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Essays on

Commodity Futures Markets

by

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Declaration of Original Authorship

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Robert Wichmann

To my parents

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Abstract

This thesis comprises three essays to contribute to the growing body of research on commodity futures markets.

The first essay discusses the dynamics of commodity return comovements. Comparing two distinct factor models concerning their ability to explain the covariance structure of commodity futures returns, we find that a factor model based on tradable portfolio returns can explain most of the realized comovements in commodity returns. We show that the increase in the comovement of commodity returns during the financialization period is driven by intersectoral rather than intrasectoral comovements. Dissecting the evidence, we find that the time variation of the factor covariances rather than the variation of factor exposures is the driving force behind this increase. The dynamics of return comovements are not mirrored by volatility comovements, which jump following the global financial crisis. Our results cast doubt on the long-term effects of commodity market integration and have practical relevance for risk management.

In the second essay, we study the effect of inventory news on the natural gas market. We find that more than 50% of the annual return is generated on announcement days of the EIA storage report. Surprisingly, the announcement effect cannot be explained by the announcement surprise, supply and demand, spillover effects, or other return predictors. Investigating the intraday pattern, we find that the return splits half into a pre- and post-announcement part, with the pre-announcement return entirely accumulating on days when storage levels exceed analysts' expectations. These results are difficult to reconcile with explanations based on informed trading. After transaction and funding costs, a simple trading strategy yields substantial returns.

The third essay proposes a measure for convenience yield risk that can predict commodity futures returns. The measure incorporates the seasonal patterns in convenience yield as well as the term structure and time variation of its volatility. Portfolios sorted by convenience yield risk provide a significant excess return over common commodity factors. The predictive power of convenience yield risk in the cross-section is not subsumed by commodity or time fixed effects. Dissecting our measure, we find it to be driven by the term structure variation of convenience yields and closely related to the Samuelson effect and the basis. On average, commodities with high convenience yields experience high convenience yield risk and vice versa. This dynamic breaks down at higher frequencies.

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Chapter 1

Introduction

During the 20^{th} century, the distinct role of commodity futures markets was to serve as a hedging tool for commercial market participants in facilitating the trading of future production and consumption of commodities. With the deregulation and inflow of non-commercial capital in the 21^{st} century, however, commodity futures markets have also attracted the attention of financial investors. From an academic point of view, this puts research on commodity futures markets at an important intersection of macroeconomics and finance. In this chapter, we introduce the necessary concepts and highlight the contribution of this thesis to the literature on commodity futures markets.

The transformation of commodity markets, also referred to as "financialization" (Tang and Xiong, 2012), has been widely discussed in the literature on commodity markets. The importance of such analysis derives from the desirable characteristics of commodity markets for financial investors, such as being a hedge against inflation (Bodie, 1983) and exhibiting negative correlation with equity and bond returns (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). Although there is ample evidence for a change in co-movements (Tang and Xiong, 2012; Silvennoinen and Thorp, 2013; Ohashi and Okimoto, 2016), research has not been conclusive on whether the changes are of a temporary or permanent nature (Christoffersen et al., 2019). The work of Pindyck and Rotemberg (1990) constitutes an important guideline in this discussion as it defines excess comovement of commodities as any comovement that is not explained by macroeconomic factors.

Chapter 2 of this thesis contributes to the discussion on the comovements of commodity futures returns and starts from first principles. How should one model the comovements of commodity returns? We set a level playing field by allowing not only macroeconomic factor models Le Pen and Sévi (2017), but also factor models based on return predictors from the more recent literature on commodity risk premia (Szymanowska et al., 2014; Bakshi et al., 2019; Boons and Prado, 2019). With respect to multiple metrics and after rigorous robustness checks, the evidence is clearly in favor of a factor model based on tradable portfolio returns. This model can explain 96% of the realized commodity return comovement, leaving only a negligible part of excess comovement. In consequence, this enables us to use the estimated comovement and investigate the drivers of financialization.

Next, we dissect the comovements and show that intersectoral rather than intrasectoral comovements are the cause of the general increase in comovements during financialization. Commodities of different sectors are more likely to move together because of investments in commodity indices, while intrasectoral comovements depend more on common drivers and substitutability within sectors. Therefore, our results support the view that the increase of comovements is related to financialization.

The second research question concerns the persistence of the increase in comovements of commodity returns since a temporary or permanent change call for different responses from regulators and practitioners. For example, the Masters (2009) hypothesis that speculators were the main reason for the price surge of agricultural commodities, has been used as an argument to implement stricter regulation in commodity trading (Irwin and Sanders, 2012). In our work, the use of a simple factor model allows us to decompose the comovement of commodity futures returns into two parts, one driven by the covariance of factor returns, and one driven by the exposures of the commodities towards those factors. Bekaert et al. (2009) point out that returns moving together because of fluctuations in the common risk factors rather than the exposure towards those factors poses a challenge to theories of persistent higher degree of market integration. Factor covariances exhibit substantial time variation in the short term, but permanent trend changes in comovements are more likely to be induced by changes in betas. The evidence presented in our work suggests that the factor covariances are the driving force behind comovements in the financialization period, therefore, casting doubt on a persistently higher degree of commodity market integration.

Instead of focusing on the financial aspects to commodity futures markets, a distinct strand of literature regards commodity prices as entirely determined by macro aggregates (Kilian, 2009; Kilian and Bilnder, 2009). Between supply and demand, inventories act as a buffer in commodity markets and play a vital role in determining market expectations. Oversupply will increase stock holdings, while meeting unexpected demand decreases inventories. As prices fully reflect all available information in an efficient market (Fama, 1970), traders are closely monitoring news regarding the inventory levels (Gorton et al., 2013). In consequence, days on which important and new information is released will attract the attention of market participants. For stock markets, Savor and Wilson (2013) document that 60% of the annual equity risk premium can be earned by only investing when macroeconomic news is released. Further, Engelberg et al. (2018) find that anomaly returns are 50% higher on corporate news days and even six times higher on earnings announcement days. To perform an analogous analysis for commodity futures markets poses two challenges. First, inventory data is empirically hard to obtain obtain as it is mostly private information. Second, public reports do often not only include inventory news, but also forecasts on future production or consumption, which impedes the statistical inference. The natural gas market provides an ideal exception from these limitations as inventory levels are well documented by the Energy Information Administration (EIA) within a weekly report that only covers storage.

In Chapter 3, we examine the effect of inventory news on the natural gas futures market and find that more than 50% of the annual average return on natural gas is realized on EIA announcement days. We confirm increased volatility and trading volume on EIA announcement days as well as an inverse relationship between the announcement return and the announcement surprise (Linn and Zhu, 2004; Gay et al., 2009; Halova et al., 2014), i.e., when inventory levels are higher than expected, gas prices fall, and vice versa. The motivation for this study, however, arises from the question whether the return difference between announcement and non-announcement days can be fully explained or whether we can document a sizeable premium on such days. In light of this, our results are surprising, as we do not find that the announcement surprise can explain the difference in returns between EIA announcement days and non-announcement days. Additionally, the excess return on announcement days is negative, hence it cannot be interpreted as a premium for bearing the uncertainty about inventory news (Savor and Wilson, 2013). We scrutinize these results by allowing for other channels to affect natural gas prices, such as asymmetric effects due to seasonal demand patterns arising from the use of natural gas for heating, weather (Brown and Yücel, 2008), spillovers (Wolfe and Rosenman, 2014), or other return predictors.

In a second part, we analyze the announcement effect at the intraday level to obtain a more comprehensive idea of how gas prices react to storage news. Similar studies in equity and fixed income markets have found pre- and post-announcement drifts for events such as earnings announcements (Ball and Brown, 1968; Bernard and Thomas, 1989; Sadka, 2006) or meetings of the Federal Open Market Committee (FOMC) (Kuttner, 2001; Bernanke and Kuttner, 2005). Therefore, our work gives an insight into how information is transmitted in commodity markets. While a pre-announcement drift as documented by Lucca and Moench (2015) for the FOMC meetings indicates that the information is leaked before the official publication, post-announcement effects support an underreaction of markets (Mendenhall, 2004).

Also in this regard, our results are puzzling. On the one hand, we find that the effect is fully generated from the two-hour window around the announcement starting 90 minutes before and ending 30 minutes after the publication. On the other hand, the return splits equally into a pre-announcement part realized over the 90 minutes before the storage news, and a post-announcement part as an immediate reaction to the news release. Therefore, our results are hard to reconcile with an explanation based on informed trading (Gu and Kurov, 2018).

The important role of inventory news for commodity futures markets derives from the theory of storage, i.e., the concept of a price for storage that is related to the price difference between spot and futures markets (Working, 1949). When the market is in contango, i.e., futures prices exceed spot prices, the price of storage is high as it compensates for storage costs and forgone interest. In backwardation, i.e., spot prices exceed futures prices, storing the commodity is seemingly unprofitable, because futures trade at a discount. Within the theory of storage, this phenomenon is rationalized by the convenience yield Kaldor (1939), the reward that arises from holding physical commodities as it embeds the implied option to sell the commodity or use it to meet sudden demand shocks. Consequently, the convenience yield affects spot and futures prices and is a key figure for investors in commodity futures markets. While the convenience yield has been proxied by the interest rate adjusted basis Gorton et al. (2013) or estimated within a stochastic model Schwartz (1997), the literature has not developed a measure for the risk associated with the convenience yield.

The main contribution of Chapter 4 of this thesis is to propose a measure for convenience yield risk. We show that this measure can predict commodity futures returns as commodities with higher convenience yield risk outperform commodities with lower convenience yield. While the literature has identified many commodity return predictors, such as the basis Szymanowska et al. (2014), momentum (Miffre and Rallis, 2007), basis-momentum (Boons and Prado, 2019), idiosyncratic volatility (Fernandez-Perez et al., 2016), open interest (Hong and Yogo, 2012), hedging pressure, (Basu and Miffre, 2013) or speculative pressure (Fan et al., 2020), we find convenience yield risk to provide excess return beyond the list of known predictors.

Apart from the time variation and seasonal behavior due to supply and demand cycles, the convenience yield has a term structure dimension like interest rates. Our study ought to extract information from the term structure dimension of commodity futures. While most of the literature focuses on the first two nearby contracts, some work has already included further deferred contracts. Gu et al. (2019) find that measuring the differential between first and second basis provides a better approximation of inventory levels. By choosing the contracts with the lowest roll yield along the term structure, de Groot et al. (2014) propose an optimized momentum strategy. Boons and Prado (2019) allow the return on the second nearby to impact their trading signal, while Paschke et al. (2020) propose a strategy that works within one commodity market, effectively using the basis-momentum signal in a timing strategy. However, the most known observation for the volatilities of commodity futures is the Samuelson (1965) effect, i.e., the empirical fact that the volatility of commodity futures increases as they approach expiration, also documented by the works of Bessembinder et al. (1996) and Duong and Kalev (2008). Our measure of convenience yield risk is driven by term structure variation in convenience yields and can be interpreted as a measure for the strength of the Samuelson effect certain conditions.

Lastly, we discuss the link between convenience yield risk and the convenience yield itself within the theory of storage. Similar to the classic risk-return relationship, we find that commodity markets that experience higher average convenience yield risk have higher convenience yields and vice versa. However, in a conditional analysis based on rolling window estimates this relationship breaks down. The inverse relationship between inventory and basis has proven to be much stronger in low inventory conditions. In a period of shortage the probability of a stock-out increases, the basis is more elastic and spot price volatility increases (Working, 1949). Under such circumstances, although stored commodities are more valuable, this valuation is also more volatile, hence the convenience yield risk is higher. At the same time, a sharp fall of spot prices following a negative demand shock might turn markets into contango, but convenience yield risk still increases as the reward from storing the commodity might turn negative.

Each of the following chapters of this thesis is self-contained. Figures and tables are self-explanatory within the respective chapter. Therefore, we repeat definitions and explanations where necessary. Chapter 2 studies the dynamics of commodity return comovements, Chapter 3 investigates the effect of EIA announcements on natural gas markets, and Chapter 4 discusses convenience yield risk. Each chapter is followed by an appendix including additional material. Finally, Chapter 5 concludes with a summary of the findings and suggestions for future research.

Chapter 2

The Dynamics of Commodity Return Comovements

2.1 Introduction

Since the beginning of the century commodity markets have undergone a massive transformation. Surging demand from emerging countries, deregulation, and an increase of index investment by financial players have affected the correlations of commodity market returns.[1] Average pairwise correlations of commodity futures returns increased from 10% before 2004 to 24% after 2004. This increase in correlations is even stronger for return volatilities which rose from 12% to 33% during the same period. This shift has not only occurred to a specific group of commodities but to the whole cross-section.[2]

This chapter aims to shed light on the dynamics of these comovements. Is it the correlation (1) within sectors or (2) between different sectors that drives the time variation

[1]In 2000, the Commodity Futures Modernization Act (CFMA) was enacted and changed the regulation of over-the-counter derivatives. As argued in Prokopczuk et al. (2017), this regulation lowered the barriers to entry of speculators in commodity markets. According to Tang and Xiong (2012), the value of index-related commodity investments increased from \$15 billion in 2003 to over \$200 billion in 2008. As of December 2017, Barclays reported global commodity assets under management haven risen to \$311 billion. Bhardwaj et al. (2015) show that the proportion of open interest from non-commercial traders has more than doubled between 1993 and 2014 as reported by the Commodity Futures Trading Commission (CFTC).

[2]The data sample comprises daily futures returns for 34 commodity markets from April 1990 to December 2018 and is divided in half at the end of 2003 (Tang and Xiong, 2012). The respective numbers are presented in Tables A.1 and A.2 in Appendix A.

in comovements? How much of the comovements can be explained by factor models and thus what proportion was unexpected? Is this increase due to the time variation in (1) the factor sensitivities or (2) the factor covariances?

The main results of this chapter are threefold. First, we find that a simple factor model can explain 96% of the realized comovements in commodity returns. Second, we document that the high comovements observed during and after financialization are mostly driven by comovements between different commodity sectors rather than within sectors. Third, the time variation in factor covariances as opposed to the time variation in factor sensitivities is the main contributor to the dynamics of comovements during this period.

We begin by comparing two recently proposed empirical models for commodity futures returns: (1) a four-factor model, that includes the market, carry, momentum, and basis-momentum factors (Bakshi et al., 2019; Boons and Prado, 2019) and (2) a macro factor model that builds on the information content of 184 macroeconomic variables (Le Pen and Sévi, 2017). We compare the models' ability to fit the covariance structure of commodity returns and find that the model with tradable factors outperforms the macro factor model.

Dissecting the comovement into the part driven by *intrasectoral* correlations and the part driven by *intersectoral* correlations, we find that while both parts have increased during and after financialization, it is the comovement between commodities of different sectors that drives the time variation in the total comovement. Next, we decompose the return comovements into a model-implied component and a surprise component. In the data, we find that the model-implied component accounts for virtually all of the realized comovements. Pushing the analysis further, we show that the model-implied component is the product of factor sensitivities (β) and the covariance matrix of factors (Σ). By fixing one of the two parts to its time series average, all variation is induced by the other part. Comparing the results shows that while the time series with fixed factor coefficients is still able to reproduce the main features of the comovement, with fixed factor covariances a meaningful interpretation of commodity return comovements is not possible.

Our work relates to the literature on excess return comovements. Pindyck and Rotemberg (1990) regress commodity returns on 6 selected U.S. macroeconomic variables. Their analysis is extended by Le Pen and Sévi (2017) who consider the information content of 184 macroeconomic variables related to the U.S., but also international markets. Filtering out the effects of these macro variables on commodity returns, both studies interpret the correlation of the filtered returns as evidence of excess comovement. We find that a simple four-factor model (Bakshi et al., 2019; Boons and Prado, 2019) provides a better fit to the comovement of commodity returns, casting doubt on the amount of excess comovement prevailing in the market once accounted for these factors.

Our work also relates to the broader literature on the modelling of commodity return comovements. Several studies use GARCH-type models to directly model the correlation structure of returns (Deb et al., 1996; Berben and Jansen, 2005; Silvennoinen and Thorp, 2013; Ohashi and Okimoto, 2016). Our approach is different. We use a factor model for commodity returns and explore its implications for comovements. Thus, our methodology enables us to derive the covariance as a product of betas and factor variances and assess their contribution to the model-implied comovements.

Our study also contributes to the growing literature on commonalities of return volatilities. Christoffersen et al. (2019) document an interesting result. They show that while the increase in return comovements of commodities has been temporary, volatility comovements have increased during the crisis and there is no evidence of a reversal in the more recent period. One key question that directly follows from this result is: How can the increase in volatility comovements persist, while return comovements are temporary? Our results show that volatility comovements are indeed lower during the financialization period, before they jump to a persistently higher regime after the financial crisis of 2008/2009. The increase in return comovements on the other hand is marked by a gradual increase starting before the financial crisis. Thus, it is important to draw a clear distinction between the effects of financialization and the financial crisis on commodity market comovements.

We contribute to the strand of literature on the integration of commodity markets.[3]

[3]We concentrate on the financial aspects, but acknowledge that there is also a large macroeconomic literature on this topic, well summarized by Fattouh et al. (2013). Further literature is focusing on

Tang and Xiong (2012) show that correlations of commodity futures returns have increased substantially and this effect is especially pronounced for commodities that are part of commodity indices. Cheng and Xiong (2014) discuss the impact of financial investors on commodity markets, arguing that they mitigate hedging pressure and improve risk sharing, but also induce shocks due to risk constraints and financial distress. Henderson et al. (2015) use a novel dataset of commodity-linked notes allowing them to identify the relation between price movements and hedging trades. Our findings shed light on how financialization has affected commodity markets. We define financialization as the increase of institutional investors that follow momentum strategies (Bhardwaj et al., 2014), or invest in different generations of commodity indices, incorporating carry and momentum strategies, as well as long-short strategies (Miffre and Fernandez-Perez, 2015). While it is undisputed that correlations between commodity markets have risen during financialization, the fact that the time variation of factor covariances is the main contributor to the increase in return comovements, helps to explain the long-term effects of financialization. As Bekaert et al. (2009) argue, returns moving together because of fluctuations in the common risk factors rather than the exposure towards these factors casts doubt on a persistent higher degree of market integration since factor covariances exhibit substantial time variation in the short term, but permanent trend changes in comovements are more likely to be induced by changes in betas. Therefore, financialization has affected commodity futures returns in the short run, but has limited effects on the integration of commodity markets in the long run.

Whether changes in factor sensitivities or factor variances drive the increased comovement is of fundamental importance as it calls for different reactions of regulators and practitioners. From a regulatory perspective, our findings question the view that a stricter regulation of financial trading in commodity markets will reduce comovements.[4] From an asset and risk management perspective, we emphasize the necessity to model the correlation dynamics using tradable factors rather than macroeconomic factors. Our

spillover effects and contagion, especially during the financial crisis and the boom and bust of commodities (Singleton, 2014).

[4]See also the literature on the 'Masters Hypothesis' (Irwin and Sanders, 2012), that tries to explain the links between index investment and commodity prices.

results indicate that failing to model the change in factor variances leads to erroneous risk assessment. For example, using the empirical distribution of the returns with fixed factor covariances results in an estimated 3% decrease of Value-at-Risk (VaR) within the period of financialization, while the realized or model-implied returns show that VaR has increased by 21%.

The remainder of this chapter is organized as follows. Section 2.2 describes the data and methodology. Section 2.3 introduces and compares the factor models. Section 2.4 dissects the commodity comovements. Section 2.5 discusses the implications of our findings, Section 2.6 documents several robustness checks, and Section 2.7 concludes.

2.2 Data & Methodology

2.2.1 Data

We obtain daily commodity futures prices and volumes from Bloomberg covering 34 major commodity futures markets, divided into 8 sectors: Energy, Grains, Industrial Metals, Livestock, Materials, Oilseeds, Precious Metals, and Softs.[5] We gather financial data on Treasury rates, credit spreads, corporate bond yields, and stock volatility data from the Federal Reserve Bank of St. Louis (FRED). Furthermore, we collect the same 184 macroeconomic variables as Le Pen and Sévi (2017) from DataStream. Our main analysis concentrates on the period from April 1990 to December 2018.[6]

We roll the contract closest to maturity over at the end of the month preceding the month prior to delivery. This approach is analogous to Szymanowska et al. (2014) and enables us to avoid liquidity concerns of futures contracts close to maturity. We roll over all nearbys at the same time, i.e., if t is a rollover date, for any n the $(n+1)^{th}$ nearby becomes the n^{th} nearby after the rollover. This has further implications on the

[5] This choice of sectors is equivalent to Szymanowska et al. (2014), except for the metal sector, which we split into precious and industrial metals.

[6] The whole sample comprises data dating back to July 1959. Within this early period the composition of the sample changes drastically, when new commodities are introduced, affecting comovements. Hence, we concentrate on the later period, during which the composition of the sample is constant. Details on the data are listed in Tables A.1 and A.2 in Appendix A.

computation of the return series, as on the day before a rollover day, we have to account for the fact, that the $(n+1)^{th}$ nearby will be the n^{th} nearby on the following day. By doing this, we guarantee that the computed return is realizable (Singleton, 2014). In formulas, we can write the return on the n^{th} nearby on day t as

$$R_t^{(n)} := \begin{cases} \frac{F_t^{(n)}}{F_{t-1}^{(n+1)}} - 1, & \text{if } t-1 \text{ is a rollover day} \\ \frac{F_t^{(n)}}{F_{t-1}^{(n)}} - 1, & \text{otherwise,} \end{cases} \tag{2.1}$$

where $F_t^{(n)}$ is the price of the n^{th} nearby futures contract on day t. The summary statistics for the first nearby returns provided in Table 2.1 show common characteristics of commodity markets, annualized mean returns differ strongly between commodities (7.8% for copper, but -5.2% for corn) and within sectors (13.9% for gasoline, but -9.0% for natural gas), and volatility ranges from 13.9% for live cattle to 44.8% for natural gas.

2.2.2 Methodology

Having constructed the return series of commodity futures, we now aim to decompose the covariance of returns. Suppose that for a commodity i the return on the first nearby, R_i, emerges from its linear exposure to K factors. For every commodity market i, we run the time series regression:

$$R_i = \alpha_i + X\beta_i + \epsilon_i, \tag{2.2}$$

where α_i is the intercept, X is the $T \times K$ matrix of factors, β_i is the $K \times 1$ vector of slope coefficients and ϵ_i denotes the residual. The covariance of two commodity returns R_i and R_j is then given by

$$\underbrace{\text{Cov}(R_i, R_j)}_{\text{Realized Covariance}} = \underbrace{\beta_i' \cdot \Sigma_X \cdot \beta_j}_{\text{Model-Implied Covariance}} + \underbrace{\text{Cov}(\epsilon_i, \epsilon_j)}_{\text{Residual Covariance}}, \tag{2.3}$$

where Σ_X denotes the $K \times K$ covariance matrix of the factors. Equation (2.3) illustrates that we can always decompose the realized covariance into a model-implied component and a residual component. This identity is useful in order to evaluate how much of the realized comovement can be explained by the respective model.

Table 2.1: Summary Statistics for Commodity Futures Returns

This table reports the summary statistics of daily commodity futures returns on 34 commodities obtained from Bloomberg for the period from April 1990 to December 2018. We report mean, median, minimum (Min), maximum (Max), standard deviation (SD), Sharpe ratio (SR), first order autocorrelation (AR(1)), skewness (Skew), kurtosis (Kurt), the p-value of a Jarque-Bera test (JB), and the number of observations (Obs). Figures are in percentage points. The mean, standard deviation, and Sharpe ratios are annualized. The eight sectors, Energy, Grains, Industrial Metals, Livestock, Oilseeds, Precious Metals, and Softs are each separated by horizontal lines.

Commodity	Mean	Median	Min	Max	SD	SR	AR(1)	Skew	Kurt	JB	Obs
WTI Crude	6.87	0.06	-31.89	14.27	34.42	0.20	-0.02	-0.48	12.63	0.00	7218
Brent Crude	11.53	0.06	-32.00	14.95	33.94	0.34	-0.03	-0.41	13.76	0.00	7170
Heating Oil	7.48	0.01	-29.60	13.66	31.78	0.24	-0.02	-0.35	11.82	0.00	7218
Natural Gas	-8.98	-0.05	-17.46	20.64	44.81	-0.20	-0.03	0.23	5.86	0.00	7217
Gasoil	9.01	0.00	-26.90	13.94	29.93	0.30	0.02	-0.30	13.19	0.00	7173
Gasoline	13.89	0.06	-25.78	13.85	32.83	0.42	-0.01	-0.29	8.78	0.00	7216
Corn	-5.22	0.00	-7.80	9.05	24.37	-0.21	0.04	0.14	5.67	0.00	7239
Kansas Wheat	-2.36	-0.05	-8.60	8.43	25.12	-0.09	0.04	0.19	5.11	0.00	7236
Oats	-1.15	0.00	-11.25	11.74	28.93	-0.04	0.07	0.07	5.06	0.00	7196
Rough Rice	-7.47	-0.04	-7.32	7.67	22.66	-0.33	0.09	0.16	4.67	0.00	7197
Chicago Wheat	-5.90	-0.07	-9.49	9.19	27.32	-0.22	0.02	0.19	5.18	0.00	7239
Copper	7.84	0.01	-11.05	12.35	25.50	0.31	-0.06	-0.02	7.33	0.00	7220
Aluminium	-1.59	-0.02	-7.89	6.10	20.85	-0.08	-0.03	-0.13	5.44	0.00	5303
Lead	9.92	0.01	-12.25	13.70	30.90	0.32	0.04	-0.02	6.69	0.00	5276
Nickel	9.40	-0.00	-16.67	14.06	35.89	0.26	-0.00	0.06	6.26	0.00	5303
Tin	10.60	0.03	-10.83	16.22	25.54	0.41	0.03	0.05	10.43	0.00	5298
Zinc	2.45	0.00	-11.73	10.35	28.87	0.08	-0.03	-0.04	6.13	0.00	5299
Feeder Cattle	2.34	0.02	-5.82	4.34	13.97	0.17	0.07	-0.12	4.69	0.00	7245
Live Cattle	1.17	0.00	-6.16	3.77	13.93	0.08	0.02	-0.10	4.53	0.00	7245
Lean Hogs	-4.82	0.00	-6.65	7.12	23.27	-0.21	0.03	-0.03	4.26	0.00	7245
Cotton	-2.01	-0.01	-6.68	7.18	24.37	-0.08	0.04	0.03	4.50	0.00	7230
Lumber	-7.19	-0.06	-6.34	7.24	27.06	-0.27	0.11	0.13	3.00	0.00	7245
Soybean Oil	-1.98	-0.04	-6.98	8.42	22.08	-0.09	0.02	0.23	5.14	0.00	7240
Canola	0.14	0.00	-7.89	6.65	18.17	0.01	0.05	-0.18	7.38	0.00	7065
Soybeans	3.98	0.00	-7.03	6.92	22.07	0.18	-0.01	-0.05	5.47	0.00	7236
Soybean Meal	10.65	0.00	-8.19	8.10	24.34	0.44	0.02	0.06	5.41	0.00	7238
Gold	2.72	0.00	-9.34	9.23	16.08	0.17	-0.01	-0.06	10.94	0.00	7217
Palladium	13.02	0.06	-13.38	16.81	30.71	0.42	0.08	-0.06	8.12	0.00	7216
Platinum	4.15	0.05	-9.04	10.83	21.11	0.20	0.04	-0.25	7.14	0.00	7218
Silver	4.86	0.04	-17.71	13.28	28.36	0.17	-0.03	-0.53	9.74	0.00	7218
Cocoa	-0.57	0.00	-9.52	12.92	29.13	-0.02	-0.00	0.13	5.54	0.00	7207
Orange Juice	-3.51	0.00	-12.77	16.27	29.73	-0.12	0.06	0.21	6.71	0.00	7234
Coffee	-2.30	-0.03	-12.53	26.15	35.72	-0.06	-0.01	0.69	12.30	0.00	7205
Sugar	2.85	0.00	-11.63	10.45	30.81	0.09	-0.01	-0.06	5.01	0.00	7207

2.3 Model Selection

In this section, we introduce two factor models. The first model uses tradable factors and the second model uses macroeconomic variables to explain commodity futures returns. After describing different ways to estimate both models, we compare their ability to describe commodity market comovements.

2.3.1 Commodity Factor Model

The first empirical model we consider is an extension of Bakshi et al. (2019), who find that the market, basis, and momentum factors can describe the cross-sectional and time series variation in commodity futures returns. We augment this model with the recently proposed basis-momentum factor (Boons and Prado, 2019), i.e., we set $X = (R^{\mathrm{MRKT}}, R^{\mathrm{BAS}}, R^{\mathrm{MOM}}, R^{\mathrm{BASMOM}})$ in Equation (2.2).

The market portfolio (MRKT) is an equally-weighted long-only portfolio of all commodity markets.[7] For the basis portfolio, we compute the basis $B_i^{(1,2)}$ for each commodity market i as:

$$B_i^{(1,2)} = \left(\frac{F_i^{(1)}}{F_i^{(2)}} \right)^{\frac{365}{M_i^{(2)} - M_i^{(1)}}}, \tag{2.4}$$

where $F_i^{(1)}(F_i^{(2)})$ is the price of the first (second) nearby contract and $M_i^{(1)}(M_i^{(2)})$ is the time to maturity in days of the first (second) nearby contract. Note that by compounding the basis, we correct for differences in maturities. After sorting the cross-section of commodities by their basis, we construct the basis portfolio as an equally-weighted long-short portfolio, that opens a long position in the 17 commodities with the highest basis and opens a short position in the 17 commodities with the lowest basis.

For the momentum factor, we consider the past performance of each market over the last 12 months and construct an equally-weighted portfolio opening a long position in the 17 commodities with the highest historical returns and opening a short position in the 17 commodities with the lowest historical returns.

[7] While equally weighting the market factor is common in the commodity literature Bakshi et al. (2019), we address issues with respect to the weights in Section 2.6.

The basis-momentum factor is based on the difference between the first nearby momentum and the second nearby momentum in each market. The portfolio consists of a long position in the 17 commodities with the highest difference in historical returns and a short position in the 17 commodities with the lowest difference in historical returns. All portfolios are rebalanced each month.

2.3.2 Macro Factor Model

The second model builds on the work of Pindyck and Rotemberg (1990). They define excess comovement as any comovement which is well in excess of what can be explained by fundamentals. Therefore, they regress commodity futures returns on macro variables and define excess comovement as the comovement of the residuals. While Pindyck and Rotemberg (1990) use only 6 variables (industrial production, inflation, currency index, interest rates, money supply, and stock returns), Le Pen and Sévi (2017) extend the variable set to 184 macro variables from emerging as well as developed countries. Delle Chiaie et al. (2017) and Alquist et al. (2019) connect commodity price comovements with global economic activity.

