0.67)	(−1.07)	(−0.89)
SP500	2.87	−0.36	0.93	0.87	0.69	0.73	1.35	2.53	−0.24	−0.64	−0.36
	(1.75)	(−0.67)	(1.79)	(1.02)	(1.00)	(0.59)	(1.69)	(1.62)	(−0.28)	(−1.23)	(−0.95)
R^2	71.42	90.70	84.27	79.86	71.58	78.32	71.82	50.62	62.55	72.49	80.15

	Livestock			**Metal**			**Energy**	
	DE	*FC*	*LC*	*GC*	*HG*	*SI*	*CL*	*NG*
Commodity Specific Factors								
Basis	0.04	**0.76**	0.13	0.00	0.12	−0.08	−0.02	**0.08**
	(0.87)	(3.37)	(0.89)	(−0.03)	(1.30)	(−0.94)	(−1.11)	(2.43)
Spec	−1.78	−0.71	−0.65	**0.37**	−0.05	−0.11	−0.15	**−0.59**
	(−1.71)	(−1.59)	(−1.48)	(2.26)	(−0.49)	(−1.46)	(−0.42)	(−3.48)
VRP	−1.16	−0.30	−1.73	**−3.89**	**−1.67**	**−0.19**	**−0.61**	**−1.61**
	(−1.80)	(−0.38)	(−1.84)	(−3.36)	(−2.15)	(−2.79)	(−4.76)	(−5.61)
Commodity Market Factors								
Average	−2.29	**2.02**	1.83	−1.64	−0.22	**−3.27**	**−2.82**	0.63
	(−1.38)	(2.54)	(1.32)	(−1.76)	(−0.28)	(−3.41)	(−3.88)	(0.65)
Momentum	3.58	−0.20	0.37	−0.14	−0.05	0.46	**0.62**	0.63
	(1.93)	(−0.48)	(0.90)	(−0.31)	(−0.14)	(1.34)	(1.99)	(1.17)
Carry	0.27	1.14	0.20	0.81	0.13	−0.28	−0.04	0.27
	(0.40)	(1.92)	(0.39)	(1.40)	(0.41)	(−0.84)	(−0.16)	(0.56)
Equity Market Factors								
VIX	**0.01**	−0.01	0.00	**−0.01**	0.00	0.00	0.00	0.00
	(2.70)	(−1.88)	(−1.47)	(−4.52)	(0.59)	(1.02)	(1.85)	(0.44)
LTSP	**−0.78**	**2.27**	**0.78**	**2.69**	0.38	0.46	**0.35**	−0.20
	(−1.99)	(2.44)	(2.33)	(4.38)	(1.24)	(1.93)	(3.13)	(−0.74)
SP500	1.56	0.40	0.29	1.35	−0.64	0.45	−0.65	−0.70
	(1.10)	(0.90)	(1.14)	(1.56)	(−1.53)	(0.80)	(−1.87)	(−1.43)
R^2	17.46	27.77	56.05	93.11	90.51	94.95	95.03	85.46

Table 4.5: Determinants of Right Tail Risks

This table reports the results for the following regression

$$RT_{j,t} = a + \gamma CS_{j,t} + \theta CM_t + \Omega EM_t + \beta RT_{j,t-1} + \sum_{k=1}^{11} S_{k,t}^{D} + \epsilon_{j,t},$$

where CS is a vector of the commodity specific variables (basis, speculation, and variance risk premium). CM is a vector of commodity market factors (average portfolio return, return of a momentum portfolio, and return of a carry portfolio). EM is a vector for equity market factors (volatility index, right tail variation of the S&P 500, and the return of the S&P 500). Additionally we include the own lagged tail variation and seasonal dummies ($S_{k,t}^{D}$). We will not report the dummies for brevity. We scale the right tail variation to have a mean of zero and standard deviation of 1. We use Newey and West (1987) standard errors, the coefficient estimates in **bold** indicate a significance level of 5%. The t-statistic is indicated in brackets below the estimates.

	Agricultural						**Softs**				
	BO	*C−*	*O−*	*S−*	*SM*	*W−*	*CC*	*CT*	*JO*	*KC*	*SB*
Commodity Specific Factors											
Basis	0.14	−0.02	0.04	0.02	0.01	−0.05	**−0.27**	0.06	−0.21	**0.19**	0.12
	(0.56)	(−0.45)	(1.31)	(0.20)	(0.32)	(−0.35)	(−2.34)	(1.03)	(−1.83)	(2.80)	(1.51)
Spec	**−1.30**	**−2.86**	**−0.31**	**−1.02**	**−0.90**	**−1.03**	0.05	−0.04	**−0.21**	−0.23	**−0.72**
	(−5.27)	(−6.38)	(−3.29)	(−4.33)	(−5.58)	(−5.09)	(0.34)	(−0.45)	(−2.03)	(−1.85)	(−3.64)
VRP	0.30	**−1.81**	−0.06	**−2.37**	−0.03	**−2.09**	**−0.72**	**−0.75**	**−0.67**	**−0.94**	**−2.00**
	(0.47)	(−4.94)	(−1.88)	(−8.17)	(−0.96)	(−4.47)	(−4.10)	(−2.68)	(−4.88)	(−5.54)	(−1.97)
Commodity Market Factors											
Average	1.92	**6.48**	**2.18**	**6.36**	1.61	**4.67**	0.24	2.78	0.91	**3.94**	**1.98**
	(1.47)	(5.52)	(2.99)	(4.11)	(1.44)	(3.05)	(0.32)	(1.89)	(1.06)	(4.91)	(3.65)
Momentum	0.77	0.65	0.14	0.86	0.63	**1.28**	0.00	1.26	0.49	0.38	0.60
	(1.42)	(1.47)	(0.34)	(1.64)	(1.37)	(2.31)	(0.00)	(1.60)	(1.26)	(1.01)	(1.94)
Carry	−1.33	−1.14	−0.15	−0.03	**−1.26**	−1.50	0.33	−0.46	−0.28	**−1.56**	−0.23
	(−1.73)	(−1.62)	(−0.34)	(−0.04)	(−2.10)	(−1.42)	(0.63)	(−0.51)	(−0.49)	(−3.51)	(−0.56)
Equity Market Factors											
VIX	0.00	**0.01**	**0.00**	**0.00**	0.00	**0.00**	**0.01**	0.00	**0.00**	0.00	0.00
	(1.03)	(2.68)	(4.44)	(2.90)	(0.31)	(2.97)	(4.21)	(1.96)	(3.42)	(1.44)	(1.67)
RTSP	**1.57**	**1.11**	−0.10	0.27	**0.75**	**0.84**	−0.04	**0.51**	−0.08	−0.07	−0.58
	(4.32)	(4.09)	(−0.78)	(0.95)	(3.10)	(2.74)	(−0.20)	(2.62)	(−0.45)	(−0.49)	(−1.38)
SP500	0.16	0.13	−0.01	0.07	**1.42**	1.13	0.87	0.16	0.75	−0.53	0.10
	(0.27)	(0.17)	(−0.02)	(0.12)	(2.62)	(1.51)	(1.77)	(0.30)	(1.42)	(−1.13)	(0.23)
R^2	72.23	78.58	86.89	77.21	81.89	80.88	87.22	90.63	87.43	90.55	77.52

	Livestock			**Metal**			**Energy**	
	DE	*FC*	*LC*	*GC*	*HG*	*SI*	*CL*	*NG*
Commodity Specific Factors								
Basis	−0.01	0.05	0.02	−0.31	0.06	−0.05	0.03	**0.09**
	(−0.36)	(0.70)	(1.12)	(−1.94)	(1.07)	(−0.70)	(1.24)	(2.36)
Spec	−0.92	0.12	0.08	0.01	**−0.22**	**−0.42**	−0.08	**−1.14**
	(−1.16)	(0.53)	(1.29)	(0.12)	(−3.42)	(−3.99)	(−0.24)	(−2.79)
VRP	−0.51	**−1.31**	**−0.33**	**−3.42**	**−0.92**	**−0.14**	**−0.53**	**−1.54**
	(−1.34)	(−2.38)	(−2.95)	(−4.51)	(−5.78)	(−2.79)	(−3.95)	(−3.08)
Commodity Market Factors								
Average	1.64	**−3.39**	−0.47	1.27	−0.24	−0.53	**−2.22**	**2.29**
	(0.70)	(−2.61)	(−1.01)	(1.67)	(−0.35)	(−0.69)	(−3.48)	(2.88)
Momentum	0.08	0.15	0.39	−0.06	0.03	0.35	**1.00**	0.61
	(0.09)	(0.24)	(1.55)	(−0.16)	(0.10)	(1.14)	(3.62)	(1.30)
Carry	−0.83	0.88	−0.12	0.78	0.05	−0.19	0.29	−0.37
	(−1.10)	(1.54)	(−0.34)	(1.80)	(0.16)	(−0.66)	(1.11)	(−0.48)
Equity Market Factors								
VIX	**0.01**	0.00	0.00	0.00	**0.00**	0.00	**0.00**	0.00
	(2.00)	(−0.49)	(0.50)	(0.90)	(3.46)	(1.81)	(2.94)	(−1.54)
RTSP	−0.32	1.04	0.30	**1.58**	0.28	**0.55**	**0.46**	0.05
	(−1.46)	(1.89)	(1.60)	(6.19)	(1.51)	(2.31)	(4.00)	(0.25)
SP500	−0.35	**1.01**	0.40	0.08	−0.29	0.27	−0.32	**−1.24**
	(−0.38)	(2.14)	(1.90)	(0.12)	(−0.81)	(0.48)	(−0.89)	(−2.05)
R^2	70.49	57.84	86.86	94.25	95.35	95.86	94.56	89.02

For both the left and right tail risk (in Tables 4.4 and 4.5) we observe links to the speculation in commodity markets. A higher proportion of short (long) speculators decrease left (right) tail risk substantially. This link, however, is only observable for the agricultural market for both left and right tail risk. For right tail risk this effect can also be observed for copper and silver. The effect is larger for right tail risk, compared to left tail risk, which indicates that speculative activity increases liquidity and therefore reduces uncertainty in the tails of the distribution. This finding is consistent with findings from Brunetti et al. (2016), who find that speculative activity reduces volatility for the agricultural market and natural gas.

Furthermore, we do find links to the VIX and the left and right tail risk of the S&P 500. These links exist for the agricultural, metal markets, and crude oil. Especially for left tail risk the coefficients are significantly larger; this indicates that especially in a period of a economic uncertainty this seems to occur in both the commodity market and equity markets. For right tail risk, we also observe a link between the average return on a commodity portfolio and some commodities. This link is especially present in the agricultural market, where it is positive. Hence, in tranquil periods, when returns are large, demand increases right tail risk substantially.

For the total tail risk and asymmetry of the tails in Tables C4 and C5, we still observe a link to speculation for both asymmetry and total tail risk. The asymmetry of the tails is still weakly linked to the variance risk premium, while the total tail risk is not. The total tail risk still has links to the total tail risk of the equity market and the VIX, while asymmetry has no such links. For speculation this shows that both left and tight tail risk are reduced by speculation, except for crude oil, but this effect is stronger for the right tail. The variance risk premium seems to be mainly driven by the left tail risk. While the link to the equity market disappears for asymmetry, it is still present for total tail risk, which shows that the common factor of the commodity left and right tail risk is crucial to understanding the linkages with the equity market.

In this section we have gained an understanding about the links of tail risk. In the following section, we investigate the economic importance of tail risk in the cross-section.

4.3.3 Portfolio sorts

After having provided a descriptive analysis of tail risk, we now test if tail risk is priced in the cross-section of commodity futures. Therefore, we sort commodities each month into portfolio quartiles based on right and left tail risk, respectively. The commodities in our sample are quite heterogeneous with respect to their production region, period, storage suitability, and designated use. This might not only have an impact on commodity prices, but also on higher moments of the risk-neutral and physical return distributions. Figure 4.1 provides evidence in favour of heterogeneous risk-neutral tail risk. Consequently, we detrend the tail risk measures before comparing them cross-sectionally.[6] Thereby, we account for variation in their levels, but also their time-variation (see also Gao, 2017). At the end of each month, the detrended tail risk measure is given as

$$DTR_{j,t} = TR_{j,t} - \frac{1}{12}\sum_{\tau=1}^{12} TR_{j,t-\tau}, \tag{4.11}$$

where $TR_{j,t}$ denotes either the right or left tail risk measure of commodity j at time t. At the end of each month t, we allocate commodities into quartile portfolios. Portfolio 1 comprises commodities with highest right (left) tail risk innovation, whereas portfolio 4 contains commodities with lowest right (left) tail risk innovation. Commodities are equally weighted within each portfolio. We then construct a long-short strategy. The strategy buys commodities in portfolio 1 and shorts commodities in portfolio 4. We calculate the excess return for each portfolio and the return of the long-short portfolio at $t + 1$.

[6] As Appendix B shows, our results remain quantitatively and qualitatively the same when we sort commodities according to the change in left and right tail risk, respectively.

Table 4.6: Return of Portfolios Sorted by Tail Risk

This table reports descriptive statistics of commodity portfolios sorted on the tail risk measure at $t-1$ detrended by the previous 12-month average $\frac{1}{12}\sum_{\tau=1}^{12} TR_{t-\tau}$ (see Equation 4.5). The "High" ("Low") portfolio entails commodities with highest (lowest) innovation in tail risk. Portfolios are rebalanced monthly. Returns are displayed in percentage and annualized. t-stats are based on Newey and West (1987) standard errors with optimal bandwidth with *, **, *** indicating significance at the 10%, 5%, and 1% level, respectively. Furthermore, we report the annualized standard deviation (Sdev), skewness (Skew), kurtosis (Kurtosis), Sharpe ratio (SR) and first lag auto-correlation coefficient (AC(1)). Panel A shows results for detrended left tail risk, whereas Panel B shows statistics for detrended right tail risk. The data sample is from January 1996 to April 2020.

	Mean	$t-stat$	*Sdev*	*Skew*	*Kurtosis*	*SR*	*AC*(1)
Panel A: Detrended Left Tail Risk							
High	3.16	0.93	14.89	0.07	0.64	0.21	0.04
2	0.43	0.12	15.25	−0.09	2.76	0.03	−0.01
3	2.04	0.63	14.21	−0.21	0.92	0.14	0.07
Low	−5.34	−1.40	19.32	−0.04	1.37	−0.28	−0.10
High-Low	8.50**	1.96	20.31	0.14	1.01	0.42	0.01
Panel B: Detrended Right Tail Risk							
High	1.71	0.51	14.87	0.21	1.59	0.12	0.00
2	4.60	1.50	14.45	−0.14	1.26	0.32	0.00
3	3.43	0.94	16.16	−0.24	1.90	0.21	0.11
Low	−8.89**	−2.27	18.49	−0.05	1.35	−0.48	−0.06
High-Low	10.60**	2.46	19.32	0.36	0.92	0.55	0.03

Table 4.6 reports results. Panel A of Table 4.6 shows results when sorting by left tail risk innovations. In contrast to the right tail, the results suggest that innovation in left tail risk is also cross-sectionally priced. Though the long-short strategy yields an annualized return of 8.50%, it is significant at the 5% level. As Panel B shows, the long-short strategy that buys commodities with highest right tail risk innovation and sells commodities with lowest right tail risk innovation yields an annualized return of 10.60%, which is statistically significant at the 5% level, as well. The Sharpe Ratio is 0.55. Most of the strategy's return originates from the short leg. The portfolio with the lowest tail risk innovation yields an annualized loss of 8.89%, which is significant at the 5% level. Conversely, the portfolio with highest tail risk innovation returns 1.71% annually, which is not significantly different from zero.

Table 4.7: Risk Factors in the Tail Risk Strategies

This table reports descriptive statistics of regressing the monthly return of the tail risk measure strategy on a constant (Intercept), an average commodity factor (Commodity), a commodity momentum factor (Momentum), and a commodity carry factor (Carry). The factors are described in Bakshi et al. (2017). Panel A shows results for detrended left tail risk, whereas Panel B shows statistics for detrended right tail risk. The data sample is from January 1996 to April 2020. t-stats are calculated via Newey and West (1987) standard errors with optimal bandwidth with *, **, *** indicating significance at the 10%, 5%, and 1% level, respectively.

	Intercept	*Commodity*	*Momentum*	*Carry*
Panel A: Detrended Left Tail Risk				
beta	8.54*	0.09	−0.01	−0.01
$t - stat$	1.94	0.74	−0.21	−0.16
Panel B: Detrended Right Tail Risk				
beta	11.21***	0.07	0.05	−0.11*
$t - stat$	2.59	0.76	1.00	−1.88

Next, we seek to determine whether the long-short returns can be explained by known risk factors in commodity markets. Therefore, we regress long-short portfolio returns on the set of risk factors proposed by Bakshi et al. (2017), comprising an average commodity factor, a commodity momentum factor, and a commodity carry factor. If the factors can price returns of our long-short strategy, the results should exhibit a small and statistically insignificant intercept, statistically significant slope coefficients, and a high adjusted R^2. Panel A in Table 4.7 details the results for the long-short portfolio based on left tail risk innovations. None of the three risk factors is significantly related to the strategy's returns. Panel B in Table 4.7 shows that the same is true for the long-short strategy based on right tail risk innovations. Only the carry factor is statistically significantly related to tail risk. This indicates that cross-sectionally tail risk seems to be related to inventory risk. Moreover, the intercept is significantly different from zero, economically large, and approximately matches its sample average. Finally, the adjusted R^2 is close to zero. Concluding, the long-short strategy cannot be explained by the three risk factors.

In Table C1 and C2, we report the same results for the monthly change in tail risk measures, showing that the detrending did not contribute to the cross-sectional predictive power.

4.4 Conclusion

In this study, we study tail risk in commodity markets. We find that tail risk is priced in the cross-section of the commodity market. This is the case for right and left tail risk. Moreover, we investigate possible links with tail risk and numerous commodity factors. We find that the variance risk premium has the greatest influence for left and right tail risk. Speculation is only linked to tail risk in the agricultural, metal market and crude oil. We also document links to the equity market which seem to be driven by the common variation in left and right tail risk, which is general uncertainty. These links are particularly strong for the agricultural, metal, and energy market, and are likely exacerbated by the higher impact of speculative activity, which might lead to a transmission of uncertainty throughout markets.

C1 Appendix

C1.1 CRB Data Handling

We follow the algorithm by Hollstein et al. (2021) that implements the algorithm to determine the "fair" strike price for each option, because CRB denotes every strike price with four digits; if there is space left, it fills them with zeros on the right hand side. For a commodity you might have the choice between a strike price of \$1.4, \$14, \$140, and \$1400. To calculate the value of an American option, we need to calculate two components, the early exercise payoff and an early exercise premium. Especially for short-term options early exercise premia are negligible, because we also have options up to 365 days into the term structure. But we argue that this approach is still feasible, because the difference between the potential strike prices is very large (by a factor of 10x), and the choice of the fair strike price is unlikely to be influenced by the early exercise premium even for longer maturity options.

To determine the fair strike, we only need to minimize the distance between the early exercise payoff and the price for an option:

$$\epsilon_{C,K_i} = |C - max(S - K_i, 0)|$$
$$\epsilon_{P,K_i} = |P - max(K_i - S, 0)|,$$

where ϵ_{K_i} refer to a call and put option. C, and P are the prices for call and put options. S and K_i represent the underlying futures and strike prices. With this data source you can make four guesses about potential strike prices, you can divide the price by 1000, 100, 10, or 1. The algorithm compares successively (from in-the-money to out-of-the-money) pricing errors, until the next pricing error is larger. The strike guess with the smallest error is the fair strike price.

In order to provide some robustness (as the strike price might be time varying), we compute the mode of the strike price for each contract. Further we ensure that the resulting options comply with monotonicity and no-arbitrage restrictions. We apply the following restrictions:

$$max(K - S_t, 0) \leq P_t \leq K$$

$$max(S_t - K, 0) \leq C_t \leq S_t$$

We calculate the implied volatility with the method of Barone-Adesi and Whaley (1987). As a further robustness check, we delete options with an implied volatility greater than 3 times the median implied volatility that day.