We follow the authors by using the same 184 variables and taking logarithms and/or first or second differences to obtain stationary variables.[8] Subsequently, we transform the variable set using principal component analysis and use the first nine components as factors for the macro factor model, i.e., we set $X = (\mathrm{PC}_1, \ldots, \mathrm{PC}_9)$ in Equation (2.2).[9]

2.3.3 Estimation of Factor Sensitivities

2.3.3.1 Constant Beta

Up to this point, we have assumed the exposure of commodity returns to the pricing factors is constant, i.e., $\beta_{it} = \beta_i$ for every t. In practice, this means we use the full sample period to estimate the parameters of interest.

[8] Panel B of Table A.2 in Appendix A provides a list of variables and transformations.

[9] The total variation of the first nine components jointly explains 34.4% of the total variation in all 184 dimensions. For a slightly smaller sample, Le Pen and Sévi (2017) find the first nine principal components to jointly explain 37% of the total variation.

2.3.3.2 Re-Estimated Beta

However, it is possible that these factor exposures change over time. The simplest way to introduce time variation is by re-estimating the models. We do this using a rolling window of the past 36 months, and obtain a monthly series of coefficients.[10]

2.3.3.3 Parametric Beta

Another approach is to model the time variation explicitly. We follow Bekaert et al. (2009) and use several financial variables to capture the dynamics of β. More formally, we model β_{it} using K_M factors as:

$$\beta_{it}^k = \gamma_{ik}^0 + M_t \gamma_{ik} \tag{2.5}$$

where β_{it}^k is the k^{th} entry of the coefficient vector β_{it}, γ_{ik}^0 is the intercept, γ_{ik} is the $K_M \times 1$ vector of sensitivities, and M_t is the $1 \times K_M$ vector of financial variables. Specifically, we use the following variables: the 3-month T-bill rate (US3M) to capture interest rates, the spread between 3-month and 10-year Treasury rates (TERM) as a measure for the term premium, the spread between Moody's Seasoned Baa and Aaa Corporate Bond Yield (DEF) to account for credit risk, the spread between 3-month LIBOR and Treasury rate (TED) as a measure of funding liquidity, and the CBOE Volatility Index (VIX) as a measure for stock market volatility. This choice reflects the view that commodity traders also engage in financial markets and hence adjust their risk exposures according to financial conditions.

This approach requires only one estimation, because by extending the baseline regression in Equation (2.2) to include the $K \times K_M$ combinations of factors and financial variables, we only need to estimate

$$R_{it} = \alpha_i + X_t \beta_{it} + \epsilon_{it} = \alpha_i + X_t \gamma_i^0 + \sum_{k=1}^{K} X_{tk} M_t \gamma_{ik} + \epsilon_{it}, \tag{2.6}$$

[10] This choice of rolling window size ensures a sufficient number of observations for estimation, while keeping the window as small as possible. We also use smaller and larger window sizes in robustness checks.

and compute the coefficients, β_{it}, by plugging the estimated coefficients, γ_i^0 and γ_{ik}, into Equation (2.5). Note that effectively the 'Constant Beta' approach is nested within Equation (2.6), if we set the financial variables M_t to zero.

2.3.4 Model Comparison

As we are interested in how comovements of commodity returns change over time, we will look at the decomposition from Equation (2.3) in a rolling window manner. Let τ be a rolling window of 36 months, then the correlation of two commodity returns can be written as

$$\begin{array}{ccccc} \dfrac{\mathrm{Cov}_\tau(R_i, R_j)}{\sqrt{\mathrm{Var}_\tau(R_i)\,\mathrm{Var}_\tau(R_j)}} & \overset{(2.3)}{=} & \dfrac{\beta_i' \cdot \Sigma_{X,\tau} \cdot \beta_j}{\sqrt{\mathrm{Var}_\tau(R_i)\,\mathrm{Var}_\tau(R_j)}} & + & \dfrac{\mathrm{Cov}_\tau(\epsilon_i, \epsilon_j)}{\sqrt{\mathrm{Var}_\tau(R_i)\,\mathrm{Var}_\tau(R_j)}}, \\ \rho_{ij}^{\mathrm{real}}(\tau) & = & \rho_{ij}^{\mathrm{model}}(\tau) & + & \rho_{ij}^{\mathrm{resid}}(\tau) \end{array} \tag{2.7}$$

where R_i and R_j are the returns on the respective commodities i and j, β_i and β_j are the respective slope coefficients, $\Sigma_{X,\tau}$ is the covariance matrix of pricing factors within the window, and ϵ_i and ϵ_j are the respective error terms. As for the covariance in Equation (2.3), the correlation decomposes into a realized, a model-implied, and a residual part.

Since correlations are conditional on volatilities, heteroskedasticity can bias the conditional correlation coefficients. Therefore, we follow Forbes and Rigobon (2002) and adjust the correlation coefficient for heteroskedasticity. We denote the heteroskedasticity-adjusted correlation coefficient as

$$\rho_{ij}{}^* = \frac{\rho_{ij}}{\sqrt{1 + \delta_i(1 - \rho_{ij}^2)}} \quad \text{with } \delta_i = \frac{\mathrm{Var}_{\mathrm{short}}(R_i)}{\mathrm{Var}_{\mathrm{long}}(R_i)} - 1, \tag{2.8}$$

where ρ_{ij} is the non-adjusted correlation coefficient, $\mathrm{Var}_{\mathrm{short}}(R_i)$ is the variance of R_i over half the observations compared to $\mathrm{Var}_{\mathrm{long}}(R_i)$. In our baseline model this refers to 36 months for $\mathrm{Var}_{\mathrm{long}}(R_i)$ and 18 months for $\mathrm{Var}_{\mathrm{short}}(R_i)$. Applying this adjustment to the left and right-hand side of Equation (2.7), we obtain the heteroskedasticity-adjusted correlations, $\rho_{ij}^{\mathrm{real}}(\tau)^*$, $\rho_{ij}^{\mathrm{model}}(\tau)^*$ and $\rho_{ij}^{\mathrm{resid}}(\tau)^*$ for the realized, model-implied, and residual part, respectively.

Now, we can define the comovement measure (CM) as the weighted average of the off-diagonal correlation coefficients. More precisely, we define

$$\mathrm{CM}^{\mathrm{real}}(\tau) := \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{\mathrm{real}}(\tau)^{*} \qquad \text{and} \qquad \mathrm{CM}^{\mathrm{model}}(\tau) = \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{\mathrm{model}}(\tau)^{*}, \tag{2.9}$$

where w_{ij} are weights such that $\sum_{i,j,i\neq j} w_{ij} = 1$.[11] Following from Equation (2.3), the realized comovement, $\mathrm{CM}^{\mathrm{real}}$, can be decomposed into a model-implied and a residual part.

To assess the performance of the different models, we measure mean absolute error (MAE) and root mean squared error (RMSE) between the realized and model-implied comovement measures. Bekaert et al. (2009) use these measures for equity comovement and Anderson (2017) for credit default swaps.

Before we compare the models with respect to the comovements, we take a look at the results of the time series regressions for the commodity factor model in Table A.3 of the Appendix A and the macro factor model in Table A.4 of the Appendix A. The reported coefficients are the coefficients for the whole sample period, i.e., the 'Constant Beta' approach. As a first indication, we look at the R^2 and find that the commodity factor model can explain 25.0% of the return variation over all commodities on average, while the macro factor model can only explain 12.2%. Separating the single commodities into sectors also shows that the commodity factor model performs reasonably well in all sectors apart from livestock. The macro factor model, however, only explains more than 10% of the variation in the energy and metal commodities, which are more closely related to macroeconomic conditions in general.

These preliminary results are clearly in favor of the commodity factor model, but they are only informative about the model's ability to fit each single commodities variation in the time series. For the comovement of commodity markets instead, the model needs

[11] Note that we sum over all non-diagonal elements instead of only the above-diagonal part because the transformation in Equation (2.8) is not symmetric. The weights are calculated as the average market value of traded contracts over the rolling window τ. The necessary multipliers to obtain the value of a contract are listed in Table A.1 in Appendix A.

to account for the connections between different commodity markets, which cannot be deducted from time series regressions that are estimated separately for each commodity market.

Table 2.2 reports MAE and RMSE for both models and all three estimation methods, Constant, Parametric, and Re-estimated Beta. The conclusions conveyed are twofold. First, for all three estimation methods and both performance measures, the commodity factor model outperforms the macro factor model by a large margin. Using the 'Re-estimated Beta' approach, the MAE is only 0.0290 for the commodity factor model compared to 0.1452 for the macro factor model. In relative terms, the average mistake in estimating the correlation with the macro factor model as compared to the commodity factor model is more than five times larger. Independent of the measure and estimation technique the error is always at least twice as large for the macro factor model.

Second, the results are clearly advocating the re-estimation method over the 'Constant Beta' and the 'Parametric Beta' approach. While the introduction of time-varying betas in general reduces the RMSE by only 5% from 0.0949 to 0.0903 for the commodity factor model, re-estimating the parameters reduces the error by 63% from 0.0903 to 0.0344. These results also hold for the MAE and for the macro factor model, although re-estimating does improve the MAE (RMSE) for the macro factor model by only 11% (14%), suggesting less variation in coefficients for the macro factor model.

Overall, the commodity factor model with re-estimated coefficients emerges as the best model to fit the comovement structure of commodity futures returns and will thus be the benchmark for the dissection of commodity comovements in the following section. We provide several robustness test that confirm this choice in Section 2.6.

Table 2.2: Model Error of Commodity and Macro Factor Model

This table reports the mean absolute error (Panel A) and the root mean squared error (Panel B) between the realized and model-implied comovement measure as defined in Equation (2.9),

$$CM^{real}(\tau) := \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{real}(\tau)^{*} \qquad and \qquad CM^{model}(\tau) = \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{model}(\tau)^{*}, \tag{2.9}$$

where τ is a 36-months rolling window, $\rho_{ij}^{real}(\tau)^{*}$ and $\rho_{ij}^{model}(\tau)^{*}$ are the heteroskedasticity-adjusted correlation coefficients of the realized and model-implied commodity returns, and w_{ij} are weights such that $\sum_{i,j,i\neq j} w_{ij} = 1$. The commodity factor model is based on the returns of an equally-weighted market portfolio, as well as the returns of long-short portfolios on basis, momentum, and basis-momentum. The macro factor model is based on the first 9 principal components of a set of 184 macro variables following Le Pen and Sévi (2017). In Rows 'Constant Beta', the respective models are estimated once for the whole sample period. In Rows 'Parametric Beta', the coefficients are parametrized using the 3-month U.S. LIBOR rate, the term spread between 10-year and 3-months U.S. Treasury bills, the default spread between Moody's BAA and AAA Corporate Bonds Indices, the TED-spread between 3-month LIBOR and the Treasury rate, and the CBOE Volatility Index. In Rows 'Re-estimated Beta', the coefficients are re-estimated for each rolling window.

Panel A: Mean Absolute Error (MAE)

Estimation	**Commodity Factor Model**	**Macro Factor Model**
Constant Beta	0.0818	0.1934
Parametric Beta	0.0723	0.1615
Re-estimated Beta	0.0290	0.1452

Panel B: Root Mean Squared Error (RMSE)

Estimation	**Commodity Factor Model**	**Macro Factor Model**
Constant Beta	0.0949	0.2132
Parametric Beta	0.0903	0.1809
Re-estimated Beta	0.0344	0.1582

2.4 Dissecting Commodity Comovements

This section introduces two ways of decomposing the proposed commodity comovement measure to obtain insights over the drivers of the time variation in commodity comovements. Further, we look at differences between return and volatility comovements in commodity markets. Following the previous section, we use the best model and estimation method to fit the commodity return comovements, i.e., the four-factor model using market, basis, momentum, and basis-momentum factors with re-estimated betas. While restricted to the monthly frequency for the model comparison, we can now use the daily frequency.[12]

2.4.1 Intra- vs. Intersectoral Return Comovements

We can decompose the comovement measure into comovements within the same sector and between different sectors. This is interesting as they indicate different ways of market integration. A change in intrasectoral comovements is more likely to be caused by sector specific shocks, e.g., the shale boom in energy markets or extreme weather conditions in agricultural markets. Intersectoral comovements, however, indicate a more general form of market integration as associated with financialization.

To disentangle these effects, we simply partition the realized comovement into those correlation coefficients of commodities within the same sector and those of different sectors and obtain two disjoint parts,

$$\mathrm{CM}^{\mathrm{real}}(\tau) = \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{\mathrm{real}}(\tau)^* = \underbrace{\sum_{\substack{i,j,i\neq j,\\ S_i=S_j}} w_{ij}\rho_{ij}^{\mathrm{real}}(\tau)^*}_{\textbf{Intrasectoral Component}} + \underbrace{\sum_{\substack{i,j,i\neq j,\\ S_i\neq S_j}} w_{ij}\rho_{ij}^{\mathrm{real}}(\tau)^*}_{\textbf{Intersectoral Component}}, \quad (2.10)$$

where S_i and S_j denote the commodity sector of commodity i and j, respectively, such that, i and j are in the same sector, if and only if $S_i = S_j$.

The decomposition in Equation (2.10) does not take into account the number of

[12]Robustness checks show that the commodity factor model performs even better in matching the comovement at the daily frequency than at the monthly frequency.

weighted correlation pairs in the disjoint parts. In our sample of 34 commodities covering 8 sectors, there are 561 different commodity market correlations pairs. From those 561 pairs, 62 are intrasectoral pairs and 499 are intersectoral pairs. Therefore, the intersectoral part comprises more than eight times as many correlation pairs than the intrasectoral part. However, intrasectoral correlations are higher on average since commodities of the same sector are closer related to each other. To adjust for this imbalance, we scale both sums accordingly and obtain the intersectoral and intrasectoral comovement measures,

$$\mathrm{CM}^{\mathrm{intra}}(\tau) = \frac{1}{W_{\mathrm{intra}}} \sum_{\substack{i,j,i\neq j,\\ S_i=S_j}} w_{ij}\rho_{ij}^{\mathrm{real}}(\tau)^*, \quad \mathrm{CM}^{\mathrm{inter}}(\tau) = \frac{1}{W_{\mathrm{inter}}} \sum_{\substack{i,j,i\neq j,\\ S_i\neq S_j}} w_{ij}\rho_{ij}^{\mathrm{real}}(\tau)^*, \quad (2.11)$$

where W_{intra} and W_{inter} are scalars such that $\sum_{\substack{i,j,i=j,\\ S_i\neq S_j}} w_{ij} = W_{\mathrm{intra}}$ and $W_{\mathrm{inter}} = 1 - W_{\mathrm{intra}}$.

We split the sample into three subperiods before, during, and after financialization. The pre-financialization period lasts until December 2000, when the Commodity Futures Modernization Act (CFMA) was enacted, allowing investors to directly trade in commodity derivatives (Prokopczuk et al., 2017). The increase of index investment into commodities during the first decade of the twenty-first century culminated in the boom and bust of commodity prices during the financial crisis (Singleton, 2014) which ended in June 2009 (NBER trough) and hence serves as the end of the financialization period. This sample split also ensure three periods of roughly equal size.[13]

Panel A of Table 2.3 confirms that comovements have increased during financialization and remain on a higher level afterwards. The realized comovement increased by 130% from 0.172 before to 0.395 after financialization. This increase is matched in both parts, intrasectoral as well as intersectoral comovements, but is relatively much stronger for intersectoral comovements, which increased by 177% from 0.093 to 0.258, while intra sectoral comovements increased by 17% from 0.663 to 0.775. All changes are significant at the 1% level.

[13]In Appendix A, we also provide statistics dividing the sample only once in December 2004 following Bhardwaj et al. (2015).

Table 2.3: Intra- and Intersectoral Commodity Comovements

This table reports summary statistics of the commodity return comovement measure for the commodity factor model based on the returns of the equally-weighted market portfolio, as well as the returns of long-short portfolios on basis, momentum, and basis-momentum. Panel A reports the average comovement, Panel B the standard deviation, and Panel C the correlation of the comovement with the realized comovement. The first column reports the realized comovement, CM^{real}, *the second column reports the intrasectoral comovement,* CM^{intra}, *and the third column reports the intersectoral comovement* CM^{inter}.

Panel A: Average Comovement

	Realized	Intrasectoral	Intersectoral
1990 – 2018	0.298	0.735	0.166
Pre-Financialization	0.172	0.690	0.093
Financialization	0.306	0.732	0.131
Post-Financialization	0.395	0.776	0.258

Panel B: Volatility of Comovement

	Realized	Intrasectoral	Intersectoral
1990 – 2018	0.118	0.066	0.112
Pre-Financialization	0.021	0.079	0.019
Financialization	0.074	0.050	0.080
Post-Financialization	0.100	0.034	0.120

Panel C: Correlation with Realized Comovement

	Realized	Intrasectoral	Intersectoral
1990 – 2018	1.000	0.674	0.929
Pre-Financialization	1.000	0.524	0.545
Financialization	1.000	0.870	0.963
Post-Financialization	1.000	0.605	0.999

Panels B and C of Table 2.3 report the standard deviation of the comovement measures and their correlation with the realized comovement for the different periods. The volatility of comovement increases throughout the sample period. However, the volatility of the intrasectoral comovement has decreased after financialization, exhibiting only 34% of the realized comovements volatility in the most recent period. The intersectoral comovement instead, shows the same pattern as the realized comovement with a steady increase of volatility. Together with the high correlation between intersectoral and realized comovements of 0.929 over the whole sample, these results show that the time variation in comovements is driven by intersectoral comovements rather than intrasectoral comovements during and after financialization.

Figure A.3 of Appendix A shows the time series of comovements and the decomposition into the intra- and intersectoral part, confirming the discussed observations. The increase in comovements during financialization can be clearly attributed to intersectoral comovements. In fact, a regression of $\mathrm{CM}^{\mathrm{real}}$ on $\mathrm{CM}^{\mathrm{inter}}$ yields an R^2 of 92%, while the intrasectoral comovements can only explain 18% of the total variation in commodity return comovements.

2.4.2 Factor Sensitivities vs. Factor Covariances

Within the commodity factor model, the time variation of comovements has two potential sources, the fluctuations in factor sensitivities (β) and the fluctuation in factor covariances (Σ_X). We follow Bekaert et al. (2009) and set one of the two channels to its time series average, so all time variation is induced by the other part. We denote the respective correlations as

$$\rho_{ij}^{\mathrm{fixed}\beta}(\tau) = \frac{\overline{\beta_i}'\Sigma_{X,\tau}\overline{\beta_j}}{\sqrt{\mathrm{Var}_\tau(R_i)\,\mathrm{Var}_\tau(R_j)}} \quad \text{and} \quad \rho_{ij}^{\mathrm{fixed}\Sigma}(\tau) = \frac{\beta_{i\tau}'\overline{\Sigma_X}\beta_{j\tau}}{\sqrt{\mathrm{Var}_\tau(R_i)\mathrm{Var}_\tau(R_j)}} \tag{2.12}$$

where $\overline{\Sigma_X}$ is the time series average of factor covariances and $\overline{\beta_i}$ is the time series average of factor sensitivities for asset i. We denote the heteroskedasticity-adjusted version as $\rho_{ij}^{\mathrm{fixed}\beta}(\tau)^*$ and $\rho_{ij}^{\mathrm{fixed}\Sigma}(\tau)^*$, respectively, and obtain the comovement measure with fixed factor exposures and the comovement measure with fixed factor covariances, i.e.,

$$\mathrm{CM}^{\mathrm{fixed}\beta}(\tau) = \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{\mathrm{fixed}\beta}(\tau)^* \quad \text{and} \quad \mathrm{CM}^{\mathrm{fixed}\Sigma}(\tau) = \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{\mathrm{fixed}\Sigma}(\tau)^*. \tag{2.13}$$

Table 2.4 reports the mean and standard deviation of the realized, model-implied, and the two new comovement measures, as well as the correlation of each with the realized comovement. We find that the model-implied comovement also captures the increase in average comovement and volatility of comovement at the daily frequency. For the whole sample and all subsamples, the model-implied comovement and the realized comovement measure have a correlation of at least 0.95.

With fixed time variation in factor sensitivities (β), the comovement measure $\mathrm{CM}^{\mathrm{fixed}\beta}$ is still closely related to the realized and model-implied comovements, showing an increasing trend in average comovement as well as in the volatility of comovement. The correlation with the realized comovement exceeds 0.95 for the financialization and post-financialization period indicating that we capture the time variation in comovement for this period.

Fixing the time variation in factor covariances (Σ), however, we find that the level of comovement is decreasing throughout the sample, contrary to what we observe during financialization. The volatility of the comovement measure $\mathrm{CM}^{\mathrm{fixed}\Sigma}$ is only slightly increasing and the correlation with the realized comovement over the whole sample is -0.716, with 0.197 before, -0.828 during, and -0.527 after financialization.

Overall, the time series of comovements is mainly driven by changes in the factor covariance structure rather than the sensitivities towards these factors.[14] While factor covariances exhibit substantial time variation in the short term, permanent trend changes in comovements are more likely to come from changes in betas (Bekaert et al., 2009). Therefore, the evidence suggests that financialization has affected the factor covariance structure rather than the intensity to which commodities are exposed to these factors.

[14]The graphs in Figure A.4 of Appendix A confirm this result.

Table 2.4: Comovement with Fixed Betas and Fixed Factor Covariances

This table reports summary statistics of the commodity return comovement measure for the commodity factor model based on the returns of the equally-weighted market portfolio, as well as the returns of long-short portfolios on basis, momentum, and basis-momentum.. Panel A reports the average comovement, Panel B the standard deviation, and Panel C the correlation of the comovement with the realized comovement. The first column reports the realized comovement, CM^{real}*, the second column reports the model-implied comovement,* CM^{model}*, the third column reports the comovement measure with fixed factor sensitivities,* $\mathrm{CM}^{fixed\beta}$*, and the fourth column reports the comovement measure with fixed factor covariances,* $\mathrm{CM}^{fixed\Sigma}$*.*

Panel A: Average Comovement

	Realized	Model	Fixed β	Fixed Σ
1990 – 2018	0.298	0.287	0.291	0.339
Pre-Financialization	0.172	0.193	0.188	0.425
Financialization	0.306	0.278	0.249	0.316
Post-Financialization	0.395	0.374	0.415	0.289

Panel B: Volatility of Comovement

	Realized	Model	Fixed β	Fixed Σ
1990 – 2018	0.118	0.103	0.151	0.100
Pre-Financialization	0.021	0.030	0.031	0.066
Financialization	0.074	0.059	0.099	0.074
Post-Financialization	0.100	0.100	0.166	0.099

Panel C: Correlation with Realized Comovement

	Realized	Model	Fixed β	Fixed Σ
1990 – 2018	1.000	0.980	0.923	-0.716
Pre-Financialization	1.000	0.952	0.711	0.197
Financialization	1.000	0.988	0.978	-0.828
Post-Financialization	1.000	0.983	0.952	-0.527

2.4.3 Return vs. Volatility Comovements

The previous results are especially interesting with respect to the study of Christoffersen et al. (2019), who argue that commodity return correlations have returned to their pre-crisis level, but find a persistent higher degree of volatility correlations after financialization, suggesting another way of market integration. To address this point, we also look at comovements between commodity return volatilities, by applying the same framework as before to return volatilities as the underlying variables. Let V_i be the series of monthly return volatilities for a commodity market i and

$$\rho_{V,ij}(\tau) = \frac{\mathrm{Cov}_\tau(V_i, V_j)}{\sqrt{\mathrm{Var}_\tau(V_i)\,\mathrm{Var}_\tau(V_j)}}, \tag{2.14}$$

the correlation of the monthly volatilities of the return volatilities of commodity market i and j over a rolling window τ of 36 months.

Then, we can define the comovement measure of volatilities (CMV) analogously to returns as the weighted average of all correlation pairs:

$$\mathrm{CMV}(\tau) := \sum_{i,j,i\neq j} w_{ij}\rho_{V,ij}(\tau), \tag{2.15}$$

where w_{ij} are weights such that $\sum_{i,j,i\neq j} w_{ij} = 1$.

In Table 2.5, we present the mean and standard deviation of the comovement measure for returns (CM) and volatilities (CMV). In Panel A, we report the statistics for the 34 individual commodities as underlying assets, while in Panel B, we use the sector portfolios, eliminating the intrasectoral part of the comovement.

As for return comovements, we find an increase in volatility comovements over the sample period confirming the results of Christoffersen et al. (2019). However, the increase in volatility comovements during the financialization period from 0.177 to 0.203 is not significant (t-stat = -1.61), instead the jump in the post-financialization period to a significantly higher average of 0.468 is significant (t-stat = -15.55). The results for sector returns in Panel B even show a significant decrease of comovements during the financialization period from 0.141 to 0.027 (t-stat = 4.92), before a sharp increase to 0.402 in the post-financialization period.

The graphs in Figure A.5 of Appendix A emphasize the differences between the evolution of return and volatility comovements. Both have increased significantly after financialization, but while the shift in commodity return comovements has been gradual over the financialization period, commodity volatility comovements jumped to a higher regime during the financial crisis.

These results advocate a clear differentiation between the gradual effects of financialization on the one hand, and the eruptive effect of the financial crisis on the other hand.

Table 2.5: Return Comovement and Volatility Comovement

This table reports summary statistics of the comovement measure for commodity returns (CM) and the comovement measure for commodity volatiltiies (CMV). Results in Panel A (Panel B) are based on 34 individual commodity markets (8 commodity sector portfolios) as underlying assets.

Panel A: Individual Commodities

	Mean		**Standard Deviation**	
	CM	CMV	CM	CMV
1990 – 2018	0.298	0.293	0.118	0.175
Pre-Finacialization	0.172	0.177	0.021	0.078
Financialization	0.306	0.203	0.074	0.139
Post-Financialization	0.395	0.468	0.100	0.111

Panel B: Sector Portfolios

	Mean		**Standard Deviation**	
	CM	CMV	CM	CMV
1990 – 2018	0.219	0.200	0.161	0.230
Pre-Finacialization	0.096	0.141	0.029	0.105
Financialization	0.174	0.027	0.112	0.202
Post-Financialization	0.361	0.402	0.156	0.166

2.5 Implications

2.5.1 Market Integration and Financialization

Our results add to the discussion on market integration and financialization of commodity markets. We show that a four-factor model extension of Bakshi et al. (2019) is able to explain most of the comovement within commodity markets leaving only a negligible part of excess comovement. This is in contrast to the literature on excess comovement which usually finds larger parts of unexplained comovement.

This result demonstrates that it is crucial how to define excess comovement. Pindyck and Rotemberg (1990) say excess comovement is anything that cannot be explained by the common effects of inflation, changes in aggregate demand, interest rates, or exchange rates. Even after extending this set of variables to 184 macro variables (Le Pen and Sévi, 2017), these models leave a significant amount of excess comovement which they try to explain with non-economic variables. Instead, we are able to internalize this excess comovement using a model with tradable factors, enabling us to analyze the whole comovement subsequently.

Since we are able to capture the entire comovement with this parsimonious model, we can analyze which part of the model is contributing the most to the time variation and therefore the increase in comovements during the financialization period. This gives an insight into whether the change is persistent or not. We find that it is mostly the covariance of the factors that introduces the time variation into comovements. As the factor covariance (Σ) is more affected by short-term changes than the factor sensitivities (β), which relate factor returns to the commodity returns, this is evidence that the effects of financialization are less strong in the long term.

However, that financialization has affected commodity markets as a whole is evident from the dissection of intra- and intersectoral comovements. We document a significant increase in comovements between different commodity sectors during financialization. This result supports the argument that index investment in commodity markets has increased seemingly unrelated commodity markets through financial channels, rather than only intensifying existing linkages between commodities of the same sector.

Finally, we have shown that return comovements and volatility comovements are effected differently by financialization. While both have increased significantly after financialization, the channels are arguably not the same. The gradual increase of commodity return comovements during financialization is not matched in volatility comovements. Instead volatilities even comove less during the financialization period, before they jump significantly during the financial crisis. This observation motivates a discussion of the distinct effects of financialization and the financial crisis on commodity markets.

2.5.2 Risk Management

For practitioners in risk management, the covariance and hence comovements are crucial as they determine the riskiness of a portfolio. We therefore look into the effect of the comovement on the Value-at-Risk (VaR), which we compute for a portfolio P as

$$\mathrm{VaR}_\alpha(P) := \mathrm{Notional} \cdot \Phi^{-1}(1-\alpha) \cdot \sigma_P, \tag{2.16}$$

where α is the confidence level, the notional amount is \$1,000,000, Φ^{-1} is the inverse normal distribution function and σ_P is the portfolio's volatility. The covariance of commodity returns enters the VaR through the volatility of the portfolio, since

$$\sigma_P^2 = \mathrm{Var}\left(\sum_{i=1}^N w_i R_i\right) = \sum_{i=1}^N w_i^2 \mathrm{Var}(R_i) + \sum_{j \neq i} w_i w_j \mathrm{Cov}(R_i, R_j), \tag{2.17}$$

where w_i are weights such that $\sum_{i=1}^N w_i = 1$. Hence, changes in the covariance structure will affect the risk measure. Anderson (2017) uses the VaR to illustrate changes in the covariance of credit default swaps. In a similar fashion, we will analyze the change of VaR using different versions for the commodity covariance as before. For a rolling window τ

of 36 months, we denote

$$\begin{aligned} &\mathrm{Cov}^{\mathrm{real}}(\tau) = \mathrm{Cov}_\tau(R_i, R_j), && \mathrm{Cov}^{\mathrm{model}}(\tau) = \beta_{i\tau}' \Sigma_{X,\tau} \beta_{j\tau}, \\ &\mathrm{Cov}^{\mathrm{fixed}\beta}(\tau) = \overline{\beta_i}' \Sigma_{X,\tau} \overline{\beta_j} && \mathrm{Cov}^{\mathrm{fixed}\Sigma}(\tau) = \beta_{i\tau}' \overline{\Sigma_X} \beta_{j\tau}, \end{aligned} \tag{2.18}$$

as the realized covariance, the model-implied covariance, the estimated covariance with fixed betas, and the estimated covariance with fixed factor covariances, where $\beta_{i\tau}$ and $\beta_{j\tau}$ are the coefficients from the time series regression and $\Sigma_{X,\tau}$ is the covariance of the factors. Again, $\overline{\beta_i}$, $\overline{\beta_j}$, and $\overline{\Sigma_X}$ denote the time series averages.

In Table 2.6 we compare the VaR before, during, and after financialization to see whether the model-implied covariance estimates are able to capture the changes in risk. We find that the model-implied covariance gives a good estimate of the realized VaR, capturing the increasing risk during and after financialization.

In the third and fourth column of Table 2.6, we compute VaR without time variation in the factor sensitivities or factor covariances, respectively. When not allowing for time variation in the coefficients, VaR estimates are reasonably close to the realized and model-implied estimates. They are especially able to capture the increased risk after financialization. The VaR based on covariances without time variation in factor covariances, however, cannot capture this change of risk. Instead, the 5% VaR is stable throughout the sample from \$12,119 per \$1,000,000 before financialization to \$12,492 per \$1,000,000 during financialization and \$12,491 per \$1,000,000 after financialization. We find a similar pattern for the 1% VaR in Panel B of Table 2.6.

This result emphasizes the importance of the variation in factor covariances for the comovements. It is crucial for investors to adjust for the changes in factor covariances to be able to assess the risks of a commodity portfolio correctly. On the other hand, variations in the sensitivities of a portfolio to certain factors do only affect the VaR negligibly.

Table 2.6: Value-at-Risk for Estimated Covariances

This table reports the Value-at-Risk (VaR) for a commodity portfolio using different covariance matrices for the computation of the volatility. The Value-at-Risk for a portfolio P is computed as in Equation (2.16)

$$VaR_\alpha(P) := Notional \cdot \Phi^{-1}(1-\alpha) \cdot \sigma_P, \tag{2.16}$$

where α *is the confidence level, the notional is $1,000,000,* Φ^{-1} *is the inverse normal distribution function and* σ_P *is the standard deviation of portfolio returns* R_P*. The portfolio's volatility is based on the different covariance matrices in Equation* (2.18)

$$\begin{aligned} &\mathrm{Cov}^{real}(\tau) = \mathrm{Cov}_\tau(R_i, R_j), && \mathrm{Cov}^{model}(\tau) = \beta_{i\tau}' \Sigma_{X,\tau} \beta_{j\tau}, \\ &\mathrm{Cov}^{fixed\beta}(\tau) = \overline{\beta_i}' \Sigma_{X,\tau} \overline{\beta_j} && \mathrm{Cov}^{fixed\Sigma}(\tau) = \beta_{i\tau}' \overline{\Sigma_X} \beta_{j\tau}, \end{aligned} \tag{2.18}$$

where $\mathrm{Cov}^{real}(\tau)$ *is the realized covariance over the rolling window* τ *of 36 months,* $\mathrm{Cov}^{model}(\tau)$ *is the model-implied covariance using the estimated returns from the time series regression,* $\mathrm{Cov}^{fixed\beta}(\tau)$ *is the covariance without time variation in the betas, replacing them with the time series averages* $\overline{\beta_i}$ *and* $\overline{\beta_j}$*, and* $\mathrm{Cov}^{fixed\Sigma}(\tau)$ *is the covariance without time variation in the factor covariances using the time series average* $\overline{\Sigma_X}$*. Panel A shows the VaR for* $\alpha = 0.05$ *and Panel B for* $\alpha = 0.01$*.*

Panel A: 5% Value-at-Risk

	$\mathrm{Cov}^{\mathrm{real}}$	$\mathrm{Cov}^{\mathrm{model}}$	$\mathrm{Cov}^{\mathrm{fixed}\beta}$	$\mathrm{Cov}^{\mathrm{fixed}\Sigma}$
1990 – 2018	$12,672	$12,822	$12,514	$12,495
Pre-Financialization	$8,076	$8,367	$8,465	$12,119
Financialization	$12,038	$12,050	$12,078	$12,492
Post-Financialization	$15,361	$15,341	$15,369	$12,491

Panel A: 1% Value-at-Risk

	$\mathrm{Cov}^{\mathrm{real}}$	$\mathrm{Cov}^{\mathrm{model}}$	$\mathrm{Cov}^{\mathrm{fixed}\beta}$	$\mathrm{Cov}^{\mathrm{fixed}\Sigma}$
1990 – 2018	$17,922	$18,135	$17,698	$17,672
Pre-Financialization	$11,423	$11,833	$11,972	$17,140
Financialization	$17,026	$17,043	$17,082	$17,668
Post-Financialization	$21,725	$21,696	$21,737	$17,667

2.6 Robustness Checks

To eliminate possible concerns about the choice of model, we run several robustness checks and discuss the results in this section organized by potential reasons.

2.6.1 Model Settings

To start with, we want to convince the reader that the choice of model is not dependent on some of the parameters chosen within the regression setup. Therefore, we repeat the analysis of Section 2.3 altering the size of the rolling window to 24 months and 60 months (Table A.5 in Appendix A), omitting the adjustment for heteroskedasticity, or changing the computation of $\text{Var}_{\text{short}}$ in Equation (2.8) to be the 12-month or 6-month variance (Table A.6 in Appendix A).

As the referred tables show, the specification of these parameters does not change the general result that the commodity factor model with re-estimated betas is the best model to explain the comovement of commodity futures returns.

2.6.2 Sample Choice

There are several reasons, why we decided to concentrate our analysis on the set of 34 commodities over the sample period from 1990 to 2018. First, the availability of certain variables restricts our sample choice. The macro variables used in the model of Le Pen and Sévi (2017) for emerging markets are largely unavailable before 1990, as is volume data to compute market weights. Second, the composition of the entire commodity market changes through time. Starting with only agricultural commodities in 1959, metals are introduced in the 1970s, and energy commodities become tradable in the 1980s. The introduction of new commodity markets, which are supposedly less correlated with the existing ones, would bias the comovement measure and make a comparison through time difficult. With respect to the commodity markets chosen, the portfolio of 34 markets is the broadest representation of the different sectors and commodities, allowing us to get the most complete view of all interactions.

However, to address any concerns about our results being dependent on the sample choice, we repeat the analysis using the smaller set of 21 commodities used in Szymanowska et al. (2014) for the period from 1990 to 2018 (Table A.7, Panel A, of Appendix A). To rule out that results are driven by the effect of a certain sector, we also repeat the analysis each time excluding all commodities of one of the eight sectors (Table A.7, Panel B, of Appendix A).

2.6.3 Number of Factors

We have shown that the model of Bakshi et al. (2019) extended by the basis-momentum factor is able to explain the comovements between commodity returns. Hence, it is natural to ask which of the four factors, market, basis, momentum, and basis-momentum contributes most to this result. To shed light on this, we run the same analysis using different subsets of factors and compare their performance in the same way as before.

It is evident from Panel A of Table A.8 in Appendix A that the market factor alone is able to explain much more of the comovement than the other three factors. Since we use the whole cross-section of commodities to compute all factors, this effect is unlikely to originate from the choice of commodities within the portfolios. To rule out the possibility that the performance of the model is driven by the fact that the factors include the commodity returns themselves, we repeat the analysis using unique factor portfolios for each commodity market that exclude the market itself, e.g., the market portfolio for corn includes all commodity markets but the corn market itself. Results in Panel B of Table A.8 in Appendix A are qualitatively similar.

Finally, we check whether adding the principal components of the macro variables to the set of factors can further improve the model, but the additional nine factors only decrease the MAE by 12%, from 0.0229 to 0.0202, with respect to the parsimony of a four-factor model this is only a small change, considering the number of factors more than triples to 13.

2.6.4 Alternative Comovement Measures

One concern is that our model comparison might be biased by the way we measure comovements. Part of the literature has addressed commodity comovements methodologically using Vector Autoregressive models for the return volatility as in Diebold et al. (2017) or assessing the excess comovement, i.e., the comovement of the error term ϵ in Equation (2.3), with a GARCH framework as in Ohashi and Okimoto (2016).[15] Nevertheless, we favor a simple factor model as we are interested in the explainable part of the commodity future returns. We look at the pairwise correlations as they appear to be at the heart of the financialization debate (Bhardwaj et al., 2015).

However, the high explanatory power of the market factor for the comovement measure casts doubts on whether this is induced by how we measure comovement. Let us illustrate this with a simple example. Consider a simple one-factor model only including an equally-weighted market factor, i.e.,

$$R_i = \alpha_i + \beta_i R^{\text{MRKT}} + \epsilon_i \quad \Rightarrow \quad \text{Cov}(R_i, R_j) = \beta_i \beta_j \operatorname{Var}(R^{\text{MRKT}}) + \text{Cov}(\epsilon_i, \epsilon_j) \tag{2.19}$$

with α_i, β_i, and ϵ_i as intercept, slope, and residual, respectively. Recall that since the market factor here is an equally-weighted average of all constituents, the average exposure to this factor (β) must equal one and hence the average of all possible products of β_i and β_j must equal 1 as well, i.e.,

$$\frac{1}{N}\sum_{i=1}^{N}\beta_i = 1 \quad \Rightarrow \quad \frac{1}{N^2}\sum_{i,j=1}^{N}\beta_i\beta_j = \left(\frac{1}{N}\sum_{i=1}^{N}\beta_i\right)\cdot\left(\frac{1}{N}\sum_{j=1}^{N}\beta_j\right) = 1. \tag{2.20}$$

If we additionally assume the comovement measure to be equally-weighted, i.e., $w_{ij} = \frac{1}{N^2}$ for a number of N commodity markets, and we average over all covariances including the

[15] Although Forbes and Rigobon (2002) state that using correlation coefficients is the most straight forward framework.

variances on the diagonal, then

$$\begin{aligned}\sum_{i,j=1}^{N} w_{ij}\operatorname{Cov}(R_i,R_j) &\overset{(2.19)}{=} \sum_{i,j=1}^{N}\frac{1}{N^2}\left(\beta_i\beta_j\operatorname{Var}(R^{\mathrm{MRKT}})+\operatorname{Cov}(\epsilon_i,\epsilon_j)\right)\\ &= \operatorname{Var}(R^{\mathrm{MRKT}})\frac{1}{N^2}\sum_{i,j=1}^{N}\beta_i\beta_j+\frac{1}{N^2}\sum_{i,j=1}^{N}\operatorname{Cov}(\epsilon_i,\epsilon_j)\\ &\overset{(2.20)}{=} \operatorname{Var}(R^{\mathrm{MRKT}})+\frac{1}{N^2}\sum_{i,j=1}^{N}\operatorname{Cov}(\epsilon_i,\epsilon_j). \end{aligned} \tag{2.21}$$

Because in this case, the market variance, $\operatorname{Var}(R^{\mathrm{MRKT}})$, is equal to the comovement measure, we obtain zero average residual covariance, i.e.,

$$\operatorname{Var}(R^{\mathrm{MRKT}})=\sum_{i,j=1}^{N}\frac{1}{N^2}\operatorname{Cov}(R_i,R_j) \quad\Rightarrow\quad \frac{1}{N^2}\sum_{i,j=1}^{N}\operatorname{Cov}(\epsilon_i,\epsilon_j)=0. \tag{2.22}$$

There are three reasons, we think our results are not driven by this tautology. First, the comovement measure, we use, differs from the simplified example above as we do not consider the diagonal elements, i.e., the variances, and we do not equally-weight the covariances, more specifically we do not use the same weights for market factor and comovement measure. Second, since we apply the adjustment for heteroskedasticity by Forbes and Rigobon (2002) the equations for covariances do not hold for correlations. Third, we conduct the following robustness check to address this issue. We define the partial comovement measure

$$\mathrm{CM}_i^{\mathrm{real}}(\tau)=\sum_{j\neq i} w_j\left(\rho_{ij}^{\mathrm{real}}(\tau)^{*}+\rho_{ji}^{\mathrm{real}}(\tau)^{*}\right), \tag{2.23}$$

where $\rho_{ij}^{\mathrm{real}}(\tau)^{*}$ is the heteroskedasticity-adjusted correlation coefficient between commodity return i and j during the period τ and $\sum_{j\neq i} w_j = 1$. Analogously to Equation (2.23), we define the model-implied partial comovement measure $\mathrm{CM}_i^{\mathrm{model}}$.

Table A.9 in Appendix A reports the mean absolute error and root mean squared error for the partial commodity measure. Although the averaging effect is visible, it does not drive the results. We find an average MAE (RMSE) of 0.0474 (0.0532) over the 34 partial commodity comovements, while it is 0.0229 (0.0308) for the cumulated measure including all commodity pairs (see Table A.8 in Appendix A).

2.7 Conclusion

This chapter examines the comovements of commodity futures returns and variances. We start from first principles and show that a four-factor model based on tradable portfolio returns is able to explain a large proportion of the realized comovements. Importantly, this result suggests that there is little evidence of excess comovements.

We confirm previous evidence of increased comovement during and after financialization and pin its source down to the intersectoral comovements. Dissecting the evidence further, we show that changes in coefficients play a minor role in our understanding of comovements. This result poses a challenge to the literature on the integration of commodity markets. The increase of return comovements during financialization is mainly driven by a temporary increase in factor covariances casting doubt on commodity markets becoming more integrated in the long run. Lastly, we find increased comovement of volatilities following the financial crisis, advocating a discussion of the distinct effects of financialization and the financial crisis on commodity comovements.

A Appendix

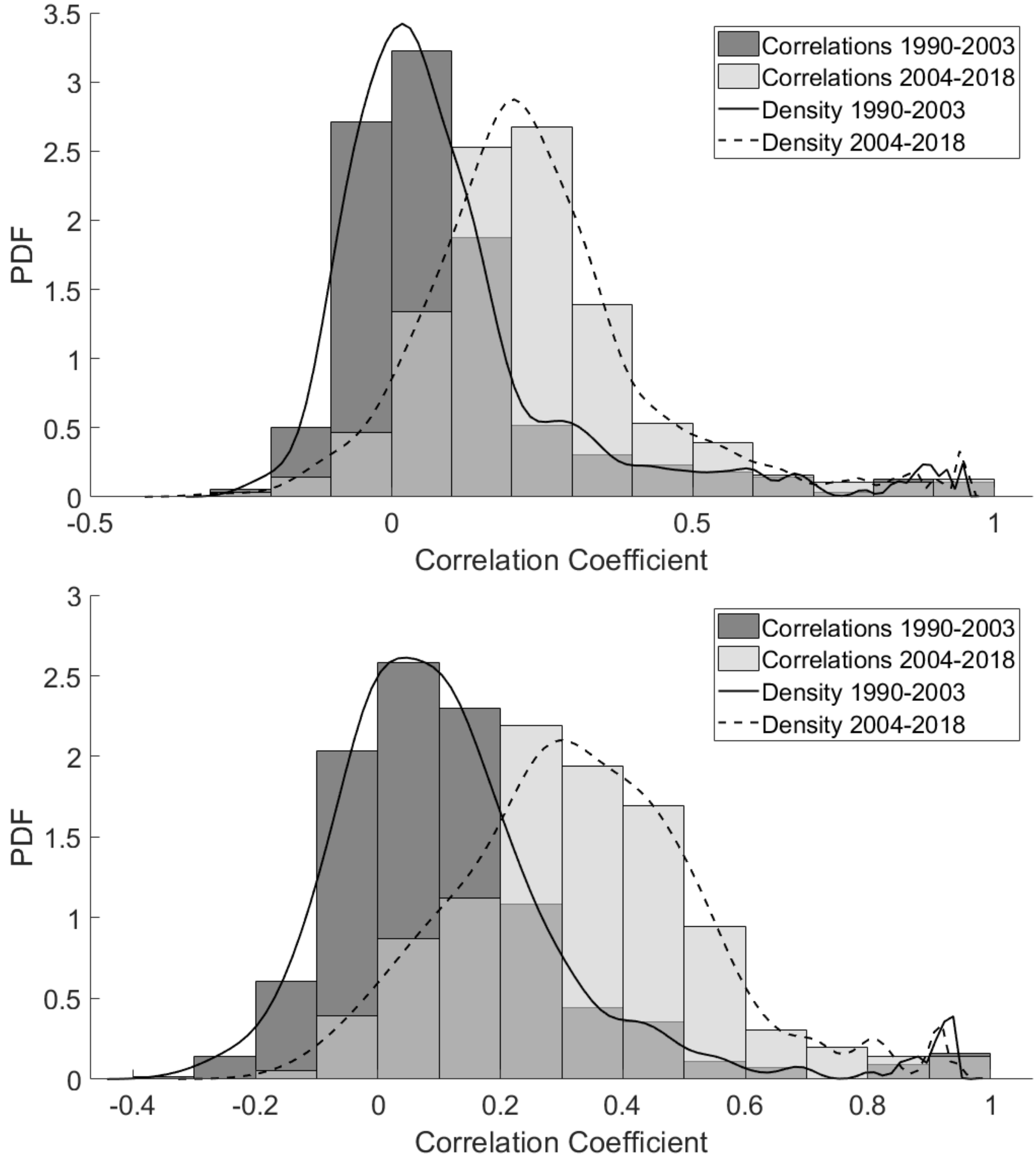

Figure A.1: Distribution of Pairwise Correlation Coefficients

This figure shows the distribution of the correlation coefficients for 34 commodity returns (return volatilities) in the upper (lower) panel. The sample period comprises monthly commodity returns and volatilities from April 1990 to December 2018. The dark shaded bars depict the histogram of correlation coefficients within the period from 1990 to 2003, while brightly shaded bars depict the histogram for the period from 2004 to 2018. The solid and dashed lines are density estimates using a normal kernel function for the distribution.

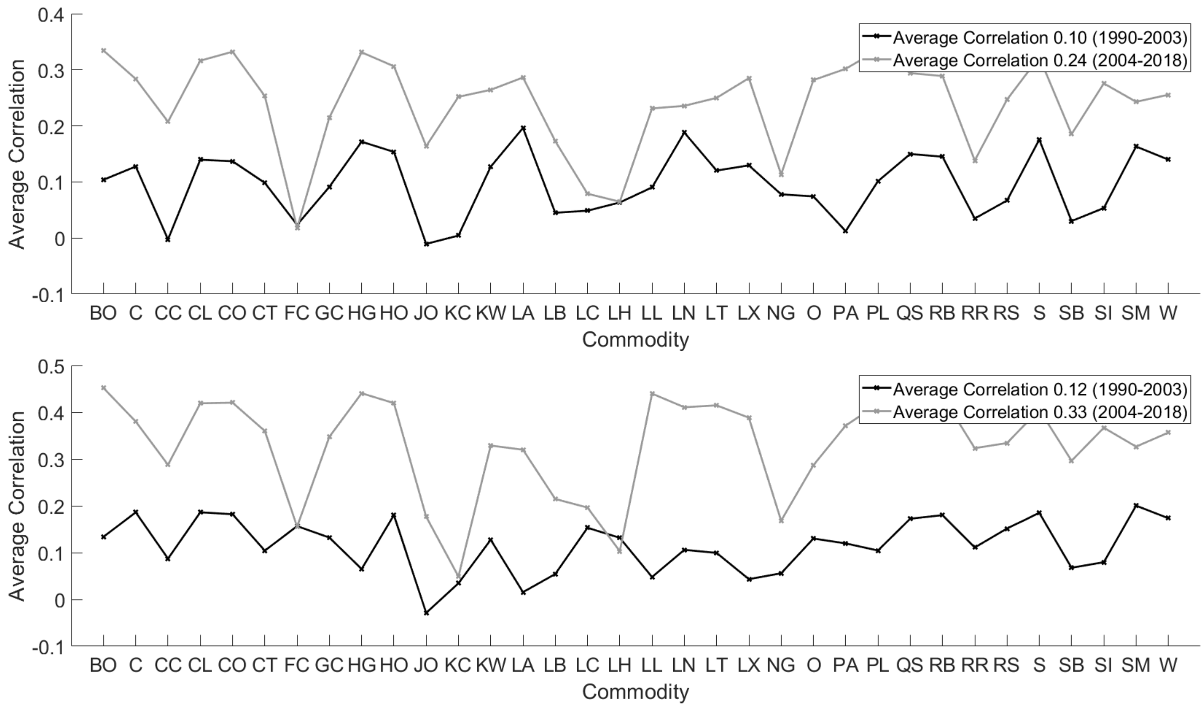

Figure A.2: Average Pairwise Correlation Coefficients

This figure shows the average pairwise correlation coefficient of each of the 34 commodity returns with all other 33 commodity returns in the upper panel and the average pairwise correlation coefficient of each of the 34 commodity return volatilities with all other 33 commodity return volatilities in the lower panel. The sample period comprises monthly commodity returns and volatilities from April 1990 to December 2018. The black line shows period from 1990 to 2003, while the gray line shows the period from 2004 to 2018. The average correlation rose from 10% to 24% for returns and from 12% to 33% for volatilities between the two periods. The horizontal axis lists the commodity ticker symbols, for details see Table A.1 in Appendix A.

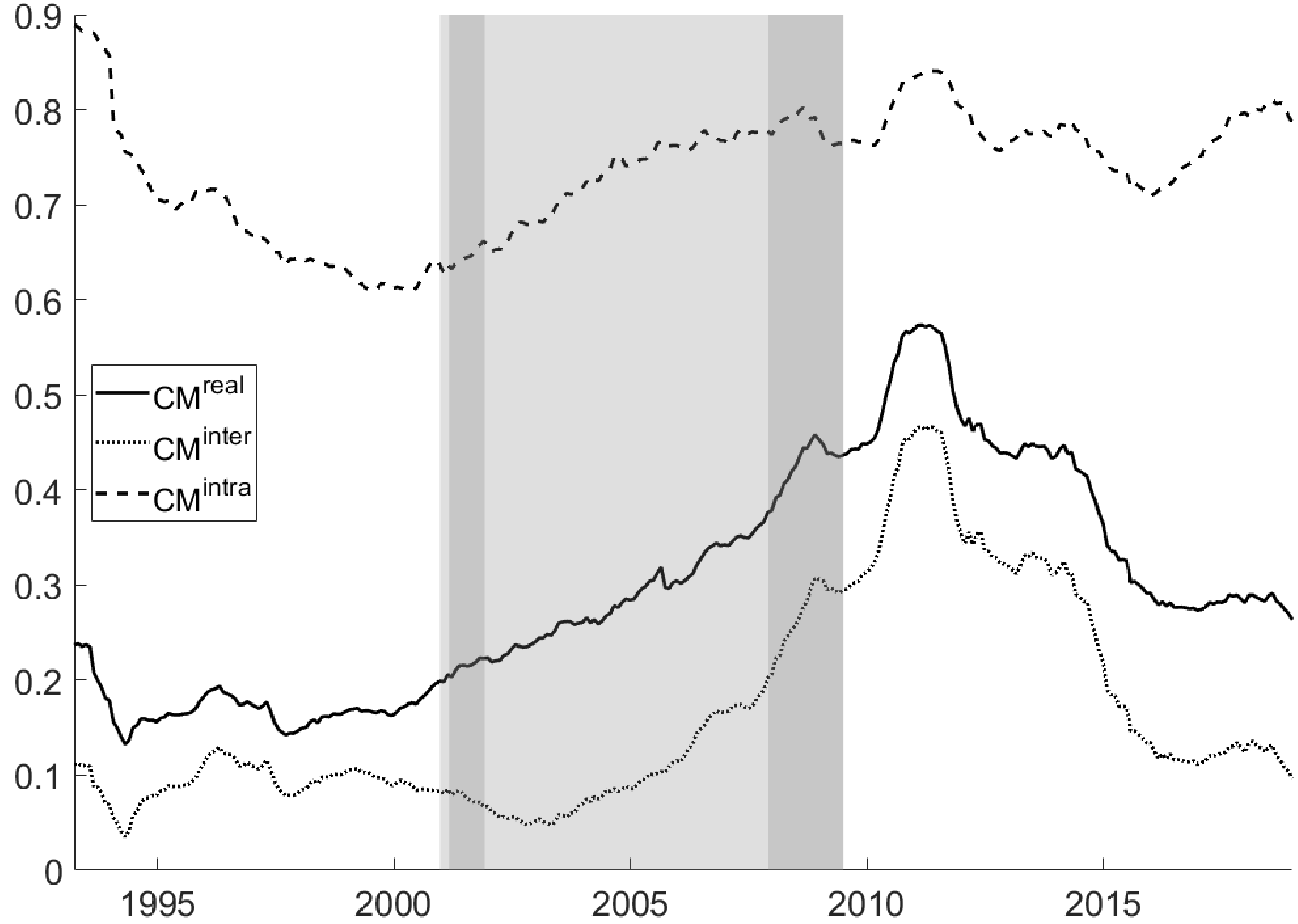

Figure A.3: Inter- and Intrasectoral Commodity Comovements

This figure shows the realized commodity return comovement measure, CM^{real}*, the intersectoral comovement measure,* CM^{inter}*, and the intrasectoral comovement measure,* CM^{intra}*, as defined in Equation* (2.11)*. Comovements are measured as the weighted average of all correlation pairs, and then dissected into pairs within the same and from different sectors. The correlations are adjusted for heteroskedasticity (Forbes and Rigobon, 2002) and computed over a rolling window of 36 months. The light gray shaded area marks the period of financialization from December 2000 to July 2009, including dark shaded NBER recessions.*

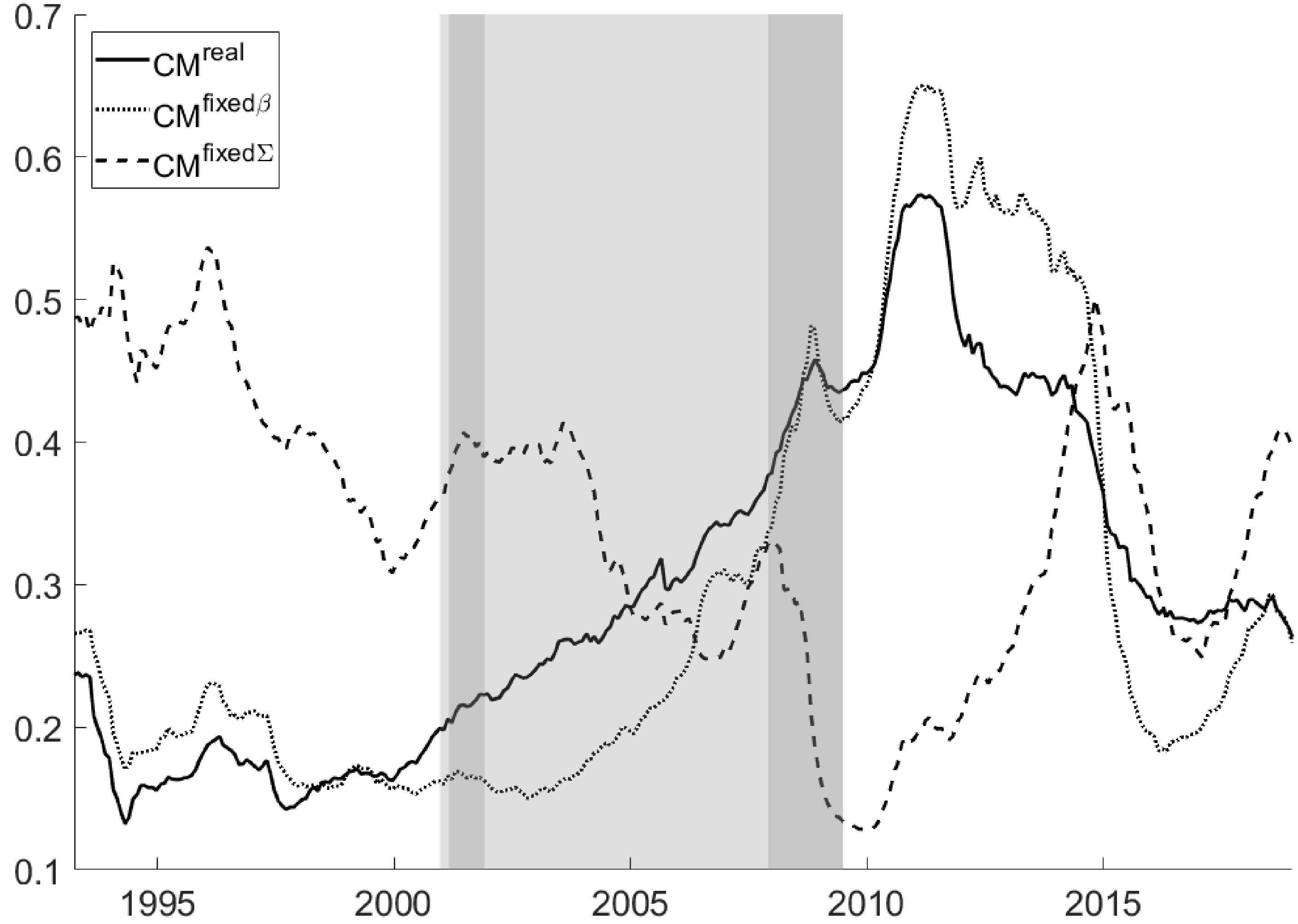

Figure A.4: Comovement with Fixed Betas and Fixed Factor Covariances

This figure shows the realized commodity return comovement measure, CM^{real}*, the comovement measure with fixed factor exposures ,* $\mathrm{CM}^{fixed\beta}$*, and the comovement measure with fixed factor covariances,* $\mathrm{CM}^{fixed\Sigma}$*, as defined in Equation* (2.13). *The correlations are adjusted for heteroskedasticity (Forbes and Rigobon, 2002) and computed over a rolling window of 36 months. The light gray shaded area marks the period of financialization from December 2000 to July 2009, including dark shaded NBER recessions.*

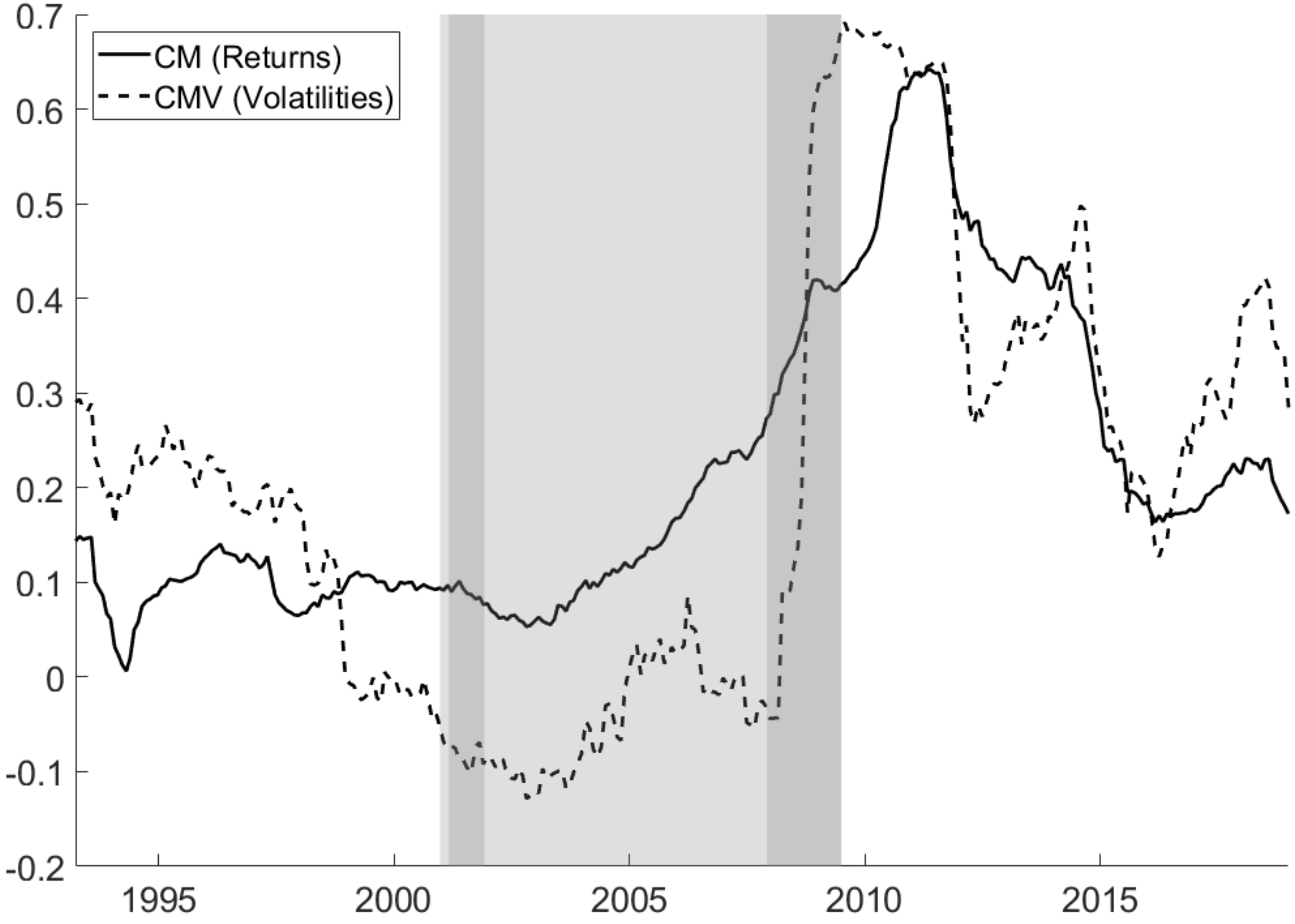

Figure A.5: Return Comovement and Volatility Comovement

This figure shows the realized commodity return comovement measure, CM^{real}*, and the realized commodity volatility comovement measure,* CMV^{real}*, as defined in Equation* (2.15)*. The correlations are adjusted for heteroskedasticity (Forbes and Rigobon, 2002) and computed over a rolling window of 36 months. The light gray shaded area marks the period of financialization from December 2000 to July 2009, including dark shaded NBER recessions.*

Table A.1: Bloomberg Commodity Futures Data

This table lists the commodity futures price series obtained from Bloomberg. The second column lists the Bloomberg ticker, the third column the commodity sector. The fourth column reports the exchange on which the contracts is traded using abbreviations for the Intercontinental Exchange (ICE), the New York Mercantile Exchange (NYMEX), the Commodity Exchange (COMEX), the Chicago Board of Trade (CBOT), the London Metal Exchange (LME), and the Chicago Mercantile Exchange (CME). The fifth column reports the expiry month and the sixth column reports the size of one contract.