C1.2 Change in Tail Risk as Cross-sectional Predictor

Table C1: Return of Portfolios Sorted by Tail Risk

The table reports descriptive statistics of commodity portfolios sorted on the change in the tail risk measure at $t-1$. The "High" ("Low") portfolio entails commodities with the highest (lowest) innovation in tail risk. Portfolios are rebalanced monthly. Returns are displayed in percentage and annualized. t-stats are based on Newey and West (1987) standard errors with optimal bandwidth with *, **, *** indicating significance at the 10%, 5%, and 1% level, respectively. Furthermore, we report the annualized standard deviation (Sdev), skewness (Skew), kurtosis (Kurtosis), Sharpe ratio (SR) and first lag auto-correlation coefficient (AC(1)). Panel A shows results for changes in left tail risk, whereas Panel B shows statistics for changes in right tail risk. The data sample is from January 1996 to April 2020.

	$Mean$	$t-stat$	$Sdev$	$Skew$	$Kurtosis$	SR	$AC(1)$
Panel A: Change in Left Tail Risk							
High	1.93	0.65	15.92	0.10	0.56	0.12	−0.15
2	2.40	0.82	13.46	0.64	1.31	0.18	0.07
3	4.57	1.15	16.61	−0.18	2.19	0.28	0.11
Low	−7.54*	−1.75	18.68	−0.38	1.45	−0.40	−0.01
High-Low	9.47**	2.02	20.19	0.09	1.20	0.47	0.08
Panel B: Change in Right Tail Risk							
High	2.28	0.72	15.95	0.19	0.87	0.14	−0.12
2	0.67	0.24	12.97	0.63	1.66	0.05	0.02
3	3.52	0.87	17.08	−0.50	2.18	0.21	0.10
Low	−5.87	−1.38	17.97	−0.26	1.18	−0.33	0.02
High-Low	8.15*	1.81	18.86	0.27	0.94	0.43	0.09

Table C2: Risk Factors in the Tail Risk Strategies

The table reports descriptive statistics of regressing the monthly return of the tail risk measure strategy on a constant (Intercept), an average commodity factor (Commodity), a commodity momentum factor (Momentum), and a commodity carry factor (Carry). The factors are described in Bakshi et al. (2017). Panel A shows results for changes in left tail risk, whereas Panel B shows statistics for changes right tail risk. The data sample is from January 1996 to April 2020. t-stats are calculated via Newey and West (1987) standard errors with optimal bandwidth with *, **, *** indicating significance at the 10%, 5%, and 1% level, respectively.

	Intercept	*Commodity*	*Momentum*	*Carry*
Panel A: Change in Left Tail Risk				
beta	9.66^{**}	-0.10	0.04	-0.03
$t-stat$	2.04	-0.94	0.77	-0.52
Panel B: Change in Right Tail Risk				
beta	8.75^{*}	-0.11	0.02	-0.06
$t-stat$	1.94	-1.07	0.49	-0.99

C1.3 Total Tail Risk

Table C3: Total Tail Risk

This table shows the summary statistics of the total tail risk. We order the commodities by sector. First, we have the agricultural sector, with soybean oil (BO), corn ($C-$), oats ($O-$), soybeans ($S-$), soybean meal (SM), and wheat ($W-$). Second, we have the softs sector, with cocoa (CC), cotton (CT), orange juice (JO), coffee (KC), and sugar (SB). Third, we have livestock, with milk (DE), feeder cattle (FC), and live cattle (LC). Fourth, we have metals, with gold (GC), copper (HG), and silver (SI). Finally, we have the energy sector, with WTI crude oil (CL) and natural gas (NG). We present the mean ($Mean$), the median ($Median$), the standard deviation (*Std*), the skewness (*Skew*), and the excess kurtosis ($Kurtosis$).

	$Mean$	$Median$	*Std*	*Skew*	$Kurtosis$
Soybean Oil	38.18	31.83	23.43	1.58	2.70
Corn	54.70	46.36	32.97	0.87	0.06
Oats	70.22	65.32	25.68	1.11	1.36
Soybeans	42.34	33.96	30.75	1.81	3.48
Soybean Meal	51.18	42.72	34.62	2.45	9.18
Wheat	61.27	50.41	34.33	1.52	2.23
Cocoa	72.25	65.52	38.77	0.73	−0.14
Cotton	47.90	37.55	30.57	1.68	3.11
Orange Juice	76.40	65.66	42.78	1.10	1.03
Coffee	108.96	100.42	50.22	1.39	2.99
Sugar	85.12	78.93	50.67	0.66	0.20
Milk	19.22	16.30	13.94	1.65	3.38
Feeder Cattle	12.67	8.99	11.86	3.61	20.46
Livestock	22.18	17.88	18.18	3.76	23.74
Gold	22.07	16.36	20.09	3.04	12.35
Copper	55.02	43.78	43.60	2.26	6.46
Silver	68.09	57.88	43.34	1.51	3.17
Crude Oil	98.10	85.45	66.31	3.05	15.12
Natural Gas	168.42	155.01	86.30	0.91	1.38

Table C4: Determinants of Total Tail Risks

This table reports the results for the following regression

$$LTRT_{j,t} = a + \gamma CS_{j,t} + \theta CM_t + \Omega EM_t + \beta LTRT_{j,t-1} + \sum_{k=1}^{11} \zeta_k S^D_{k,t} + \epsilon_{j,t},$$

where CS is a vector of the commodity specific variables (basis, speculation, and variance risk premium). CM is a vector of commodity market factors (average portfolio return, return of a momentum portfolio, and return of a carry portfolio). EM is a vector for equity market factors (volatility index, total tail variation of the S&P 500, and the return of the S&P 500). Additionally we include the own lagged tail variation and seasonal dummies ($S^D_{k,t}$). We will not report the dummies for brevity. We scale the standardized total tail variation to have a mean of zero and standard deviation of 1. We use Newey and West (1987) standard errors, the coefficient estimates in **bold** indicate a significance level of 5%. The t-statistic is indicated in brackets below the estimates.

	Agricultural						**Softs**				
	BO	*C−*	*O−*	*S−*	*SM*	*W−*	*CC*	*CT*	*JO*	*KC*	*SB*
Commodity Specific Factors											
Basis	0.07	−0.05	−0.01	0.01	−0.08	**−0.62**	**−1.35**	0.18	−0.30	**0.41**	**0.16**
	(0.51)	(−1.44)	(−0.11)	(0.60)	(−1.31)	(−2.70)	(−3.02)	(1.07)	(−1.00)	(3.50)	(3.34)
Spec	0.30	**−0.77**	**−1.29**	−0.48	**−1.75**	**−2.69**	0.37	0.51	0.11	−0.01	**−0.76**
	(0.58)	(−4.84)	(−4.60)	(−1.60)	(−4.18)	(−5.08)	(0.55)	(0.95)	(0.74)	(−0.03)	(−3.64)
VRP	−0.14	**0.68**	**0.31**	0.79	−0.02	0.41	**−1.26**	−0.23	−0.31	−0.30	**0.44**
	(−0.26)	(3.96)	(3.07)	(1.21)	(−0.70)	(0.81)	(−2.44)	(−1.09)	(−1.05)	(−1.76)	(2.56)
Commodity Market Factors											
Average	3.95	−0.38	1.47	2.40	−0.45	−0.58	−1.27	−2.30	−5.98	−2.96	**1.69**
	(0.95)	(−0.64)	(1.05)	(1.47)	(−0.40)	(−0.56)	(−0.82)	(−0.84)	(−0.97)	(−0.90)	(2.84)
Momentum	−0.57	0.20	−0.55	−1.30	0.11	**1.41**	−1.77	0.38	−1.17	2.65	**1.30**
	(−0.96)	(0.85)	(−1.01)	(−1.06)	(0.21)	(1.99)	(−0.83)	(1.19)	(−1.18)	(1.37)	(2.62)
Carry	0.22	**−0.72**	2.46	−0.18	−0.52	0.14	−0.41	−1.28	3.26	−0.88	−0.49
	(0.87)	(−2.04)	(1.31)	(−0.14)	(−0.77)	(0.11)	(−0.50)	(−0.92)	(1.18)	(−1.72)	(−0.82)
Equity Market Factors											
VIX	0.00	**0.01**	0.01	0.00	**0.01**	**0.02**	**0.02**	0.01	0.00	**0.01**	**0.01**
	(1.06)	(3.98)	(1.91)	(0.49)	(2.97)	(3.61)	(5.04)	(1.10)	(0.52)	(2.68)	(3.79)
LTRTSP	0.07	**−0.30**	−0.46	0.03	−0.32	**−0.92**	**−0.87**	−0.33	−0.23	**−0.85**	**−0.61**
	(0.58)	(−2.68)	(−1.54)	(0.22)	(−1.61)	(−2.45)	(−3.37)	(−1.02)	(−1.11)	(−2.34)	(−3.26)
SP500	−0.99	0.41	0.50	0.23	**1.37**	0.77	0.65	0.02	−0.81	−0.38	−0.16
	(−0.98)	(1.59)	(0.88)	(0.26)	(2.11)	(0.64)	(1.46)	(0.16)	(−1.40)	(−0.84)	(−0.32)
R^2	0.22	11.53	10.14	0.35	43.98	27.62	3.33	4.12	0.60	1.23	80.56
	Livestock			**Metal**			**Energy**				
	DE	*FC*	*LC*	*GC*	*HG*	*SI*	*CL*	*NG*			
Commodity Specific Factors											
Basis	0.00	**0.56**	0.04	**−0.46**	0.03	−0.07	0.22	0.06			
	(−0.06)	(2.67)	(0.49)	(−3.12)	(0.39)	(−1.54)	(1.57)	(1.74)			
Spec	−0.23	−0.08	−0.51	0.17	**−0.59**	**−0.67**	**5.89**	**−2.30**			
	(−0.45)	(−0.25)	(−1.53)	(0.38)	(−4.04)	(−2.43)	(2.75)	(−6.15)			
VRP	0.54	0.67	**−0.50**	−0.12	−0.04	0.34	−0.05	−0.14			
	(0.75)	(1.58)	(−2.02)	(−0.21)	(−0.45)	(1.90)	(−0.16)	(−1.00)			
Commodity Market Factors											
Average	−0.33	1.00	0.13	0.62	−0.11	0.49	−3.14	0.35			
	(−0.25)	(0.77)	(0.09)	(0.75)	(−0.14)	(0.49)	(−1.30)	(0.37)			
Momentum	−1.50	−0.72	−0.02	0.32	−0.31	−0.70	1.28	−0.66			
	(−1.12)	(−1.14)	(−0.04)	(0.74)	(−0.75)	(−1.01)	(1.17)	(−1.19)			
Carry	3.40	1.54	0.58	0.53	0.18	−0.10	−0.23	−0.53			
	(1.27)	(1.41)	(0.62)	(1.24)	(0.26)	(−0.06)	(−0.36)	(−0.73)			
Equity Market Factors											
VIX	0.01	0.00	0.00	**0.01**	**0.00**	0.01	**0.04**	0.00			
	(1.94)	(−0.74)	(−1.52)	(3.52)	(3.17)	(1.69)	(3.81)	(1.47)			
LTRTSP	−0.38	0.54	**0.58**	−0.15	−0.13	0.01	**−1.35**	**−0.47**			
	(−1.31)	(1.84)	(2.58)	(−0.95)	(−1.33)	(0.03)	(−2.39)	(−2.16)			
SP500	−1.72	**1.35**	1.14	−0.06	0.71	−0.30	0.99	−0.40			
	(−1.02)	(2.07)	(1.82)	(−0.13)	(1.33)	(−0.38)	(1.50)	(−0.62)			
R^2	0.67	54.52	66.62	32.88	77.13	11.14	17.61	67.03			

Table C5: Determinants of Asymmetry

This table reports the results for the following regression

$$LTMRT_{j,t} = a + \gamma CS_{j,t} + \theta CM_t + \Omega EM_t + \beta LTMRT_{j,t-1} + \sum_{k=1}^{11} \zeta_k S^D_{k,t} + \epsilon_{j,t},$$

where CS is a vector of the commodity specific variables (basis, speculation, and variance risk premium). CM is a vector of commodity market factors (average portfolio return, return of a momentum portfolio, and return of a carry portfolio). EM is a vector for equity market factors (volatility index, tail asymmetry of the S&P 500, and the return of the S&P 500). Additionally we include the own lagged tail variation and seasonal dummies ($S^D_{k,t}$). We will not report the dummies for brevity. We scale the standardized asymmetry to have a mean of zero and standard deviation of 1. We use Newey and West (1987) standard errors, the coefficient estimates in **bold** indicate a significance level of 5%. The t-statistic is indicated in brackets below the estimates.

	Agricultural						**Softs**				
	BO	*C−*	*O−*	*S−*	*SM*	*W−*	*CC*	*CT*	*JO*	*KC*	*SB*
Commodity Specific Factors											
Basis	−0.05	**0.09**	**0.24**	0.00	0.10	**0.61**	**1.33**	−0.15	0.27	−0.15	−0.07
	(−0.36)	(2.06)	(3.16)	(−0.13)	(1.94)	(2.75)	(2.84)	(−0.85)	(0.95)	(−1.22)	(−1.83)
Spec	−0.32	**0.51**	**1.86**	0.46	**1.55**	**2.27**	0.36	−0.49	−0.04	0.21	**0.84**
	(−0.60)	(2.93)	(5.44)	(1.66)	(4.47)	(4.57)	(0.51)	(−0.95)	(−0.26)	(0.65)	(3.91)
VRP	0.22	**−0.87**	**−0.45**	−0.70	−0.01	**−0.83**	**1.17**	0.10	0.25	0.22	**−0.34**
	(0.43)	(−4.36)	(−3.83)	(−1.18)	(−0.34)	(−2.39)	(2.35)	(0.54)	(0.82)	(1.21)	(−2.27)
Commodity Market Factors											
Average	−3.98	0.32	−2.28	−2.17	**2.11**	0.33	0.67	2.27	5.12	1.55	**−2.15**
	(−0.97)	(0.55)	(−1.60)	(−1.51)	(2.24)	(0.34)	(0.37)	(0.91)	(0.90)	(0.51)	(−3.48)
Momentum	0.55	−0.24	0.58	1.32	−0.08	−1.06	2.54	−0.33	1.31	−2.53	**−1.02**
	(1.01)	(−0.96)	(1.03)	(1.05)	(−0.20)	(−1.73)	(1.15)	(−1.19)	(1.38)	(−1.37)	(−2.40)
Carry	−0.23	**0.76**	−2.09	0.36	0.35	−0.55	0.35	1.31	−3.56	1.13	0.26
	(−0.95)	(2.13)	(−1.08)	(0.31)	(0.59)	(−0.61)	(0.46)	(0.95)	(−1.35)	(1.73)	(0.52)
Equity Market Factors											
VIX	0.00	0.00	−0.01	0.00	0.00	**−0.01**	**−0.01**	0.00	0.00	−0.01	0.00
	(−1.25)	(−1.84)	(−1.56)	(−1.94)	(−1.44)	(−2.20)	(−2.92)	(−1.06)	(0.58)	(−1.76)	(−0.79)
LTRTSP	0.03	**0.55**	1.01	0.16	0.59	**1.72**	2.24	0.59	0.24	**2.42**	0.16
	(0.17)	(2.00)	(1.54)	(1.04)	(1.31)	(2.29)	(1.66)	(1.15)	(0.60)	(2.57)	(0.48)
SP500	1.04	−0.42	−0.52	−0.37	**−1.43**	−0.52	−0.17	−0.11	1.13	0.39	−0.41
	(1.01)	(−1.57)	(−1.08)	(−0.48)	(−2.56)	(−0.44)	(−0.37)	(−0.78)	(1.14)	(0.72)	(−0.82)
R^2	0.23	12.92	10.71	0.34	51.24	35.66	2.30	4.32	0.57	1.88	75.35

	Livestock			**Metal**			**Energy**	
	DE	*FC*	*LC*	*GC*	*HG*	*SI*	*CL*	*NG*
Commodity Specific Factors								
Basis	0.01	**0.34**	0.18	**0.40**	−0.03	−0.02	−0.32	**−0.10**
	(0.12)	(3.75)	(1.42)	(3.48)	(−0.40)	(−0.18)	(−1.66)	(−2.51)
Spec	0.34	**−0.73**	**−1.52**	−0.18	**0.81**	**2.75**	−2.08	**3.65**
	(0.84)	(−3.05)	(−4.00)	(−0.51)	(3.98)	(6.08)	(−0.91)	(9.44)
VRP	−0.45	0.34	**−0.67**	−0.42	**−0.33**	−0.08	**−0.80**	**−0.29**
	(−0.68)	(1.17)	(−2.34)	(−0.99)	(−2.62)	(−0.57)	(−1.99)	(−2.33)
Commodity Market Factors								
Average	0.09	**3.07**	2.35	−0.99	0.45	**−2.02**	1.61	−2.08
	(0.08)	(2.61)	(1.68)	(−1.38)	(0.73)	(−2.06)	(0.67)	(−1.64)
Momentum	1.84	−0.93	−0.90	0.16	0.37	0.65	−2.18	0.70
	(1.35)	(−1.36)	(−1.54)	(0.40)	(1.02)	(1.03)	(−1.91)	(1.16)
Carry	−3.22	−0.02	0.12	−0.60	−1.04	0.91	0.33	0.20
	(−1.23)	(−0.02)	(0.12)	(−1.51)	(−1.76)	(0.54)	(0.46)	(0.20)
Equity Market Factors								
VIX	0.00	0.00	0.00	**−0.01**	**−0.01**	0.00	**−0.02**	0.00
	(−1.18)	(0.00)	(−1.37)	(−3.64)	(−2.89)	(−0.82)	(−2.34)	(−1.72)
LTRTSP	0.30	0.40	−0.13	**1.66**	0.17	0.15	2.41	**2.55**
	(0.76)	(1.22)	(−0.36)	(2.66)	(0.47)	(0.26)	(1.66)	(3.40)
SP500	1.44	−0.05	−0.62	0.06	**−0.92**	1.19	−0.94	0.25
	(0.94)	(−0.09)	(−1.37)	(0.13)	(−2.00)	(1.76)	(−1.48)	(0.33)
R^2	0.63	67.62	52.86	48.67	76.84	10.31	27.48	54.44

Chapter 5

Market Power and Systematic Risk*

5.1 Introduction

Competition between firms and the lack thereof is one of the most important recent topics both in the academic literature and in the financial press. The Economist, for example, states that analogous to "Physicists' quest for a 'theory of everything'" the "leading economic theory of everything is that competition has weakened as markets have become more concentrated."[1]

In a number of studies market power is linked to various macroeconomic trends in the economy: E.g., a decrease in labor share (Autor et al., 2020), lower investment and lower productivity growth (Covarrubias et al., 2020), an increase in capital share, a decrease in low-skill wages, a decrease in labor force participation, a decrease in labor flows, and a decrease

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[1] The Economist April 6th 2019, Article: "The IMF adds to a chorus of concern about competition".

in migration rates (De Loecker et al., 2020), lagging innovation and a slowdown in aggregate output (Bae et al., 2021). Cairó and Sim (2020) show that these effects can be generated by market power in product and labor markets and can lead to financial instability.

Even more obvious than the impact on the aggregate economy, market power has strong implications for individual firms. Firms with market power can limit production or refrain from investment. This leads to a higher stability of cash flows, and lower idiosyncratic volatility (Gaspar and Massa, 2006; Hoberg and Phillips, 2010b; De Loecker et al., 2020; Gutiérrez and Philippon, 2019).

Several previous studies examine the relation between market power and systematic risk on a theoretical basis.[2] Depending on the assumptions made, the model predictions range from no clear effect (e.g., Peyser, 1994; Wong, 1995; Alexander and Thistle, 1999) to a negative relation between the two (e.g., Subrahmanyam and Thomadakis, 1980; O'Brien, 2011). Empirical studies appear to similarly be in disagreement, with some documenting a negative effect (e.g., Sullivan, 1978; Binder, 1992). However, for every study documenting a negative relation, there seem to be as many studies detecting no relation at all (e.g., Curley, Hexter, and Choi, 1982; Moyer and Chatfield, 1983; Bernier, 1987; Abdoh and Varela, 2017). Thus, based on the literature, there might or might not be a (weak?) negative relation between market power and firm betas.