Commodity	Ticker	Sector	Exchange	Expiry Month	Contract Size
Crude Oil (Brent)	CO	Energy	ICE	Jan-Dec	1,000 Barrels
Crude Oil (WTI)	CL	Energy	NYMEX	Jan-Dec	1,000 Barrels
Heating Oil	HO	Energy	NYMEX	Jan-Dec	42,000 Gallons
Natural Gas	NG	Energy	NYMEX	Jan-Dec	10,000 Million Btu
Gasoil	QS	Energy	NYMEX	Jan-Dec	100 Tonnes
Gasoline (unleaded)	HU	Energy	NYMEX	Jan-Dec	42,000 Gallons
Gasoline (RBOB)	XB	Energy	NYMEX	Jan-Dec	42,000 Gallons
Corn	C	Grains	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
Oats	O	Grains	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
Rough Rice	RR	Grains	CBOT	Jan,Mar,May,Jul,Sep,Nov	2,000 Hundredweights
Wheat (Chicago)	W	Grains	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
Wheat (Kansas)	KW	Grains	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
Aluminium	LA	Industrial Metals	LME	Jan-Dec	25 Tonnes
Copper	HG	Industrial Metals	COMEX	Mar,May,Jul,Sep,Dec	25,000 Pounds
Lead	LL	Industrial Metals	LME	Jan-Dec	25 Tonnes
Nickel	LN	Industrial Metals	LME	Jan-Dec	6 Tonnes
Tin	LT	Industrial Metals	LME	Jan-Dec	6 Tonnes
Zinc	LX	Industrial Metals	LME	Jan-Dec	25,000 Tonnes
Feeder Cattle	FC	Livestock	CME	Jan,Mar,Apr,May,Aug,Sep,Oct,Nov	50,000 Pounds
Lean Hogs	LH	Livestock	CME	Feb,Apr,May,Jun,Jul,Aug,Oct,Dec	40,000 Pounds
Live Cattle	LC	Livestock	CME	Feb,Apr,Jun,Aug,Oct,Dec	40,000 Pounds
Cotton	CT	Materials	ICE	Mar,May,Jul,Oct,Dec	50,000 Pounds
Lumber	LB	Materials	CME	Jan,Mar,May,Jul,Sep,Nov	110,000 Feet
Gold	GC	Precious Metals	COMEX	Feb,Apr,Jun,Aug,Oct,Dec	100 Troy Ounces
Palladium	PA	Precious Metals	NYMEX	Mar,Jun,Sep,Dec	100 Troy Ounces
Platinum	PL	Precious Metals	NYMEX	Jan, Apr, Jul, Oct	50 Troy Ounces
Silver	SI	Precious Metals	COMEX	Mar,May,Jul,Sep,Dec	5,000 Troy Ounces
Canola	RS	Oilseeds	ICE	Jan,Mar,May,Jul,Nov	20 Metric Tonnes
Soybeans	S	Oilseeds	CBOT	Jan,Mar,May,Jul,Aug,Sep,Nov	5,000 Bushels
Soybean Meal	SM	Oilseeds	CBOT	Jan,Mar,May,Jul,Aug,Sep,Oct,Dec	100 Short Tons
Soybean Oil	BO	Oilseeds	CBOT	Jan,Mar,May,Jul,Aug,Sep,Oct,Dec	60,000 Pounds
Cocoa	CC	Softs	ICE	Mar,May,Jul,Sep,Dec	10 Metric Tonnes
Coffee	KC	Softs	ICE	Mar,May,Jul,Sep,Dec	37,500 Pounds
Orange Juice	JO	Softs	ICE	Jan,Mar,May,Jul,Sep,Nov	15,000 Pounds
Sugar	SB	Softs	ICE	Mar,May,Jul,Oct	112,000 Pounds

Table A.2: Financial and Macroeconomic Data

Panel A of this table reports the financial data we obtain from the Federal Reserve Bank of St. Louis (FRED) and the Center for Reserach in Security (CRSP). Panel B lists macroeconomic variables from DataStream. The third column in Panel C reports the transformation used to achieve stationarity. As in Le Pen and Sévi (2017) lv, ln, Δlv, Δln, and $\Delta^2 ln$ denote the level, logarithm, first difference, first difference of logarithms, and the second difference of logarithms, respectively.

Panel A: Financial Data

Variable	Symbol	Source
Moody's Seasoned Aaa Corporate Bond Yield	AAA	FRED
Moody's Seasoned Baa Corporate Bond Yield	BAA	FRED
TED Spread	TED	FRED
3-Month Treasury Constant Maturity Rate	US3M	FRED
10-Year Treasury Constant Maturity Rate	US10Y	FRED
CBOE Volatility Index	VIX	FRED
CRSP Value-Weighted Stock Market Index	CRSP	CRSP

Panel B: Macroeconomic Data

Variable	Mnemonic	Transformation
IP: USA	USIPMAN.G	Δln
IP: France	FRIPMAN.G	Δln
IP: France	FRINDSYNQ	lv
IP: Germany	BDIPMAN.G	Δln
IP: UK	UKIPMAN.G	Δln
IP: Japan	JPIPMAN.G	Δln
IP: Japan	JPIPTOT.G	Δln
Capacity Utilization: USA	USCUMANUG	Δlv
Manufacturing New Orders: USA	USNOCOGMC	Δln
Manufacturing New Orders: USA	USNOMXTRB	Δln
New Orders: Canada	CNNEWORDB	Δln
Manufacturing Orders: Germany	BDNEWORDE	Δln
Manufacturing New Orders: Japan	JPNEWORDB	Δln
Operating Ratio: Japan	JPCAPUTLQ	Δlv
Business Failures: Japan	JPBNKRPTP	Δln
Housing Permits: USA	USHOUSE.O	Δln
Housing Permits: Canada	CNHOUSE.O	Δln
Housing Permits: Germany	BDHOUSE.G	Δln
Housing Permits: Australia	AUHOUSE.A	Δln
Housing Permits: Japan	JPHOUSSTF	ln
Car Registration: USA	USCAR.P	Δln
Car Registration: France	FRCARREGP	Δln
Car Registration: Germany	BDRVNCARP	ln
Car Registration: UK	UKCAR.P	Δln

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Variable	Mnemonic	Transformation
Car Registration: Japan	JPCARREGF	ln
Consumer Sentiment: USA	USUMCONEH	Δln
Personal Consumption Expenditure: USA	USPERCONB	Δln
Personal Saving: USA	USPERSAVE	Δlv
Retail Sale: Canada	CNRETTOTB	Δln
Household Confidence: France	FRCNFCONQ	Δlv
Household Confidence: Germany	BDCNFCONQ	lv
Retail Sales: UK	UKRETTOTB	Δln
Household Confidence: UK	UKCNFCONQ	Δlv
Retail Sales: Australia	AURETTOTT	Δln
Household Confidence: Australia	AUCNFCONR	lv
Household Expenditure: Japan	JPHLEXPWA	Δln
Retail Sales: Japan	JPRETTOTA	Δln
Average Hourly Real Earnings: USA	USWRIM.D	Δln
Average Overtime Hours: USA	USOOL024Q	Δlv
Average Weekly Hours: USA	USHKIM.O	Δlv
Average Hourly Real Earnings: Canada	CNWAGES.A	Δln
Labour Productivity: Germany	BDPRODVTQ	Δln
Wages: Germany	BDWAGES.F	Δln
Wages Index: Japan	JPWAGES.E	Δln
Unemployment Rate: USA	USUNEM15Q	Δlv
Unemployment Rate: USA	USUNTOTQ.pc	Δlv
Employment: Canada	CNEMPTOTO	Δln
Unemployment All: Germany	BDUNPTOTP	Δln
Unemployment Rate: UK	UKUNTOTQ.pc	Δlv
Employment: Australia	AUEMPTOTO	Δln
Unemployment All: Australia	AUUNPTOTO	Δln
Unemployment Rate: Japan	JPUNTOTQ.pc	Δlv
Exports: USA	USI70.A	Δln
Exports: France	FREXPGDSB	Δln
Exports: Germany	BDEXPBOPB	Δln
Exports: UK	UKI70_A	Δln
Exports: Australia	AUEXPG&SB	Δln
Exports: Japan	JPEXPGDSB	Δln
Imports: USA	USIMPGDSB	Δln
Imports: France	FRIMPGDSB	Δln
Imports: Germany	BDIMPGDSB	Δln
Imports: UK	UKIMPBOPB	Δln
Imports: Australia	AUIMPG.SB	Δln
Imports: Japan	JPOXT009B	Δln
Terms of Trade: UK	UKTOTPRCF	Δln
Terms of Trade: Japan	JPTOTPRCF	Δln
Money Supply: USA	USM0_A	Δln
Money Supply: USA	USM2_B	Δln
Money Supply: France	FRM2_A	Δln
Money Supply: France	FRM3_A	Δln
Money Supply: Germany	BDM1_A	Δln
Money Supply: Germany	BDM3_B	Δln
Money Supply: UK	UKM1_B	Δln
Money Supply: UK	UKM3_B	Δln
Money Supply: Australia	AUM1_B	Δln

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Variable	Mnemonic	Transformation
Money Supply: Australia	AUM3_B	Δln
Money Supply: Japan	JPM1_A	Δln
Money Supply: Japan	JPM2_A	Δln
Credit: USA	USCOMILND	Δln
Credit: USA	USCILNNCB	lv
Credit: USA	USCRDNRVB	Δln
Credit: France	FRBANKLPA	Δln
Credit: Germany	BDBANKLPA	$\Delta^2 ln$
Credit: Australia	AUCRDCONB	$\Delta^2 ln$
Credit: Japan	JPBANKLPA	$\Delta^2 ln$
Stock Index: USA	USSHRPRCF	Δln
Stock Index: France	FRSHRPRCF	Δln
Stock Index: Germany	BDSHRPRCF	Δln
Stock Index: UK	UKOSP001F	Δln
Stock Index: Japan	JPSHRPRCF	Δln
Interest Rate: USA	USFEDFUN	Δlv
Interest Rate: USA	USCRBBAA	Δlv
Interest Rate: USA	USGBOND	Δlv
Interest Rate: France	FRPRATE	Δlv
Interest Rate: France	FRGBOND	Δlv
Interest Rate: Germany	BDPRATE	Δlv
Interest Rate: Germany	BDGBOND	Δlv
Interest Rate: UK	UKPRATE	Δlv
Interest Rate: UK	UKGBOND	Δlv
Interest Rate: Australia	AUPRATE	Δlv
Interest Rate: Australia	AUBOND	Δlv
Interest Rate: Japan	JPGBOND	Δlv
Exchange Rate: DM to USD	BBDEMSP	Δln
Exchange Rate: SK to USD	SDXRUSD	Δln
Exchange Rate: GBP to USD	UKDOLLR	Δln
Exchange Rate: JPY to USD	JPXRUSD	Δln
Exchange Rate: AUS to USD	AUXRUSD	Δln
PPI: USA	USPFDOFGE	Δln
PPI: Canada	CNPROPRCF	Δln
PPI: Germany	BDPROPRCF	Δln
PPI: UK	UKPROPRCF	Δln
PPI: Japan	JPPROPRCF	Δln
CPI: USA	USCONPRCE	Δln
CPI: Canada	CNCONPRCF	Δln
CPI: France	FRCONPRCE	Δln
CPI: Germany	BDCONPRCE	Δln
CPI: UK	UKCONPRCF	Δln
CPI: Japan	JPCONPRCF	Δln
IP: Argentina	AGIPTOT.G	Δln
IP: Chile	CLIPMAN.H	Δln
IP: Brazil	BRIPTOT_G	Δln
IP: Brazil	BRIPMAN.G	Δln
IP: China	CHPBRENTP (electricity)	Δln
IP: Korea	KOIPTOT.G	Δln

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Variable	Mnemonic	Transformation
IP: Korea	KOIPMAN.G	Δln
IP: Mexico	MXIPTOT_H	Δln
IP: Philippines	PHIPMAN_F	Δln
IP: South Africa	SAIPMAN.G	Δln
IP: Taiwan	TWIPMAN.H	Δln
Operating Ratio: Brazil	BRCAPUTLR	Δlv
Machine Orders: Korea	KONEWORDA	Δln
Manufacturing Production Capacity: Korea	KOCAPUTLF	Δlv
Car Sales: Argentina	AGCARSLSP	Δln
Retail Sales: Chile	CLRETTOTH	Δln
Gasoline Consumption: Korea	KOOPCGSLP	Δln
Retail Sales: Singapore	SPRETTOTG	Δlv
Retail Sales: Russia	RSRETTOTA	Δln
Labor Cost: Brazil	BRLCOST.F	Δln
Unemployment: Hong Kong	HKUNPTOTP	Δln
Unemployment Rate: Taiwan	TWUN%TOTQ	Δlv
Unemployment: Russia	RSUNPTOTP	Δln
Exports: Brazil	BREXPBO5A	Δln
Exports: China	CHEXPGDSA	Δln
Exports: India	INEXPGDSA	Δln
Exports: Indonesia	IDEXPGDSA	Δln
Exports: Korea	KOEXPGDSA	Δln
Exports: Philippines	PHEXPGDSA	Δln
Exports: Singapore	SPEXPGDSA	Δln
Exports: Taiwan	TWEXPGDSA	Δln
Imports: Brazil	BRIMPBO5A	Δln
Imports: China	CHIMPGDSA	Δln
Imports: Korea	KOIMPGDSA	Δln
Imports: Singapore	SPIMPGDSA	Δln
Imports: Taiwan	TWIMPGDSA	Δln
Terms of Trade: Brazil	BRTOTPRCF	Δln
Money Supply: Brazil	BRM1_A	Δln
Money Supply: Brazil	BRM3_A	Δln
Money Supply: China	CHM0_A	Δln
Money Supply: China	CHM1_A	Δln
Money Supply: India	INM1_A	$\Delta^2 ln$
Money Supply: India	INM3_A	$\Delta^2 ln$
Money Supply: Indonesia	IDM1_A	Δln
Money Supply: Indonesia	IDM2_A	Δln
Money Supply: Korea	KOM2_B	Δln
Money Supply: Mexico	MXM1_A	Δln
Money Supply: Mexico	MXM3_A	$\Delta^2 ln$
Money Supply: Philippines	PHM1_A	Δln
Money Supply: Philippines	PHM3_A	Δln
Money Supply: Russia	RSM 0_A	Δln
Stock Index: Brazil	BRSHRPRCF	Δln
Stock Index: Hong Kong	HKSHRPRCF	Δln
Exchange Rate: Br.R. to USD	BRXRUSD	Δln

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Variable	Mnemonic	Transformation
Exchange Rate: Ch.Y. to USD	CHXRUSD	Δln
Exchange Rate: In.R. to USD	INXRUSD	Δln
Exchange Rate: Id.R. to USD	IDXRUSD	Δln
Exchange Rate: Mx.P. to USD	MXXRUSD	Δln
Exchange Rate: Rs.R. to USD	RSXRUSD	Δln
CPI: Brazil	BRCPIGENF	Δln
CPI: China	CHCONPRCF	Δln
CPI: India	INCPINWKF	Δln
CPI: Korea	KOCONPRCF	Δln
CPI: Mexico	MXCONPRCF	Δln
CPI: Philippines	PHCONPRCF	Δln
CPI: Russia	RSCONPRCF	Δln

Table A.3: Time Series Regressions for Commodity Factor Model

This table reports the time series regression results of commodity futures returns on the returns of the equally-weighted market portfolio (MRKT), as well as the returns of long-short portfolios on basis (BAS), momentum (MOM), and basis-momentum (BASMOM). t-statistics reported in parentheses are based on Newey and West (1987) standard errors with two lags. Commodity sectors are separated by horizontal lines.

Commodity	Intercept	MRKT	BAS	MOM	BASMOM	R^2
WTI Crude	-0.10 (-0.23)	1.56 (11.07)	-0.05 (-0.29)	0.33 (1.56)	0.08 (0.47)	0.39
Brent Crude	0.23 (0.53)	1.58 (11.00)	-0.01 (-0.05)	0.27 (1.13)	0.15 (0.82)	0.40
Heating Oil	0.04 (0.11)	1.52 (10.96)	0.10 (0.55)	0.25 (1.17)	-0.01 (-0.05)	0.39
Natural Gas	-0.37 (-0.51)	1.43 (7.35)	0.04 (0.15)	0.31 (1.14)	-0.89 (-2.58)	0.14
Gasoil	0.13 (0.31)	1.44 (10.66)	0.01 (0.06)	0.30 (1.33)	0.11 (0.56)	0.37
Gasoline	0.62 (1.46)	1.58 (10.45)	0.01 (0.04)	0.35 (1.42)	-0.13 (-0.51)	0.37
Corn	-0.41 (-1.14)	1.16 (11.02)	-0.39 (-2.58)	0.01 (0.06)	-0.02 (-0.15)	0.34
Kansas Wheat	-0.05 (-0.12)	1.17 (11.85)	-0.59 (-4.10)	0.13 (0.89)	-0.10 (-0.71)	0.33
Oats	-0.06 (-0.15)	1.17 (9.31)	-0.42 (-2.78)	-0.04 (-0.28)	0.03 (0.20)	0.27
Rough Rice	-0.31 (-0.72)	0.57 (5.41)	-0.21 (-1.18)	0.16 (1.15)	-0.42 (-2.77)	0.10
Chicago Wheat	-0.35 (-0.92)	1.18 (11.95)	-0.62 (-4.10)	0.02 (0.16)	-0.04 (-0.23)	0.34
Copper	0.21 (0.68)	1.21 (12.77)	0.36 (2.53)	-0.14 (-1.15)	0.07 (0.57)	0.37
Aluminium	-0.39 (-1.49)	0.85 (11.02)	0.21 (1.47)	-0.06 (-0.60)	0.01 (0.09)	0.35
Lead	0.44 (0.95)	0.99 (7.74)	0.25 (1.06)	-0.18 (-0.76)	0.12 (0.61)	0.22
Nickel	0.07 (0.12)	1.34 (11.16)	0.53 (2.23)	0.12 (0.59)	0.02 (0.12)	0.31
Tin	0.31 (0.88)	0.88 (9.07)	0.42 (2.67)	-0.12 (-0.90)	0.17 (1.12)	0.30
Zinc	-0.32 (-0.85)	1.09 (12.24)	0.51 (3.27)	-0.05 (-0.31)	-0.02 (-0.13)	0.35
Feeder Cattle	0.18 (0.80)	0.07 (0.82)	0.13 (1.54)	-0.12 (-1.35)	0.01 (0.17)	0.01
Live Cattle	0.09 (0.44)	0.14 (1.85)	-0.05 (-0.64)	-0.05 (-0.67)	0.04 (0.57)	0.02
Lean Hogs	-0.18 (-0.50)	0.42 (3.44)	0.03 (0.24)	-0.28 (-2.29)	-0.12 (-0.90)	0.06
Cotton	-0.17 (-0.47)	0.97 (8.22)	-0.18 (-1.37)	-0.02 (-0.18)	-0.03 (-0.20)	0.21
Lumber	-0.73 (-1.60)	0.69 (5.85)	-0.09 (-0.57)	0.05 (0.33)	0.03 (0.22)	0.09
Soybean Oil	-0.23 (-0.79)	1.07 (10.46)	-0.20 (-1.29)	-0.12 (-1.14)	0.10 (0.71)	0.33
Canola	-0.08 (-0.30)	0.66 (5.88)	-0.35 (-3.00)	-0.01 (-0.11)	0.22 (1.77)	0.23
Soybeans	0.27 (0.85)	1.20 (13.74)	-0.19 (-1.32)	-0.06 (-0.59)	0.01 (0.07)	0.40
Soybean Meal	0.82 (2.10)	1.13 (10.75)	-0.19 (-1.20)	0.00 (0.03)	-0.05 (-0.26)	0.28
Gold	-0.05 (-0.22)	0.52 (7.66)	0.28 (2.73)	-0.02 (-0.37)	0.02 (0.19)	0.21
Palladium	0.64 (1.39)	1.18 (6.92)	0.49 (2.70)	-0.22 (-1.42)	0.08 (0.46)	0.22
Platinum	0.01 (0.04)	0.99 (9.12)	0.42 (3.69)	-0.06 (-0.71)	-0.07 (-0.67)	0.38
Silver	-0.20 (-0.56)	1.05 (8.47)	0.44 (2.58)	-0.12 (-0.99)	0.23 (1.38)	0.27
Cocoa	-0.05 (-0.11)	0.76 (6.53)	-0.11 (-0.65)	0.05 (0.35)	-0.14 (-0.86)	0.10
Orange Juice	-0.59 (-1.33)	0.66 (5.12)	0.10 (0.60)	-0.26 (-1.61)	0.33 (1.83)	0.09
Coffee	-0.52 (-1.02)	0.89 (6.59)	-0.52 (-2.76)	-0.24 (-1.24)	0.68 (2.54)	0.16
Sugar	0.17 (0.37)	0.86 (6.11)	0.16 (0.96)	-0.18 (-1.08)	-0.09 (-0.50)	0.11

Table A.4: Time Series Regressions for Macro Factor Model

This table reports the time series regression results of commodity futures returns on the first 9 principal components of a set of 184 macro variables following Le Pen and Sévi (2017). t-statistics reported in parentheses are based on Newey and West (1987) standard errors with two lags. Commodity sectors are separated by horizontal lines. Results for the fifth to ninth PC are omitted.

Commodity	Intercept	PC_1	PC_2	PC_3	PC_4	R^2
WTI Crude	0.58 (1.34)	0.84 (7.16)	-0.65 (-4.56)	0.11 (0.51)	0.40 (1.63)	0.23
Brent Crude	0.94 (2.15)	0.79 (6.10)	-0.74 (-4.69)	0.05 (0.22)	0.42 (1.64)	0.25
Heating Oil	0.62 (1.53)	0.74 (5.83)	-0.61 (-3.98)	0.03 (0.15)	0.36 (1.60)	0.21
Natural Gas	-0.63 (-0.85)	0.68 (3.43)	-0.21 (-0.86)	-0.29 (-1.06)	0.35 (1.12)	0.06
Gasoil	0.79 (1.91)	0.74 (5.83)	-0.67 (-4.45)	-0.06 (-0.29)	0.29 (1.32)	0.23
Gasoline	1.12 (2.62)	0.70 (4.74)	-0.58 (-3.90)	0.01 (0.03)	0.52 (2.12)	0.21
Corn	-0.46 (-1.15)	0.03 (0.29)	-0.14 (-1.28)	0.40 (2.76)	0.43 (2.59)	0.06
Kansas Wheat	-0.17 (-0.43)	0.03 (0.30)	-0.23 (-2.10)	0.37 (2.49)	0.41 (2.42)	0.06
Oats	-0.09 (-0.21)	0.09 (0.60)	-0.24 (-1.57)	0.40 (2.42)	0.49 (2.43)	0.05
Rough Rice	-0.58 (-1.45)	0.20 (2.16)	-0.15 (-1.36)	0.11 (0.78)	0.44 (2.56)	0.05
Chicago Wheat	-0.52 (-1.32)	-0.02 (-0.16)	-0.13 (-1.28)	0.47 (3.12)	0.53 (3.11)	0.06
Copper	0.62 (1.84)	0.47 (5.15)	-0.43 (-3.68)	0.55 (3.41)	0.90 (5.72)	0.23
Aluminium	-0.13 (-0.43)	0.32 (3.88)	-0.43 (-4.06)	0.47 (3.71)	0.62 (4.33)	0.27
Lead	0.57 (0.91)	0.23 (1.67)	-0.51 (-2.62)	0.40 (1.63)	1.00 (4.07)	0.19
Nickel	0.31 (0.54)	0.22 (1.60)	-0.37 (-1.91)	1.06 (4.98)	1.33 (5.52)	0.24
Tin	0.59 (1.38)	0.32 (3.34)	-0.46 (-3.55)	0.58 (3.31)	0.67 (3.54)	0.26
Zinc	-0.13 (-0.27)	0.11 (0.90)	-0.34 (-2.00)	0.73 (3.49)	0.98 (4.60)	0.22
Feeder Cattle	0.20 (0.92)	0.11 (1.78)	-0.16 (-2.25)	0.11 (1.25)	0.09 (1.06)	0.04
Live Cattle	0.09 (0.45)	0.09 (1.63)	-0.17 (-2.80)	0.14 (1.62)	0.08 (1.03)	0.05
Lean Hogs	-0.43 (-1.23)	0.03 (0.31)	-0.20 (-1.94)	0.06 (0.44)	0.14 (0.84)	0.03
Cotton	-0.17 (-0.43)	0.14 (1.22)	-0.30 (-2.53)	0.52 (3.14)	0.56 (3.17)	0.08
Lumber	-0.58 (-1.33)	0.13 (1.10)	-0.13 (-0.97)	0.51 (3.01)	0.64 (3.28)	0.08
Soybean Oil	-0.17 (-0.53)	0.20 (2.11)	-0.24 (-2.41)	0.36 (2.79)	0.66 (4.56)	0.12
Canola	0.04 (0.12)	0.08 (0.95)	-0.11 (-1.18)	0.11 (0.94)	0.18 (1.38)	0.03
Soybeans	0.34 (0.99)	0.08 (0.94)	-0.16 (-1.51)	0.34 (2.65)	0.53 (3.88)	0.09
Soybean Meal	0.87 (2.20)	0.02 (0.14)	-0.11 (-0.85)	0.26 (1.84)	0.37 (2.35)	0.05
Gold	0.21 (1.04)	-0.12 (-1.40)	-0.06 (-0.68)	0.16 (1.77)	0.20 (1.54)	0.14
Palladium	1.08 (2.27)	0.21 (1.38)	-0.37 (-2.01)	0.85 (3.78)	0.53 (2.64)	0.09
Platinum	0.30 (1.04)	0.06 (0.46)	-0.33 (-2.49)	0.37 (2.49)	0.67 (4.79)	0.17
Silver	0.36 (0.98)	-0.02 (-0.19)	-0.15 (-1.20)	0.35 (2.08)	0.65 (3.81)	0.12
Cocoa	-0.14 (-0.36)	-0.23 (-1.73)	-0.12 (-0.94)	0.21 (1.11)	0.34 (1.52)	0.06
Orange Juice	-0.30 (-0.66)	0.20 (1.55)	-0.18 (-1.24)	0.26 (1.39)	0.64 (3.43)	0.05
Coffee	-0.20 (-0.35)	0.19 (1.19)	-0.27 (-1.45)	0.35 (1.78)	0.39 (1.79)	0.04
Sugar	0.25 (0.49)	0.26 (1.72)	-0.04 (-0.36)	0.35 (1.98)	0.35 (1.81)	0.04

Table A.5: Robustness Check for Size of Rolling Window

This table reports the root mean squared error for the comovement measure of the model-implied commodity returns with respect to the commodity factor model based on the returns of the equally-weighted market portfolio, as well as the returns of long-short portfolios on basis, momentum, and basis-momentum, and the macro factor model based on the first 9 principal components of a set of 184 macro variables following Le Pen and Sévi (2017). The comovement is defined as in Equation (2.9)*,*

$$CM^{real}(\tau) := \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{real}(\tau)^{*} \qquad and \qquad CM^{model}(\tau) = \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{model}(\tau)^{*}, \tag{2.9}$$

where τ is a ***24 (60)*** *months rolling window, $\rho_{ij}^{real}(\tau)^{*}$ and $\rho_{ij}^{model}(\tau)^{*}$ are the heteroskedasticity-adjusted correlation coefficients of the realized and model-implied commodity returns, and w_{ij} are weights such that $\sum_{i,j,i\neq j} w_{ij} = 1$. In Rows 'Constant Beta', the respective models are estimated once for the whole sample period. In Rows 'Parametric Beta', the coefficients are parametrized using the 3-month U.S. LIBOR rate, the term spread between 10-year and 3-months U.S. Treasury bills, the default spread between Moody's BAA and AAA Corporate Bonds Indices, the TED-spread between 3-month LIBOR and the Treasury rate, and the CBOE Volatility Index. In Rows 'Re-estimated Beta', the coefficients are re-estimated for each rolling window.*

Panel A: Rolling Window = 24 Months

Estimation	**Commodity Factor Model**	**Macro Factor Model**
Constant Beta	0.1067	0.2116
Parametric Beta	0.1035	0.1803
Re-estimated Beta	0.0350	0.1379

Panel B: Rolling Window = 60 Months

Estimation	**Commodity Factor Model**	**Macro Factor Model**
Constant Beta	0.0777	0.2105
Parametric Beta	0.0702	0.1749
Re-estimated Beta	0.0346	0.1707

Table A.6: Robustness Check for Heteroskedasticity Adjustment

This table reports the root mean squared error (RMSE) for the comovement measure of the model-implied commodity returns with respect to the commodity factor model based on the returns of the equally-weighted market portfolio, as well as the returns of long-short portfolios on basis, momentum, and basis-momentum, and the macro factor model based on the first 9 principal components of a set of 184 macro variables following Le Pen and Sévi (2017). The comovement is defined as in Equation (2.9),

$$CM^{real}(\tau) := \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{real}(\tau)^{*} \qquad \text{and} \qquad CM^{model}(\tau) = \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{model}(\tau)^{*}, \tag{2.9}$$

where τ is a 36 months rolling window, $\rho_{ij}^{real}(\tau)^{*}$ and $\rho_{ij}^{model}(\tau)^{*}$ are the heteroskedasticity-adjusted correlation coefficients of the realized and model-implied commodity returns, and w_{ij} are weights such that $\sum_{i,j,i\neq j} w_{ij} = 1$. The heteroskedasticity adjustment follows Forbes and Rigobon (2002) as described in Equation (2.8)

$$\rho_{ij}^{\;*} = \frac{\rho_{ij}}{\sqrt{1+\delta_i(1-\rho_{ij}^2)}} \quad \text{with } \delta_i = \frac{\mathrm{Var}_{short}(R_i)}{\mathrm{Var}_{long}(R_i)} - 1, \tag{2.8}$$

where ρ_{ij} is the non-adjusted correlation coefficient, $\mathrm{Var}_{short}(R_i)$ is the variance of R_i over a shorter horizon compared to $\mathrm{Var}_{long}(R_i)$, which is computed over 36 months. In Panel A, there is no heteroskedasticity adjustment applied, i.e., $\mathrm{Var}_{short}(R_i)$ is equal to $\mathrm{Var}_{long}(R_i)$ or $\delta_i = 0$. In Panel B, $\mathrm{Var}_{short}(R_i)$ uses a third of the observations of $\mathrm{Var}_{long}(R_i)$, i.e., 12 months, and in Panel C $\mathrm{Var}_{short}(R_i)$ is computed over 6 months.