In this study, we comprehensively reexamine this issue. We use the measure of total product market similarity, introduced by Hoberg et al. (2014), that arguably captures market power at the firm level substantially better than the measures used in previous studies, such as the industry-wide sales concentration and even rougher measures like firm size or Tobin's q.[3] We use panel regressions and account for firm- and year-fixed effects as well as several

[2]In this paper, we use the terms "systematic risk" and "market beta" interchangeably.

[3]The industry sales concentration measure does not account for unobserved competition in the product market and does not account for a changing competitive environment. Companies are assigned a North American Industry Classification System (NAICS) classification, but can be competing against companies in different industries. Thus, the industry sales concentration is at best a noisy proxy for market power. The

other control variables that potentially determine market beta. Our main finding is that total product market similarity is significantly negatively related to market betas. The results are not only statistically but also economically significant. For example, the difference between the market beta of a company with a total product market similarity that is two standard deviations below the average to an otherwise similar company with average total product market similarity amounts to up to 0.26, which implies a substantial difference in expected returns and, thus, the cost of capital.

To examine any impact of the recent downward trend in competition, we analyze different subsamples. We find that the effect of a two-standard-deviation decrease in market power from the average on market betas increases more than threefold when comparing the post-2005 period to the first 16 years of our sample period between 1989 and 2004. Thus, (i) the effect of market power on betas appears to be substantially stronger in the current low-competition market environment. (ii) This result delivers an explanation for the conflicting results of previous studies: the effect was substantially weaker. Although we observe an effect in the earlier sample with the total product market similarity, it is more difficult to find the effect using the traditionally adopted proxies for market power. These proxies seem to contain more noise and are more inaccurate with regard to the true competition a firm faces.

We can also establish causality in the market power–beta relationship by analyzing the effect of anti-competitive mergers on market betas. If market power causally leads to lower market betas, the announcement of an anti-competitive merger should lead to a significant drop in a firm's market beta estimates. This is exactly what we find. While controlling for other effects, market betas are indeed substantially depressed after a merger announcement.

total product market similarity measure, on the other hand, also takes into account possible cross-industry competition in the product market. A measure of product market competition should be better suited to capture the demand elasticity, which is what Subrahmanyam and Thomadakis (1980) identify as the main link of market power with systematic risk.

Analyzing the relationship in more detail, we show that the starkest drop indeed occurs directly after the announcement.

We take several steps to further analyze the market power-beta relation. First, we follow Campbell and Vuolteenaho (2004) to decompose betas into parts due to cash-flow and discount-rate news. We find that it is mainly the discount rate beta that is affected by market power. Thus, firms that face only little competition appear to be partly insulated from aggregate discount-rate shocks. Second, a decomposition into upside and downside betas as proposed by Ang, Chen, and Xing (2006a) helps us to pin down the differential effects of market power on market betas in bull and bear markets. Third, we analyze the effect of market power on tail risk, documenting a significant negative relation. Thus, firms with high market power do not only have lower systematic risk, but also less left tail risk.

Finally, we perform several tests to document the robustness of these results. For a large variety of measures and alternative beta estimators we obtain qualitatively similar results.

The implications of our findings are profound: firms that thrive and face low competition in their product markets also appear to have lower costs of equity capital. Lower costs of capital for the most powerful companies further increases their competitive advantage. Thus, concentration in product markets appears to be partly self-reinforcing. Our findings thus joins the chorus calling on policymakers to tighten anti-trust rules and promote competition.

Based on different assumptions, existing theoretical models make differential predictions about the market power–beta relation. Subrahmanyam and Thomadakis (1980) and Chen, Cheng, and Hite (1986) use a model with imperfectly competitive markets and show that market beta is inversely related to market power. Binder (1992) uses a model with perfect competition and differences in productive efficiency, showing that more efficient firms may have lower betas. Thus, findings of lower betas in more concentrated industries need not necessarily be due to market power. Peyser (1994) develops a model with price and wage uncertainty, showing that there is a negative relationship between market power and beta only if wage uncertainty is neglected. Wong (1995) shows that in a Cournot oligopoly model, the negative market power–beta relation results only when the production technologies are homogeneous across firms. Alexander and Thistle (1999) use a product market oligopoly model and argue that a negative relationship between beta and measures like size, concentration, or Tobin's q need not be due to market power in the product market. Finally, O'Brien (2011) assumes isoelastic demand and Cobb–Douglas capital and labor production functions and obtains a negative market power–beta relation.

On the empirical side, Sullivan (1978) was one of the first to document a negative relation between market power and market betas. Using a different sample of firms, Curley et al. (1982), however, obtain no significant relationship. In subsequent studies, findings of a significant negative market power–beta relation appear to be the exception rather than the rule. Binder (1992) documents that market betas are negatively related to a firm's size and concentration. On the other hand, Moyer and Chatfield (1983), Bernier (1987), and Abdoh and Varela (2017) find little evidence of such a relationship.

We contribute to this literature by comprehensively reexamining the question whether market power impacts firms' market betas. Relative to the previous literature, our study provides three main advances. First, we are able to use a measure that arguably captures market power in product markets substantially better than those used in the previous literature. Second, our sample years cover the recent low-competition period. Our findings of a substantially stronger relation based on the total product market similarity measure and in the recent low-competition environment help reconcile the results of previous studies: The measures are too rough to detect the then-weaker effect. Finally, we use anti-competitive mergers to establish the causality of the relationship. This is of particular importance because, as described above, there is disagreement across theoretical models about whether the effect can indeed be ascribed to market power. We show that it can.

We also contribute to the literature on the determinants of market betas. Fama and

French (1997), Grundy and Martin (2001), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Cosemans, Frehen, Schotman, and Bauer (2015), and Chincarini, Kim, and Moneta (2020), among others, relate market betas to several firm-specific variables. By resolving the ambiguity in the results of the previous literature, we document that market betas clearly depend not only on the firm itself but also on its competitive environment in product markets.

Finally, we add to the literature on the impact of sales concentration and market power on realized stock returns. According to Schumpeter (1912), creative destruction through innovation is more likely in competitive industries. Thus, firms that face more competition are likely more risky. Hence, Schumpeter (1912) predicts that these firms should also earn higher returns. Consistent with Schumpeter's final conjecture, Hou and Robinson (2006) show that firms in more concentrated industries earn lower returns.[4] Ali et al. (2008), however, find that these results do not prevail when using a concentration measure augmented with Census data on private companies. Our focus on market betas complements these previous studies. Explaining (market) betas has not been a focus in these studies. While the relation between concentration/market power and realized stock returns does not seem to be entirely clear, we show that market power is clearly related to systematic risk. Hence, market power is related to expected returns if expected returns are related to systematic risk measured by the covariate with the market portfolio, such as in the Capital Asset Pricing Model (CAPM) but also in many other models. Our results also prevail when accounting for the effect of private companies. We thus contribute to the literature by showing that market power affects a firm's cost of equity capital, which likely has a self-reinforcing effect.

The remainder of the paper is organized as follows: In Section 5.2, we present the data,

[4]Jory and Ngo (2017) document similar results and show that those firms with high market power earn higher returns than those with low market power, even when controlling for industry sales concentration. However, Jory and Ngo (2017) use the same methodology as Hou and Robinson (2006) and do not consider the critique raised by Ali, Klasa, and Yeung (2008).

the main variables, and their summary statistics. Section 5.3 presents the results of panel regressions on the relation of market power and market betas. In Section 5.4, we use an analysis of mergers and acquisitions to establish a causal relationship. Section 5.5 digs deeper by analyzing several partial betas and tail risk. In Section 5.6, we analyze the robustness of our main results. Section 5.7 concludes. The Appendix contains further details on the estimation of the variables used in this study.

5.2 Data and Methodology

5.2.1 Data

The main data used in this study comes from the Center for Research in Security Prices (CRSP) and Compustat. We obtain data on returns, prices, and shares outstanding, as well as on several accounting items for all companies in the (merged) datasets. Details on the construction of all variables can be found in Appendices D1.1–D1.4. Our main sample period is 1989 until 2019, based on the availability of the main market power measure used in this study.

We use the merger dataset by Thompson Reuters EIKON, obtaining all mergers of companies in the United States. We calculate tail risks based on the interpolated Volatility Surface from OptionMetrics for all available companies and match them with the other datasets. The options data set begins in 1996 and ends in 2019, which constrains the analysis for tail risk to this period.

We estimate the value spread based on data from Kenneth French's webpage.[5] Additionally we obtain the price-earnings ratio from Robert Shiller's webpage and the term yield spread from Amit Goyal's webpage.[6]

[5] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[6] The corresponding URLs are `http://www.econ.yale.edu/~shiller/data.htm` (Robert Shiller) and

5.2.2 Main Variables

Market Power

The main measure of market power we use is the total product market similarity (*tsimm*) proposed by Hoberg and Phillips (2010a, 2016).[7] This measure is based on a text analysis of the business descriptions in annual 10-K forms. In particular, the authors focus on the firms' product text descriptions and form text-based network industry classifications (TNIC). They generate a matrix that includes the pairwise product cosine similarities across all firms in a given year. The bivariate cosine similarity is higher the more two firms tend to use the same words to describe their products.[8] The total similarity measure is then calculated as the sum of all bivariate cosine similarities of a firm in a given year. Thus, *tsimm* measures the intensity of competition a firm faces in its product markets. It is therefore an inverse measure of market power. The higher the product market similarity, the more competition a firm faces for its products. On the other hand, a low product market similarity indicates low competition and, hence, high market power.

For robustness, we also use the traditional industry sales concentration Herfindahl-Hirschman Index (HHI). To identify the industries, we use the North American Industry Classification System (NAICS) and use whenever available the historical NAICS from Compustat. When this is missing, we fill the remaining NAICS classifier following Grullon, Larkin, and Michaely (2019). We explain this in more detail in Appendix D1.2. Furthermore, we also use the TNIC HHI measure of Hoberg and Phillips (2016), which assigns industries based on the authors' text-based network classifications instead of the NAICS. In addition, we use the product market fluidity measure of Hoberg et al. (2014), which is

`http://www.hec.unil.ch/agoyal/` (Amit Goyal).

[7] This measure and all other Hoberg–Phillips measures can be obtained from: `https://hobergphillips.tuck.dartmouth.edu/`.

[8] To be more precise, the measure is based on the common usage of nouns. Thereby, the authors discard all words that are used by more than 25% of the firms, as well as geographic words.

a dynamic measure of market power. It is also based on the product descriptions in firms' 10-K files, and captures the cosine similarity between the words a firm uses to describe its products and the aggregate change in the word usage across other firms. Finally, to account for potential effects of the omission of private companies, we also use the fitted HHI measure, adjusted using Census data and provided by Hoberg and Phillips (2010b).[9]

Market Beta

Our main variable of interest is market beta as a measure of systematic risk. To obtain beta estimates, we use a past historical window, regressing an asset's excess return on a constant and the market excess return:

$$r_{i,\tau} - r_{f,\tau} = \alpha_{i,t} + \beta^M_{i,t}(r_{M,\tau} - r_{f,\tau}) + \epsilon_{i,\tau}, \tag{5.1}$$

where $\beta^M_{i,t}$ is the estimate for the market beta of asset i at time t. We use data from time $t-k$ to t, observed at discrete intervals τ, with k denoting the length of the past historical window. $r_{i,\tau}$, $r_{M,\tau}$, and $r_{f,\tau}$ denote the return of asset i, the return of the market portfolio, and the risk-free asset, respectively, all observed at time τ. We use the CRSP-value-weighted index as proxy for the market return and the 1-month Treasury bill rate from Kenneth French's website to proxy for the risk-free rate. To obtain conditional betas, we use an exponential weighting scheme and estimate Equation (5.1) with weighted least squares (WLS). The weights are $\frac{exp(-|t-\tau|\phi)}{\sum_{\tau=1}^{t-1} exp(-|t-\tau|\phi)}$ with $\phi = \frac{log(2)}{\iota}$. ι characterizes the horizon, to which the half-life of the weights converges for large samples. Following Hollstein et al. (2019b) and Hollstein (2020), we set ι to two-thirds of the number of observations of the estimation

[9] The authors use Census data on private companies in the manufacturing industry. For these companies they fit a model regressing the HHI measure including private companies on the Compustat HHI measure and two employment measures. They use the fitted coefficients of this regression to estimated the adjusted HHI measure ($fithhi$) for all industries. Based on the availability of the fitted measure, this analysis is limited to the period 1989 until 2005.

window.

For our main analysis, we estimate beta with monthly data, using a window of $k = 60$ months. For robustness, we also consider an unweighted beta as well as the shrinkage estimator of Vasicek (1973). In addition, we use an estimator with $k = 12$ months of daily data. The results for all these are qualitatively similar (see Section 5.6).

Partial Betas, Semivariances, and Tail Risk

To refine our analysis, we separate market betas into cash-flow and discount-rate betas ($\beta_{i,t}^{CF}$ and $\beta_{i,t}^{DR}$), as defined by Campbell and Vuolteenaho (2004). In addition, we also separate market betas into downside and upside betas ($\beta_{i,t}^{Down}$ and $\beta_{i,t}^{Up}$), as defined by Ang et al. (2006a). We estimate the betas in the following way:

$$\begin{aligned}
\beta_{i,t}^{CF} &= \frac{Cov(r_{i,t}, \widehat{N}_{CF,t})}{Var(\widehat{N}_{CF,t} - \widehat{N}_{DR,t})}, \\
\beta_{i,t}^{DR} &= \frac{Cov(r_{i,t}, -\widehat{N}_{DR,t})}{Var(\widehat{N}_{CF,t} - \widehat{N}_{DR,t})}, \\
\beta_{i,t}^{Down} &= \frac{Cov(r_{i,t}, r_{m,t} \mid r_{m,t} < r_{f,t})}{Var(r_{m,t} \mid r_{m,t} < r_{f,t})}, \text{ and} \\
\beta_{i,t}^{Up} &= \frac{Cov(r_{i,t}, r_{m,t} \mid r_{m,t} > r_{f,t})}{Var(r_{m,t} \mid r_{m,t} > r_{f,t})},
\end{aligned} \tag{5.2}$$

where $\widehat{N}_{CF,t}$ and $\widehat{N}_{DR,t}$ denote the parts of the market return related to cash-flow and discount-rate news, as defined in Appendix D1.3. All other variables are as previously defined. We also use WLS based on the same weight specification to obtain the partial betas.

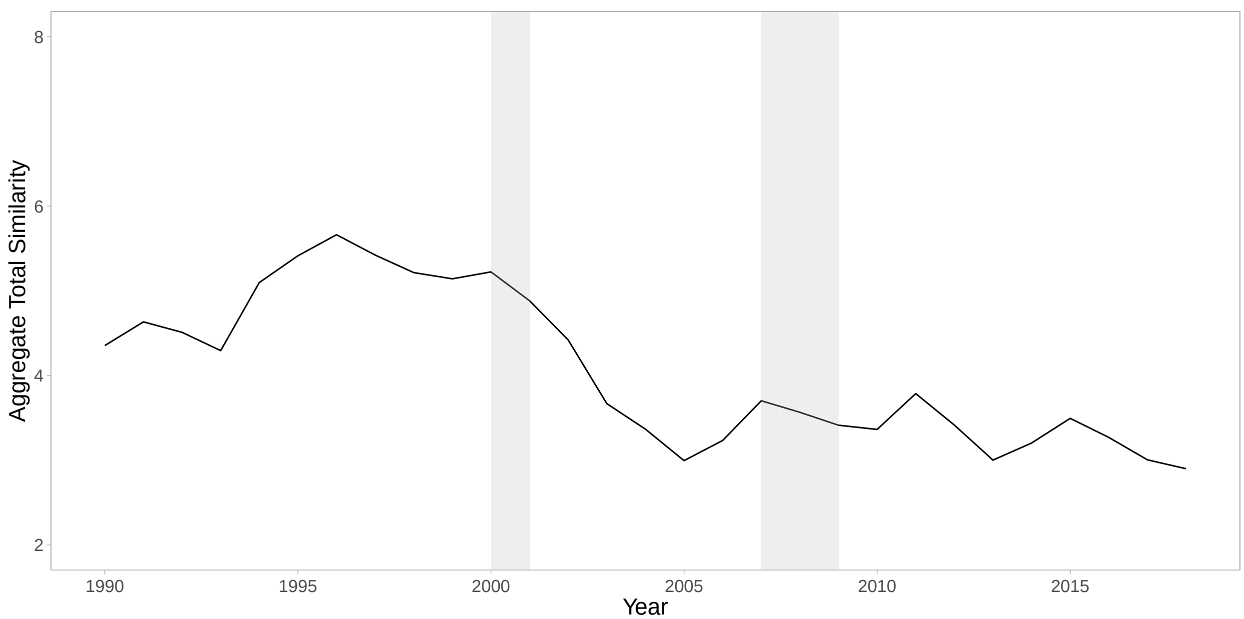
For a further analysis, we also use various firm-specific risk measures. We estimate tail risk following Bollerslev and Todorov (2011a). The Bollerslev and Todorov (2011a) tail risk measure is shown to perform better than others for both predicting tail risks and the associated risk premia (Dierkes et al., 2021). We present a more detailed description of the implementation of the tail risk measure in Appendix D1.4.

5.2.3 Summary Statistics

In Figure 5.1, we show the average sales-weighted total product market similarity. We observe a decline over time, indicating that the entire market has grown less competitive over time. The decline in competitiveness occurred mainly from 1995 until 2004. Around 2004 the aggregate total product market similarity appears to reach a new, permanently lower level. Afterwards, it fluctuates around this level.

Figure 5.1: Aggregate Total Product Market Similarity Time Series

This figure displays the sales-weighted cross-sectional average total product market similarity. Each year, we aggregate the monthly observations of total product market similarity by weighting each company's measure with the share of its sales across all sample companies that year. We thus obtain an aggregate measure of market power in the product market. We highlight in grey the business cycle contractions, as defined by the National Bureau of Economic Research (NBER).



In Table 5.1, we present the summary statistics for the main variables used in this study. The total product market similarity measure ($tsimm$) has a mean of 3.80 and an average cross-sectional standard deviation of 6.04. Its distribution is characterized by positive skewness and high kurtosis. Thus, a substantial share of the stocks appears to have extreme values of total product market similarity. For the natural logarithm of the industry sales concentration (HHI) measure, the mean is 6.48. Its standard deviation is substantially smaller with 0.75 than that for the total product market similarity . This is likely because the HHI measure is constant within industries.

Table 5.1: Summary Statistics

This table presents summary statistics of the main variables used in this study. These include the total product market similarity ($tni3simm$), industry sales concentration ($log(HHI)$), market beta (β^M), as well as partial betas, and tail risk. β^{CF} is the cash-flow beta, β^{DR} the discount-rate beta, β^{Up} is the beta if the market moves up, and β^{Down} is the beta when the market moves down. All betas are calculated with WLS based on monthly data and an estimation window of 60 months. LT and RT are the left and right tail risk measures. $Mean$ denotes the sample average, SD indicates the standard deviation of the sample, $Median$ denotes the median of the sample, Min the minimum, and Max the maximum. $Skewness$ and $Kurtosis$ present the third and fourth central moments of the distributions. All numbers presented are time-series averages of the cross-sectional summary statistics.

	$Mean$	SD	$Median$	Min	Max	$Skewness$	$Kurtosis$
$tsimm$	3.80	6.04	1.55	1.00	77.05	4.48	34.67
$log(HHI)$	6.48	0.75	6.36	4.97	9.24	0.67	3.36
β^M	1.14	0.78	1.04	−2.45	6.19	0.74	6.61
β^{CF}	0.19	0.26	0.17	−2.36	2.16	0.04	15.84
β^{DR}	0.86	0.64	0.79	−2.34	5.37	0.76	7.10
β^{Up}	0.33	0.46	0.29	−2.57	4.39	0.93	12.83
β^{Down}	0.62	0.64	0.58	−3.50	8.69	1.87	51.00
LT	0.25	0.20	0.20	0.01	1.84	2.50	15.06
RT	0.25	0.22	0.19	0.00	1.85	2.26	12.14

The average market beta is 1.14.[10] The average cross-sectional standard deviation is 0.78 and the market beta distribution is also positively skewed and characterized by positive excess kurtosis. Among the partial betas, the average level of the discount-rate beta is higher than that of the cash-flow beta, consistent with Campbell and Vuolteenaho (2004).[11]

[10]It is not exactly one because we report the equally weighted average across the stocks. The value-weighted average beta is exactly one by definition when considering all stocks in the market.

[11]Note that the cash-flow and discount-rate betas add up to the beta with respect to the unexpected market return, as shown by Campbell and Vuolteenaho (2004). Since we use the standard beta definition with the "raw" market return, and not that with respect to the unexpected market return, the sum of the

Downside beta has a higher average than upside beta, which is also consistent with Ang et al. (2006a). The distributions of all partial betas are also characterized by a positive skewness and high excess kurtosis.

Left and right tail risk have the same size. Empirically the left hand side for individual stocks is driven more by market wide events, compared to the right hand side (Lin and Todorov, 2019).

Table 5.2 further presents the correlations between the main variables used in this study. Consistent with our motivation, the magnitude of the correlation between the total product market similarity and industry sales concentration measures is rather small with -0.24. The negative correlation is consistent with the diverse interpretation of the two measures. While the industry sales concentration is a direct measure, the total product market similarity is an inverse measure of market power. The small magnitude of the correlation is in part a reflection of the constancy within an industry of the industry sales concentration measure. Since the competitors for the total product market similarity measure are identified based on the product descriptions, there is also substantial variation in the measures within industries. Both measures of market power are largely uncorrrelated with all control variables. None of these correlations exceeds a magnitude of 0.1.

cash-flow and discount-rate betas does not exactly match with the market beta.

Table 5.2: Correlations

This table presents the pairwise correlations of the total product market similarity ($tsimm$) and industry sales concentration ($log(HHI)$) measures with all control variables used in this study. Detailed definitions of the control variables are in Appendix D1.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) $tsimm$	1.00															
(2) $log(HHI)$	−0.24	1.00														
(3) $log(Age)$	−0.10	−0.05	1.00													
(4) $log(AT)$	0.06	−0.01	0.41	1.00												
(5) $Default\ spread$	−0.01	0.03	0.04	0.09	1.00											
(6) $Dividend$	−0.08	−0.02	0.44	0.46	−0.01	1.00										
(7) $Financial\ leverage$	0.04	0.02	−0.01	0.04	0.04	−0.02	1.00									
(8) $log(Firm\ size)$	0.08	−0.05	0.36	0.88	0.05	0.42	−0.09	1.00								
(9) $Illiquidity$	−0.02	0.03	−0.01	−0.11	−0.01	−0.02	0.03	−0.14	1.00							
(10) $Investment\ rate$	0.00	−0.01	−0.00	0.00	0.00	0.00	0.01	0.00	−0.00	1.00						
(11) $iVol$	0.09	−0.02	−0.37	−0.52	−0.00	−0.48	0.05	−0.48	0.04	0.00	1.00					
(12) $log(Mkt/Book)$	0.10	−0.07	−0.07	−0.01	−0.10	−0.04	−0.17	0.28	−0.07	−0.00	0.08	1.00				
(13) $Momentum$	−0.02	0.01	0.03	0.00	−0.08	0.01	−0.02	0.15	0.00	−0.00	−0.00	0.03	1.00			
(14) $Operating\ leverage$	0.00	−0.00	0.00	0.01	−0.01	0.00	−0.00	0.01	−0.01	−0.00	−0.00	0.00	0.00	1.00		
(15) q	0.05	−0.03	−0.02	−0.02	−0.01	−0.02	−0.01	0.02	−0.01	0.00	0.04	0.07	0.03	0.00	1.00	
(16) ROE	−0.03	0.01	0.03	0.03	−0.00	0.03	−0.01	0.03	0.00	0.00	−0.06	−0.14	0.01	−0.00	−0.00	1.00

5.3 Market Power and Market Betas

In this section, we estimate the effects of market power on beta in a contemporaneous panel regression. For this analysis, we use year and firm fixed effects and double-cluster the standard errors at the industry and year levels.

The following regression describes our main setup:

$$\beta^M_{i,t} = \gamma_1 tsimm_{i,t} + \gamma_2 tsimm^2_{i,t} + \theta_1 HHI_{i,t} + \theta_2 HHI^2_{i,t} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t}, \qquad (5.3)$$

where $tsimm_{i,t}$ is the total product market similarity of company i at time t. $HHI_{i,t}$ denotes the Herfindahl-Hirschman Index of sales concentration in the NAICS industry of company i at time t. Dalton and Penn (1976), investigate the relation between profitability and concentration, and suggest that there is a concentration threshold. To account for potential non-linearities, we therefore include the orthogonal second order polynomial of both market power variables in the regression. $C_{i,t}$ is a vector including all control variables, which are described in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_y is a set of dummy variables capturing year fixed effects and α_i a set of dummy variables capturing firm fixed effects. $\epsilon_{i,t}$ is the regression residual for firm i in month t.

Note that in order to analyze the robustness of the results and study the potential causes of the differential results obtained by the previous literature, we include both our main measure *tsimm* and the traditional HHI industry sales concentration. We examine both measures first in separate regressions and then in one comprehensive regression.

We begin the analysis with panel regressions of market betas on total product market similarity. We present the results in Table 5.3. In a single regression of market betas on total product market similarity (column (i)), we obtain a highly significant positive coefficient of

0.060. The coefficient on the orthogonal square of total product market similarity is -0.034. Thus, (i) firms with higher market power tend to have lower market betas. (ii) The effect is not linear and substantially stronger for firms with low total product market similarity and, hence, high market power. Economically, the effect is large. A company with total product market similarity two standard deviations below the average has a market beta that is 0.26 lower compared to an otherwise similar company with average total product market similarity.[12]

A single regression with the HHI industry sales concentration measure (column (ii)) yields qualitatively similar insights. As the industry sales concentration increases, the market betas of the firms in the industry decrease significantly. However, the analysis also delivers one indication for why the results of the previous literature may vary across studies: Based on the HHI, the relation is both statistically and economically weaker than based on the total product market similarity measure. A two-standard-deviation increase in the HHI measure from its mean only implies a decrease in market betas of 0.06.[13] This finding underlines the notion that accurate measurement of market power is important. Nevertheless, with our main empirical setup and based on a large sample spanning almost 30 years, we are also able to uncover a significant relationship based on the more imprecise HHI industry sales concentration measure.

[12] We obtain this figure as follows. The *tsimm* measure is standardized, so that unit changes can be interpreted as changes in the measure by one standard deviation. The figure in the text can be obtained as $0.060 \cdot (-2) - 0.034 \cdot (-2)^2 = -0.256$. The effect of a two-standard-deviation increase in the total product market similarity from the mean, on the other hand, has very little impact on the firm's market beta: $0.060 \cdot 2 - 0.034 \cdot 2^2 = -0.016$.

[13] Note that since the HHI is a direct, rather than an inverse measure of market power, we examine the effect of an increase in the measure. The interpretation is similar to that for a decrease in the total product market similarity, which is an inverse measure of market power. The figure in the text can be obtained by $-0.047 \cdot 2 + 0.008 \cdot 2^2 = -0.062$.

Table 5.3: Market Power and Market Beta

This table presents the results of a regression of firms' market betas on measures of market power as well as several control variables. Conditional market betas are calculated via WLS based on the past 60 months of monthly returns. As measures for market power, we use the total product market similarity ($tsimm$) as well as the natural logarithm of the HHI industry sales concentration measure. We include the measures as well as their orthogonal squares. The regression equation is:

$$\beta^M_{i,t} = \gamma_1 tsimm_{i,t} + \gamma_2 tsimm^2_{i,t} + \theta_1 HHI_{i,t} + \theta_2 HHI^2_{i,t} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables, detailed definitions of which are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_i and α_y are dummy variables that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the total number of observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(i)	(ii)	(iii)	(iv)	(v)
$tsimm$	0.060***		0.044***		0.041***
	(4.641)		(4.720)		(4.765)
$tsimm^2$	−0.034**		−0.021*		−0.020*
	(−2.527)		(−1.900)		(−1.875)
$log(HHI)$		−0.047**		−0.044**	−0.041**
		(−2.293)		(−2.555)	(−2.508)
$log(HHI)^2$		0.008		0.006	0.005
		(0.677)		(0.591)	(0.546)
$log(Age)$			−0.092**	−0.093***	−0.094***
			(−2.738)	(−2.758)	(−2.875)
$log(AT)$			0.186***	0.194***	0.184***
			(4.910)	(5.053)	(4.925)
$Default\ spread$			0.003	0.003	0.003
			(0.597)	(0.591)	(0.558)
$Dividend$			−0.092***	−0.094***	−0.092***
			(−4.378)	(−4.438)	(−4.339)
$Financial\ leverage$			0.009	0.009	0.009
			(1.460)	(1.445)	(1.455)
$log(Firm\ size)$			0.032	0.030	0.031
			(0.919)	(0.856)	(0.887)
$Illiquidity$			−0.020***	−0.020***	−0.020***
			(−6.750)	(−7.088)	(−6.687)
$Investment\ rate$			0.001	0.001	0.001
			(0.406)	(0.325)	(0.376)
$iVol$			0.336***	0.338***	0.336***
			(9.557)	(9.563)	(9.587)
$log(Mkt/Book)$			0.013	0.014	0.013
			(1.037)	(1.109)	(1.018)
$Momentum$			−0.027*	−0.027*	−0.027*
			(−1.968)	(−1.959)	(−1.950)
$Operating\ leverage$			0.005**	0.005**	0.005**
			(2.742)	(2.566)	(2.583)
q			−0.003	−0.004	−0.004
			(−0.910)	(−1.048)	(−0.960)
ROE			0.002	0.001	0.001
			(0.485)	(0.476)	(0.456)
R^2	55.44	55.36	60.26	60.25	60.32
$NObs$	1,011,287	1,011,287	1,011,287	1,011,287	1,011,287
FE	Yes	Yes	Yes	Yes	Yes

When controlling for other potential determinants of market betas, the results are qualitatively similar (columns (iii) to (v)). The impact of total product market similarity on the market betas is positive, statistically significant, and economically large. In addition, the significant negative coefficient on its square indicates that the effect is larger for low-total product market similarity firms. For the industry sales concentration measure, the regression coefficient is also significantly negative.

Finally, when including both the total product market similarity measure and the industry sales concentration measure, both yield statistically significant coefficients. This result underlines that market power has a negative impact on a firm's market beta. Furthermore, the fact that both the total product market similarity and the industry sales concentration measures impact market betas indicates that both measures capture different aspects of market power.

The effects of the control variables on market betas are consistent with those documented in the literature. Age has a significant negative impact, consistent with Chincarini et al. (2020). Furthermore, the firm's total assets positively affect market betas. Paying a dividend and stock-level illiquidity appear to decrease a firm's beta. Idiosyncratic volatility, on the other hand, appears to have a positive impact on market betas. Operating leverage positively affects market betas, as in Cosemans et al. (2015). Momentum has a weak negative effect on betas, consistent with the results of Grundy and Martin (2001).

To shed further light on the differential results documented in the previous literature, we analyze subsample periods. That is, we split the sample roughly by half into a period before 2005 and one starting from 2005. The time of the sample split broadly coincides with the shift in aggregate total product market similarity to a lower level in the years starting around 2005, which is visible from Figure 5.1. In an overall less competitive environment, the effect of market power on beta might also be stronger.

Indeed, the results presented in Table 5.4 show exactly that. In the first half of our sample period until the end of 2004 the effect of market power on beta is substantially weaker than in the more recent sample period starting from 2005. We observe a significant positive effect for our main measure, the total product market similarity, during the first half of the sample period. The effect, however, is both economically and statistically weaker than for the full sample period (see Table 5.3). More importantly, for the industry sales concentration measure, there is no effect discernible during the first part of the sample period. This analysis is thus informative about why the previous literature presents differential findings: (i) The effect of market power on betas was not that large and (ii) the industry sales concentration appears to be too rough a measure of market power to be able to pick it up. This is likely why most previous studies fail to document a significant effect based on the industry sales concentration or other imprecise market power proxies. For an arguably better measure, the total product market similarity, we show that there is a significant effect even in the early years.

The picture changes strongly for the second part of the sample period. The impact of total product market similarity on market beta is substantially stronger, both economically and statistically. The impact of a two-standard-deviation decrease from the mean increases more than threefold for the more recent period.[14] Interestingly, for the 2005-onward period, we cannot reject that the effect is linear. The coefficient on the square of total product market similarity is small and not statistically significant. Finally, even with the industry sales concentration measure, the relation between market power and market betas is clearly discernible.

[14] To see this, calculate the impact of a two-standard-deviation decrease from the mean in both cases. The figure for the pre-2005 period can be obtained, for example for column (*iii*) as $0.020 \cdot (-2) - 0.012 \cdot (-2)^2 = -0.088$. The corresponding figure for the period starting in 2005 is $0.098 \cdot (-2) - 0.018 \cdot (-2)^2 = -0.268$.

Table 5.4: Market Power and Market Beta - Subsample Analysis

This table presents the results of a regression of firms' market betas on measures of market power. In contrast to the main analysis, we split the sample into two subsamples, one before and one starting from 2005. Conditional market betas are calculated via WLS based on the past 60 months of monthly returns. As measures for market power, we use the total product market similarity ($tsimm$) as well as the natural logarithm of the HHI industry sales concentration measure. We include the measures as well as their orthogonal squares. The regression equation is:

$$\beta^M_{i,t} = \gamma_1 tsimm_{i,t} + \gamma_2 tsimm^2_{i,t} + \theta_1 HHI_{i,t} + \theta_2 HHI^2_{i,t} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables ($Controls$), detailed definitions of which are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_i and α_y are dummy variables that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the total number of observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(i)	(ii)	(iii)	(iv)	(v)
Before 2005					
$tsimm$	0.034^{***}		0.020^{*}		0.019^{*}
	(3.135)		(1.948)		(1.871)
$tsimm^2$	-0.021^{*}		-0.012		-0.011
	(-2.120)		(-1.451)		(-1.389)
$log(HHI)$		-0.024		-0.021	-0.020
		(-1.269)		(-1.250)	(-1.207)
$log(HHI)^2$		0.007		0.004	0.004
		(0.660)		(0.536)	(0.516)
R^2	64.53	64.50	66.35	66.35	66.36
$NObs$	$576,784$	$576,784$	$576,784$	$576,784$	$576,784$
$Controls$	No	No	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes
From 2005					
$tsimm$	0.128^{***}		0.098^{***}		0.092^{***}
	(4.315)		(4.525)		(4.660)
$tsimm^2$	-0.031		-0.018		-0.019
	(-1.381)		(-1.072)		(-1.122)
$log(HHI)$		-0.108^{***}		-0.076^{***}	-0.069^{***}
		(-3.213)		(-3.282)	(-3.171)
$log(HHI)^2$		0.054		0.044	0.039
		(1.634)		(1.561)	(1.481)
R^2	58.14	58.09	64.20	64.16	64.30
$NObs$	$434,503$	$434,503$	$434,503$	$434,503$	$434,503$
$Controls$	No	No	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes

5.4 Mergers and Acquisitions

To establish a causal relationship between market power and systematic risk, we examine mergers and acquisitions. The main idea of this analysis is, that, if a firm's systematic risk is causally related to market power, then an event that increases a firm's market power should have an immediate negative effect on its market beta. Mergers and acquisitions (within an industry) provide such an event. A large literature shows both theoretically and empirically how horizontal mergers are used to increase the market power of incumbent firms (Stigler, 1950, 1964; Perry and Porter, 1985; Farrell and Shapiro, 1990; Fathollahi, Harford, and Klasa, 2021). Thus, following a merger announcement, we expect to observe a lasting decrease in a firm's market beta.

We only consider completed mergers and acquisitions. Our focus is in particular on anti-competitive mergers that lead to a material change in the degree of economic control an acquiring company exerts on its target.[15] In total, we identify 12,360 such mergers during our sample period. We run the following regression:

$$\beta^M_{i,t} = \gamma_1 M^D_{i,t} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t}, \tag{5.4}$$

where $M^D_{i,t}$ is a dummy, which is one starting from the month during which the merger is announced as well as and for the next 24 months after the announcement and zero at all other times.[16] We limit the time the post-merger dummy is one because the strongest effects of the merger likely occur during a limited time period, while the competitive environment may change subsequently due to other forces, diluting the immediate effect of the merger

[15] We apply the following restrictions: (1) The acquiring company can at most hold below 10% of the target (the reporting threshold) and needs to at least acquire 50% of the shares during the transaction. (2) The mergers have one of these purposes: "Acquire competitors technology/strategic assets", "Strengthen existing operations/expand presence in primary market", "Strengthen operations", "Create synergies", "Concentrate on core businesses/assets".

[16] For robustness, we also consider other time horizons.

event. All other variables are as previously defined.

We present the results in Table 5.5. Indeed, we find that the market beta declines substantially after the announcement of an anti-competitive merger. The coefficient on the merger dummy in our main specification is -0.049 and strongly significant. Thus, as a company engages in an anti-competitive merger to increase its market power, the beta decreases by 0.05 on average.

Changing the length of $M_{i,t}^{D}$ leads to similar conclusions. We also run a robustness test in which we include all 43,022 mergers in the sample, independent of whether they are flagged as anti-competitive or not. Consistent with what one would expect, the effect is economically weaker, but still statistically significant (results presented in the final column of Table 5.5).

Finally, to further analyze the development of market betas following the merger announcement, we also run a regression with monthly dummy variables, considering both the time before and after the announcement. We present the results in Figure 5.2. We find that indeed the largest drop occurs in the month of the merger announcement. The market betas are significantly lower than 12 months before the announcements. Thus, this further analysis underlines that market power has a negative impact on market betas. The announcement of an anti-competitive merger clearly seems to be the driving force of the decline in beta. We also observe a slight decrease in beta already before the merger announcement. This is likely due to anticipation of the merger based on rumors or merger activity in the same industry, which tends to be clustered (Cai, Song, and Walkling, 2011).