Panel A: No Adjustment

Estimation	**Commodity Factor Model**	**Macro Factor Model**
Constant Beta	0.0972	0.2115
Parametric Beta	0.0917	0.1800
Re-estimated Beta	0.0331	0.1575

Panel B: $\mathbf{Var_{short}}$ over 12 Months

Estimation	**Commodity Factor Model**	**Macro Factor Model**
Constant Beta	0.0948	0.2141
Parametric Beta	0.0912	0.1817
Re-estimated Beta	0.0355	0.1578

Panel C: $\mathbf{Var_{short}}$ over 6 Months

Estimation	**Commodity Factor Model**	**Macro Factor Model**
Constant Beta	0.0984	0.2163
Parametric Beta	0.0989	0.1846
Re-estimated Beta	0.0394	0.1566

Table A.7: Robustness Check for Sample Choice

This table reports the root mean squared error for the comovement measure of the model-implied commodity returns with respect to the commodity factor model and the macro factor model. The comovement is defined as in Equation (2.9),

$$CM^{real}(\tau) := \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{real}(\tau) \qquad \textit{and} \qquad CM^{model}(\tau) = \sum_{i,j,i\neq j} w_{ij}\rho_{ij}^{model}(\tau), \tag{2.9}$$

where τ is a 36 months rolling window, $\rho_{ij}^{real}(\tau)$ and $\rho_{ij}^{model}(\tau)$ are the correlation coefficients of the realized and model-implied commodity returns, and w_{ij} are weights such that $\sum_{i,j,i\neq j} w_{ij} = 1$. In Rows 'Constant Beta', the respective models are estimated once for the whole sample period. In Rows 'Parametric Beta', the coefficients are parametrized using the 3-month U.S. LIBOR rate, the term spread between 10-year and 3-months U.S. Treasury bills, the default spread between Moody's BAA and AAA Corporate Bonds Indices, the TED spread between 3-month LIBOR and the Treasury rate, and the CBOE Volatility Index. In Rows 'Re-estimated Beta', the coefficients are re-estimated for each rolling window. Panel A uses the same set of 21 commodities as Szymanowska et al. (2014). Panel B uses the set of 34 commodities excluding the commodities of the sector listed in the first column.

Panel A: Dataset – Szymanowska et al. (2014)

Estimation	**Commodity Factor Model**	**Macro Factor Model**
Constant Beta	0.0710	0.1925
Parametric Beta	0.0647	0.1661
Re-estimated Beta	0.0282	0.1390

Panel B: Excluding Sectors with Re-Estimated Beta

Excluded Sector	**Commodity Factor Model**	**Macro Factor Model**
Energy	0.0383	0.1451
Grains	0.0486	0.1680
Industrial Metals	0.0405	0.1662
Live Stock	0.0356	0.1695
Materials	0.0361	0.1606
Oilseeds	0.0552	0.1706
Precious Metals	0.0510	0.1787
Softs	0.0407	0.1725

Table A.8: Model Error of Single- vs. Multifactor Model

*This table reports the mean absolute error (MAE) and the root mean squared error (RMSE) between the realized and the model-implied commodity return comovement measure for various versions of the commodity factor model. The first column lists the factors included in the model, where the market factor (**MRKT**) is an equally-weighted average over all commodity returns. The basis factor (**BAS**) is the return on a long-short portfolio that buys the 17 commodities with the highest basis and sells the 17 commodities with the lowest basis. The momentum factor (**MOM**) is the return on a long-short portfolio that buys the 17 commodities with the best 12-months performance and sells the 17 commodities with worst 12-month performance. The basis-momentum factor (**BASMOM**) is the return on a long-short portfolio that buys the 17 commodities with the best 12-months basis performance and sells the 17 commodities with the worst basis performance. The last row augments the model with the first nine PCs of the set of 184 macro variables as in Le Pen and Sévi (2017). Correlation coefficients are adjusted for heteroskedasticity and re-estimated every month over a rolling window of 36 months. Panel A uses the whole cross-section to compute factor returns, Panel B computes factors separately for every commodity markets based on all other 33 markets.*

Panel A: Including Commodity in Factor Computation

Factors included	MAE	RMSE
MRKT	0.0318	0.0382
CRY + MOM + BASMOM	0.2448	0.2567
MRKT + CRY + MOM + BASMOM	0.0246	0.0294
MRKT + CRY + MOM + BASMOM + Macro	0.0202	0.0235

Panel B: Excluding Commodity from Factor Computation

Factors included	MAE	RMSE
MRKT	0.0688	0.0741
CRY + MOM + BASMOM	0.2482	0.2609
MRKT + CRY + MOM + BASMOM	0.0565	0.0608
MRKT + CRY + MOM + BASMOM + Macro	0.0504	0.0562

Table A.9: Model Error for Partial Comovement Measure

This table reports mean absolute error (MAE) and root mean squared error (RMSE) betweem the realized and the model-implied partial commodity return comovement measure of the commodity factor model based on the returns of the equally-weighted market portfolio, as well as the returns of long-short portfolios on basis, momentum, and basis-momentum. The comovement is defined as in Equation (2.23)

$$CM_i^{real}(\tau) = \frac{1}{W_i}\sum_{j\neq i} w_j \left(\rho_{ij}^{real}(\tau)^* + \rho_{ji}^{real}(\tau)^*\right), \quad CM_i^{model}(\tau) = \frac{1}{W_i}\sum_{j\neq i} w_j \left(\rho_{ij}^{model}(\tau)^* + \rho_{ji}^{model}(\tau)^*\right), \tag{2.23}$$

where τ is a 36 months rolling window, $\rho_{ij}^{real}(\tau)^*$ and $\rho_{ij}^{model}(\tau)^*$ are the heteroskedasticity-adjusted correlation coefficients of the realized and model-implied commodity returns, which are re-estimated over a rolling window of 36 months, and w_j are weights such that $W_i = \sum_{j\neq i} w_j$. The average over all assets is reported in bold at the end.

Commodity	RMSE	MAE	Commodity	RMSE	MAE
Soybean Oil	0.0296	0.0335	Corn	0.0464	0.0551
Cocoa	0.0346	0.0402	WTI Crude	0.0615	0.0725
Brent Crude	0.0795	0.0927	Cotton	0.0360	0.0383
Feeder Cattle	0.0269	0.0330	Gold	0.0302	0.0356
Copper	0.0501	0.0553	Heating Oil	0.0984	0.1138
Orange Juice	0.0482	0.0511	Coffee	0.0592	0.0628
Kansas Wheat	0.0407	0.0491	Aluminium	0.0398	0.0430
Lumber	0.0448	0.0466	Live Cattle	0.0380	0.0428
Lean Hogs	0.0382	0.0407	Lead	0.0477	0.0497
Nickel	0.0506	0.0535	Tin	0.0412	0.0431
Zinc	0.0498	0.0509	Natural Gas	0.0325	0.0393
Oats	0.0491	0.0578	Palladium	0.0315	0.0388
Platinum	0.0280	0.0333	Gasoil	0.0501	0.0605
Gasoline	0.0949	0.1092	Rough Rice	0.0407	0.0430
Canola	0.0430	0.0476	Soybeans	0.0710	0.0771
Sugar	0.0499	0.0532	Silver	0.0235	0.0284
Soybean Meal	0.0548	0.0584	Chicago Wheat	0.0524	0.0601
Average	**0.0474**	**0.0532**			

Chapter 3

The Natural Gas Announcement Day Puzzle

3.1 Introduction

The natural gas market has undergone massive changes throughout the last decades, starting with its deregulation in the 1980s, the inception of the futures market in 1990, the inflow of financial investors at the beginning of the twenty-first century, and recent shifts in supply and demand due to shale gas, a growing industry for liquefied natural gas (LNG), as well as increased attention related to climate change. Natural gas inventory levels have always been an important indicator of changes due to their natural role as a buffer between supply and demand. As such, the release of the Weekly Natural Gas Storage Report by the Energy Information Administration (EIA), which contains information about the current inventory level, draws attention from all market participants. When new information is released to an efficient market, participants adjust their expectations and prices accordingly. Figure B.1 in Appendix B shows that more than 50% of the annual return of natural gas futures is generated on EIA announcement days. Therefore, returns on natural gas futures are significantly different on EIA announcement days compared to non-announcement days. However, after controlling for the information of the announcement this difference should disappear.

This chapter documents a significant difference between the average returns observed on EIA announcement and non-announcement days. Puzzlingly, this difference in returns between announcement and non-announcement days cannot be explained by the announcement surprise. Indeed, we find a strong significant negative relationship between natural gas futures returns and the announcement surprise, but we cannot explain the return difference between announcement and non-announcement days. This result is robust after augmenting the model with supply and demand measures, spillover effects from options, energy or equity markets, as well as commodity specific variables such as the slope of the futures curve, hedging pressure, liquidity, or volatility measures.

At the intraday level, we decompose the return within a two-hour window surrounding the announcement into a pre- and post-announcement part. Curiously, the overall return divides equally into the pre-announcement part (49.4%) and the post-announcement part (50.6%). While we find some evidence of information leakage, this can only be a partial explanation as there is still a significant effect from the announcement. Lastly, we document that the pre-announcement return is only discernible on days where the announcement surprise is positive, i.e., the published inventory exceeds analysts' expectations. The asymmetry of this result casts doubt on a simple explanation based on informed trading.

From the perspective of an investor, this puzzling result raises the question whether the newly documented premium is economically large once transaction and funding costs are accounted for. Our results show that the simple strategy of opening a short position 90 minutes before the announcement and closing it 30 minutes afterwards yields a significant annual return of 12% (t-stat = 2.93) translating into a Sharpe ratio of 1.76 after transaction and funding costs. However, the time series of strategy returns and the accuracy of analysts' forecasts suggests that the anomaly has decreased in magnitude and efficiency has returned to natural gas markets, leaving open the possibility that our strategy was new to investors who are now arbitraging it away.

Our work contributes to the literature on storage effects in energy markets. Linn and Zhu (2004) show that the intradaily volatility of natural gas futures is significantly higher in the hour surrounding the American Gas Association (AGA) report and this effect has carried on after the EIA took over the reporting. Gay et al. (2009) show that the announcement return is negatively related to the inventory surprise, i.e., futures returns tend to be negative when the reported inventory level is higher than analysts' expectations. Halova et al. (2014) find seasonal patterns relating to the withdrawal period from November to March and the injection period from April to October. During the winter, when inventories are lower than on average, inventory shocks have a smaller effect on futures returns, while the effect is stronger in the summer. They also find that the effect is weaker, when forecast dispersion is higher which in general is the case in winter, when demand shocks due to weather are an important driver of energy prices. Chiou-Wei et al. (2014) show that the announcement effect is unique to the day of the announcement. Bu (2014), Ye and Karali (2016), and Miao et al. (2018) find similar results for oil and gasoline using the EIA Petroleum Report announcements. Ederington et al. (2019) revisit these studies, and find that analysts' natural gas forecasts efficiently impound the available time series information but crude oil forecasts do not. Demirer and Kutan (2010) and Schmidbauer and Rösch (2012) study the effect of OPEC announcements on crude oil markets. Wolfe and Rosenman (2014) show that announcements in oil and gas markets cause spillover effects to each other. Compared to studies for other energy markets and studies on the effect of crop reports on agricultural commodities (Adjemian, 2012; Mattos and Silveira, 2016), focusing on the EIA Weekly Natural Gas Storage Report provides a unique setting. The report only includes storage information without any supplementary information on supply, demand, or future prospects of production, hence the effect can be clearly referred to the changes in inventory.

Our work also relates to the broader literature on the effects of scheduled news on energy prices. Basistha and Kurov (2015) study the effect of Federal Open Market Committee (FOMC) announcements on energy prices. For crude oil, Kilian and Vega (2011) and Chatrath et al. (2012) find no evidence to suggest that energy prices respond to macroeconomic news. They conclude that crude oil prices are predetermined with respect to macro aggregates, confirming the view of Kilian (2009), that prices are determined by flow supply and flow demand.

Moreover, our work adds to the growing literature analyzing risk premia on announcement days. Savor and Wilson (2013) find that 60% of the annual equity risk premium can be earned by only investing when important macroeconomic news is released. They interpret this finding as the premium investors demand for bearing macroeconomic risk. Ai and Bansal (2018) develop a theoretical framework that explains the announcement premium with the generalized risk sensitivity of investors used as evidence for a class of non-expected utility models. Relative to these studies, we focus on announcements of natural gas inventories, which are presumably asset specific news. We find a sizeable premium on these days suggesting a risk premium for idiosyncratic news.

The intraday analysis in this chapter is related to the work of Lucca and Moench (2015), who document the pre-FOMC announcement drift in the U.S. equity market. As Brusa et al. (2020) show, the Fed is unique in channelling such an effect compared to other international central banks. The EIA report plays a similar role for the U.S. natural gas market. Gu and Kurov (2018) find a pre-announcement drift, and link it to informed trading caused by superior forecasting abilities of certain participants. Rousse and Sévi (2019) find evidence of an asymmetric response of crude oil returns to the EIA Petroleum Report. Our study reveals that the documented pre-announcement effect in the natural gas market is asymmetric and only accounts for half of the entire return, and therefore casts doubt on an explanation based on informed trading.

Lastly, our work relates to the literature on the pricing of commodity futures. Brown and Yücel (2008) show that natural gas markets are driven by weather, inventories and spillovers from crude oil markets. Besides these supply and demand driven factors, we relate to the growing literature on factor models for commodity futures that include hedging pressure (De Roon et al., 2000), open interest (Hong and Yogo, 2012), idiosyncratic volatility (Fernandez-Perez et al., 2016), or the slope of the futures curve (Szymanowska et al., 2014). We confirm earlier studies that the listed variables affect natural gas returns. They are, however, not able to explain the EIA announcement effect.

The remainder of this chapter is organized as follows. Section 3.2 describes the data and introduces the main variables. Section 3.3 documents the EIA announcement effect and explores possible explanations. Section 3.4 looks at the intraday frequency, Section 3.5 discusses robustness checks, and Section 3.6 concludes.

3.2 Data & Variables

From Bloomberg, we obtain the daily price, trading volume and open interest series of 499 Henry Hub Natural Gas futures contracts (Ticker: NG) from March 2003 to December 2018.[1] Since we are dealing with futures contracts, we need to construct an investable price series by rolling over contracts before expiry.[2] We follow Szymanowska et al. (2014) and roll over the entire curve at the end of the month preceding the month prior to delivery, i.e., the log return on the futures price series is defined as

$$r_t^{(n)} := \begin{cases} \log(F_t^{(n)}) - \log(F_{t-1}^{(n+1)}), & \text{if } t-1 \text{ is a rollover day} \\ \log(F_t^{(n)}) - \log(F_{t-1}^{(n)}), & \text{otherwise,} \end{cases} \tag{3.1}$$

where $F_t^{(n)}$ is the price of the n^{th} nearby on day t. We provide summary statistics on the returns of the first six nearby contracts in Table 3.1, that confirm common characteristics of natural gas markets. We find a strongly negative average return of −31.65%, as has been documented in other studies (de Groot et al., 2014; Paschke et al., 2020). Further, we see high volatility of up to 45% per annum and a decreasing pattern of volatility in line with the Samuelson effect.

[1]The start of the sample is motivated by the inception of the Bloomberg forecast for the EIA report. An alternative approach would be to use physical spot data. Unfortunately, spot trading involves a number of costs that can affect the response of spot prices to news. In order to guard against this challenge, we focus on the futures market.

[2]This is an important distinction to the pure price series of the front contract or the spot price (Singleton, 2014). The large difference between the spot price series (or futures prices series without rollover) and a constructed total return price series that uses the realized returns from a rolled futures position are illustrated in Figure B.2 in Appendix B.

Table 3.1: Summary Statistics for Natural Gas Returns

This table reports the summary statistics of daily log returns for the first six nearby contracts in Henry Hub Natural Gas Futures for the period from March 2003 to December 2018. Contracts have been rolled over at the end of the month preceding the month prior to delivery. Column 'n' denotes the order of nearby, column 'Mean' reports the annualized mean return, columns 'Min' and 'Max' report the minimal and maximal daily return, column 'Std. Dev.' reports the annualized standard deviation, and column 'SR' the annualized Sharpe ratio. Column 'AR(1)' reports the first order autocorrelation. The columns 'Skew' and 'Kurt' report skewness and kurtosis of the returns, respectively, and column 'JB' reports the p-value of the Jarque-Bera test for normality. Returns and standard deviations are reported in percentage points.

n	Mean	Min	Max	Std. Dev.	SR	AR(1)	Skew	Kurt	JB
1	-31.65	-19.18	18.76	44.99	-0.70	-0.06	0.15	5.88	0.00
2	-24.74	-20.21	17.13	40.71	-0.61	-0.05	0.07	6.21	0.00
3	-17.32	-21.80	18.63	36.81	-0.47	-0.05	0.08	7.49	0.00
4	-15.89	-12.05	10.58	32.95	-0.48	-0.04	0.07	4.55	0.00
5	-14.13	-11.03	10.31	30.67	-0.46	-0.04	0.04	4.57	0.00
6	-11.43	-11.08	10.13	28.96	-0.39	-0.04	0.02	4.75	0.00

Also from Bloomberg, we collect the EIA weekly total storage level and the corresponding survey forecast. Natural gas storage levels and changes show strong seasonal patterns resulting from demand cycles. Storage levels decrease during the withdrawal period from November to March as the demand of gas for heating in winter exceeds the stable supply. Inventories build up again during the injection period from April to October. Since the economics of natural gas markets are known to market participants, these patterns are also included in analysts' forecasts. Therefore, the actual new information of the announcement is the deviation of the announced figures from the market's expectation. As a proxy of this market expectation, we use the Bloomberg median survey forecast. It is regarded as a proxy for the market expectation by academics and practitioners (Chiou-Wei et al., 2014) and provides additional information beyond seasonal and historic patterns to market participants (Ederington et al., 2019). We define the non-scaled announcement surprise, S^{level}, as

$$S_t^{\text{level}} := A_t - E_t \tag{3.2}$$

where A_t is the announced inventory level on day t and E_t is the market expectation as measured by the median survey forecast. To normalize the surprise measure, we follow Andersen et al. (2003) and define the standardized announcement surprise as

$$S_t := \frac{S_t^{\text{level}}}{\sigma(S^{\text{level}})} \tag{3.3}$$

where $\sigma(S^{\text{level}})$ is the standard deviation of the time series S^{level}. For robustness, we also use a relative and a dispersion-adjusted surprise measure defined as

$$S_t^{\text{rel}} := \frac{S_t^{\text{level}}}{A_{t-1}}, \qquad S_t^{\text{disp}} := \frac{S_t^{\text{level}}}{\sigma_t(E)}, \tag{3.4}$$

where A_{t-1} is the previous inventory level and $\sigma_t(E)$ is the dispersion among forecasters for the announcement on day t.[3] We provide summary statistics for the inventory, the survey forecast, and the surprise measures in Table 3.2.[4]

Further, we obtain weather data on Heating Degree Days (HDD) and Cooling Degree Days (CDD) from the American Gas Association (AGA). Heating Degree Days are a measure of the coldness of the weather experienced, based on the extent to which the daily mean temperature falls below the reference temperature of 65° F.[5] Cooling Degree Days are a measure of the need for air conditioning (cooling) based on the extent to which the daily mean temperature rises above the reference temperature. The AGA Heating Degree Day Report contains heating and cooling degree data aggregated on a weekly basis for nine census regions and the United States.

Lastly, we collect financial variables and macroeconomic variables as well as other macroeconomic announcements and their survey forecasts from Bloomberg. A detailed list of tickers is provided in Table B.1 of Appendix B. We also collect the Commitment of Traders (CoT) report for Henry Hub natural gas from the Commodity Futures Trading Commission (CFTC).

[3] Note that in Equation (3.3), $\sigma(S^{\text{level}}) = \sigma(A_t - E_t)$ is the standard deviation over the whole sample, hence a constant that scales S_t to have unit standard deviation, while A_{t-1} and $\sigma_t(E)$ are not constant, but varying denominators in Equation (3.4).

[4] For further information see also histograms and density plots in Figure B.4 of Appendix B.

[5] The daily mean temperature is computed as the sum of the high and the low readings divided by two.

Table 3.2: Summary Statistics for Inventory, Forecast, and Surprise

This table reports the summary statistics on the EIA Natural Gas Storage report and its Bloomberg survey forecast for the period from March 2003 to December 2018 (699 observations). The first two rows report statistics on the level and change of the natural gas storage in billion cubic feet. The third and fourth row report statistics for the median and average forecast values of the Bloomberg median survey forecast. The fifth row reports the forecast dispersion between the different survey analysts. The last three rows report the statistics for the non-scaled announcement surprise, S^{level}*, the normalized surprise,* S*, the relative surprise,* S^{rel}*, and the dispersion-adjusted surprise,* S^{disp}*, as defined in Equations* (3.2)*,* (3.3)*, and* (3.4)*:*

$$S_t^{level} = A_t - E_t, \quad S_t = \frac{S_t^{level}}{\sigma(S_t^{level})}, \quad S_t^{rel} := \frac{S_t^{level}}{A_{t-1}}, \quad S_t^{disp} := \frac{S_t^{level}}{\sigma(E_t)}, \qquad (3.2, 3.3, 3.4)$$

where A_t *is the actual inventory level on day* t*,* E_t *is the median forecast,* $\sigma(S^{level})$ *is the standard deviation of the forecast error,* A_{t-1} *is the previous inventory level and* $\sigma(E_t)$ *is the dispersion among forecasters on day* t*. The columns report mean, median, standard deviation, first order autocorrelation, skewness, and kurtosis.*

	Mean	Median	Std. Dev.	AR(1)	Skew	Kurt
Inventory Level	2553.92	2614.00	793.69	0.98	-0.24	2.23
Inventory Change	6.35	43.00	93.93	0.88	-1.10	3.25
Median Forecast	6.04	45.00	92.44	0.90	-1.09	3.25
Average Forecast	6.06	44.00	92.21	0.90	-1.09	3.24
Forecast Dispersion	6.87	6.00	3.52	0.54	1.88	8.98
Surprise Level	0.31	0.00	8.57	-0.03	0.29	5.77
Normalised Surprise	0.04	0.00	1.00	-0.03	0.29	5.77
Relative Surprise	0.03	0.00	0.48	-0.04	0.79	18.25
Dispersion-adjusted Surprise	0.06	0.00	1.32	-0.05	0.81	8.59

3.3 The EIA Announcement Effect

3.3.1 The Facts

Every Thursday at 10:30 a.m. Eastern Time (ET), the EIA releases the Weekly Natural Gas Storage Report, which lists the underground storage net changes for five regions of the United States.[6] The report provides fundamental information to the natural gas markets. Therefore, it is interesting to see how prices behave on EIA announcement days compared to non-announcement days.

Table 3.3 reports summary statistics of futures returns on EIA announcement days and non-announcement days, respectively. For the first nearby contract, the mean daily return on EIA announcement days is −0.37%, while it is only −0.09% on the remaining days. The difference is statistically significant at the 5% level. Annualized volatility on announcement days is 49.2% compared to 43.3% on non-announcement days, with the difference being statistically significant at the 1% level.[7] The return and volatility differentials prevail also for longer maturities. Figure B.1 of Appendix B shows that more than 50% of the negative average return on natural gas futures is earned on EIA announcement days, with this figure being even larger for more deferred contracts. A two–sample Kolmogorov–Smirnov test in Panel B of Table 3.3, rejects the hypothesis of both subsamples stemming from the same distribution. Overall, the data provide strong evidence of natural gas prices behaving differently on EIA days as opposed to non-announcement days. While the fact, that natural gas markets behave differently on EIA days, is to be expected since fundamental information is released, we want to investigate whether the published information fully explains the observed differences.

[6] If national holidays like Thanksgiving, Christmas or Independence day fall on a Thursday, the report is released on Wednesday or Friday. However, the release schedule is known in advance, so all announcements are scheduled. We exclude observations on which the announcement of the report coincides with the Weekly Petroleum Status Report by the EIA, that is usually published on Wednesdays.

[7] We also provide a subsample analysis of the effect in Table B.2 of Appendix B that shows that the effect is not present in the most recent period (2014–2018), which saw a sharp decline in energy prices. In the earlier subsamples (2003–2007 and 2007–2014), however, the effect was even stronger.We exclude daily returns over 10% to see whether the results are driven by extreme observations. Further, we exclude days on which the EIA has revised the published figure as reported on their website, and the first year of the EIA report which includes highly shows volatile forecast errors. Table B.3 in Appendix B confirms that these observations do not affect the results significantly.

Table 3.3: Comparison of Natural Gas Return Moments on EIA Days

This table reports summary statistics of log returns on the first six nearby contracts in Henry Hub Natural Gas Futures on announcement days of the EIA Weekly Gas Storage Report (Columns 'EIA') and non-announcement days (Columns 'Non-EIA'). Column 't-Test' reports the t-statistic and p-value in parentheses for a two-sample t-test on equal means assuming unequal variances. Column 'F-Test' reports the F-statistic and p-value in parentheses for a F-test on equal variances. Column 'KS-Test' reports the test-statistic and p-value in parentheses for a two–sample Kolmogorov–Smirnov test on different distributions. Means and standard deviations are reported in percentage points, standard deviations are annualized. The sample includes 3982 daily returns from March 2003 to December 2018.

Panel A: First and Second Moment

Nearby	**Mean**			**Standard Deviation**		
	EIA	Non-EIA	t-Test	EIA	Non-EIA	F-Test
1	-0.37	-0.09	-2.19 (0.029)	49.2	43.3	1.29 (0.000)
2	-0.28	-0.07	-1.84 (0.067)	45.2	39.2	1.33 (0.000)
3	-0.24	-0.04	-1.94 (0.052)	40.6	35.6	1.30 (0.000)
4	-0.22	-0.04	-1.93 (0.054)	37.3	31.7	1.38 (0.000)
5	-0.20	-0.03	-1.87 (0.062)	34.7	29.5	1.39 (0.000)
6	-0.17	-0.03	-1.74 (0.082)	32.6	27.9	1.37 (0.000)

Panel B: Third and Fourth Moment

Nearby	**Skewness**		**Kurtosis**		KS-Test
	EIA	Non-EIA	EIA	Non-EIA	
1	0.10	0.11	4.17	5.79	0.09 (0.000)
2	0.14	0.09	4.22	6.42	0.09 (0.000)
3	0.10	0.14	4.21	8.32	0.08 (0.001)
4	0.02	0.14	4.13	4.23	0.08 (0.002)
5	0.01	0.10	4.12	4.29	0.08 (0.003)
6	0.06	0.06	4.30	4.37	0.07 (0.008)

3.3.2 Potential Explanations

3.3.2.1 The Announcement Surprise

We start with three intuitive explanations for the documented return difference. First, one could think that the news on EIA announcement days are on average 'bad', i.e., positive surprises, and hence the more negative effect. If that were the case, the surprise should be significantly greater than zero. Although we find a slightly positive surprise on average, it is not significantly different from zero (t-stat = 0.95). Second, it could be the case that positive surprises are on average larger, and therefore have a stronger effect. If that were the case, we should find a significant difference in the absolute value of positive and negative surprises. However, we find the difference in means to be indistinguishable from zero (t-stat = 0.69). Third, there could be a different effect on returns between negative and positive surprises. If this was the case, the demeaned announcement returns should be larger in absolute value on days with a positive surprise. We do find the opposite. Returns are slightly larger on negative surprise days, although the difference is not significant (t-stat = 1.37).