Table 5.5: Merger Analysis

This table presents the results of a regression of the monthly market betas on a dummy (M^D) as in Equation (5.4). The merger dummy is 1 for a certain period after the merger announcement. We only consider completed mergers and acquisitions. Our focus is in particular on anti-competitive mergers, for which we apply the following restrictions: (1) The acquiring company can at most hold below 10% of the target (the reporting threshold) and needs to at least acquire 50% of the shares during the transaction. (2) The mergers have either of these purposes: "Acquire competitors technology/strategic assets", "Strengthen existing operations/expand presence in primary market", "Strengthen operations", "Create synergies", "Concentrate on core businesses/assets". We consider post-merger horizons of 36, 24, and 12 months. In the final column, we consider all mergers without filtering for anti-competitiveness. Detailed definitions of the control variables are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. All panel regressions include dummies that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the number of merger observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

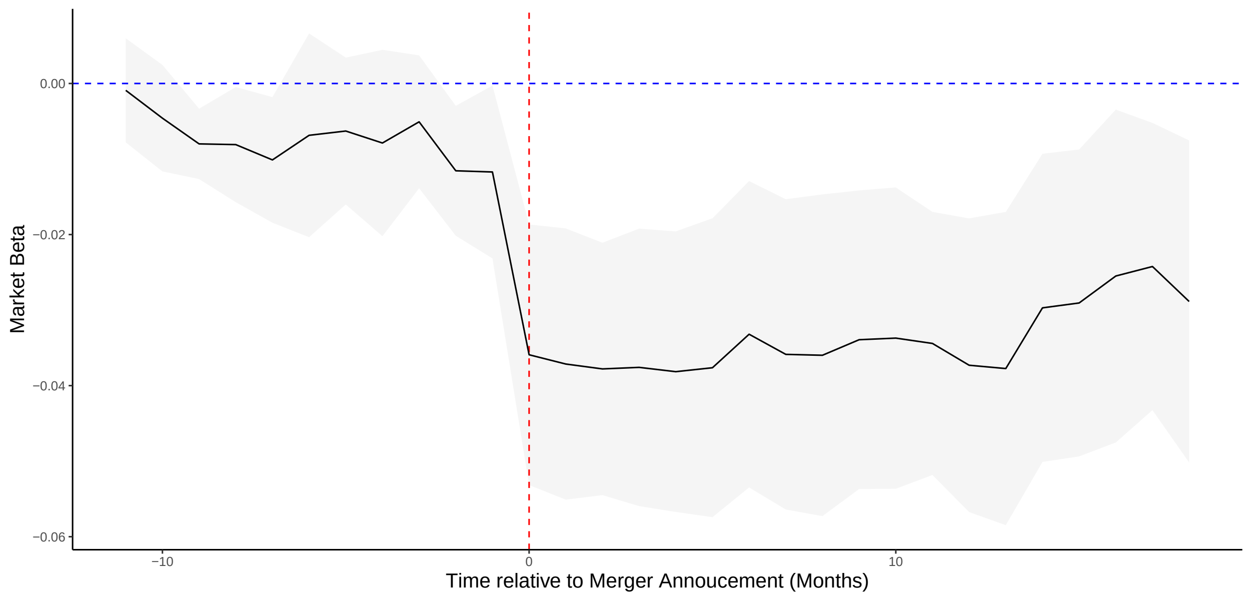
	Anti-Competitive Mergers				All Mergers
	24 $Months$	36 $Months$	60 $Months$	12 $Months$	24 $Months$
M^D	-0.049^{***}	-0.046^{***}	-0.041^{**}	-0.043^{***}	-0.024^{**}
	(-3.817)	(-3.241)	(-2.322)	(-3.316)	(-2.256)
$log(Age)$	-0.093^{**}	-0.093^{**}	-0.093^{**}	-0.092^{**}	-0.092^{**}
	(-2.652)	(-2.657)	(-2.652)	(-2.627)	(-2.632)
$log(AT)$	0.200^{***}	0.201^{***}	0.201^{***}	0.197^{***}	0.198^{***}
	(5.178)	(5.199)	(5.216)	(5.110)	(5.119)
$Default\ spread$	0.003	0.003	0.003	0.003	0.003
	(0.649)	(0.644)	(0.648)	(0.621)	(0.643)
$Dividend$	-0.095^{***}	-0.095^{***}	-0.095^{***}	-0.095^{***}	-0.094^{***}
	(-4.524)	(-4.513)	(-4.503)	(-4.512)	(-4.492)
$Financial\ leverage$	0.009	0.009	0.009	0.009	0.009
	(1.444)	(1.444)	(1.443)	(1.448)	(1.446)
$log(Firm\ size)$	0.034	0.033	0.033	0.033	0.034
	(0.952)	(0.944)	(0.924)	(0.941)	(0.960)
$Illiquidity$	-0.020^{***}	-0.020^{***}	-0.020^{***}	-0.020^{***}	-0.020^{***}
	(-7.023)	(-7.077)	(-7.065)	(-6.976)	(-7.011)
$Investment\ rates$	0.001	0.001	0.001	0.001	0.001
	(0.345)	(0.342)	(0.345)	(0.357)	(0.350)
$iVol$	0.338^{***}	0.338^{***}	0.338^{***}	0.338^{***}	0.338^{***}
	(9.537)	(9.537)	(9.532)	(9.535)	(9.531)
$log(Mkt/Book)$	0.014	0.014	0.014	0.014	0.014
	(1.128)	(1.127)	(1.133)	(1.131)	(1.147)
$Momentum$	-0.028^{*}	-0.028^{*}	-0.028^{*}	-0.028^{*}	-0.028^{*}
	(-1.996)	(-1.989)	(-1.980)	(-1.992)	(-2.002)
$Operating\ leverage$	0.005^{**}	0.005^{***}	0.005^{**}	0.005^{**}	0.005^{**}
	(2.745)	(2.764)	(2.740)	(2.614)	(2.752)
q	-0.004	-0.004	-0.004	-0.004	-0.004
	(-0.998)	(-1.000)	(-1.003)	(-1.000)	(-1.005)
ROE	0.001	0.002	0.002	0.002	0.002
	(0.471)	(0.479)	(0.489)	(0.475)	(0.501)
R^2	60.57	60.57	60.57	60.57	60.56
$NObs$	12,360	12,360	12,360	12,360	43,022
FE	Yes	Yes	Yes	Yes	Yes

Figure 5.2: Merger Dummies over Time

This figure shows the coefficients of γ_{-11} to γ_{18} of the following regression:

$$\beta^M_{i,t} = \phi_0 M^0_{i,j} + \sum_{j=-11}^{-1} \gamma_j M^D_{i,j} + \gamma_0 M^D_{i,0} + \sum_{j=1}^{18} \gamma_j M^D_{i,j} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $\beta^M_{i,t}$ is the market beta of company i at time t, $M^0_{i,j}$ is a dummy variable that is equal to one at all times more than 12 months before and more than 18 months after a merger announcement. $M^D_{i,j}$ is set of monthly dummy variables, which are one in a certain month period j from 11 months before until 18 months after a merger announcement of company i and zero otherwise. $M^D_{i,0}$ is one for the month of the merger announcement. Thus, the firms' betas from 12 months before the merger announcement serve as baseline. The dummy coefficients directly capture the average difference. We plot the coefficients for each dummy variable along with the corresponding 90% confidence interval in the shaded gray area. The standard errors are double-clustered at the industry and year levels. The red vertical line indicates the month of the merger announcement. We show the horizontal zero reference line in blue.



5.5 Partial Betas and Tail Risk

In this section, we further analyze the impact of market power on different parts of market betas. The primary goal is to find out more about the exact economic channel through which market power affects market betas.

Table 5.6: Market Power and Partial Betas

This table presents the results of a regression of firms' partial market betas on measures of market power as well as several control variables. Conditional market betas are calculated via WLS based on the past 60 months of monthly returns. As measures for market power, we use the total product market similarity ($tsimm$) as well as the natural logarithm of the HHI industry sales concentration measure. We include the measures as well as their orthogonal squares. The regression equation is:

$$\beta^X_{i,t} = \gamma_1 tsimm_{i,t} + \gamma_2 tsimm^2_{i,t} + \theta_1 HHI_{i,t} + \theta_2 HHI^2_{i,t} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where X indicates either cash-flow (CF), discount-rate (DR), upside (Up) or downside ($Down$) betas. $C_{i,t}$ is a vector of control variables, detailed definitions of which are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_i and α_y are dummy variables that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the total number of observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	β^{CF}	β^{DR}	β^{Up}	β^{Down}
$tsimm$	0.002	0.036^{***}	0.012^{*}	0.018^{*}
	(0.380)	(5.305)	(1.912)	(1.949)
$tsimm^2$	-0.006^{*}	-0.016^{**}	-0.005	0.011
	(-1.741)	(-2.169)	(-0.949)	(1.071)
$log(HHI)$	-0.001	-0.030^{**}	-0.012	-0.004
	(-0.339)	(-2.364)	(-1.684)	(-0.588)
$log(HHI)^2$	0.001	0.006	-0.001	-0.002
	(0.341)	(0.654)	(-0.437)	(-0.723)
$log(Age)$	-0.030^{***}	-0.084^{***}	0.000	-0.083^{***}
	(-2.874)	(-3.219)	(0.024)	(-3.999)
$log(AT)$	-0.006	0.123^{***}	0.056^{*}	0.128^{**}
	(-0.351)	(4.130)	(1.728)	(2.713)
$Default\ spread$	-0.001	0.009	0.005	0.018
	(-0.229)	(0.875)	(0.315)	(0.887)
$Dividend$	-0.022^{***}	-0.064^{***}	-0.033^{***}	-0.044^{***}
	(-2.840)	(-3.954)	(-2.908)	(-3.080)
$Financial\ leverage$	0.005^{*}	0.004	0.010	0.000
	(1.723)	(1.119)	(1.526)	(-0.122)
$log(Firm\ size)$	0.060^{***}	0.053^{*}	-0.006	-0.007
	(2.865)	(1.836)	(-0.196)	(-0.151)
$Illiquidity$	-0.002^{***}	-0.018^{***}	-0.004^{***}	0.009
	(-3.610)	(-8.692)	(-4.363)	(1.511)
$Investment\ rate$	0.000	0.001	0.003	-0.002
	(-0.049)	(0.246)	(0.699)	(-1.199)
$iVol$	0.043^{**}	0.262^{***}	0.095^{***}	0.205^{***}
	(2.619)	(9.695)	(4.182)	(5.247)
$log(Mkt/Book)$	-0.004	0.015	0.003	0.022^{*}
	(-0.789)	(1.293)	(0.262)	(1.788)
$Momentum$	-0.010	-0.027^{*}	-0.005	-0.016
	(-1.164)	(-1.820)	(-0.553)	(-1.171)
$Operating\ leverage$	0.001	0.003^{**}	0.001	0.003
	(0.974)	(2.285)	(0.579)	(1.629)
q	-0.002^{**}	-0.002	-0.002	-0.004
	(-2.292)	(-0.623)	(-0.873)	(-1.547)
ROE	-0.002	0.003^{*}	-0.002	0.001
	(-0.594)	(1.707)	(-0.750)	(0.249)
R^2	45.96	57.05	46.98	45.23
$NObs$	$1,011,287$	$1,011,287$	$1,011,287$	$1,011,287$
FE	Yes	Yes	Yes	Yes

5.5.1 Cash-Flow and Discount-Rate Betas

We start by separately examining the effect of market power on cash-flow and discount-rate betas. The corresponding results are in Table 5.6. We find that market power has almost no impact on cash-flow betas. Hence, market power does not seem to shield companies from the effects of aggregate cash-flow news. On the other hand, the results show that market power has a strong negative impact on discount-rate betas. The coefficient on total product market similarity is significantly positive. That on industry sales concentration is significantly negative, although the effect is again weaker.

Thus, having market power to some extent appears to insulate firms from aggregate discount-rate shocks. Hence, when the market return is negative due to an expected decrease in total future cash flows, i.e., a substantial worsening of investment opportunities, even market power cannot prevent firms from this aggregate worsening of conditions. However, things are different if the drop in the market return is simply due to an increase in the discount rate, i.e., current wealth decreases but future investment opportunities improve. Then market power appears to help companies to be less affected. They are likely more able to increase product prices to keep the current wealth effect on their stock prices limited.

In Table 5.7, we analyze the effect of anti-competitive mergers on cash-flow and discount-rate betas. We find that both partial betas decrease significantly after the merger announcement. Consistent with the panel regressions on total product market similarity, the effect appears to be substantially stronger for discount rate betas. However, the merger analysis indicates that market power may, to some extent, also partially help to reduce firms' cash-flow betas.

Table 5.7: Merger Analysis - The Effect on Partial Betas

This table presents the results of a regression of the monthly partial market betas on a dummy (M^D) as in Equation (5.4). The merger dummy is 1 for 24 months after the merger announcement. We only consider completed mergers and acquisitions. Our focus is in particular on anti-competitive mergers, for which we apply the following restrictions: (1) The acquiring company can at most hold below 10% of the target (the reporting threshold) and needs to at least acquire 50% of the shares during the transaction. (2) The mergers have either of these purposes: "Acquire competitors technology/strategic assets", "Strengthen existing operations/expand presence in primary market", "Strengthen operations", "Create synergies", "Concentrate on core businesses/assets". Detailed definitions of the control variables are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. All panel regressions include dummies that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the number of merger observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	β^{CF}	β^{DR}	β^{Up}	β^{Down}
M^D	-0.016^{***}	-0.037^{***}	-0.021^{**}	0.000
	(−3.039)	(−3.877)	(−2.335)	(0.022)
$log(Age)$	-0.031^{***}	-0.082^{***}	0.000	-0.081^{***}
	(−2.997)	(−2.945)	(0.018)	(−4.229)
$log(AT)$	−0.004	0.135^{***}	0.061^{*}	0.132^{***}
	(−0.236)	(4.490)	(1.843)	(2.794)
$Default\ spread$	−0.001	0.010	0.005	0.018
	(−0.229)	(0.923)	(0.324)	(0.895)
$Dividend$	-0.022^{***}	-0.032^{***}	-0.035^{***}	-0.044^{***}
	(−2.868)	(−4.157)	(−2.971)	(−3.119)
$Financial\ leverage$	0.005^{*}	0.004	0.010	−0.001
	(1.752)	(1.097)	(1.517)	(−0.247)
$log(Firm\ size)$	0.060^{***}	0.055^{*}	−0.005	−0.008
	(2.892)	(1.879)	(−0.163)	(−0.176)
$Illiquidity$	-0.002^{***}	-0.018^{***}	-0.004^{***}	0.009
	(−3.644)	(−8.845)	(−4.671)	(1.492)
$Investment\ rates$	0.000	0.001	0.003	−0.002
	(−0.069)	(0.216)	(0.686)	(−1.227)
$i\ Vol$	0.043^{**}	0.264^{***}	0.095^{***}	0.205^{***}
	(2.626)	(9.656)	(4.202)	(5.265)
$log(Mkt/Book)$	−0.004	0.016	0.003	0.022^{*}
	(−0.789)	(1.397)	(0.293)	(1.838)
$Momentum$	−0.010	-0.027^{*}	−0.005	−0.016
	(−1.180)	(−1.848)	(−0.586)	(−1.161)
$Operating\ leverage$	0.001	0.003^{**}	0.001	0.003
	(1.118)	(2.696)	(0.581)	(1.627)
q	-0.002^{**}	−0.003	−0.002	−0.004
	(−2.353)	(−0.667)	(−0.931)	(−1.646)
ROE	−0.002	0.003^{*}	−0.002	0.001
	(−0.596)	(1.776)	(−0.744)	(0.248)
R^2	46.46	57.33	47.45	45.71
$NObs$	12,360	12,360	12,360	12,360
FE	Yes	Yes	Yes	Yes

5.5.2 Upside and Downside Betas

Next we turn to the decomposition of market betas into upside and downside betas. This analysis allows us to check whether market power has an asymmetric effect given bull and bear markets. The results for this analysis are also in Table 5.6 and 5.7. We find that total product market similarity has a positive effect on both upside and downside beta. The effect is both economically and statistically weaker than for the total market beta, which is likely due to the additional noise one inevitably faces when estimating partial betas. For the industry sales concentration, we detect no significant effect once controlling for total product market similarity. The merger analysis indicates that the effect of market power is larger for upside than for downside betas, as the downside coefficient is zero.

5.5.3 Tail Risk

In a further analysis, we test the impact of market power on option implied tail risks. Gaspar and Massa (2006) and Abdoh and Varela (2017) both investigate the impact of market power on idiosyncratic realized volatility, but they do not incorporate forward-looking information by option markets. By looking at tail risk, we aim to investigate whether companies with market power are more insulated from risks stemming from jumps in the stock market.[17]

In Table 5.8, we show the results. We find that the left tail risk increases significantly with an increase in the total product market similarity. A two-standard-deviation decrease in total product market similarity decreases left tail risk by 0.0278.[18] For right tail risk, on the other hand, only the orthogonal square to the total product market similarity (and that of the HHI) has a significant impact.

[17]The correlation of idiosyncratic volatility and tail risk is only around 0.5.
[18]This figure can be obtained as $0.0085 \cdot (-2) - 0.0027 \cdot (-2)^2 = -0.0278$.

Table 5.8: Tail Risk

This table presents the results of a regression of firms' tail risk on measures of market power. We calculate option-implied conditional left and right tail risk (LT and RT) using the approach of Bollerslev and Todorov (2011b). As measures for market power, we use the total product market similarity ($tsimm$) as well as the natural logarithm of the HHI industry sales concentration measure. We include the measures as well as their orthogonal squares. The regression equation is:

$$LT_{i,t} = \gamma_1 tsimm_{i,t} + \gamma_2 tsimm^2_{i,t} + \theta_1 HHI_{i,t} + \theta_2 HHI^2_{i,t} + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables, detailed definitions of which are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_i and α_y are dummy variables that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the total number of observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	LT	RT
$tsimm$	0.0085^{*}	0.0074
	(1.9475)	(1.6402)
$tsimm^2$	-0.0027	-0.0046^{*}
	(-0.9491)	(-1.7855)
$log(HHI)$	-0.0047	-0.0037
	(-1.3544)	(-0.9762)
$log(HHI)^2$	0.0018^{**}	0.0016^{**}
	(2.5028)	(2.1099)
$log(Age)$	-0.0310^{***}	-0.0347^{***}
	(-3.3259)	(-3.1295)
$log(AT)$	0.0109	0.0108
	(0.6842)	(0.6281)
$Default\ spread$	-0.0126	-0.0122
	(-0.9068)	(-0.8870)
$Dividend$	-0.0011	-0.0013
	(-0.1909)	(-0.2008)
$Financial\ leverage$	0.0164^{***}	0.0154^{***}
	(4.3188)	(4.6939)
$log(Firm\ size)$	-0.0913^{***}	-0.1093^{***}
	(-5.8883)	(-6.5473)
$Illiquidity$	0.0052	0.0085
	(1.3522)	(1.5237)
$Investment\ rate$	-0.0001	-0.0004
	(-0.2377)	(-0.9367)
$iVol$	0.0539^{***}	0.0559^{***}
	(6.6721)	(6.3825)
$log(Mkt/Book)$	0.0144^{***}	0.0151^{***}
	(5.1709)	(5.1872)
$Momentum$	-0.0478^{***}	-0.0547^{***}
	(-5.3706)	(-6.0759)
$Operating\ leverage$	-0.0019	-0.0019
	(-1.4326)	(-1.3142)
q	0.0005	-0.0017
	(0.2575)	(-0.8033)
ROE	-0.0015^{**}	-0.0014^{**}
	(-2.7655)	(-2.4564)
R^2	61.99	66.00
$NObs$	324,638	324,638
FE	Yes	Yes

Table 5.9: Market Power and Market Beta – All Coefficients

This table presents the results of regressions of firms' market betas on measures of market power as well as several control variables. Conditional market betas are calculated via OLS, WLS, OLS with Shrinkage, or WLS with Shrinkage, based on the past 60 months of monthly returns. As measures for market power, we use the natural logarithm of the HHI industry sales concentration measure, the fitted HHI ($log(fithhi)$), the product market fluidity ($prodmktfluid$), the TNIC HHI measures ($tnic3hhi$), and the total product market similarity ($tsimm$). We include the measures ($MP_{i,t}$) as well as their orthogonal squares. The regression equation is:

$$\beta_{i,t}^{M} = \gamma_1 MP_{i,t} + \gamma_2 MP_{i,t}^2 + \eta C_{i,t} + \alpha_y + \alpha_i + \epsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables, detailed definitions of which are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_i and α_y are dummy variables that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the total number of observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

β^M	*unweighted*	*weighted*	*shrunk*	*weighted & shrunk*
$log(HHI)$	-0.0441^{**}	-0.0441^{**}	-0.0432^{**}	-0.0432^{**}
	(-2.519)	(-2.555)	(-2.532)	(-2.568)
$log(HHI)^2$	0.0052	0.0062	0.0052	0.0061
	(0.513)	(0.591)	(0.522)	(0.596)
R^2	60.99	60.25	60.94	60.26
$log(fithhi)$	-0.0598^{***}	-0.0598^{***}	-0.0581^{***}	-0.0564^{***}
	(-4.988)	(-4.988)	(-5.003)	(-4.738)
$log(fithhi)^2$	0.0189	0.0189	0.0184	0.0199
	(1.434)	(1.434)	(1.440)	(1.533)
R^2	68.23	68.23	68.23	67.01
$prodmktfluid$	0.0509^{***}	0.0511^{***}	0.0500^{***}	0.0502^{***}
	(3.352)	(3.325)	(3.367)	(3.335)
$prodmktfluid^2$	-0.0230^{***}	-0.0233^{***}	-0.0224^{***}	-0.0227^{***}
	(-3.338)	(-3.375)	(-3.313)	(-3.358)
R^2	61.04	60.31	60.99	60.31
$tnic3hhi$	-0.0269^{***}	-0.0270^{***}	-0.0262^{***}	-0.0264^{***}
	(-3.647)	(-3.853)	(-3.670)	(-3.869)
$tnic3hhi^2$	0.0094	0.0098^{*}	0.0092	0.0095^{*}
	(1.598)	(1.834)	(1.615)	(1.846)
R^2	60.95	60.22	60.91	60.22
$tsimm$	0.0429^{***}	0.0442^{***}	0.0419^{***}	0.0431^{***}
	(4.749)	(4.720)	(4.807)	(4.746)
$tsimm^2$	-0.0214^{**}	-0.0206^{*}	-0.0210^{**}	-0.0201^{*}
	(-2.058)	(-1.900)	(-2.084)	(-1.915)
R^2	60.99	60.26	60.95	60.26

5.6 Robustness

We test the robustness of our main results in various dimensions. First, we consider alternative measures of market power. We use an the alternative industry sales concentration measure of Hoberg and Phillips (2010b) ($fithhi$), which corrects for the underrepresentation of private companies in the traditional Compustat-based measure. In addition, we consider the product market fluidity ($prodmktfluid$) and the industry sales concentration measure based on the Hoberg and Phillips (2016) classification ($tnic3hhi$). Regarding the second dimension, we also use different beta estimation methods without weighting (*unweighted*), with shrinkage (*shrunk*), and with both weighting and shrinkage (*weighted* & *shrunk*).

We present the results for all market-power-measure and beta-estimation combinations in Table 5.9. As in Equation (5.3), all regressions account for fixed effects and include the complete set of control variables. We find that for all different market power measures and independent of the method to estimate the betas, the negative relation between market power and market betas persists.

We also repeat the analysis using market betas based on daily instead of monthly data. We use the same estimation window of $k = 60$ months and a shorter window of $k = 24$ months as proposed by Hollstein et al. (2019b). The results, presented in Table 5.10, are qualitatively similar.

Finally, we test the robustness of the merger analysis to the way the betas are estimated. We use all methods considered so far (without weighting, with shrinkage, with weighting and shrinkage, and betas based on daily return data). The results, presented in Table 5.11, are qualitatively similar in every single case.

Table 5.10: Market Power and Market Beta – Daily Betas

This table presents the results of a regression of firms' market betas on measures of market power as well as several control variables. Conditional market betas are calculated via WLS based on the past 60 and 24 months of daily data. As measures for market power, we use the total product market similarity ($tsimm$) as well as the natural logarithm of the HHI industry sales concentration measure. We include the measures as well as their orthogonal squares. The regression equation is:

$$\beta_{i,t}^{M} = \gamma_1 tsimm_{i,t} + \gamma_2 tsimm_{i,t}^2 + \theta_1 HHI_{i,t} + \theta_2 HHI_{i,t}^2 + \alpha_y + \alpha_i + \eta C_{i,t} + \epsilon_{i,t},$$

where $C_{i,t}$ is a vector of control variables, detailed definitions of which are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. α_i and α_y are dummy variables that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the total number of observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(i)	(ii)	(iii)	(iv)	(v)
60 Months					
$tsimm$	0.042^{***}		0.028^{**}		0.027^{**}
	(3.065)		(2.638)		(2.644)
$tsimm^2$	-0.022		-0.012		-0.011
	(-1.391)		(-0.865)		(-0.849)
$log(HHI)$		-0.030^{**}		-0.024^{**}	-0.023^{**}
		(-2.110)		(-2.136)	(-2.070)
$log(HHI)^2$		-0.001		-0.002	-0.003
		(-0.503)		(-1.120)	(-1.414)
R^2	70.99	70.88	74.22	74.20	74.27
24 Months					
$tsimm$	0.039^{***}		0.024^{**}		0.023^{**}
	(2.948)		(2.516)		(2.520)
$tsimm^2$	-0.022		-0.010		-0.009
	(-1.419)		(-0.778)		(-0.760)
$log(HHI)$		-0.030^{*}		-0.023^{*}	-0.021^{*}
		(-1.980)		(-2.004)	(-1.918)
$log(HHI)^2$		-0.003		-0.004	-0.004
		(-0.908)		(-1.360)	(-1.403)
R^2	59.39	59.32	63.30	63.29	63.33
$NObs$	1,011,003	1,011,003	1,011,003	1,011,003	1,011,003
$Controls$	No	No	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes

Table 5.11: Merger Analysis – Robustness

This table presents the results of a regression of the monthly and daily market betas on a dummy (M^D) as in Equation (5.4). Conditional market betas are calculated via OLS, WLS, OLS with Shrinkage, or WLS with Shrinkage, based on the past 60 months of monthly returns. Furthermore, we also present the results for daily market betas, which are calculated via WLS based on the past 60 and 24 months of daily data. The merger dummy is 1 for 24 months after the merger announcement. We only consider completed mergers and acquisitions. Our focus is in particular on anti-competitive mergers, for which we apply the following restrictions: (1) The acquiring company can at most hold below 10% of the target (the reporting threshold) and needs to at least acquire 50% of the shares during the transaction. (2) The mergers have either of these purposes: "Acquire competitors technology/strategic assets", "Strengthen existing operations/expand presence in primary market", "Strengthen operations", "Create synergies", "Concentrate on core businesses/assets". Detailed definitions of the control variables are in Appendix D1.1. All explanatory variables are standardized to have a mean of zero and a standard deviation of one. All panel regressions include dummies that account for company and year fixed effects (FE). The standard errors are double-clustered at the industry and year levels. R^2 presents the adjusted coefficient of determination of the regressions (in percentage points). $NObs$ denotes the number of merger observations. We show the t-statistics in parentheses below the estimates. *,**, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Monthly				Daily (weighted)	
β^M	*unweighted*	*weighted*	*shrunk*	*weighted & shrunk*	60 *Months*	24 *Months*
M^D	−0.047***	−0.049***	−0.046***	−0.047***	−0.034***	−0.034***
	(−3.752)	(−3.817)	(−3.729)	(−3.803)	(−3.358)	(−2.999)
$log(Age)$	−0.092**	−0.093**	−0.090**	−0.091**	−0.068**	−0.083**
	(−2.702)	(−2.652)	(−2.673)	(−2.636)	(−2.295)	(−2.632)
$log(AT)$	0.201***	0.200***	0.196***	0.194***	0.183***	0.116***
	(5.941)	(5.178)	(5.954)	(5.191)	(6.420)	(3.299)
$Default\ spread$	0.002	0.003	0.002	0.003	0.002	−0.001
	(0.296)	(0.649)	(0.329)	(0.663)	(0.708)	(−0.174)
$Dividend$	−0.099***	−0.095***	−0.046***	−0.091***	−0.077***	−0.084***
	(−4.788)	(−4.524)	(−4.758)	(−4.499)	(−5.001)	(−5.285)
$Financial\ leverage$	0.005	0.009	0.004	0.009	0.006*	0.007
	(0.916)	(1.444)	(0.890)	(1.422)	(1.968)	(1.441)
$log(Firm\ size)$	0.014	0.034	0.014	0.033	0.151***	0.260***
	(0.450)	(0.952)	(0.453)	(0.954)	(5.550)	(6.749)
$Illiquidity$	−0.020***	−0.020***	−0.019***	−0.020***	−0.003	−0.007***
	(−6.865)	(−7.023)	(−6.718)	(−6.921)	(−1.501)	(−4.492)
$Investment\ rate$	0.000	0.001	0.000	0.001	−0.001	−0.001
	(0.128)	(0.345)	(0.128)	(0.344)	(−0.822)	(−0.545)
$iVol$	0.321***	0.338***	0.311***	0.327***	0.112***	0.127***
	(8.661)	(9.537)	(8.612)	(9.494)	(7.424)	(8.555)
$log(Mkt/Book)$	0.011	0.014	0.010	0.013	0.020***	0.037***
	(1.169)	(1.128)	(1.128)	(1.102)	(4.557)	(5.393)
$Momentum$	−0.024**	−0.028*	−0.023**	−0.027*	−0.037***	−0.054***
	(−2.196)	(−1.996)	(−2.178)	(−1.986)	(−5.671)	(−5.531)
$Operating\ leverage$	0.004**	0.005**	0.004**	0.004**	0.001	0.002**
	(2.434)	(2.745)	(2.394)	(2.704)	(0.705)	(2.230)
q	−0.005	−0.004	−0.005	−0.004	−0.004*	−0.003
	(−1.402)	(−0.998)	(−1.397)	(−0.992)	(−1.761)	(−1.515)
ROE	0.001	0.001	0.001	0.001	0.001	0.002
	(0.315)	(0.471)	(0.279)	(0.437)	(0.225)	(1.323)
R^2	61.29	60.57	61.25	60.57	74.40	63.60
$NObs$	12,360	12,360	12,360	12,360	12,360	12,360
FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

5.7 Conclusion

In this study, we show that market power significantly negatively affects market betas. We believe we can resolve the debate in the literature about this relation by using a new measure that arguably substantially better captures market power in the product sector. Analyzing subsamples, we show that the effect is substantially stronger in the most recent period. An analysis of anti-competitive mergers underlines that the effect of market power on betas is indeed causal. Finally, we document that market power primarily affects the discount rate channel, indicating that firms that face little competition are in part insulated from aggregate discount rate shocks.

These results indicate that the firms that are already most powerful reap additional benefits in capital markets stemming from a lower cost of equity capital. Thus, market power to some degree seems to be self-reinforcing. By documenting another negative effect of market power, our findings support the ever louder voices calling for policymakers to strengthen competition.

D1 Appendix

D1.1 Control Variables

We use several variables to control for market beta determinants documented in the previous literature (Kogan and Papanikolaou, 2013; Cosemans et al., 2015; Chincarini et al., 2020). Item numbers quoted below refer to the Legacy CST Item Number quoted in the Compustat/CRSP Merged database. For all accounting measures, we use the information starting from four months after the fiscal year end (Hou, Mo, Xue, and Zhang, 2021).

- **Age** is the number of years (plus 1) since a firm first entered the CRSP database.
- **Total assets (AT)** is total assets (item 6).
- **Default spread** The default spread is the difference between the yields of Baa and Aaa rated cooperate bonds. We obtain this series from Amit Goyal's webpage.
- **Dividend** is a dummy variable that is one if the company paid a dividend during the last fiscal year (item 26 or item 201).
- **Financial leverage** is the ratio of the book value of assets (item 6) over the market value of equity, which is calculated as the product of the closing price (item 24) and the number of shares outstanding (item 25).
- **Firm size** is a stock's market capitalization calculated as the product of the stock price at the end of a month times the corresponding number of shares outstanding.
- **Illiquidity** is constructed by dividing the absolute stock return divided by the dollar volume (excluding zero-volume days). We then take the mean over the previous year (Amihud, 2002).
- **Investment rate** is measured as the ratio of capital expenditures (item 128) to the lagged book value of capital (item 7).
- **Idiosyncratic volatility (iVol)** is defined as the standard deviation of the residuals

of a regression of stock excess returns on the Fama and French (1993) factors using monthly returns during the previous 60 months.

- **Market-to-book Ratio (Mkt/Book)** is market equity divided by book equity. Market equity is constructed by multiplying the common stock price at fiscal year-end (item 199) by common shares outstanding (item 25). Book equity is stockholders' equity plus balance sheet deferred taxes and investment tax credit (item 35) minus the book value of preferred stock. Stockholders' equity is calculated in this order: (i) item 216, (ii) 60 + 130 or (iii) 6 − 181. The book value of preferred stock is calculated in this order: (i) 56, (ii) 10 or (iii) 130.
- **Momentum** is the cumulative stock return during months $t-12$ until $t-1$.
- **Operating leverage** is computed as three-year moving average of the ratio of the percentage change in operating income before depreciation (item 13) to the percentage change in sales (item 12).
- **Tobin's q (q)** Tobin's q is the ratio of common equity (CRSP December Market capitalization) plus the book value of debt (item 9) plus the book value of preferred stock (item 56) minus inventories (item 3) and minus deferred taxes (item 74), divided by the book value of capital (item 7).
- **Return on equity (ROE)** is earnings divided by last year's book equity. Earnings are calculated as income before extraordinary items available to common stockholders (item 237) plus deferred taxes from the income statement (item 50) plus investment tax credit (item 51).

D1.2 Herfindahl-Hirschman Index

To identify the industries, we use the NAICS classification. We follow Grullon et al. (2019) to fill the missing NAICS values. Grullon et al. (2019) follow the following process:

(1) First, use Compustat's historical NAICS, whenever available (NAICSH). (2) Second, then use CRSP historical values (from the msenames table). (3) Third, use NAICS from the Compustat names table. (4) Finally, if none is available, we populate the remaining NAICS values by converting the SIC codes to NAICS using the conversion tables from the US Census Bureau.

With the NAICS classifications, we can calculate the Herfindahl-Hirschman Index (HHI) for each industry and infer the degree of concentration in sales. The HHI is calculated as follows:

$$HHI_{j,t} = \sum_{i,k=j} \left(\frac{Sales_{i,k,t}}{\sum_{i,k=j} Sales_{i,k,t}} \right)^2 ,$$

where $Sales_{i,k,t}$ are the sales (item 117) of firm i, which is in industry k in fiscal year t. This results in one value for $HHI_{j,t}$ each industry at each point in time.

D1.3 Cash-Flow and Discount-Rate News

In this section, we show how to calculate the cash-flow and discount-rate news following Campbell and Vuolteenaho (2004). First, we obtain the excess log market return, the term yield spread, and the price-earnings ratio. Second, we calculate the small-stock value spread, for which we need to obtain data from Kenneth French's website. We use the two size portfolios, with the breakpoint of the median NYSE ME at the end of June and three BE/ME portfolios with size breakpoints at 30% and 70%. The value spread is then calculated as the difference between the log(BE/ME) of the small high-book-to-market portfolio and the log(BE/ME) of the small low-book-to-market portfolio. We add the cumulative log return on the small low-book-to market portfolio and substract the cumulative log return on the small-high-book-to-market portfolio.

The cash-flow and discount rate news are then estimated with a vector autoregressive

(VAR) Model:

$$\begin{aligned}N_{CF,t+1} =&(e1' + e1'\lambda)u_{t+1}\\ N_{DR,t+1} =&e1'\lambda u_{t+1}\ .\end{aligned}$$

The VAR shocks are mapped by λ, where $\lambda = \rho\Gamma(I - \rho\Gamma)^{-1}$. The VAR model is estimated by $z_{t+1} = a + \Gamma z_t + u_{t+1}$, where Γ is an m times m matrix, with the coefficient estimates from a VAR type regression for each of the input coefficients. z_t is the state vector including the excess log market return, the term yield spread, the price-earnings ratio, and the small-stock value spread. u_{t+1} represents the residuals from these regressions. ρ is set at $0.95^{1/12}$. For further information, we refer to Campbell and Vuolteenaho (2004).

D1.4 Tail Risk

Bollerslev and Todorov (2011b) construct a measure of tail risk perceived by investors that is based on close-to-maturity deep out-of-the-money options. They use the insights of the quadratic variation to decompose the volatility into two separate parts in a model-free fashion. To isolate extreme tail risks, they use only deep out-of-the-money options. Only a rare event will be large enough to affect the prices of these derivatives significantly. Bollerslev and Todorov (2011b) construct the model-free risk-neutral jump right tail (RT) and left tail (LT) measures as:

$$\begin{aligned}RT_t^{\mathbb{Q}}(k) \equiv \frac{1}{T-t}\int_t^T \int_{\mathbb{R}} max(0, e^x - e^k)\mathbb{E}_t^{\mathbb{Q}}(v_S^{\mathbb{Q}}(dx))ds \approx \frac{e^{r(t,T]}C_t(K)}{(T-t)F_{t-}}\\ LT_t^{\mathbb{Q}}(k) \equiv \frac{1}{T-t}\int_t^T \int_{\mathbb{R}} max(0, e^k - e^x)\mathbb{E}_t^{\mathbb{Q}}(v_S^{\mathbb{Q}}(dx))ds \approx \frac{e^{r(t,T]}P_t(K)}{(T-t)F_{t-}}.\end{aligned} \tag{D1}$$

where $r_{(t,T]}$ is the risk-free interest rate between t and the options' maturities T. $C_t(K)$ and $P_t(K)$ are the current call and put prices with strike price K and maturity T. F_{t-} is the current option-implied forward price.

We use the approximation above for the calculation of the tail risk measures. The log-moneyness is $k = log(K/F_{t-})$. For the estimation, Bollerslev and Todorov (2011b) use options with at least 8 days to expiration and interpolate the option price to the desired moneyness levels, 1.1 for RT and 0.9 for LT, using Black and Scholes (1973) implied volatilities. Because the term structure of individual stock options can be sparse, we use a set of standardized options from OptionMetrics.

Chapter 6

Conclusion and Further Research

6.1 Summary and Conclusion

This thesis investigates the implications and drivers on an asset's volatility, tail and systematic risks in financial markets. Chapter 2 studies the volatility term structure in the commodity market and what the dependencies of the commodity term structures are. We find that the term structure of commodities has large intra-dependencies that are associated with information transmission, because these dependencies are increasing on macroeconomic announcement days. The financialization of the commodity market has led to a faster information transmission within the commodity market, which decreases spillovers, but increased contemporaneous co-movement. Furthermore we show that the level of volatility is related to influences that can be ascribed to employment and speculation.

In Chapter 3 we analyze a wide range of tail risk measures. We find that the tail risk measures are only mildly correlated. After conducting a range of comprehensive tests, we find that the option-implied measure of Bollerslev and Todorov (2011b), $BT11Q$, performs best. $BT11Q$ performs well for all tests: It can predict the occurrence of a crash, and the future variation in the left tail. $BT11Q$ also predicts excess returns up to one year and can predict the cross-section of stock returns. $BT11Q$ is as well related to real economic activity. Other measures may perform well for part of the tasks, while $BT11Q$ consistently performs well.

In Chapter 4 we study the tail risk in commodity markets. We find several interesting features of tail risks in commodity markets: (i) Tail risks seem to be large for both the left and right tail risk (ii) The correlation of tail risks in the commodity market is small, within sector correlation is larger (iii) the variance risk premium is the largest determinant of left and right tail risk, (iv) speculation and equity market variables are as well important for the tail risk of some commodities , and (v) finally, tail risk is priced in the cross-section of the commodity markets.

In Chapter 5 we study the impact of product market power on the systematic risk. We show that market power reduces the beta of firms. We confirm causality by investigating anti-competitive mergers. After such a merger announcement, betas decrease. This effect primarily affects the discount-rate channel. Our results show that firms that have a larger product market power, they are isolated from discount rate shocks.

The findings presented in this thesis have important implications for both academics and market participants in practice. First of all, studying risk and dependencies of risks is important for market participants to understand the behaviour and dependencies in the commodity market and their portfolios. Market participants should study the entire commodity market, including the dependencies in the volatility term structure and the tail risks, in order to accurately evaluate the size and sources of risks in their portfolio. The studies in Chapter 2 and Chapter 4 as well show that especially for the commodity market, market participants need to consider connections to the equity market and particularly look at periods of macroeconomic announcements, to evaluate their risk exposure at any given day. From Chapter 3, market participants need to be aware that tail risk measures should not be treated as interchangable. They need to carefully evaluate the tail risk models they use with regard to the information content they actually capture and adjust them if necessary. This chapter also sheds light on the general necessity that market participants should be aware which effects the models they use actually capture and how they move with the variables they are supposed to approximate. Finally, Chapter 5 is especially useful for regulators, it shows that firms with a larger product market power can obtain cheaper equity financing and they can, through this cheaper financing, further increase their market power in a self perpetuating cycle. This send a warning to regulators, especially in combination with the other negative macroeconomic effects, that this era of firms with large market power might not be waning on its own.

The findings presented in this study have also several implications for academics. First, academics should be as well careful not to treat tail risk measures as interchangable. It is as well important to include these tests when they present a new tail risk measure in the future. Furthermore it is important to develop a more rigorous framework to test the informatitive content of different tail risk measures. Finally, it is questionable to look at a commodity in isolation, because of the dependencies, between commodities, but as well to other markets. This is especially true for the variance term structure and tail risks.