Having ruled out these explanations, we want to quantify the effect of the announcement surprise on the return difference in the following regression,

$$r_t = \alpha_0 + \alpha_1 I_{EIA,t} + \beta_0 S_t + \beta_1' X_t + \epsilon_t, \tag{3.5}$$

where r_t is the log return on the first nearby, $I_{EIA,t}$ is an indicator variable with value 1, if t is an EIA announcement day and 0 otherwise, S_t is the announcement surprise as defined in Equation (3.3) and set to zero for non-announcement days, X_t is a set of control variables, and ϵ_t is the error term.[8] The coefficient of interest is α_1, as it represents the difference in average returns between announcement and non-announcement days after controlling for the announcement surprise and other potential explanatory variables.

[8]Note that because returns exhibit different magnitudes of volatility on announcement and non-announcement days, we adjust for this heteroskedasticity by scaling the residuals on non-EIA days by the fraction of volatilities between EIA and non-EIA days. Therefore, the standard errors we obtain are most conservative.

We use several sets of control variables for X_t in Equation (3.5), and report the main results in Table 3.4. The first column only includes a constant and the indicator variable I_{EIA}, α_1 therefore represents the difference in means as documented before ($-0.37\% - (-0.09\%) = -0.28\%$). In the second column, we add the surprise variable and confirm earlier results by Halova et al. (2014). A one standard deviation surprise in inventories decreases futures prices by 1.04%, the return differnce however reduces only slightly to -0.24%.[9] The remaining columns present similar results while controlling for several alternative channels. We discuss the different channels in the following paragraphs, and present detailed regression results for the columns (III) to (VI) of Table 3.4 in Appendix B, Tables B.5 to B.8.

3.3.2.2 Asymmetric Effects

Table B.5 in Appendix B reports the result of the baseline regression in Equation (3.5) using the surprise interacted with indicator variables. This way, we test whether the return difference is due to asymmetric price reactions to the surprise under specific conditions. The results show that in times of low forecast dispersion, i.e., when analysts' opinions are less diverging, the surprise effect doubles, since a given deviation comes as a bigger surprise. The same is true during the injection period from April to October, when demand is rather stable compared to higher volatility in winter. During these times, markets are more supply-driven and production is naturally easier to foresee than the demand side which is heavily dependent on weather. Therefore, an equally-sized surprise will have a larger effect during the injection period. Further, we find a stronger effect during recessions and after 2009, but no significant differences during the hurricane season from June to November.[10] Altogether, we find that the announcement surprise explains part of the announcement return, but still leaves a significant negative average return on announcement days.

[9] These results are robust to the definition of the announcement surprise, see Table B.4 of Appendix B.

[10] Halova et al. (2014) identify December 2009 as a structural break point following the modification of the sample selection and estimation procedure by the EIA. This finding is also in line with Dehnavi et al. (2015) who study changes in the natural gas market due to the increasing role of LNG.

Table 3.4: Summary of Regressions for Potential Explanatory Channels

This table reports the results of the time series regression in Equation (3.5) *of the first nearby log return on an indicator variable, I_{EIA}, equal to 1 on EIA days and 0 otherwise, the announcement surprise, S, and several control variables. Column (I) includes only a constant and the dummy for EIA days, and column (II) adds the surprise variable. Columns (III) to (VI) add several sets of control variables such as dummy variables interacted with the surprise (III), macroeconomic measures for supply and demand of natural gas (IV), return spillovers from other markets (V), and commodity return predictors (VI). The last column combines all set of control variables. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.*

Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Constant	-0.09	-0.09	-0.09	-0.09	-0.05	0.46	0.10
	(0.04)	(0.04)	(0.04)	(0.07)	(0.20)	(0.00)	(0.50)
I_{EIA}	-0.28	-0.24	-0.23	-0.25	-0.23	-0.27	-0.27
	(0.03)	(0.05)	(0.05)	(0.05)	(0.02)	(0.03)	(0.01)
S		-1.04	-0.41	-1.03	-0.78	-1.04	-0.31
		(0.00)	(0.13)	(0.00)	(0.00)	(0.00)	(0.09)
Control Dummies	No	No	Yes	No	No	No	Yes
Control Macro	No	No	No	Yes	No	No	Yes
Control Spillover	No	No	No	No	Yes	No	Yes
Control Predictors	No	No	No	No	No	Yes	Yes
R^2	0.00	0.03	0.03	0.03	0.29	0.03	0.30
Obs	3982	3982	3982	3649	3980	3844	3529

3.3.2.3 Supply, Demand, and Market Conditions

The demand on natural gas is highly dependent on the weather because of its use for heating and cooling. To measure the influence of the weather, we use Heating Degree Days (HDD) and Cooling Degree Days (CDD) obtained from the American Gas Association (AGA). Since these variables are highly seasonal, we deseasonalize the variables using the five year average for each week, i.e.,

$$\Delta \mathrm{HDD}_t = \mathrm{HDD}_t - \frac{1}{5}\sum_{j=1}^{5} \mathrm{HDD}_{t-52\cdot j}, \tag{3.6}$$

$$\Delta \mathrm{CDD}_t = \mathrm{CDD}_t - \frac{1}{5}\sum_{j=1}^{5} \mathrm{CDD}_{t-52\cdot j}, \tag{3.7}$$

where t is a weekly subscript. Because Cooling Degree Days are only measured from April to October and Heating Degree Days only for November to March, we set all remaining values to zero. To account for the fact that expected temperature might be more important than current temperature, we also include the variable led by one week.[11] For the supply side, we collect the monthly change in U.S. natural gas production from the EIA.

Energy markets, as a fundamental part of the economy, are exposed to general financial conditions. Therefore, we augment the model with the term spread (TERM), defined as the difference in yields between a 3-month and a 10-year U.S. Treasury bill, to measure economic conditions and we include changes in the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) to capture general market volatility. All variables are scaled by their standard deviation to obtain comparable coefficient estimates.

Table B.6 in Appendix B summarizes the results adding the aforementioned variables one by one. We find some evidence for the effect of weather on natural gas prices as well as a negative effect of increased market volatility. However, the daily average return difference between announcement and non-announcement days remains significantly

[11] We acknowledge, that the use of these variables is limited due to their weekly and monthly frequency, reducing the likelihood of influencing returns at the daily frequency. We thank a reviewer for suggesting to use the leading weather variables to account for forecasts.

negative at around −0.25%.

3.3.2.4 Spillover Effects from other Markets

The growing integration of commodity markets referred to as financialization (Tang and Xiong, 2012; Cheng and Xiong, 2014; Basak and Pavlova, 2016) and links between commodity markets and equity markets increasingly affect natural gas markets. Further, its role as a substitute for energy production links natural gas markets to the oil market. Wolfe and Rosenman (2014) find a bidirectional causal relationship between the two markets, which could also bias the announcement effect. Brown and Yücel (2009) and Dehnavi et al. (2015) study gas-to-gas arbitrage between Europe and the U.S. through the development of the market for liquefied natural gas (LNG).

Therefore, the EIA announcement effect might be driven by events in larger markets, that spill over to the natural gas market. To account for this possibility, we augment the model in Equation (3.5) with the return on the first nearby contract of West Texas Intermediate (WTI) crude oil futures, as traded on the New York Mercantile Exchange (Ticker: CL). On a broader level, we also include the return on the Standard & Poors Goldman Sachs Commodity Index (SPGSCI) as a proxy for overall commodity market returns.[12] Within the natural gas market, we account for reversal or momentum effects by including the lagged return into the regression. Lastly, we add the excess return on the value-weighted market index from the Center for Research in Security Prices (CRSP) as a proxy for stock market returns.

Table B.7 of Appendix B presents the regression results. All variables have a highly significant effect on natural gas returns. We find a reversal effect within the natural gas markets, while crude oil, commodity index and stock market returns are positively related to natural gas return. Altogether, the variables can explain nearly 30% of the variation in natural gas returns. However, they do not crowd out the EIA announcement effect. We still find a significant daily average return difference of −0.23% between announcement and non-announcement days.

[12] We favor the SPGSCI for its larger loading on energy markets here. As a robustness check, we also include the less energy-weighted Bloomberg Commodity Index. We find similar results.

3.3.2.5 Commodity Return Predictors

Apart from market integration, the financialization of commodity markets has also increased index investing and the rise of rule-based strategies. The literature has identified several factors that can predict commodity returns and serve as trading signals. The slope of the futures curve or basis serves as an indicator for the scarcity of the commodity and hence predicts commodity returns (Szymanowska et al., 2014). In times of backwardation, when the spot price exceeds the futures price, inventories shrink as it is more profitable to sell than to store. We define the log basis as

$$b_t^{(1,2)} = \frac{365}{M_t^{(2)} - M_t^{(1)}} \left[\log\left(F_t^{(1)}\right) - \log\left(F_t^{(2)}\right)\right] \tag{3.8}$$

where $F_t^{(1)}$ $\left(F_{(t)}^{(2)}\right)$ is the price of the first (second) nearby, and $M_t^{(1)}$ $\left(M_t^{(2)}\right)$ denotes the time to maturity of the first (second) nearby.[13]

Another force driving futures risk premia is the positions of traders (Hirshleifer, 1990). Producers (hedgers) who need to hedge their production are offering a risk premium to speculators for agreeing to enter the futures contract. Using the Commodity Futures Trading Commission (CFTC) report on the Commitment of Traders (CoT), we construct the hedging pressure following De Roon et al. (2000)

$$\mathrm{HP}_t = \frac{\#\text{short hedge positions}_t - \#\text{long hedge positions}_t}{\#\text{hedge positions}_t}, \tag{3.9}$$

such that HP_t is a relative measure of the direction in which producers are hedging, with $\mathrm{HP}_t = 1$ indicating only short positions and $\mathrm{HP}_t = -1$ indicating only long positions.[14]

We include a measure of idiosyncratic volatility, which has been shown to have predictive power for commodity returns (Fernandez-Perez et al., 2016). The factor is con-

[13] Alternatively, we also use a seasonality-adjusted basis by replacing the second with the thirteenth nearby such that, $b_t^{(1,13)} = \frac{365}{M_t^{(13)} - M_t^{(1)}} \left[\log\left(F_t^{(1)}\right) - \log\left(F_t^{(13)}\right)\right]$, where $F_t^{(13)}$ and $M_t^{(13)}$ are the price and time to maturity of the thirteenth nearby contract. This way the basis measures the price differential between two contracts with the same expiry month.

[14] Since the CFTC only reports these figures on a weekly basis, again this variable is only measured at the weekly frequency.

structed from the residuals of the time series regression,

$$r_t = a + b' X_t + \epsilon_t, \tag{3.10}$$

where a is the intercept, b is the vector of sensitivities towards the factors X_t, ϵ_t is the residual, and $\mathrm{IVOL}_t = \sigma(\epsilon_t)$ is the rolling 30-day standard deviation of the residuals. We use a 4-factor model including the return on an equally-weighted commodity market portfolio, as well as the returns on long-short portfolios sorted by basis, momentum, and basis-momentum.[15] Lastly, we also control for changes in the volume traded to allow for a possible liquidity channel.

The results are presented in Table B.8 in Appendix B. We find a strong positive relationship between the basis and returns, i.e., returns are higher, when the market is in backwardation. This is in line with the literature relating the basis to inventory and thus reflecting the markets' expectation on prices (Gorton et al., 2013). We also confirm the negative pricing of idiosyncratic volatility as reported by Fernandez-Perez et al. (2016). However, none of the variables is able to explain away the difference in returns between EIA announcement and non-announcement days.

3.3.2.6 Macroeconomic News

To isolate the effect of the EIA storage report on natural gas returns, we excluded those days on which the report coincides with the EIA petroleum report. However, another possibility is that other important news are coinciding with the EIA report and hence the econometrician might mistake the observed effect for the EIA announcement effect when, in fact, it is other macro news.

Table B.9 in Appendix B reports summary statistics of the returns on EIA announcement days and non-announcement days excluding days on which EIA days coincide with other news days. We find that the return difference remains significant after excluding other events, even when aggregating news on certain topics.

[15] This way, we include the most recent studies on commodity return predictors by Bakshi et al. (2019) and Boons and Prado (2019). Details on how the factors are constructed can be found in Appendix B.

3.4 Intraday Analysis

Having established, that there is a significant return difference between EIA announcement and non-announcement days, it is interesting to see how this return accrues throughout an announcement day. For this purpose, in this section we employ 5-minute data obtained from Thomson Reuters Tick History over the same sample period, and decompose the return into different parts.

3.4.1 Intraday Return Decomposition

The graphs in Figure B.5 of Appendix B show the average volume traded and the return volatility across time for every 5-minute interval. On EIA announcement days, there is a clear spike in volume and volatility at exactly 10:30 a.m. with volumes sixfold and volatility fivefold compared to non-announcement days.[16] The patterns indicate an immediate and short-lived reaction.

To see how the return is distributed around the announcement, we decompose the daily announcement return into the return from 90 minutes before to 30 minutes after the announcement, $(-90, 30)$, and the remaining parts from market closure of the previous day to 90 minutes before the announcement, $(C_{t-1}, -90)$, and from 30 minutes after the announcement to market closure of the announcement day, $(30, C_t)$. Panel A of Table 3.5 shows that the entire effect (99%) stems from the two-hour window surrounding the announcement.

Panel B of Table 3.5 decomposes the intraday return from 90 minutes before to 30 minutes after the announcement into a pre-announcement return, $(-90, -5)$, and a post-announcement return $(-5, 30)$.[17] If the reason for the announcement return were a pre-announcement drift because of informed trading (Gu and Kurov, 2018) or information leakage (Rousse and Sévi, 2019), we would expect that the post-announcement return is

[16]Note that the volume also spikes at 14:30 p.m., but this is due to the fact that daily prices are settled at the volume-weighted average price of all trades that are executed between 14:28:00 p.m. and 14:30:00 p.m. ET. Another indication for this not having any price effect is that there is no complementing spike in volatility during the same period.

[17]To clarify the wording, we will always refer to the post-announcement return as including the actual announcement.

not significantly different from zero, since the information would be already priced before. However, Panel B of Table 3.5 reveals that 49.4% of the return is generated before the announcement and 50.6% after the announcement. This bisection of the return is puzzling as it neither completely rules out nor proves a pre-announcement drift.[18]

Table 3.5: EIA Announcement Return Decomposition

This table reports the average returns on Henry Hub natural gas futures on EIA announcement days. Panel A decomposes the daily return from market closure on the previous day to market closure on the announcement day, (C_{t-1}, C_t)*, into an intraday component from 90 minutes before the announcement to 30 minutes after the announcement,* $(-90, 30)$*, and the sum of the return from the close price of the previous day to 90 minutes before the announcement,* $(C_{t-1}, -90)$*, and the return from 30 minutes after the announcement to the close price of the announcement day,* $(30, C_t)$*. Panel B decomposes the intraday return,* $(-90, 30)$*, into the pre-announcement return,* $(-90, -5)$*, and the post-announcement return,* $(-5, 30)$*, that also includes the announcement.*

Panel A: Daily and Intraday Return

	(C_{t-1}, C_t)	$(-90, 30)$	$(C_{t-1}, -90)\&(30, C_t)$
Average Return	-0.37	-0.37	-0.00
p-value	(0.002)	(0.000)	(0.963)
% of Daily Return	100%	99.0%	1.0%

Panel B: Pre- and Post-Announcement Return

	$(-90, 30)$	$(-90, -5)$	$(-5, 30)$
Average Return	-0.37	-0.18	-0.19
p-value	(0.000)	(0.000)	(0.010)
% of (-90,30) Return	100%	49.4%	50.6%

[18] There is no evidence that this effect has been caused by price limits being hit before the EIA announcement.

3.4.2 Regression Analysis

To control for the effects discussed in the previous section, we repeat the regression analysis and regress the intraday returns on a constant, the indicator variable I_{EIA}, the announcement surprise, S_t and control variables X_t as in Equation (3.5).[19]

We report the results using different dependent variables in Table 3.6. For the $(-90, 30)$ return, we find an even stronger result than for the daily returns with a return difference of -0.30% between EIA and non-EIA days after controlling for announcement surprise and other effects (-0.24% for daily returns). Splitting up the return into a pre- and post-announcement part, we again find that the return difference halves into -0.15% for the pre-announcement return, $(-90, -5)$, and -0.15% for the post-announcement return, $(-5, 30)$.[20] More surprisingly, we find a significant negative relationship between the announcement surprise and the pre-announcement return, indicating leakage of the information.[21] Previous literature does not find evidence of leakage (Bjursell et al., 2015; Ederington et al., 2019), but this can only be a partial explanation as there is still a significant surprise effect when the actual announcement is made.

Focusing on the pre-announcement return, we document the returns conditional on the sign of the surprise in Panel A of Table 3.7. Surprisingly, we find that the pre-announcement return is only significantly different from non-EIA intraday returns when the surprise is positive. There is a negative effect of -0.36%, significant at the 1% level, when the announcement surprise is positive. If the surprise is negative, there is no significant price reaction before the event, suggesting that the pre-announcement drift is only identifiable, when storage levels exceed expectations. This result is puzzling as it does not align with a story of superior forecasting ability. Assuming informed traders extract additional information from the Bloomberg forecast to anticipate the surprise, the pre-announcement drift should show up independent of the sign of the surprise.

[19] We use the variables that have shown significant effects on returns in the previous section, i.e., the basis, idiosyncratic volatility, as well as spillovers from the previous day, oil markets, commodity markets and stock markets.

[20] Results for smaller windows of 60 or 30 minutes in Table B.10 of Appendix B show that the effect steadily decreases.

[21] Control variables such as the basis or idiosyncratic volatility, that are significant at the daily level, do not influence intraday returns.

Table 3.6: Intraday Return Regressions

This table reports regression results of the regression in Equation (3.5) *using intraday returns*

$$r_t = \alpha_0 + \alpha_1 I_{EIA,t} + \beta_0 S_t + \beta_1' X_t + \epsilon_t, \quad (3.5)$$

where r_t is the first nearby log return, I_{EIA} is an indicator variable, equal to 1 on EIA days and 0 otherwise, S_t is the announcement surprise, X_t are additional exogenous variables, and ϵ_t is the residual. The dependent variable changes in every column, starting with the daily return, (C_{t-1}, C_t), the return from 90 minutes before the announcement to 30 minutes after the announcement, (-90,30), the pre-announcement return from 90 before until 5 minutes before the announcement, (-90,-5), and the post-announcement return from 5 minutes before the announcement until 30 minutes after the announcement, (-5,30), respectively. Results for the basis and idiosyncratic volatility are reported, the control variables are not reported, they include spillovers from the previous day, oil markets, commodity markets and stock markets. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.

Dep. Var.	Daily Return	Intraday Return	Pre-Announce	Post-Announce
Constant	0.34	0.14	0.05	0.09
	(0.00)	(0.04)	(0.28)	(0.07)
I_{EIA}	-0.24	-0.30	-0.15	-0.15
	(0.01)	(0.00)	(0.00)	(0.00)
Surprise	-0.77	-1.01	-0.14	-0.87
	(0.00)	(0.00)	(0.00)	(0.00)
Basis	0.42	-0.03	-0.00	-0.03
	(0.00)	(0.51)	(0.96)	(0.38)
IVOL	-0.12	-0.06	-0.03	-0.03
	(0.00)	(0.01)	(0.09)	(0.04)
Control	Yes	Yes	Yes	Yes
R^2	0.29	0.15	0.03	0.16
Obs	3979	3979	3979	3979

Since the phenomenon is unique to positive surprises, we want to investigate how it evolved over time by looking into three subsamples from 2003 to the beginning of the financial crisis in December 2007, from then until the peak of oil prices after the crisis in June 2014, as well as the most recent period. The results in Panel B of Table 3.7 show that the pre-announcement effect has been even stronger in the past with average values of -0.38% and -0.47% for the first and second period, respectively. In the most recent period after 2014, it has more than halved to only -0.15%. At the same time returns on negative surprise days have increased from -0.08% to 0.08%.

Table 3.7: Summary Statistics for Pre-Announcement Return

This table reports summary statistics on the pre-announcement returns of natural gas futures on EIA announcement days. Panel A reports the daily mean returns on Non-EIA days, days with a positive surprise and days with a negative surprise. The pre-announcement returns are measured from 90 minutes before the announcement until 5 minutes before the announcement. Panel B reports the mean returns for different subsamples from March 2003 until November 2007, from December 2007 until June 2014, as well as from July 2014 until December 2018. The p-value of a two-sample t-test on equal means is reported in parentheses. Rows 'No. of Obs.' denote the number of observations.

Panel A: Positive and Negative Surprise

	Non-EIA	Positive Surprise	Negative Surprise
Average Return	-0.03	-0.36 (0.000)	0.02 (0.300)
No. of Obs.	3419	345	319

Panel B: Subsample Analysis

Subsample	Non-EIA	Positive Surprise	Negative Surprise
2003–2007	-0.08	-0.38 (0.000)	-0.08 (0.981)
No. of Obs.	918	102	80
2007–2014	-0.00	-0.47 (0.000)	0.04 (0.609)
No. of Obs.	1519	153	142
2014–2018	-0.02	-0.15 (0.070)	0.08 (0.147)
No. of Obs.	981	90	97

3.5 What About ...

3.5.1 Forecasting Accuracy?

The previous section has shown that the pre-announcement drift only occurs for positive surprises. Therefore, it is crucial to see how accurate the Bloomberg median survey forecast is, as it decides, whether the surprise is positive, i.e., the reported storage level exceeds the forecasted value. We test the accuracy of the median forecast by regressing the actual reported values on the median forecast such that

$$A_t = \alpha + \beta E_t + u_t, \tag{3.11}$$

where A_t is the actual reported value, α is the intercept, β is the regression coefficient, E_t is expected value or median forecast, and u_t is the residual.

If the analysts predicted the natural gas storage without any bias, the intercept of the regression should be equal to zero, and the coefficient for the median forecast should be one. The results in Table B.12 of Appendix B reject the hypothesis of α being significantly different from zero, and find a regression coefficient β that is slightly larger than one.[22] Although we find the intercept not to be significantly different from zero, and the estimates for β being close to unity, a joint F-test of the hypothesis, $\alpha = 0$ and $\beta = 1$, is rejected at the 1% level.

Considering that the EIA has changed the selection procedure of underground storage facilities in 2008 (Halova et al., 2014) and industry forecasts have improved throughout, we also carry out the above analysis using a rolling window of 5 years (approximately 260 observations) to see how estimates have changed over time. In Appendix B, Figure B.7 shows the estimates for α and β and Figure B.8 the p-value of the F-test on $\alpha = 0$ and $\beta = 1$. The graphs for the coefficient estimates both show a trend towards the values for unbiased prediction highlighted in red. At the same time, the p-value of the F-test on $\alpha = 0$ and $\beta = 1$ is increasing throughout the sample and is not rejected at the 10% for

[22] Note that the p-value for β refers to a test on whether β equals zero and is therefore not informative.

the first time at the beginning of 2010 coinciding with growing attention of the literature on pre-announcement drifts (Lucca and Moench, 2015).

3.5.2 Spreads?

An interesting question is whether the documented return difference is related to the maturity of the contract. From the previous analysis, we know that while the magnitude of the effect is smaller in absolute terms for deferred contracts (see Table 3.3 of Appendix B), it amounts to a higher share of the annual average return (see Figure B.1). Therefore, it is not clear a priori whether we should find a significant return difference on EIA days, if we were to repeat the analysis from before using the spread return between the first and second nearby as the dependent variable.

The results in Table B.11 in Appendix B document a strongly significant negative return difference for spreads on EIA days of -0.06% resulting in a five times larger return on EIA days. This magnitude is similar in relative terms to what we find for the first nearby return. Again this return remains significant after controlling for the announcement surprise and other channels. This is another interesting result because the first and second nearby contract are written on the same underlying only differing by expiry date.

3.5.3 Limits to Arbitrage?

For practitioners, it is especially interesting to investigate whether the observed effect can be exploited and the return withstands funding and transaction costs. We follow the strategy, to open a short position 90 minutes before the announcement, and to close it 30 minutes after the announcement. This way, we can harvest the pre-announcement return and the effect from the announcement, while minimizing the investment window reduces funding costs.

Table 3.8 reports the returns on the described strategy. The first row of Panel A reports the raw return on the futures amounting to an annual average of 17.86% with a Sharpe ratio of 2.57. However, this is based on returns from the settlement prices.

To incorporate trading costs, we instead use the bid and ask quotes, i.e., when we open the short position, we sell the futures contract at the last bid, and when we close the position, we buy back at the last ask. The return in the second row in Panel A of Table 3.8 incorporates these costs and shows, that the return is reduced to 12.21% per annum, still securing a Sharpe ratio of 1.79. Lastly, we also take into account the funding cost of the position. Although futures contracts can be entered holding only a fraction of the contract value, since we are opening a short position and for robustness, we consider a fully funded position. We use the Overnight London Interbank Offer Rate (ONR), which serves as a globally accepted benchmark rate for borrowing costs between banks. The reported return in the third row drops further to 12.01%, with a Sharpe ratio of 1.76.[23]

Panels B and C of Table 3.8 show that the strategy has worked much better in the past, yielding annual returns of 25% after transaction and funding costs with a Sharpe ratio of 3.26. In the more recent period, this has declined to only 3% and a Sharpe ratio of 0.5, which do not withstand transaction and funding costs. Figure B.9 of Appendix B shows the risk-adjusted five-year moving average return of the strategy, controlling for the returns on a commodity market portfolio and long-short portfolios using basis, momentum, and basis-momentum factors. We see a constantly significant excess return during the first 10 years of the sample, gradually decreasing to become insignificantly different from zero in the most recent period.

[23]Note that while returns are annualized using a multiplier of 52 to represent the realizable return within a year, the corresponding Sharpe ratio is annualized with a multiplier of $\sqrt{252}$, since means and standard deviation are based on daily returns.

Table 3.8: Returns on Investment Strategy

This table reports the average annualized return and the Sharpe ratio on an investment strategy in Henry Hub natural gas futures. The strategy opens a short position 90 minutes before the EIA storage report announcement, usually Thursdays at 10:30 a.m. ET, and closes the position 30 minutes after the announcement. Panel A reports the statistics for the whole sample, Panel B for the period before 2011, and Panel C for the period after 2011. The first row of each panel reports the raw return based on mid prices. The second row takes into account transaction cost (TC) by using the bid and ask prices for buying and selling. The third row also subtracts funding costs (FC), assuming a fully funded futures position funded at the Overnight London Interbank Offered Rate (ONR). The p-value for a t-test on difference to zero is reported in parentheses. Returns are reported in percentage points and Sharpe ratios are annualized using 252 days.

Panel A: Whole Sample

	Average Return	Sharpe Ratio
Raw (-90,30)	17.86 (0.000)	2.57
Raw + TC	12.21 (0.003)	1.79
Raw + TC + FC	12.01 (0.003)	1.76

Panel B: Before 2011

	Average Return	Sharpe Ratio
Raw (-90,30)	32.85 (0.000)	4.22
Raw + TC	25.36 (0.000)	3.30
Raw + TC + FC	25.02 (0.000)	3.26

Panel C: After 2011

	Average Return	Sharpe Ratio
Raw (-90,30)	2.91 (0.558)	0.50
Raw + TC	-0.90 (0.854)	-0.16
Raw + TC + FC	-0.97 (0.843)	-0.17

3.6 Conclusion

We study the relationship between inventory news and the natural gas market, and find a significant return difference between announcement and non-announcement days, that can neither be explained by the announcement surprise, nor after controlling for general market conditions, spillover effects, commodity return predictors, or concurrent macroeconomic news. One half of the return is generated as a pre-announcement effect, that is unique to positive surprises, while the other half is realized after the announcement. These results are puzzling and have three interesting implications for academics and practitioners.

First, the fact that the announcement days of the EIA storage report account for more than 50% of the annual return on the first nearby of natural gas futures and even more than 60% for more deferred contracts, should attract the attention of investors and regulators. It opens up the possibility to harvest a significant amount of the annual return on natural gas futures without committing capital for more than 20% of the year.[24] At the same time, it calls for increased attention of regulators towards ensuring that the information is not released before the announcement and the information is gathered avoiding any possible bias.

Second, the significantly negative average return for natural gas returns on EIA announcement days poses a challenge to the academic literature, as it cannot be explained by the announcement surprise, market specific variables, spillover effects or factor investing. The negative sign is important since it also opposes the interpretation of a premium investors demand for bearing the risk of holding the asset during uncertain events (Savor and Wilson, 2013).

Third, the time series dimension of the effect suggests a decline in the recent period where we observe an improved forecasting accuracy. However, the simple strategy of opening and closing a short position before and after the announcement yields an annual return of 12% after transaction and funding costs. The gradual decrease of this return

[24]This percentage is based on investing only 1 of 5 days a week and could be even further reduced to less than 5%, if we allow for intraday trading around the announcement.

suggests that it has not been exploited by arbitrageurs but rather disappeared over time, challenging the idea of an efficient market that does not allow for such anomalies and once they are encountered, adapts immediately.