6.2 Suggestions for Further Research

There are several ways to expand on the research presented in this study. The research in the field of volatility and tail risk can be expanded in a number of different ways.

First, with regards to tail risk, further investigation about the reason for the superior behavior of $BT11Q$ would be helpful. Information about the sources of the predictive power could help to create an even better tail risk measure and enhance our understanding of the information captured by the other tail risk measures. Furthermore this work could be extended, by including a variety of other measure, some of which are only related to tail measures but are regularly used by practitioners, like the Value-at Risk, or Macroeconomic tail risk measures.

Second, another expansion could be a further investigation about the characteristics of tail risks especially in the equity market. Which events, announcements or news lead to a buildup in uncertainty is a very interesting question. Some papers already investigate the connections of tail risks for global equity markets (Hollstein, Nguyen, Prokopczuk, and Simen, 2019a). They also show that after periods of high tail risk there are positive links to unemployment in the short term and negative links in the long term. Linking tail events of different regional scale (global/regional) akin to Fama and French (2012) and Hollstein (2021) to particular news events or announcements could help market participants to understand the connection of tail risk and these events, as well as the risk of non-diversifiable tail events. This could even further help to answer the question whether tail risk is priced and to what extend investors try to diversify it.

Third, another way to calculate tail risks, by Lu and Murray (2019) was the use of portfolios of options that generate a payoff for left tail events. One can use this approach to create digital options, which pay when the option matures below or above a threshold. One could use these option portfolio strategies in order to gain insights about market expectations about the entire range of strike prices. This could help to gain further insights, by evaluating other moments of these strategy, as well along the right tail of the distribution. This can be particularly helpful for commodity markets or stock options, because the size of the right tail is non-trivial, as discussed in Chapter 4 and by Lin and Todorov (2019) for single stock options.

Tail risk might occur for rational reasons. A recent paper (Fusari, Jarrow, and Lamichhane, 2021) shows that it is possible to estimate bubbles from option markets. Especially commodity markets are associated with speculative price bubbles (Gutierrez, 2013). Financial bubbles are often associated with the financialization of the commodity market. This new estimation procedure can therefore provide insights into the build up, causes and time series variation of bubbles in commodity markets.

Finally, Hoberg and Phillips (2010b) assess the product market competition of companies from 10-K forms, which performs better than traditional market power measures, with text analysis. This tool could be helpful to evaluate risks of companies in a different manner. Companies need to disclose risks in their statements, these could be evaluated via text analysis in order to have a better idea of the different risk exposures of a company. These can especially facilitate long-term risks, which cannot be estimated from options, because it is impossible to distinguish between jump and volatility risks. This could as well be used to separate between a number of (self assessed) risk factors, for example climate risks, competition, financial risks, demand risks, or supply risks.

Bibliography

Abdoh, Hussein, and Oscar Varela, 2017, Product Market Competition, Idiosyncratic and Systematic Volatility, *Journal of Corporate Finance* 43, 500–513. [cited on p. 209, 212, and 235.]

Adams, Zeno, Roland Füss, and Reint Gropp, 2014, Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk Approach, *Journal of Financial and Quantitative Analysis* 49, 575–598. [cited on p. 32 and 33.]

Adjemian, Michael K, Valentina G Bruno, Michel A Robe, and Jonathan Wallen, 2018, What Drives Volatility Expectations in Food Markets? . [cited on p. 24.]

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone, 2019, Vulnerable Growth, *American Economic Review* 109, 1263–89. [cited on p. 82, 83, 138, and 139.]

Adrian, Tobias, and Joshua Rosenberg, 2008, Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk, *Journal of Finance* 63, 2997–3030. [cited on p. 9 and 11.]

Agarwal, Vikas, Stefan Ruenzi, and Florian Weigert, 2017, Tail Risk in Hedge Funds: A

Unique View from Portfolio Holdings, *Journal of Financial Economics* 125, 610–636. [cited on p. 78 and 79.]

Aït-Sahalia, Yacine, and Jefferson Duarte, 2003, Nonparametric Option Pricing Under Shape Restrictions, *Journal of Econometrics* 116, 9–47. [cited on p. 14.]

Alexander, Donald L., and Paul D. Thistle, 1999, Market Power, Efficiency and the Dispersion of Systematic Risk, *Review of Industrial Organization* 14, 377–390. [cited on p. 209 and 212.]

Ali, Ashiq, Sandy Klasa, and Eric Yeung, 2008, The Limitations of Industry Concentration Measures Constructed with Compustat Data: Implications for Finance Research, *Review of Financial Studies* 22, 3839–3871. [cited on p. 213.]

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31–56. [cited on p. 242.]

Andersen, Torben G., and Tim Bollerslev, 1998, Answering the Skeptics: Yes, Standard Volatility Models do provide accurate Forecasts, *International Economic Review* 39, 885–905. [cited on p. 78.]

Andersen, Torben G., Nicola Fusari, and Viktor Todorov, 2015, The Risk Premia Embedded in Index Options, *Journal of Financial Economics* 117, 558–584. [cited on p. 77 and 78.]

Andersen, Torben G., Nicola Fusari, and Viktor Todorov, 2017, Short-term Market Risks Implied by Weekly Options, *Journal of Finance* 72, 1335–1386. [cited on p. 78.]

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2006a, Downside Risk, *Review of Financial Studies* 19, 1191–1239. [cited on p. 211, 217, and 220.]

Ang, Andrew, Robert J Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006b, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299. [cited on p. 1.]

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen, 2020, The Fall of the Labor Share and the Rise of Superstar Firms, *Quarterly Journal of Economics* 135, 645–709. [cited on p. 4 and 208.]

Azen, Razia, and David V. Budescu, 2003, The Dominance Analysis Approach for Comparing Predictors in Multiple Regression, *Psychological Methods* 8, 129–148. [cited on p. 88.]

Bachmeier, Lance J, and James M Griffin, 2006, Testing for Market Integration: Crude Oil, Coal, and Natural Gas, *Energy Journal* 27, 55–71. [cited on p. 39.]

Back, Janis, Marcel Prokopczuk, and Markus Rudolf, 2013, Seasonality and the Valuation of Commodity Options, *Journal of Banking & Finance* 37, 273–290. [cited on p. 14.]

Bae, Kee-Hong, Warren Bailey, and Jisok Kang, 2021, Why Is Stock Market Concentration Bad for the Economy?, *Journal of Financial Economics* 140, 436–459. [cited on p. 5 and 209.]

Bakshi, Gurdip, Xiaohui Gao, and Alberto G. Rossi, 2017, Understanding the Sources of Risk Underlying the Cross Section of Commodity Returns, *Management Science* 65, 619–641. [cited on p. 11, 17, 173, 175, 180, 191, 198, and 203.]

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options, *Review of Financial Studies* 16, 101–143. [cited on p. 126.]

Bakshi, Gurdip, George Panayotov, and Georgios Skoulakis, 2011, Improving the predictability of real economic activity and asset returns with forward variances inferred from option portfolios, *Journal of Financial Economics* 100, 475–495. [cited on p. 9 and 11.]

Barndorff-Nielsen, Ole E., Peter R. Hansen, Asger Lunde, and Neil Shephard, 2009, Realized Kernels in Practice: Trades and Quotes, *Econometrics Journal* 12, 1–32. [cited on p. 84.]

Barndorff-Nielsen, Ole E., and Neil Shephard, 2004, Power and Bipower Variation with Stochastic Volatility and Jumps, *Journal of Financial Econometrics* 2, 1–37. [cited on p. 129.]

Barndorff-Nielsen, Ole E., and Neil Shephard, 2006, Econometrics of Testing for Jumps in Financial Economics using Bipower Variation, *Journal of Financial Econometrics* 4, 1–30. [cited on p. 129.]

Barone-Adesi, Giovanni, and Robert E. Whaley, 1987, Efficient Analytic Approximation of American Option Values, *Journal of Finance* 42, 301–320. [cited on p. 176 and 201.]

Barro, Robert J., 2006, Rare Disasters and Asset Markets in the Twentieth Century, *Quarterly Journal of Economics* 121, 823–866. [cited on p. 75 and 85.]

Basak, Suleyman, and Anna Pavlova, 2016, A Model of Financialization of Commodities, *Journal of Finance* 71, 1511–1556. [cited on p. 39.]

Bekaert, Geert, Campbell R. Harvey, Christian T. Lundblad, and Stephan Siegel, 2011, What Segments Equity Markets?, *Review of Financial Studies* 24, 3841–3890. [cited on p. 89, 141, and 143.]

Bernier, Gilles, 1987, Market Power and Systematic Risk: An Empirical Analysis using Tobin's q Ratio, *Journal of Economics and Business* 39, 91–99. [cited on p. 209 and 212.]

Bessembinder, Hendrik, Jay F Coughenour, Paul J Seguin, and Margaret Smoller, 1996, Is There a Term Structure of Futures Volatilities? Reevaluating the Samuelson Hypothesis, *Journal of Derivatives* 4, 45–58. [cited on p. 18 and 28.]

Bianchi, Daniele, 2018, Carry Trades and Tail Risk: Evidence from Commodity Markets Working Paper. [cited on p. 172.]

Binder, John J., 1992, Beta, firm size, and concentration, *Economic Inquiry* 30, 556–563. [cited on p. 209, 211, and 212.]

Black, Fischer, 1976, The Pricing of Commodity Contracts, *Journal of Financial Economics* 3, 167–179. [cited on p. 14, 176, and 181.]

Black, Fischer, and Myron Scholes, 1973, The Valuation of Options and Corporate Liabilities, *Journal of Political Economy* 81, 637–654. [cited on p. 124, 137, and 246.]

Bollerslev, Tim, Benjamin Hood, John Huss, and Lasse Heje Pedersen, 2018, Risk Everywhere: Modeling and Managing Volatility, *Review of Financial Studies* 31, 2729–2773. [cited on p. 1.]

Bollerslev, Tim, George Tauchen, and Hao Zhou, 2009, Expected Stock Returns and Variance Risk Premia, *Review of Financial Studies* 22, 4463–4492. [cited on p. 16 and 88.]

Bollerslev, Tim, and Viktor Todorov, 2011a, Estimation of Jump Tails, *Econometrica* 79, 1727–1783. [cited on p. 79, 124, 129, 130, 131, and 217.]

Bollerslev, Tim, and Viktor Todorov, 2011b, Tails, Fears, and Risk Premia, *Journal of Finance* 66, 2165–2211. [cited on p. 4, 6, 3, 76, 79, 81, 83, 86, 87, 121, 122, 123, 124, 130, 177, 178, 236, 245, 246, and 249.]

Bollerslev, Tim, and Viktor Todorov, 2014, Time-varying Jump Tails, *Journal of Econometrics* 183, 168–180. [cited on p. 80, 83, 124, and 125.]

Bollerslev, Tim, Viktor Todorov, and Lai Xu, 2015, Tail Risk Premia and Return Predictability, *Journal of Financial Economics* 118, 113–134. [cited on p. 4, 80, 83, 124, 126, 174, and 187.]

Bondarenko, Oleg, 2014, Why are Put Options so Expensive?, *Quarterly Journal of Finance* 4, 1450015. [cited on p. 73.]

Brave, Scott, and R Andrew Butters, 2012, Diagnosing the Financial System: Financial Conditions and Financial Stress, *International Journal of Central Banking* 8, 191–239. [cited on p. 138.]

Breeden, Douglas T., and Robert H. Litzenberger, 1978, Prices of State-Contingent Claims Implicit in Option Prices, *Journal of Business* 51, 621–651. [cited on p. 80 and 126.]

Britten-Jones, Mark, and Anthony Neuberger, 2000, Option Prices, Implied Price Processes, and Stochastic Volatility, *Journal of Finance* 55, 839–866. [cited on p. 14.]

Brownlees, Christian T., and Giampiero M. Gallo, 2010, Comparison of Volatility Measures: A Risk Management Perspective, *Journal of Financial Econometrics* 8, 29–56. [cited on p. 78.]

Brunetti, Celso, Bahattin Büyükşahin, and Jeffrey H Harris, 2016, Speculators, Prices, and Market Volatility, *Journal of Financial and Quantitative Analysis* 51, 1545–1574. [cited on p. 11 and 195.]

Büyükşahin, Bahattin, and Michel A Robe, 2014, Speculators, Commodities and Cross-market Linkages, *Journal of International Money and Finance* 42, 38–70. [cited on p. 175.]

Cai, Jie, Moon H. Song, and Ralph A. Walkling, 2011, Anticipation, Acquisitions, and Bidder Returns: Industry Shocks and the Transfer of Information Across Rivals, *Review of Financial Studies* 24, 2242–2285. [cited on p. 229.]

Cairó, Isabel, and Jae Sim, 2020, Market Power, Inequality, and Financial Instability, Working Paper. [cited on p. 5 and 209.]

Campa, Jose Manuel, and PH Kevin Chang, 1995, Testing the expectations hypothesis on the term structure of volatilities in foreign exchange options, *Journal of finance* 50, 529–547. [cited on p. 11.]

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Bad Beta, Good Beta, *American Economic Review* 94, 1249–1275. [cited on p. 211, 217, 219, 244, and 245.]

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate Investment and Asset

Price Dynamics: Implications for the Cross-Section of Returns, *Journal of Finance* 59, 2577–2603. [cited on p. 213.]

Carr, Peter, and Liuren Wu, 2003, What Type of Process Underlies Options? A Simple Robust Test, *Journal of Finance* 58, 2581–2610. [cited on p. 84.]

Carr, Peter, and Liuren Wu, 2009, Stock Options and Credit Default Swaps: A Joint Framework for Valuation and Estimation, *Journal of Financial Econometrics* 8, 409–449. [cited on p. 84 and 180.]

Chabi-Yo, Fousseni, Hitesh Doshi, and Virgilio Zurita, 2020, Never a Dull Moment: Entropy Risk in Commodity Markets Working Paper. [cited on p. 175.]

Chang, Bo-Young, Peter Christoffersen, Kris Jacobs, and Gregory Vainberg, 2011, Option-Implied Measures of Equity Risk, *Review of Finance* 16, 385–428. [cited on p. 14.]

Chen, K.C., David C. Cheng, and Gailen L. Hite, 1986, Systematic risk and market power: An application of tobin's q, *Quarterly Review of Economics and Business* 26, 58–72. [cited on p. 211.]

Chincarini, Ludwig B., Daehwan Kim, and Fabio Moneta, 2020, Beta and Firm Age, *Journal of Empirical Finance* 58, 50–74. [cited on p. 213, 225, and 242.]

Christoffersen, Peter, Kris Jacobs, and Chayawat Ornthanalai, 2012, Dynamic Jump Intensities and Risk Premiums: Evidence from S&P 500 Returns and Options, *Journal of Financial Economics* 106, 447–472. [cited on p. 81, 83, 131, 132, and 133.]

Christoffersen, Peter, Asger Lunde, and Kasper Olesen, 2019, Factor Structure in Commodity Futures Return and Volatility, *Journal of Financial and Quantitative Analysis* 19, 1083–1115. [cited on p. 11, 12, 23, 41, and 175.]

Cochrane, John H, and Monika Piazzesi, 2005, Bond Risk Premia, *American Economic Review* 95, 138–160. [cited on p. 17.]

Cosemans, Mathijs, Rik Frehen, Peter C. Schotman, and Rob Bauer, 2015, Estimating Security Betas Using Prior Information Based on Firm Fundamentals, *Review of Financial Studies* 29, 1072–1112. [cited on p. 213, 225, and 242.]

Covarrubias, Matias, Germán Gutiérrez, and Thomas Philippon, 2020, From Good to Bad Concentration? US Industries over the Past 30 Years, *NBER Macroeconomics Annual* 34, 1–46. [cited on p. 4 and 208.]

Covindassamy, Genèvre, Michel A Robe, and Jonathan Wallen, 2017, Sugar with your Coffee? Fundamentals, Financials, and Softs Price Uncertainty, *Journal of Futures Markets* 37, 744–765. [cited on p. 24.]

Cremers, Martijn, Michael Halling, and David Weinbaum, 2015, Aggregate Jump and Volatility Risk in the Cross-section of Stock Returns, *Journal of Finance* 70, 577–614. [cited on p. 82, 83, and 137.]

Curley, Anthony J., J. Lawrence Hexter, and Dosoung Choi, 1982, The Cost of Capital and the Market Power of Firms: A Comment, *Review of Economics and Statistics* 64, 519–523. [cited on p. 209 and 212.]

Dalton, James A., and David W. Penn, 1976, The Concentration-Profitability Relationship: Is There A Critical Concentration Ratio?, *Journal of Industrial Economics* 25, 133–142. [cited on p. 222.]

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger, 2020, The Rise of Market Power and the Macroeconomic Implications, *Quarterly Journal of Economics* 135, 561–644. [cited on p. 5 and 209.]

Demeterfi, Kresimir, Emanuel Derman, Michael Kamal, and Joseph Zou, 1999, A Guide to Volatility and Variance Swaps, *Journal of Derivatives* 6, 9–32. [cited on p. 14.]

Dew-Becker, Ian, Stefano Giglio, and Bryan Kelly, 2021, Hedging macroeconomic and financial uncertainty and volatility, *Journal of Financial Economics, forthcoming* . [cited on p. 75.]

Diebold, Francis X, and Kamil Yilmaz, 2012, Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers, *International Journal of Forecasting* 28, 57–66. [cited on p. 12.]

Dierkes, Maik, Fabian Hollstein, Marcel Prokopczuk, and Christoph Würsig, 2021, Measuring Tail Risk, Working Paper. [cited on p. 177 and 217.]

Du, Limin, and Yanan He, 2015, Extreme Risk Spillovers between Crude Oil and Stock Markets, *Energy Economics* 51, 455–465. [cited on p. 12.]

Duong, Huu Nhan, and Petko S Kalev, 2008, The Samuelson Hypothesis in Futures Markets: An Analysis Using Intraday Data, *Journal of Banking & Finance* 32, 489–500. [cited on p. 18 and 21.]

Ebrahimi, Nima, and Craig Pirrong, 2020, Oil Jump Risk, *Journal of Futures Markets* 40, 1282–1311. [cited on p. 175.]

Ellwanger, Reinhard, 2015, Driven by Fear? The Tail Risk Premium in the Crude Oil Futures Market, Technical report, Working Paper. Bank of Canada. [cited on p. 174.]

Engle, Robert F, and Simone Manganelli, 2004, CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles, *Journal of Business & Economic Statistics* 22, 367–381. [cited on p. 10, 32, and 57.]

Faff, Robert W., David Hillier, and Joseph Hillier, 2000, Time Varying Beta Risk: An Analysis of Alternative Modelling Techniques, *Journal of Business Finance & Accounting* 27, 523–554. [cited on p. 78.]

Fama, Eugene F., and Kenneth R. French, 1988, Business Cycles and the Behavior of Metals Prices, *Journal of Finance* 43, 1075–1093. [cited on p. 28 and 39.]

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3–56. [cited on p. 82, 135, and 243.]

Fama, Eugene F., and Kenneth R. French, 1997, Industry Costs of Equity, *Journal of Financial Economics* 43, 153–193. [cited on p. 212.]

Fama, Eugene F, and Kenneth R French, 2012, Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105, 457–472. [cited on p. 251.]

Fama, Eugene F., and Kenneth R. French, 2015, A Five-Factor Asset Pricing Model, *Journal of Financial Economics* 116, 1–22. [cited on p. 116 and 155.]

Fan, Zhenzhen, Juan M. Londono, and Xiao Xiao, 2021, US Equity Tail Risk and Currency Risk Premia Working Paper. [cited on p. 174.]

Farrell, Joseph, and Carl Shapiro, 1990, Horizontal mergers: An equilibrium analysis, *American Economic Review* 107–126. [cited on p. 228.]

Fathollahi, Maryam, Jarrad Harford, and Sandy Klasa, 2021, Anticompetitive effects of horizontal acquisitions: the impact of within-industry product similarity, *Journal of Financial Economics* forthcoming. [cited on p. 228.]