B Appendix

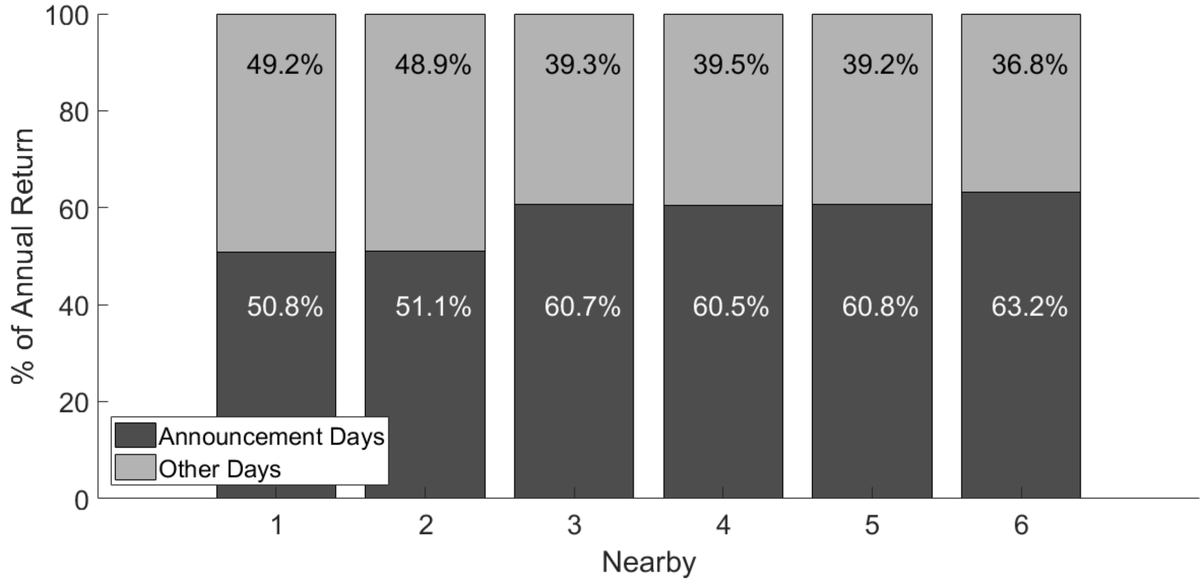


Figure B.1: Decomposition of Annual Natural Gas Futures Returns

This figure shows the decomposition of the annual return on the first to sixth nearby in Henry Hub Natural Gas Futures between days on which the Weekly Natural Gas Storage Report is published by the Energy Information Administration (EIA) (dark lower bar) and non-announcement days (light upper bar), i.e., the percentages are computed as

$$= \frac{52 \cdot \bar{r}_{EIA}}{52 \cdot \bar{r}_{EIA} + 200 \cdot \bar{r}_{Non\text{-}EIA}} \quad \textit{and} \quad = \frac{200 \cdot \bar{r}_{Non\text{-}EIA}}{52 \cdot \bar{r}_{EIA} + 200 \cdot \bar{r}_{Non\text{-}EIA}}$$

where $\bar{r}_{EIA}$ *and* $\bar{r}_{Non\text{-}EIA}$ *are the average daily log returns on EIA days and Non-EIA days, respectively, and 52 is the number of EIA days per year (weekly), which leaves 200 other trading days. The percentage contribution of announcement days is written in white inside the lower bar and the percentage contribution of non-announcement days is written in black inside the top bars. The sample period comprises daily returns from March 2003 to December 2018 (3982 days), that decompose into 699 EIA announcement days, excluding days, where the report coincides with the EIA Petroleum Report, and 3283 non-announcement days.*

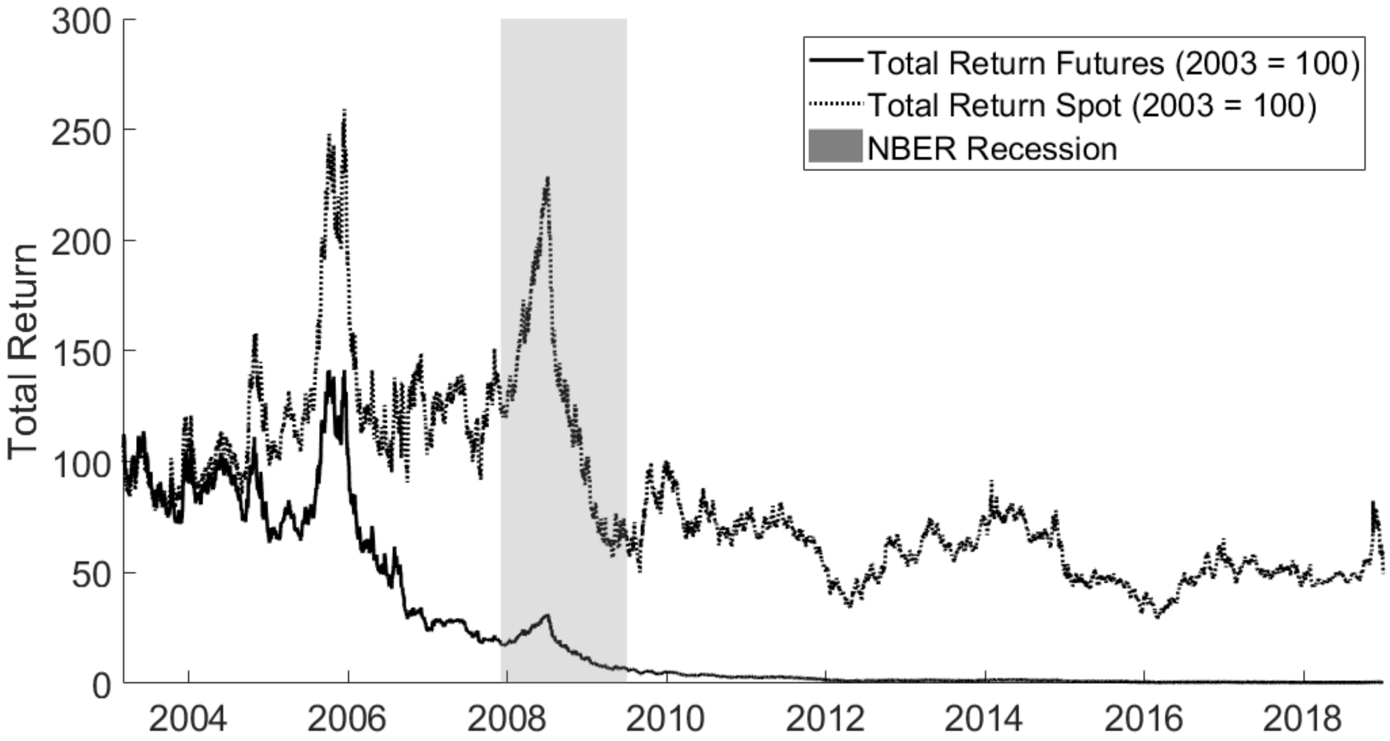


Figure B.2: Natural Gas Total Return Spot and Futures Price Series

This figure shows the total return series of the front contract in Henry Hub natural gas futures for the period from March 2003 to December 2018 obtained from Bloomberg. The dotted line represents the returns without accounting for the rolling of contracts, i.e., $r_t^{(n)} = \log(F_t^{(n)}) - \log(F_{t-1}^{(n)})$, *which refers to two different contracts on rolling days. The solid line accounts for the rollover in the returns as explained in Equation* (3.1). *Contracts are rolled over at the end of the month preceding the month prior to delivery and scaled to have value 100 at the beginning of March 2003. The gray shaded area represents the NBER recession (December 2007 - June 2009).*

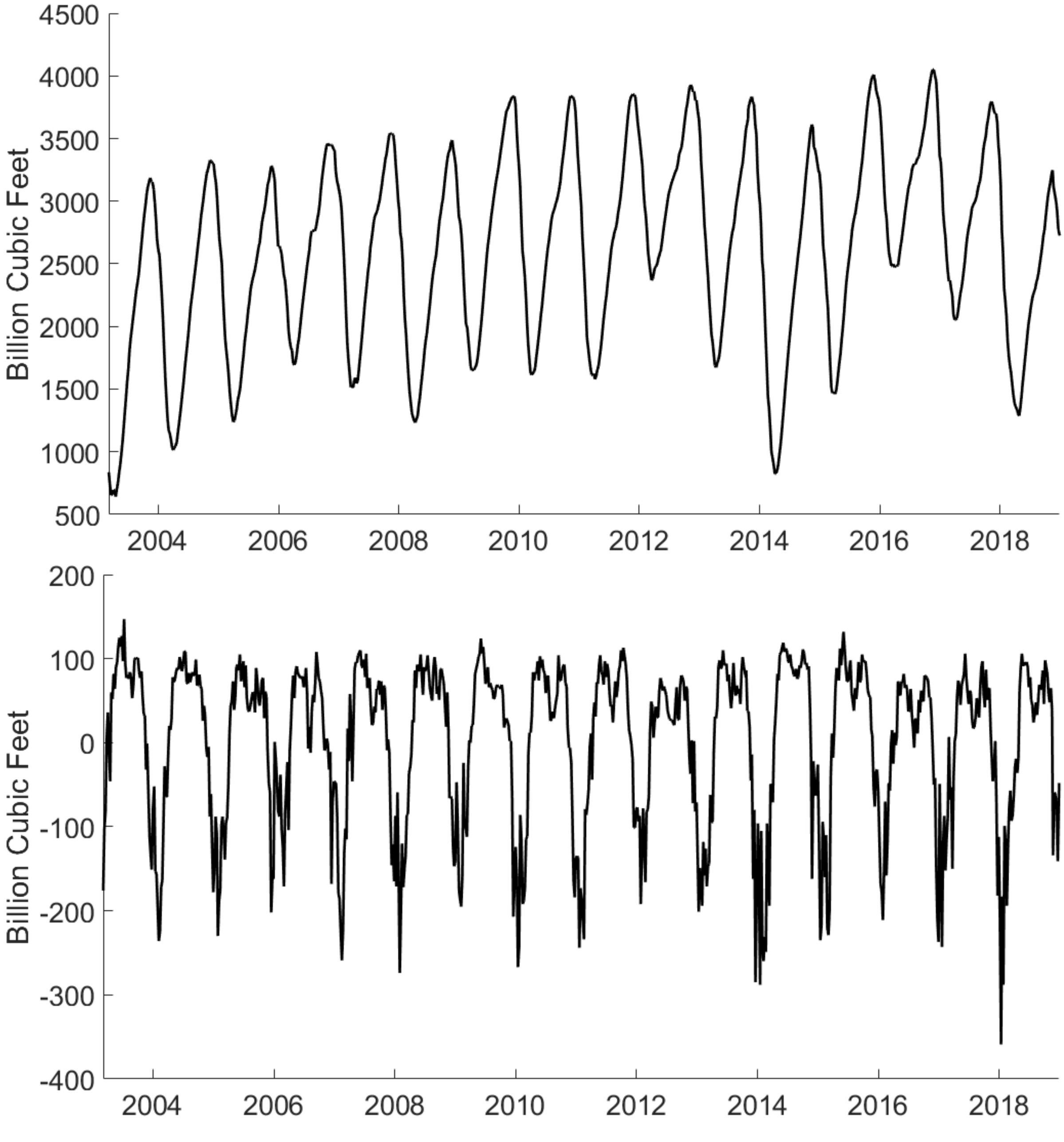


Figure B.3: Level and First Difference of Natural Gas Storage

This figure shows the inventory level as announced by the Energy Information Administration (EIA) in the Weekly Natural Gas Storage Report every Thursday at 10:30 a.m. ET. The report tracks U.S. natural gas inventories held in underground storage facilities in five regions of the 48 lower states. The upper panel shows the level of inventories and the lower panel shows the change in inventory levels. Both figures are measured in billion cubic feet over the sample period from March 2003 to December 2018.

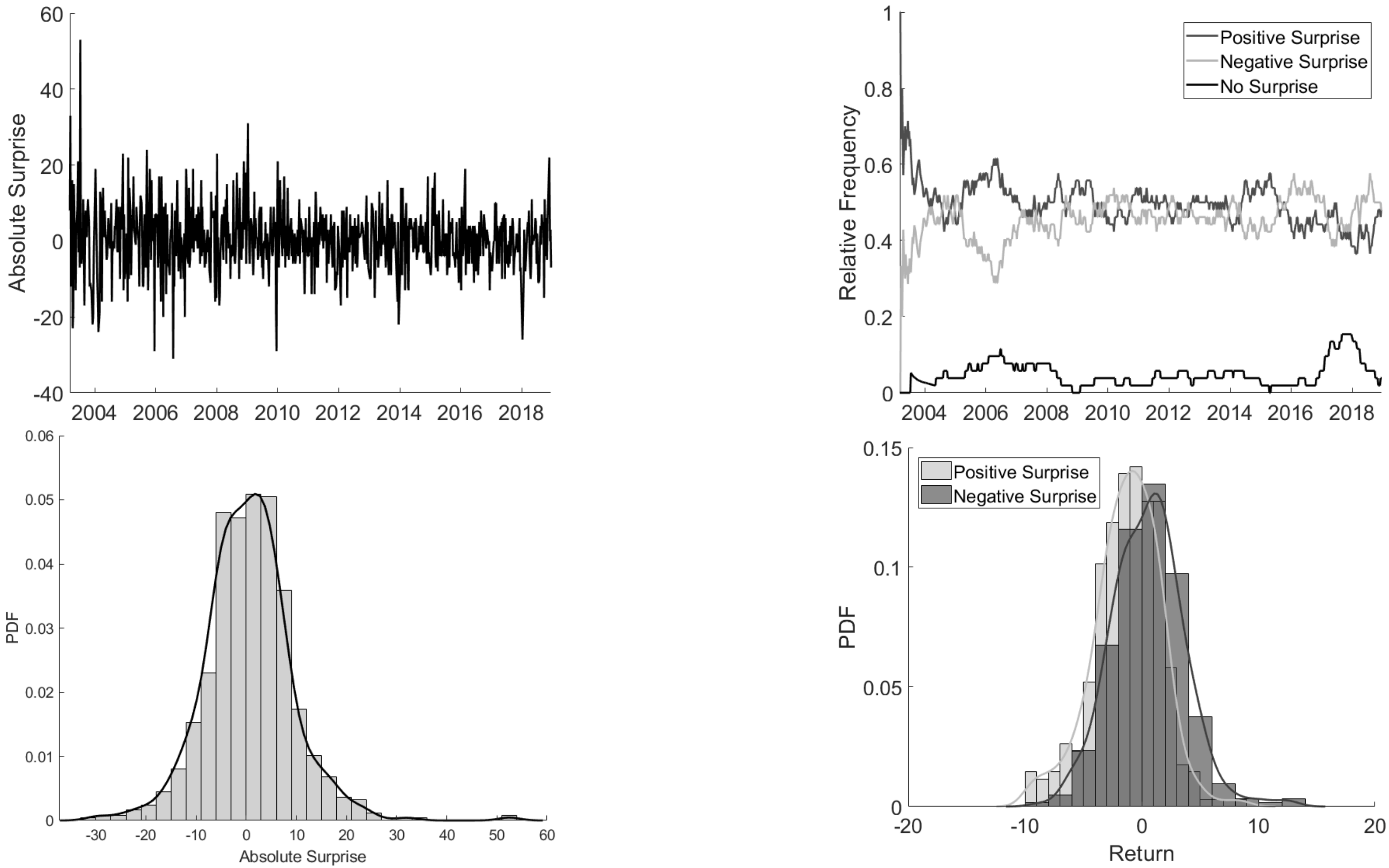
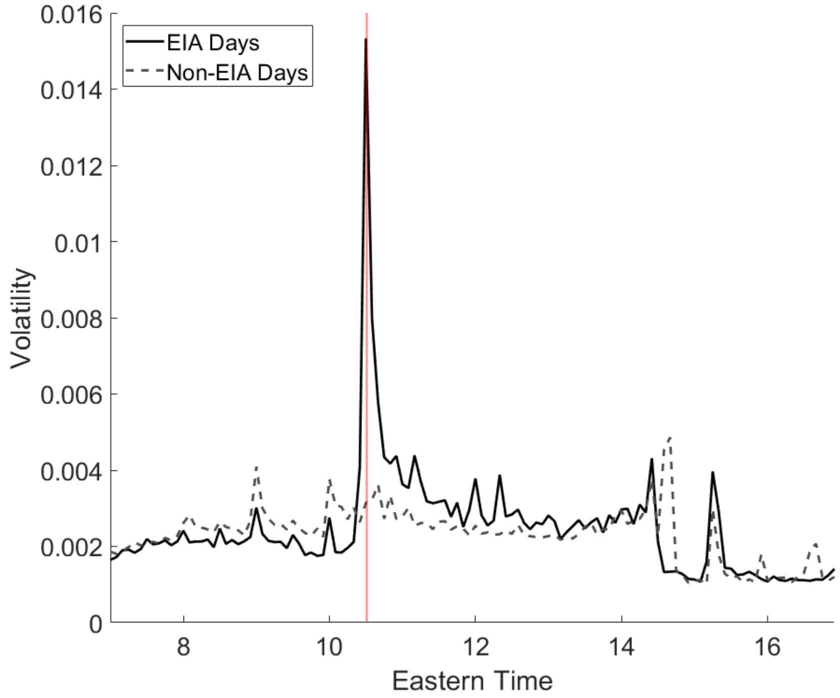


Figure B.4: Announcement Surprise, Relative Frequencies, and Return Distribution

This figure shows the time series of inventory surprises, the difference between actual value and forecast (left upper panel), the histogram and density estimation for the distribution of the surprise (left lower panel), the relative frequency of positive and negative surprises (right upper panel), and the distribution of returns on positive and negative surprise days (right lower panel).



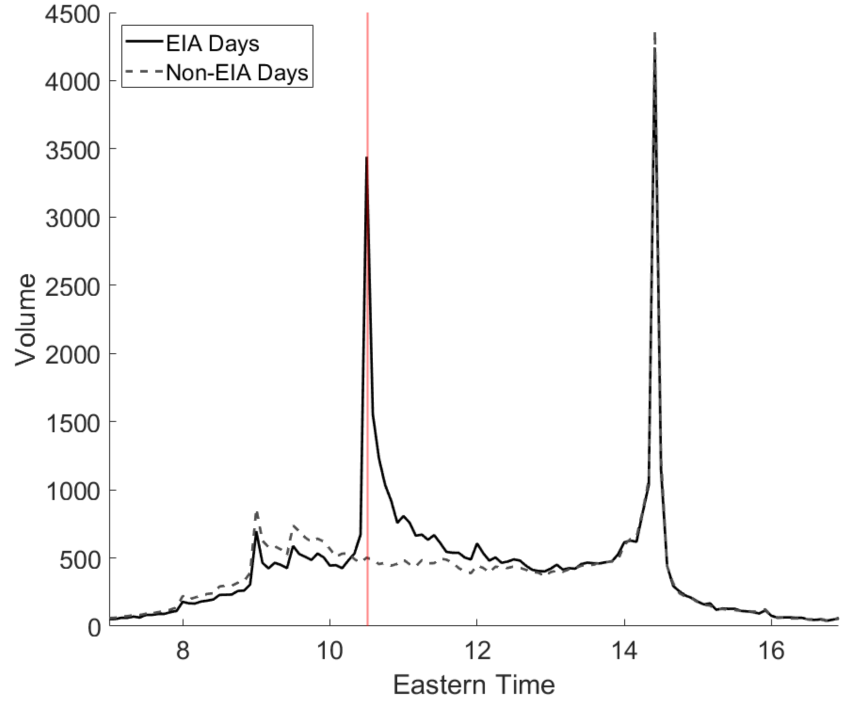


Figure B.5: Volatility and Volume on EIA Storage Report Announcement Days

The left panel of this figure shows the return volatility across time for every 5-minute interval on EIA announcement days (black solid line) and non-announcement days (gray dashed line). The right panel of this figure shows the average volume traded for every 5-minute interval on EIA announcement days (black solid line) and non-announcement days (gray dashed line). The horizontal axis covers the main trading window from 7:00 a.m. ET to 17:00 p.m. ET. The vertical line marks the publication of the report at 10:30 a.m. ET. The underlying dataset comprises the period from March 2003 to December 2018, which includes 699 announcements.

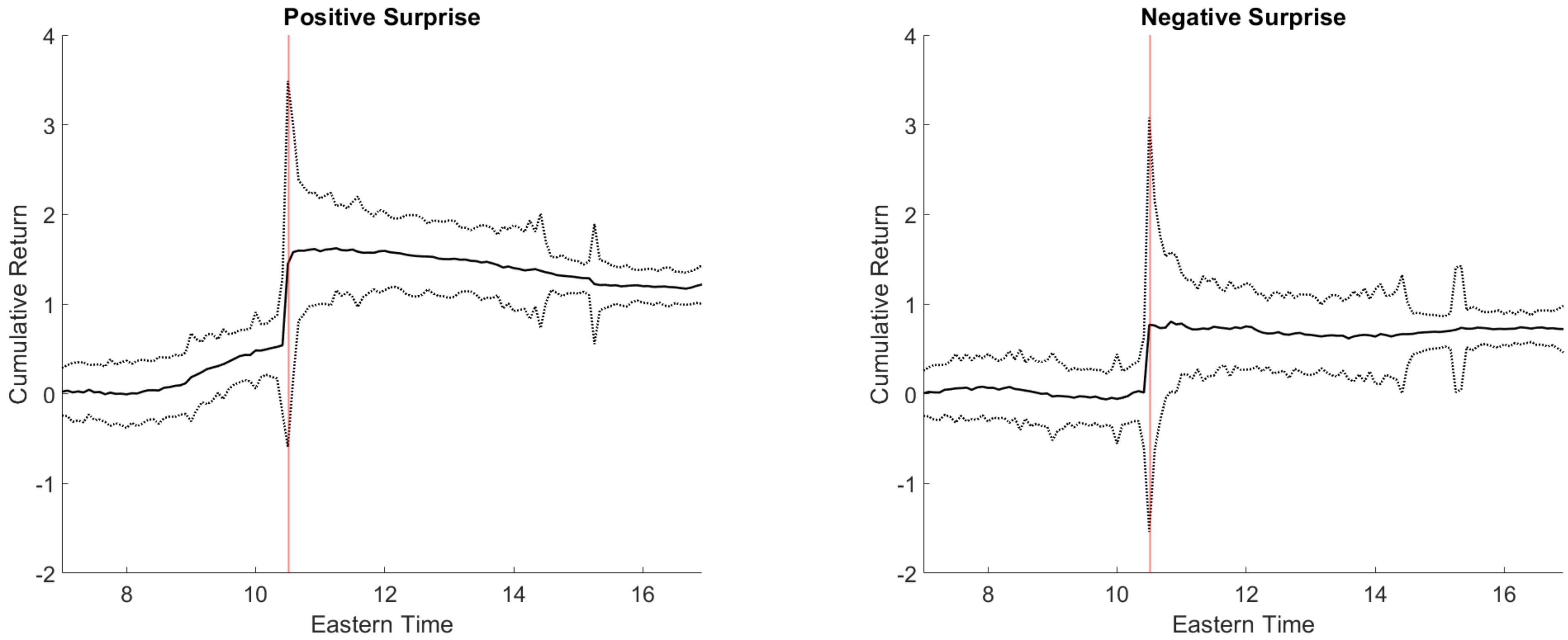


Figure B.6: Cumulative Return for Positive and Negative Surprise Days

This figure shows the cumulative average 5-minute interval return of natural gas futures on EIA announcement days. The left panel shows the returns for days on which the announced figure exceeded the Bloomberg median forecast (positive surprise) and the right panel shows the returns for days on which the announced figure fell short of the Bloomberg median forecast (negative surprise). For comparison, the return for positive surprises is mirrored at the x-axis. The horizontal axis covers the main trading window from 7:00 a.m. ET to 17:00 p.m. ET. The vertical line marks the publication of the report at 10:30 a.m. ET. The underlying dataset comprises the period from March 2003 to December 2018, which includes 699 announcements with 345 positive and 319 negative surprises.

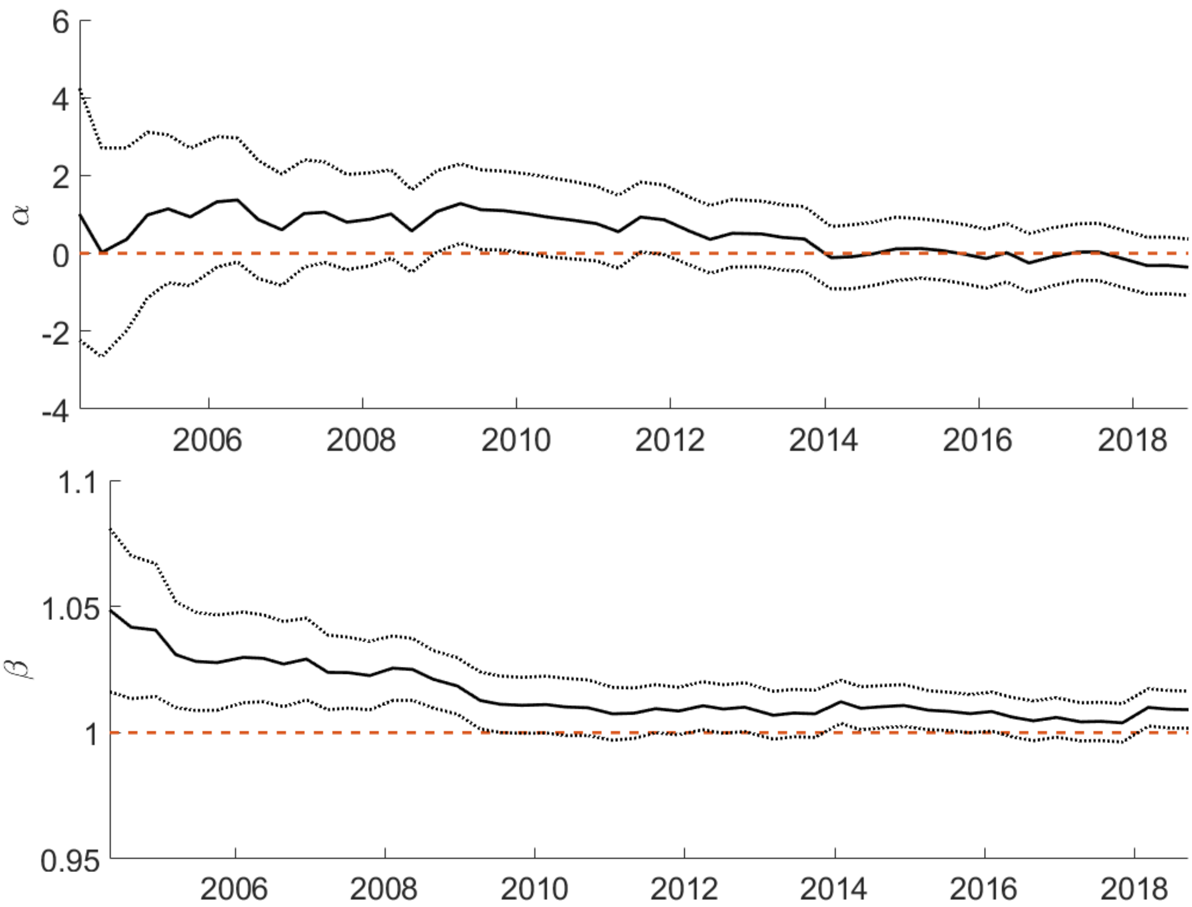


Figure B.7: Alpha and Beta of Forecast Accuracy Regression

This figure presents the results of the regression in Equation (3.11)

$$A_t = \alpha + \beta E_t + u_t, \tag{3.11}$$

where A_t is the actual storage reported by the EIA, α is the intercept, β is the regression coefficient, E_t is the Bloomberg median forecast of the storage level and u_t is the residual. Regressions are run over a rolling window of 5 years (ca. 260 observations). The first panel shows the coefficient estimates for α together with the bounds on a 5% confidence interval as a dotted line. The second panel shows the coefficient estimates for β together with the lower bound of the 5% confidence interval as a dotted line. The values for an unbiased forecast (no forecast error on average, $\alpha = 0$ and $\beta = 1$) are marked with dashed lines.

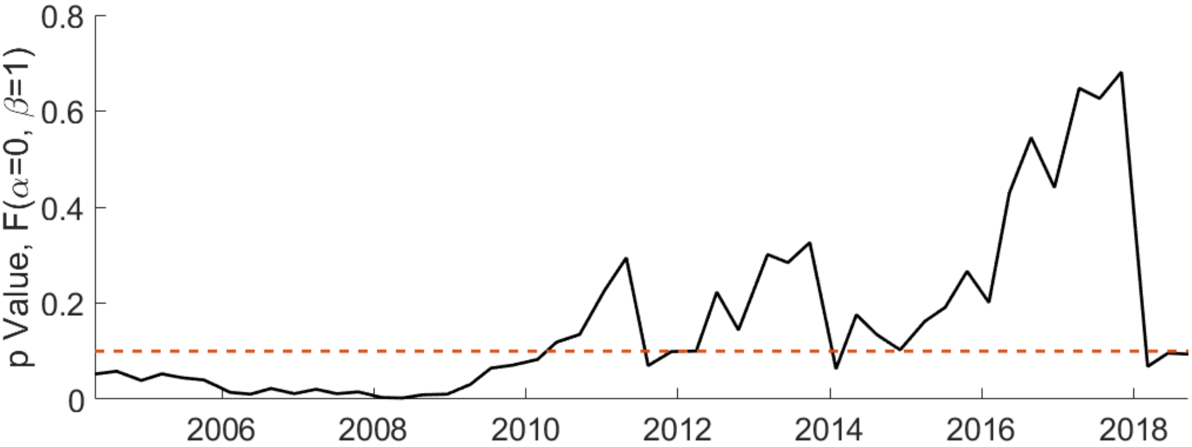


Figure B.8: Hypothesis Test for Forecast Accuracy

This figure presents the results of a hypothesis test on the regression in Equation (3.11)

$$A_t = \alpha + \beta E_t + u_t, \tag{3.11}$$

where A_t is the actual storage reported by the EIA, α is the intercept, β is the regression coefficient, E_t is the Bloomberg median forecast of the storage level and u_t is the residual. Regressions are run over a rolling window of 5 years (ca. 260 observations). The reported value is the p-value of a F-test on the hypothesis of an unbiased forecast ($\alpha = 0, \beta = 1$)*. The dashed line marks the 10% confidence level.*

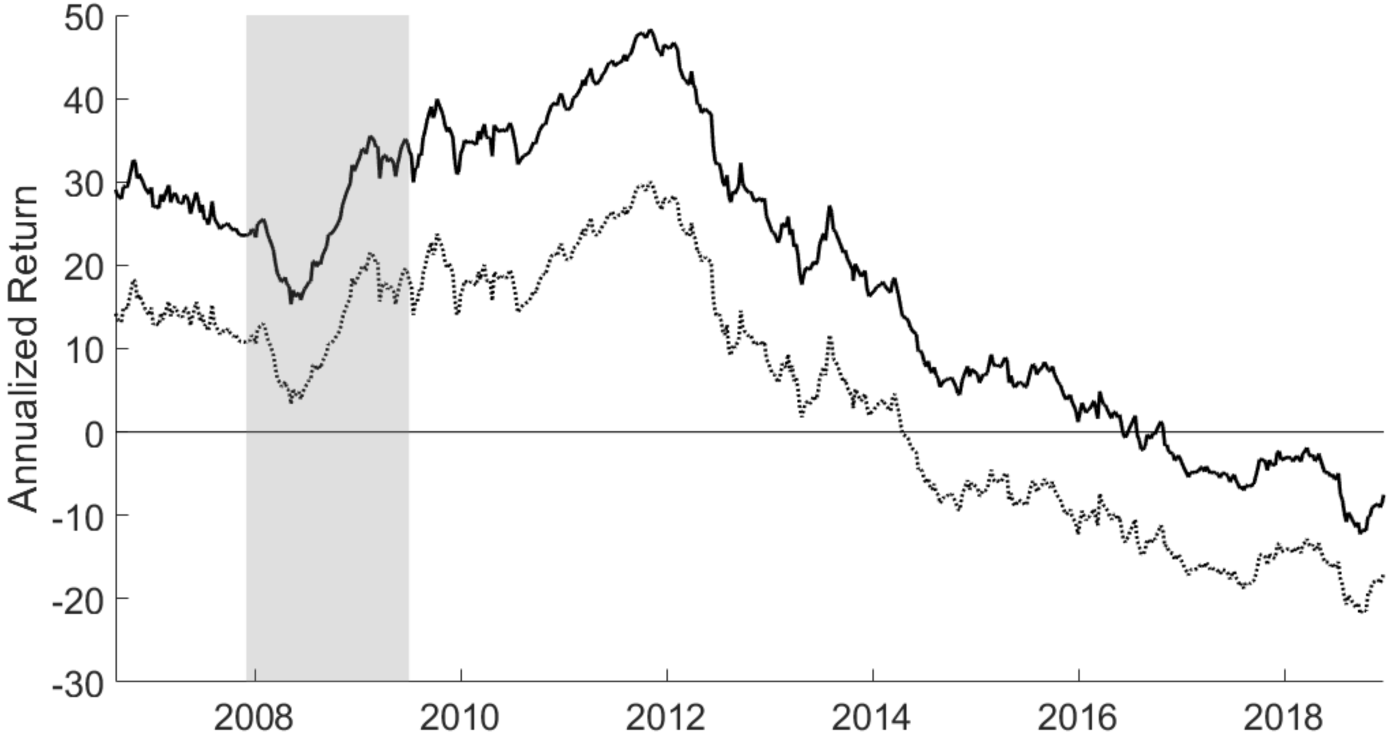


Figure B.9: Three-Year Moving Average Risk-Adjusted Returns on Investment Strategy

This figure shows the three-year moving average risk-adjusted return on the investment strategy that opens a short position 90 minutes before the announcement and closes the position 30 minutes after the announcement. The returns are adjusted for their exposure to a 4-factor model including the return on an equally-weighted commodity market portfolio, as well as the returns on long-short portfolios sorted by basis, momentum, and basis-momentum. The black line shows the annualized moving average return and the dotted line shows the one-sided 5% confidence interval.