Feunou, Bruno, Jean-Sébastien Fontaine, Abderrahim Taamouti, and Roméo Tédongap, 2013, Risk Premium, Variance Premium, and the Maturity Structure of Uncertainty, *Review of Finance* 18, 219–269. [cited on p. 1, 9, and 17.]

Fusari, Nicola, Robert Jarrow, and Sujan Lamichhane, 2021, Testing for Asset Price Bubbles using Options Data, *Working Paper* . [cited on p. 252.]

Gao, George P., Pengjie Gao, and Zhaogang Song, 2018, Do Hedge Funds exploit rare Disaster Concerns?, *Review of Financial Studies* 31, 2650–2692. [cited on p. 80, 83, and 128.]

Gao, George P., Xiaomeng Lu, and Zhaogang Song, 2019, Tail Risk Concerns Everywhere, *Management Science* 65, 3111–3130. [cited on p. 80, 83, 128, and 174.]

Gao, Lin, 2017, Commodity Option Implied Volatilities and the Expected Futures Returns Working Paper. [cited on p. 175 and 196.]

Garratt, Anthony, and Ivan Petrella, 2019, Commodity Prices and Inflation Risk, *Working Paper* . [cited on p. 4 and 172.]

Gaspar, José-Miguel, and Massimo Massa, 2006, Idiosyncratic Volatility and Product Market Competition, *Journal of Business* 79, 3125–3152. [cited on p. 5, 209, and 235.]

Gomes, Joao, Leonid Kogan, and Lu Zhang, 2003, Equilibrium Cross Section of Returns, *Journal of Political Economy* 111, 693–732. [cited on p. 213.]

Gormsen, Niels Joachim, and Christian Skov Jensen, 2020, Higher-moment risk, *University of Chicago Working Paper* . [cited on p. 80, 83, 95, 116, and 126.]

Gorton, Gary B, Fumio Hayashi, and K Geert Rouwenhorst, 2012, The Fundamentals of Commodity Futures Returns, *Review of Finance* 17, 35–105. [cited on p. 16, 17, and 180.]

Gourio, Francois, 2012, Disaster risk and business cycles, *American Economic Review* 102, 2734–66. [cited on p. 75.]

Goyal, Amit, and Ivo Welch, 2007, A Comprehensive Look at the Empirical Performance of Equity Premium Prediction, *Review of Financial Studies* 21, 1455–1508. [cited on p. 34.]

Granger, Clive WJ., 1969, Investigating Causal Relations by Econometric Models and Cross-Spectral Methods, *Econometrica* 37, 424–438. [cited on p. 10.]

Granger, Clive WJ, 1988, Some Recent Development in a Concept of Causality, *Journal of Econometrics* 39, 199–211. [cited on p. 10.]

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, 2019, Are US Industries Becoming More Concentrated?, *Review of Finance* 23, 697–743. [cited on p. 215 and 243.]

Grundy, Bruce D., and J. Spencer Martin Martin, 2001, Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing, *Review of Financial Studies* 14, 29–78. [cited on p. 213 and 225.]

Gutiérrez, Germán, and Thomas Philippon, 2019, Fading Stars, *AEA Papers and Proceedings* 109, 312–16. [cited on p. 5 and 209.]

Gutierrez, Luciano, 2013, Speculative bubbles in agricultural commodity markets, *European Review of Agricultural Economics* 40, 217–238. [cited on p. 252.]

Hall, Peter, Joel L. Horowitz, and Bing-Yi Jing, 1995, On Blocking Rules for the Bootstrap with Dependent Data, *Biometrika* 82, 561–574. [cited on p. 121.]

Hamilton, James D, and Jing Cynthia Wu, 2015, Effects of Index-Fund Investing on Commodity Futures Prices, *International Economic Review* 56, 187–205. [cited on p. 41.]

Hammoudeh, Shawkat, and Yuan Yuan, 2008, Metal Volatility in Presence of Oil and Interest Rate Shocks, *Energy Economics* 30, 606–620. [cited on p. 11.]

Hansen, Peter R., and Asger Lunde, 2005, A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH (1, 1)?, *Journal of Applied Econometrics* 20, 873–889. [cited on p. 78.]

Henderson, Brian J, Neil D Pearson, and Li Wang, 2014, New evidence on the financialization of commodity markets, *Review of Financial Studies* 28, 1285–1311. [cited on p. 173.]

Hendry, David F, 1995, *Dynamic Econometrics* (Oxford: Oxford University Press). [cited on p. 140.]

Hendry, David F, and Hans-Martin Krolzig, 2001, *Automatic econometric model selection using PcGets* (London: Timberlake Consultants). [cited on p. 140.]

Hill, Bruce M, 1975, A simple general approach to Inference about the Tail of a Distribution, *Annals of Statistics* 3, 1163–1174. [cited on p. 82 and 135.]

Hoberg, Gerard, and Gordon Phillips, 2010a, Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis, *Review of Financial Studies* 23, 3773–3811. [cited on p. 215.]

Hoberg, Gerard, and Gordon Phillips, 2010b, Real and Financial Industry Booms and Busts, *Journal of Finance* 65, 45–86. [cited on p. 5, 209, 216, 238, and 252.]

Hoberg, Gerard, and Gordon Phillips, 2016, Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy* 124, 1423–1465. [cited on p. 215 and 238.]

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product Market Threats, Payouts, and Financial Flexibility, *Journal of Finance* 69, 293–324. [cited on p. 5, 209, and 215.]

Hollstein, Fabian, 2020, Estimating Beta: The International Evidence, *Journal of Banking and Finance* 121, 105968. [cited on p. 216.]

Hollstein, Fabian, 2021, Local, regional, or global asset pricing?, *Journal of Financial and Quantitative Analysis* forthcoming. [cited on p. 251.]

Hollstein, Fabian, Duc Binh Benno Nguyen, Marcel Prokopczuk, and Chardin Wese Simen, 2019a, International tail risk and World Fear, *Journal of International Money and Finance* 93, 244–259. [cited on p. 251.]

Hollstein, Fabian, and Marcel Prokopczuk, 2016, Estimating Beta, *Journal of Financial and Quantitative Analysis* 51, 1437–1466. [cited on p. 14 and 78.]

Hollstein, Fabian, Marcel Prokopczuk, and Björn Tharann, 2021, Anomalies in commodity futures markets: Risk or mispricing?, *Quarterly Journal of Finance* forthcoming. [cited on p. 13, 176, and 200.]

Hollstein, Fabian, Marcel Prokopczuk, and Chardin Wese Simen, 2019b, Estimating Beta: Forecast Adjustments and the Impact of Stock Characteristics for a Broad Cross-Section, *Journal of Financial Markets* 44, 91–118. [cited on p. 11, 78, 216, and 238.]

Hollstein, Fabian, Marcel Prokopczuk, and Christoph Würsig, 2020, Volatility Term Structures in Commodity Markets, *Journal of Futures Markets* 40, 527–555. [cited on p. 175.]

Hollstein, Fabian, and Chardin Wese Simen, 2020, Variance Risk: A Bird's Eye View, *Journal of Econometrics* 215, 518–535. [cited on p. 16.]

Hong, Harrison, 2000, A Model of Returns and Trading in Futures Markets, *Journal of Finance* 55, 959–988. [cited on p. 16, 28, and 29.]

Hong, Yongmiao, Yanhui Liu, and Shouyang Wang, 2009, Granger Causality in Risk and Detection of Extreme Risk Spillover between Financial Markets, *Journal of Econometrics* 150, 271–287. [cited on p. 32.]

Hou, Kewei, Haitao Mo, Chen Xue, and Lu Zhang, 2021, An augmented q-factor model with expected growth, *Review of Finance* 25, 1–41. [cited on p. 242.]

Hou, Kewei, and David T. Robinson, 2006, Industry Concentration and Average Stock Returns, *Journal of Finance* 61, 1927–1956. [cited on p. 213.]

Jackwerth, Jens, and Grigory Vilkov, 2019, Asymmetric Volatility Risk: Evidence from Option Markets, *Review of Finance* 23, 777–799. [cited on p. 1.]

Jackwerth, Jens Carsten, 2000, Recovering Risk Aversion from Option Prices and Realized Returns, *Review of Financial Studies* 13, 433–451. [cited on p. 73.]

Jacobsen, Ben, Ben R Marshall, and Nuttawat Visaltanachoti, 2018, Stock Market Predictability and Industrial Metal Returns, *Management Science* forthcoming. [cited on p. 37.]

Jiang, George J., and Yisong S. Tian, 2005, The Model-Free Implied Volatility and its Information Content, *Review of Financial Studies* 18, 1305–1342. [cited on p. 78.]

Johnson, Travis L, 2017, Risk Premia and the VIX Term Structure, *Journal of Financial and Quantitative Analysis* 52, 2461–2490. [cited on p. 11 and 17.]

Jory, Surendranath, and Thanh Ngo, 2017, Firm Power in Product Market and Stock Returns, *Quarterly Review of Economics and Finance* 65, 182–193. [cited on p. 213.]

Kang, Boda, Christina Sklibosios Nikitopoulos, and Marcel Prokopczuk, 2019, Oil Futures Volatility and the Economy, Working Paper. [cited on p. 24.]

Kelly, Bryan, and Hao Jiang, 2014, Tail Risk and Asset Prices, *Review of Financial Studies* 27, 2841–2871. [cited on p. 81, 83, 91, 95, 106, 107, 113, 116, 135, and 174.]

Kilian, Lutz, 2009, Not all Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market, *American Economic Review* 99, 1053–69. [cited on p. 26.]

Kim, Abby, 2015, Does Futures Speculation Destabilize Commodity Markets?, *Journal of Futures Markets* 35, 696–714. [cited on p. 175.]

Kogan, Leonid, and Dimitris Papanikolaou, 2013, Firm Characteristics and Stock Returns: The Role of Investment-Specific Shocks, *Review of Financial Studies* 26, 2718–2759. [cited on p. 242.]

Kovács, Péter, Tibor Petres, and László Tóth, 2005, A new measure of multicollinearity in linear regression models, *International Statistical Review* 73, 405–412. [cited on p. 24.]

Lahiri, Soumendra N., 1999, Theoretical Comparisons of Block Bootstrap Methods, *Annals of Statistics* 27, 386–404. [cited on p. 121, 166, 167, 168, and 169.]

Lin, Huidi, and Viktor Todorov, 2019, Aggregate Asymmetry in Idiosyncratic Jump Risk, *Northwestern University Working Paper* . [cited on p. 80, 187, 220, and 252.]

Lindeman, Richard H., PF. Merenda, and Ruth Z. Gold, 1980, Introduction to Bivariate and Multivariate Analysis, *New York: Scott, Foresman and Co* . [cited on p. 45, 47, 49, 89, 104, 105, 108, 109, 111, 112, 156, 157, 158, 159, 161, 162, 163, 164, 165, 166, 167, 168, and 169.]

Lu, Zhongjin, and Scott Murray, 2019, Bear Beta, *Journal of Financial Economics* 131, 736–760. [cited on p. 82, 83, 136, 137, and 251.]

Lucca, David O, and Emanuel Moench, 2015, The Pre-FOMC Announcement Drift, *Journal of Finance* 70, 329–371. [cited on p. 12 and 44.]

Maheu, John M., Thomas H. McCurdy, and Xiaofei Zhao, 2013, Do Jumps Contribute to the Dynamics of the Equity Premium?, *Journal of Financial Economics* 110, 457–477. [cited on p. 81, 83, 133, and 134.]

Mancini, Cecilia, 2001, Disentangling the Jumps of the Diffusion in a geometric jumping Brownian Motion, *Giornale dell'Istituto Italiano degli Attuari* 64, 44. [cited on p. 86 and 87.]

Martin, Ian, 2017, What is the Expected Return on the Market?, *Quarterly Journal of Economics* 132, 367–433. [cited on p. 52 and 80.]

McCracken, Michael W, 2007, Asymptotics for Out of Sample Tests of Granger Causality, *Journal of Econometrics* 140, 719–752. [cited on p. 34, 35, 36, 62, 63, 64, 65, 66, 69, 70, and 71.]

Mixon, Scott, 2007, The Implied Volatility Term Structure of Stock Index Options, *Journal of Empirical Finance* 14, 333–354. [cited on p. 11.]

Moyer, R. Charles, and Robert Chatfield, 1983, Market Power and Systematic Risk, *Journal of Economics and Business* 35, 123–130. [cited on p. 209 and 212.]

Muir, Tyler, 2017, Financial crises and risk premia, *Quarterly Journal of Economics* 132, 765–809. [cited on p. 75.]

Nazlioglu, Saban, Cumhur Erdem, and Ugur Soytas, 2013, Volatility Spillover between Oil and Agricultural Commodity Markets, *Energy Economics* 36, 658–665. [cited on p. 12.]

Newey, Whitney K, and Kenneth D West, 1986, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 53, 1047–1070. [cited on p. 25, 27, 30, 34, 35, 36, 46, 47, 49, 62, 63, 64, 65, 66, 69, 70, and 71.]

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 53, 1047–1070. [cited on p. 89, 101, 102, 104, 105, 108, 109, 111, 112, 115, 117, 120, 140, 151, 152, 153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 193, 194, 197, 198, 202, 203, 205, and 206.]

Nguyen, Duc Binh Benno, and Marcel Prokopczuk, 2018, Jumps in commodity markets, *Journal of Commodity Markets* . [cited on p. 175.]

Nguyen, Duc Khuong, and Thomas Walther, 2019, Modeling and Forecasting Commodity Market Volatility with Long-Term Economic and Financial Variables, *Journal of Forecasting* . [cited on p. 24.]

Nicholls, Desmond F., and Alun L. Pope, 1988, Bias in the Estimation of Multivariate Autoregressions, *Australian Journal of Statistics* 30, 296–309. [cited on p. 139.]

O'Brien, Thomas J., 2011, Managerial economics and operating beta, *Managerial and Decision Economics* 32, 175–191. [cited on p. 209 and 212.]

Perry, Martin K, and Robert H Porter, 1985, Oligopoly and the incentive for horizontal merger, *American Economic Review* 75, 219–227. [cited on p. 228.]

Peyser, Paul S., 1994, Beta, Market Power and Wage Rate Uncertainty, *Journal of Industrial Economics* 42, 217–226. [cited on p. 209 and 211.]

Pindyck, Robert S, 2004, Volatility and Commodity Price Dynamics, *Journal of Futures Markets* 24, 1029–1047. [cited on p. 8.]

Prokopczuk, Marcel, Andrei Stancu, and Lazaros Symeonidis, 2019, The Economic Drivers of Commodity Market Volatility, *Journal of International Money and Finance* . [cited on p. 24.]

Prokopczuk, Marcel, Lazaros Symeonidis, and Chardin Wese Simen, 2017, Variance Risk in Commodity Markets, *Journal of Banking & Finance* 81, 136–149. [cited on p. 13, 173, and 180.]

Rapach, David E., Jack K. Strauss, and Guofu Zhou, 2013, International Stock Return Predictability: What is the Role of the United States?, *Journal of Finance* 68, 1633–1662. [cited on p. 89, 104, 105, 108, 109, 111, 112, 117, 139, 156, 157, 158, 159, 160, 161, 162, 163, 164, and 165.]

Rietz, Thomas A., 1988, The equity risk premium a solution, *Journal of Monetary Economics* 22, 117–131. [cited on p. 75 and 85.]

Robe, Michel A, and Jonathan Wallen, 2016, Fundamentals, Derivatives Market Information and Oil Price Volatility, *Journal of Futures Markets* 36, 317–344. [cited on p. 37.]

Rotemberg, Julio J., and Robert S. Pindyck, 1990, The Excess Co-Movement of Commodity Prices, *Economic Journal* 100, 1173–1189. [cited on p. 11.]

Samuelson, Paul A, 1965, Proof that Properly Anticipated Prices Fluctuate Randomly, *Industrial Management Review* 6, 41–49. [cited on p. 2, 9, and 28.]

Savor, Pavel, and Mungo Wilson, 2013, How Much Do Investors Care About Macroeconomic Risk? Evidence from Scheduled Economic Announcements, *Journal of Financial and Quantitative Analysis* 48, 343–375. [cited on p. 12 and 44.]

Schumpeter, Joseph A., 1912, The Theory of Economic Development, *Cambridge, MA: Harvard University Press.* . [cited on p. 213.]

Schwartz, Eduardo, and James E Smith, 2000, Short-Term Variations and Long-Term Dynamics in Commodity Prices, *Management Science* 46, 893–911. [cited on p. 17.]

Seo, Sang Byung, and Jessica A. Wachter, 2018, Option Prices in a Model with Stochastic Disaster Risk, *Management Science* 65, 3470–3469. [cited on p. 78 and 79.]

Stambaugh, Robert F., 1999, Predictive Regressions, *Journal of Financial Economics* 54, 375–421. [cited on p. 89.]

Stigler, George J, 1950, Monopoly and oligopoly by merger, *American Economic Review* 40, 23–34. [cited on p. 228.]

Stigler, George J, 1964, A theory of oligopoly, *Journal of Political Economy* 72, 44–61. [cited on p. 228.]

Stock, James H, and Mark W Watson, 2012, Generalized Shrinkage Methods for Forecasting Using Many Predictors, *Journal of Business & Economic Statistics* 30, 481–493. [cited on p. 15, 58, and 61.]

Subrahmanyam, Marti G., and Stavros B. Thomadakis, 1980, Systematic Risk and the Theory of the Firm, *Quarterly Journal of Economics* 94, 437–451. [cited on p. 209, 210, and 211.]

Sullivan, Timothy G., 1978, The Cost of Capital and the Market Power of Firms, *Review of Economics and Statistics* 60, 209–217. [cited on p. 209 and 212.]

Symeonidis, Lazaros, Marcel Prokopczuk, Chris Brooks, and Emese Lazar, 2012, Futures basis, inventory and commodity price volatility: An empirical analysis, *Economic Modelling* 29, 2651–2663. [cited on p. 175.]

Symitsi, Efthymia, Lazaros Symeonidis, Apostolos Kourtis, and Raphael Markellos, 2018, Covariance forecasting in equity markets, *Journal of Banking & Finance* 96, 153–168. [cited on p. 78.]

Szymanowska, Marta, Frans De Roon, Theo Nijman, and Rob Van Den Goorbergh, 2014, An Anatomy of Commodity Futures Risk Premia, *Journal of Finance* 69, 453–482. [cited on p. 11, 175, and 179.]

Tang, Ke, and Wei Xiong, 2012, Index Investment and the Financialization of Commodities, *Financial Analysts Journal* 68, 54–74. [cited on p. 11 and 12.]

van Oordt, Maarten RC, Philip A Stork, and Casper de Vries, 2021, On Agricultural Commodities' Extreme Price Risk, *Extremes* 24, 531–563. [cited on p. 175.]

Vasicek, Oldrich A., 1973, A Note on using Cross-Sectional Information in Bayesian Estimation of Security Betas, *Journal of Finance* 28, 1233–1239. [cited on p. 217.]

Vilkov, Grigory, and Yan Xiao, 2015, Option-implied Information and Predictability of Extreme Returns, *SAFE Working Paper* . [cited on p. 80, 83, 85, 128, and 129.]

Wachter, Jessica A., and Yicheng Zhu, 2018, The Macroeconomic Announcement Premium, *NBER Working paper* . [cited on p. 12 and 44.]

Weller, Brian, 2018, Measuring Tail Risks at High Frequency, *Review of Financial Studies* 32, 3571–3616. [cited on p. 78 and 79.]

Wong, Kit Pong, 1995, Cournot Oligopoly and Systematic Risk, *Journal of Economics and Business* 47, 385–395. [cited on p. 209 and 212.]

Working, Holbrook, 1960, Speculation on Hedging Markets, *Food Research Institute Studies* 30, 185–220. [cited on p. 16 and 180.]

Yang, Fan, 2013, Investment Shocks and the Commodity Basis Spread, *Journal of Financial Economics* 110, 164–184. [cited on p. 11 and 17.]

Zhou, Hao, 2018, Variance Risk Premia, Asset Predictability Puzzles, and Macroeconomic Uncertainty, *Annual Review of Financial Economics* 10, 481–497. [cited on p. 16.]