Table B.1: Bloomberg Data Summary

This table lists the data obtained from Bloomberg by ticker. The upper part before the horizontal line lists the tickers for which price series are obtained. For the lower part after the horizontal line only the release dates are obtained except the natural gas storage report for which median, average, high and low forecast, forecast dispersion and number of analysts is collected.

Ticker	Description
SPGSCITR Index	S&P GSCI Total Return
BCOMTR Index	Bloomberg Commodity Index Total Return
USGG3M Index	U.S. 3-month rate
USGG10YR Index	U.S. 10-year rate
US00O/N Index	Overnight LIBOR
DOENUSCH Index	EIA Weekly Natural Gas Storage Report
DOEASCRD Index	EIA Petroleum Report Crude Storage
IPMGCHNG Index	U.S. Industrial Production Industry Group Manufacturing MoM
USTBTOT Index	U.S. Trade Balance of Goods and Services SA
NHSLTOT Index	U.S. New One Family Houses Sold Annual Total SAAR
NHSPSTOT Index	U.S. New Privately Owned Housing Units Started Total
CICRTOT Index	Federal Reserve Consumer Credit Total Net Change SA
DGNOCHNG Index	U.S. Durable Goods New Orders Industries MoM SA
MWINCHNG Index	Merchant Wholesalers Inventories Total Monthly % Change
CPI YOY Index	U.S. CPI Urban Consumers YoY NSA
USPHTMOM Index	U.S. Pending Home Sales Index MoM SA
NHSPATOT Index	Private Housing Authorized by Bldg Permits by Type Total
FDTR Index	Federal Funds Target Rate - Upper Bound
IMP1YOY% Index	U.S. Import Price Index by End Use All YoY NSA
ETSLTOTL Index	U.S. Existing Homes Sales SAAR
GDPCTOT% Index	U.S. GDP Total YoY NSA

Table B.2: Subsample Analysis of EIA Announcement Return

This table reports summary statistics of the returns on the first nearby contracts in Henry Hub natural gas futures on announcement days of the EIA Weekly Gas Storage Report (Columns 'EIA') and non-announcement days (Columns 'Non-EIA'). Column 't-Test' reports the t-statistic and p-value in parentheses for a two-sample t-test on equal means assuming unequal variances. Column 'F-Test' reports the F-statistic and p-value in parentheses for a F-test on equal variances. Daily mean returns and annualized standard deviations are reported in percentage points. We split the whole sample into three subsamples in 2007 and 2014.

Subsample	**Mean**			**Standard Deviation**		
	EIA	Non-EIA	t-Test	EIA	Non-EIA	F-Test
2003 – 2018	-0.37	-0.09	-2.19 (0.029)	49.2	43.3	1.29 (0.000)
2003 – 2007	-0.52	-0.06	-1.75 (0.081)	54.0	48.3	1.25 (0.039)
2007 – 2014	-0.48	-0.09	-1.98 (0.049)	52.4	40.7	1.65 (0.000)
2014 – 2018	-0.05	-0.14	0.46 (0.642)	37.5	42.1	0.79 (0.044)

Table B.3: EIA Announcement Return Excluding Specific Observations

This table reports summary statistics of the returns on the first to sixth nearby contracts in Henry Hub Natural Gas Futures on announcement days of the EIA Weekly Gas Storage Report (Columns 'EIA') and non-announcement days (Columns 'Non-EIA'). Column 't-Test' reports the t-statistic and p-value in parentheses for a two-sample t-test on equal means assuming unequal variances. Column 'F-Test' reports the F-statistic and p-value in parentheses for a F-test on equal variances. Daily mean returns and annualized standard deviations are reported in percentage points. In Panel A, we exclude days on which the EIA has revised their estimate as reported on the EIA website and the first year of observations. In Panel B, daily returns that are larger than 10% in absolute value are excluded.

Panel A: Excluding Revision Dates

Subsample	Mean			Standard Deviation		
	EIA	Non-EIA	t-Test	EIA	Non-EIA	F-Test
1	-0.37	-0.10	-2.11 (0.035)	48.0	43.2	1.23 (0.000)
2	-0.28	-0.08	-1.73 (0.084)	44.3	39.2	1.28 (0.000)
3	-0.24	-0.04	-1.82 (0.069)	39.8	35.8	1.24 (0.000)
4	-0.22	-0.04	-1.83 (0.067)	36.6	31.9	1.32 (0.000)
5	-0.20	-0.04	-1.75 (0.080)	34.3	29.7	1.33 (0.000)
6	-0.17	-0.03	-1.66 (0.097)	32.2	28.1	1.32 (0.000)

Panel B: Excluding Absolute Returns > 10%

Nearby	Mean			Standard Deviation		
	EIA	Non-EIA	t-Test	EIA	Non-EIA	F-Test
1	-0.42	-0.11	-2.58 (0.010)	47.6	41.3	1.33 (0.000)
2	-0.33	-0.08	-2.24 (0.025)	43.7	37.5	1.36 (0.000)
3	-0.29	-0.05	-2.33 (0.020)	39.3	34.0	1.33 (0.000)
4	-0.26	-0.05	-2.27 (0.024)	36.2	31.1	1.36 (0.000)
5	-0.23	-0.04	-2.19 (0.029)	33.8	28.9	1.37 (0.000)
6	-0.20	-0.03	-2.08 (0.038)	31.7	27.3	1.35 (0.000)

Table B.4: Regression with Alternative Surprise Measures

This table reports the results of the regression in Equation (3.5) *with alternative surprise measures.* I_{EIA} *is an indicator variable, equal to 1 on EIA days and 0 otherwise,* S_t *is the announcement surprise, and* S_{t-1} *is the lagged surprise. Column (IV) and (V) include the alternative surprise measure from Equation* (3.4)

$$S_t^{disp} := \frac{A_t - E_t}{\sigma(E_t)}, \qquad S_t^{rel} := \frac{A_t - E_t}{A_{t-1}}, \tag{3.4}$$

where $\sigma(E_t)$ *is the dispersion among forecasters for the announcement on day* t*, and* A_{t-1} *is the previous inventory level. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.*

Variables	(I)	(II)	(III)	(IV)	(V)
Intercept	-0.09	-0.09	-0.09	-0.09	-0.09
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
I_{EIA}	-0.24	-0.28	-0.24	-0.23	-0.21
	(0.05)	(0.03)	(0.04)	(0.06)	(0.08)
S_t	-1.04		-1.04		
	(0.00)		(0.00)		
S_{t-1}		0.05	0.02		
		(0.67)	(0.83)		
S^{disp}				-0.88	
				(0.00)	
S^{rel}					-1.99
					(0.00)
R^2	0.03	0.00	0.03	0.03	0.02
Obs	3982	3981	3981	3982	3982

Table B.5: Regression Controlling for Assymetric Effects

This table reports the results of the regression in Equation (3.5) including several indicator variables, i.e., the first nearby log return is regressed on I_{EIA}, an indicator variable equal to 1 on EIA days and 0 otherwise, and the announcement surprise, S_t. In columns (II) to (VII), the regression is augmented with the surprise variable interacted with indicator variables for low forecast dispersion (I_{lowSD}), NBER recessions (I_{NBER}), the injection period from April to October (I_{inject}), the post-2009 period (I_{post09}), and the hurricane seasons from June to November, $I_{hurricane}$. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.

Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Intercept	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
I_{EIA}	-0.24	-0.24	-0.23	-0.23	-0.25	-0.23	-0.23
	(0.05)	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)
S	-1.04	-1.02	-0.97	-0.79	-0.88	-0.92	-0.41
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.13)
$S \times I_{lowSD}$		-1.06					-0.65
		(0.12)					(0.33)
$S \times I_{NBER}$			-0.57				-0.96
			(0.12)				(0.02)
$S \times I_{inject}$				-0.54			-0.83
				(0.03)			(0.01)
$S \times I_{post09}$					-0.43		-0.64
					(0.07)		(0.02)
$S \times I_{hurricane}$						-0.28	0.27
						(0.26)	(0.36)
R^2	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Obs	3982	3982	3982	3982	3982	3982	3982

Table B.6: Regression Controlling for Supply and Demand

This table reports the results of the regression in Equation (3.5) using macro variables related to the economics of natural gas markets, i.e., the first nearby log return is regressed on I_{EIA}, an indicator variable, equal to 1 on EIA days and 0 otherwise, and the announcement surprise, S_t. In columns (I) to (V), the regression is augmented with the deviation from the 5-year average Heating (Cooling) Degree Days, ΔHDD_t (ΔCDD_t) and the led version, the change in monthly U.S. natural production, ΔProduction, the change in term spread (ΔTERM), which is the difference between the 3-month and 10-year U.S. Treasury Bill rate, and the change in the CBOE Volatility Index, ΔVIX, respectively. All variables are scaled to have unit standard deviation. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.

Variables	(I)	(II)	(III)	(IV)	(V)	(VI)
Intercept	-0.10	-0.10	-0.08	-0.09	-0.09	-0.08
	(0.04)	(0.04)	(0.08)	(0.05)	(0.04)	(0.08)
I_{EIA}	-0.23	-0.24	-0.25	-0.25	-0.24	-0.25
	(0.07)	(0.06)	(0.04)	(0.04)	(0.05)	(0.05)
S	-1.03	-1.02	-1.05	-1.04	-1.04	-1.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ΔHDD	0.11					0.11
	(0.02)					(0.03)
Δ_{t+1}HDD	-0.02					-0.01
	(0.72)					(0.86)
ΔCDD		0.09				0.09
		(0.03)				(0.03)
Δ_{t+1}CDD		-0.08				-0.08
		(0.06)				(0.06)
ΔProduction			-0.14			-0.07
			(0.86)			(0.93)
ΔTERM				-0.07		-0.06
				(0.23)		(0.34)
ΔVIX					-0.11	-0.09
					(0.01)	(0.03)
R^2	0.03	0.03	0.03	0.03	0.03	0.03
Obs	3669	3669	3962	3981	3981	3649

Table B.7: Regression Controlling for Spillover Effects

This table reports regression results of the regression in Equation (3.5) *using variables related to spillover effects, i.e., the first nearby log return is regressed on I_{EIA}, an indicator variable, equal to 1 on EIA days and 0 otherwise, and the announcement surprise, S_t. In columns (I) to (V), the regression is augmented with the lagged return on natural gas futures, r_{t-1}, the return on WTI crude oil futures, r^{WTI}, the return on the Goldman Sachs Commodity Index, r^{GSCI}, and the excess return on the value-weighted stock market index from CRSP, r^{CRSP}, respectively. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.*

Variables	(I)	(II)	(III)	(IV)	(V)
Intercept	-0.10	-0.08	-0.07	-0.10	-0.05
	(0.03)	(0.06)	(0.10)	(0.03)	(0.20)
I_{EIA}	-0.23	-0.29	-0.30	-0.24	-0.23
	(0.05)	(0.01)	(0.01)	(0.05)	(0.02)
S	-1.05	-1.01	-0.93	-1.03	-0.78
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
r_{t-1}	-0.06				-0.07
	(0.00)				(0.00)
r^{WTI}		0.35			-1.36
		(0.00)			(0.00)
r^{GSCI}			0.74		2.72
			(0.00)		(0.00)
r^{CRSP}				0.11	-0.19
				(0.00)	(0.00)
R^2	0.03	0.10	0.18	0.03	0.29
Obs	3981	3982	3982	3981	3980

Table B.8: Regression Controlling for Commodity Return Predictors

This table reports the results of the regression in Equation (3.5) *using commodity trading signals, i.e., the first nearby log return is regressed on I_{EIA}, an indicator variable, equal to 1 on EIA days and 0 otherwise, and the announcement surprise, S_t. In columns (I) to (V), the regression is augmented with the front slope of the futures curve, $b_{(1,2)}$, the slope between the futures contracts with same expiry month one year ahead, $b^{(1,13)}$, the hedging pressure, HP, the idiosyncratic volatility, IVOL, and the change in trading volume in thousand transactions, ΔVolume, respectively. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.*

Ind. Var.	(I)	(II)	(III)	(IV)	(V)	(VI)
Intercept	-0.02	0.01	-0.08	0.28	-0.08	0.46
	(0.64)	(0.80)	(0.18)	(0.03)	(0.07)	(0.00)
I_{EIA}	-0.23	-0.24	-0.24	-0.24	-0.27	-0.27
	(0.05)	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)
S	-1.04	-1.05	-1.04	-1.04	-1.04	-1.04
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$b^{(1,2)}$	0.44					0.42
	(0.00)					(0.00)
$b^{(1,13)}$		1.99				
		(0.00)				
HP			0.15			0.31
			(0.70)			(0.43)
IVOL				-0.14		-0.18
				(0.01)		(0.00)
ΔVolume					0.08	0.08
					(0.13)	(0.15)
R^2	0.03	0.03	0.03	0.03	0.03	0.03
Obs	3982	3982	3982	3982	3844	3844

Table B.9: EIA Announcemnt Return Excluding Macro News Days

This table reports mean and standard deviation of the returns on the first nearby contract in Henry Hub natural gas futures on EIA announcement days excluding days on which the report coincides with other macroeconomic news releases. The first column lists the events to be excluded. Columns 'News' represent those days where only EIA reports are released, columns 'Rest' include all other days including those where the EIA report coincides with the release mentioned in the first column. Column 't-Test' reports the t-statistic and p-value in parentheses for a two-sample t-test on equal means assuming unequal variances. Column 'F-Test' reports the F-statistic and p-value in parentheses for a F-test on equal variances. The last column reports the number of announcements excluding the event. The first row reports the base line results only excluding coinciding release days of the EIA Petroleum Report. The last three rows exclude days on which any news on the housing market, consumption, or the macro economy are excluded. Daily mean returns and annualized standard deviations are reported in percentage points. The sample ranges from March 2003 to December 2018.

	Mean			**Standard Deviation**			
Excluded Event	News	Rest	t-Test	News	Rest	F-Test	Obs
EIA Petroleum Report	-0.37	-0.09	-2.19 (0.029)	49.15	43.28	1.29 (0.000)	699
Industrial Production	-0.38	-0.09	-2.30 (0.022)	48.76	43.40	1.26 (0.000)	679
Trade Balance	-0.37	-0.10	-2.08 (0.038)	49.60	43.23	1.32 (0.000)	670
New House Sales	-0.39	-0.09	-2.28 (0.023)	49.62	43.21	1.32 (0.000)	677
New Housing Units	-0.34	-0.10	-1.85 (0.065)	49.24	43.32	1.29 (0.000)	674
Consumer Credit	-0.37	-0.09	-2.21 (0.028)	48.91	43.37	1.27 (0.000)	679
Durable Goods	-0.35	-0.10	-1.94 (0.052)	49.82	43.19	1.33 (0.000)	670
Wholesale Inventories	-0.39	-0.09	-2.32 (0.020)	49.17	43.29	1.29 (0.000)	688
Consumer Price Index	-0.38	-0.09	-2.23 (0.026)	48.46	43.49	1.24 (0.000)	674
Pending Home Sales	-0.36	-0.10	-2.02 (0.044)	49.10	43.35	1.28 (0.000)	672
Housing Permits	-0.34	-0.10	-1.85 (0.065)	49.24	43.32	1.29 (0.000)	674
Fed Announcements	-0.33	-0.10	-1.80 (0.072)	49.30	43.30	1.30 (0.000)	674
Import Index	-0.39	-0.09	-2.27 (0.024)	48.79	43.43	1.26 (0.000)	661
Existing Home Sales	-0.40	-0.09	-2.42 (0.016)	49.31	43.29	1.30 (0.000)	672
GDP	-0.35	-0.10	-1.95 (0.052)	49.10	43.34	1.28 (0.000)	680
Housing Market	-0.37	-0.10	-2.00 (0.046)	49.89	43.32	1.33 (0.000)	598
Consumption	-0.37	-0.09	-2.21 (0.028)	48.91	43.37	1.27 (0.000)	679
Macro Economy	-0.34	-0.11	-1.71 (0.088)	49.82	43.33	1.32 (0.000)	604

Table B.10: Intraday Return Regressions for Different Investment Windows

This table reports the results of the regression in Equation (3.5) *using intraday returns, i.e., the first nearby log return is regressed on* I_{EIA}*, an indicator variable, equal to 1 on EIA days and 0 otherwise, and the announcement surprise,* S_t*, the basis, idiosyncratic volatility, crude oil returns, commodity index returns, and changes in volume. The dependent variable changes in every column, starting with the intraday return from 90 minutes before the announcement to 30 minutes after the announcement, (-90,30). The second, third and fourth column use the intraday return from 60, 30 and 5 minutes before the announcement to 30 minutes after the announcement as dependent variable, or (-60,30), (-30,30) and (-5,30), respectively. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.*

Dep. Var.	(-90,30)	(-60,30)	(-30,30)	(-5,30)
Constant	0.14	0.13	0.12	0.09
	(0.04)	(0.03)	(0.03)	(0.07)
I_{EIA}	-0.30	-0.22	-0.16	-0.15
	(0.00)	(0.00)	(0.00)	(0.00)
Surprise	-1.01	-0.97	-0.93	-0.87
	(0.00)	(0.00)	(0.00)	(0.00)
Basis	-0.03	0.01	0.00	-0.03
	(0.51)	(0.87)	(0.96)	(0.38)
IVOL	-0.06	-0.05	-0.05	-0.03
	(0.01)	(0.02)	(0.02)	(0.04)
Control	Yes	Yes	Yes	Yes
R^2	0.15	0.16	0.17	0.16
Obs	3979	3979	3979	3979

Table B.11: Regression for Spread Returns

This table reports the results of the regression in Equation (3.5) using spread returns, i.e., the log spread return is regressed on I_{EIA}, an indicator variable, equal to 1 on EIA days and 0 otherwise, and the announcement surprise, S_t, the basis, idiosyncratic volatility, crude oil returns, commodity index returns, and changes in volume. Column (I) includes only the indicator variable. Column (II) adds the surprise variable. In column (III), we also control for crude oil returns, commodity index returns, idiosyncratic volatility, and changes in volume. Returns are in percentage points and p-values in parentheses are based on Newey and West (1987) standard errors with two lags.

Variables	(I)	(II)	(III)
Constant	-0.02	-0.02	-0.02
	(0.01)	(0.01)	(0.04)
I_{EIA}	-0.06	-0.06	-0.07
	(0.00)	(0.00)	(0.00)
S		-0.06	-0.04
		(0.00)	(0.05)
Control	No	No	Yes
R^2	0.00	0.01	0.07
No. of Obs.	3982	3982	3844

Table B.12: Regression to Test the Bloomberg Survey Forecast Accuracy

This table reports regression results for the forecast accuracy of the Bloomberg median survey forecast as described in Equation (3.11)

$$A_t = \alpha + \beta E_t + u_t, \tag{3.11}$$

where A_t denotes the weekly storage reported by the EIA, α is the intercept, β is the regression coefficient, E_t is the Bloomberg median forecast of the storage level, and u_t is the residual. Column (I) uses the raw figure for A_t and E_t. Column (II) uses the seasonally-adjusted figures, removing the 5-year average for the specific week. The second to last row reports the F-statistic for the hypothesis of $\alpha = 0$ and $\beta = 1$ with the p-value reported in parentheses.

Variables	(I)	(II)
Intercept (α)	0.2385	0.3243
	(0.460)	(0.313)
Forecast (E_t)	1.0119	1.0132
	(0.000)	(0.000)
$F(\alpha = 0, \beta = 1)$	6.32	7.72
	(0.002)	(0.000)
R^2	0.99	0.99

Factor Construction

This section explains the construction of the factor returns for the computation of the idiosyncratic volatility measure, IVOL, in Equation (3.10). The market factor is computed as the equally-weighted sum of 26 commodity market log returns, excluding natural gas itself, i.e.,

$$r^{\mathrm{MRKT}} = \log\left(1 + \frac{1}{26}\sum_{i=1}^{26} R_i\right), \tag{3.12}$$

where R_i is the daily return on commodity market i. For the basis, momentum, and basis-momentum factors the 26 markets are sorted regarding the respective signal and divided along the median. The respective factor is the return on a long-short portfolio, that opens long position in the 13 commodities with the highest signal, and opens a short position in the 13 commodities with the lowest signal. The signals for basis, momentum, and basis-momentum are computed as follows:

$$\begin{aligned} b_t^{(1,2)} &= \frac{365}{M_t^{(2)} - M_t^{(1)}}\left[\log\left(F_t^{(1)}\right) - \log\left(F_t^{(2)}\right)\right], \\ \mathrm{MOM}_t &= \sum_{j=1}^{252} r_{t-j}^{(1)} \\ \mathrm{BASMOM}_t &= \sum_{j=1}^{252} r_{t-j}^{(1)} - \sum_{j=1}^{252} r_{t-j}^{(2)} \end{aligned}$$

where $F_t^{(1)}$ $\left(F_t^{(2)}\right)$ is the futures price of the first (second) nearby, $M_t^{(1)}$ $\left(M_t^{(2)}\right)$ is the time to maturity in days of the first (second) nearby, and $r_t^{(1)}$ $\left(r_t^{(2)}\right)$ is the return on the first (second) nearby.

Chapter 4

Convenience Yield Risk

4.1 Introduction

The convenience yield, a term coined by Kaldor (1939), describes the implied return that arises from holding physical commodities. Within the theory of storage (Working, 1949), it is the concept that keeps spot and futures markets in a no-arbitrage relationship. Although unobservable, the convenience yield varies over time, across commodities, and between maturities, as the conditions and incentives for holding physical commodities vary. Hence, it is not only of academic interest, but of utmost importance for the risk analysis of investors in commodity futures markets, to have an accurate and meaningful measure of the uncertainty associated with the convenience yield.

In this chapter, we propose a measure of convenience yield risk (CYR) that can be interpreted as a relative measure between short- and medium-term risks in the convenience yield in the light of Gu et al. (2019). Our measure is unique in capturing the seasonal behaviour in mean and standard deviation of the convenience yield as well as incorporating the term structure dimension of the convenience yield. Sorting commodities with respect to CYR shows that commodities with higher convenience yield risk outperform commodities with lower convenience yield risk and a long-short portfolio on 27 commodity markets sorted by CYR provides an annual return of 7.56% (t-stat = 3.63). The portfolio provides significant excess returns over known commodity return factors such as the basis (Koijen et al., 2018), momentum (Miffre and Rallis, 2007), basis-momentum (Boons and Prado, 2019), or idiosyncratic volatility (Fernandez-Perez et al., 2016), and survives robustness tests with respect to portfolio construction and sample choice. Further, the predictive power of CYR in the cross-section remains when allowing for commodity and time fixed effects. A trading strategy which buys a commodity after an increase in CYR, and does not invest if CYR decreases, is able to compete with the highly profitable time series momentum strategy documented in Moskowitz et al. (2012).

Dissecting our measure, we show that CYR is mainly driven by the term structure variation rather than the time variation of convenience yield, and under certain assumptions CYR can be interpreted as a measure for the Samuelson (1965) effect in commodity markets, i.e., the observation that the volatility of a commodity futures contract increases as it approaches expiration.

In the cross-section, convenience yield risk is positively correlated with the absolute level of convenience yield, i.e., commodities with higher average convenience yield risk tend to be in backwardation and commodities with lower average convenience yield risk tend to be in contango. This observation is in line with the theory of storage that predicts a higher elasticity of the price of storage when inventories are low (Working, 1949; Brennan, 1958; Telser, 1958). In contrast, the time series of rolling five-year correlation of the two signals does not indicate that times of high convenience yield risk coincide with times of high convenience yield. This emphasizes an important distinction between the basis as a proxy for convenience yield and our convenience yield risk measure. While Koijen et al. (2018) describe the basis as the return on a futures contract if the spot price does not change, the convenience yield risk arises from sudden changes in this return, independent of the level of basis. Further refining this difference, we show that after removing the part of the convenience yield risk, that is orthogonal to the basis, the signal still predicts commodity futures returns. Although the return on convenience yield risk is related to global financial conditions, volatility, and credit risk, they cannot fully explain the excess return.

To the best of our knowledge, we are the first to develop a measure for convenience yield risk that can predict commodity returns. While Prokopczuk and Wu (2013) analyse the determinants of the convenience yield, the works of Bessembinder et al. (1996) and Duong and Kalev (2008) find evidence and try to predict the Samuelson effect. Schneider and Tavin (2018) investigate the structure of the correlation of commodity futures returns with different maturities. Bakshi et al. (2011) improve predictability of asset returns with forward variances inferred from option portfolios. Although related, our work is different. Instead of the term structure of volatilities of the returns, we use the volatility of the convenience yield which is defined with respect to the prices of two different contracts on the same underlying.

This chapter adds to the strand of literature in commodity markets that aims to extract information from the entire term structure rather than just the first and/or second nearby. A study by de Groot et al. (2014) shows that momentum strategies using contracts with the largest expected roll yield earn significantly higher risk-adjusted returns than traditional momentum strategies. Paschke et al. (2020) propose a strategy that compares momentum within the futures curve, while Boons and Prado (2019) use the difference between the first and second nearby momentum as a cross-sectional signal. Gu et al. (2019) propose a measure for the convenience yield using the differences in slopes between first, second, and third nearby. They find their measure to be more closely related to scarcity of inventories than the basis. Our measure also uses the variation in the first, second, and third nearby contracts, and is robust against the inclusion of further deferred contracts.

Our work contributes to the literature on commodity return predictors. Yang (2013) reports that an average factor together with a high minus low slope factor explains the cross-section of commodity returns. Hong and Yogo (2012) show that commodity market interest predicts commodity returns. Bakshi et al. (2019) find that a three-factor model including a market, basis, and momentum factor explains the cross-section of commodity returns, while Boons and Prado (2019) claim that a more parsimonious model using only basis-momentum and a market factor is sufficient. Szymanowska et al. (2014) show that commodity spot and term premia can be explained by one or two basis factors, respectively, and Fernandez-Perez et al. (2016) find that idiosyncratic volatility predicts commodity returns. In spanning regression, we find that convenience yield risk has predictive power beyond the listed commodity return predictors.

Lastly, we also contribute to the literature on the convenience yield and the theory of storage. Based on the theories of Kaldor (1939) and Working (1949) spot and futures prices are related through arbitrage mechanisms affected by supply, demand, storage, speculation, and interest rates. Gorton et al. (2013) show that the convenience yield is a decreasing, non-linear function of inventories. While Schwartz and Smith (2000), Sørensen (2002), Prokopczuk and Wu (2013) model convenience yield as a continuous-time stochastic process, we use a non-parametric approach and proxy the convenience yield with the basis adjusted for interest rates.

The remainder of this chapter is structured as follows. Section 4.2 describes the data and introduces our measure of convenience yield risk. Section 4.3 presents the predictive regression results. Section 4.4 explores several explanatory channels, Section 4.5 discusses robustness checks, and Section 4.6 concludes.

4.2 Data & Variables

4.2.1 Data

We collect from Bloomberg daily futures prices and trading volumes on 27 commodities covering 6 different sectors listed in Table C.1 of Appendix C. Our dataset covers the period from July 7, 1959 to December 31, 2018. This is the broadest possible dataset with at least three liquid maturities. [1]

Continuous futures price series are constructed by rolling over each contract at the end of the month preceding the month prior to delivery in order to avoid irregular price concerns (Szymanowska et al., 2014). The summary statistics on the returns of the first nearby futures contract presented in Table C.2 of Appendix C reveal the typical

[1] The criterion applied is that the average trading volume of the third nearby futures contract needs to be at least 10% of that of the first nearby futures contract.

cross-sectional variation in average returns and standard deviations between commodity markets and sectors (de Groot et al., 2014). We also collect data on the position of commercial and non-commercial traders from the Commodity Futures Trading Commission's (CFTC) Commitment of Traders (CoT) report and financial variables from the Federal Reserve Bank of St. Louis (FRED).

4.2.2 Convenience Yield Risk

We compute the convenience yield using the known cost-of-carry relationship. For the i^{th} and j^{th} nearby series with $i < j$, it holds that

$$f_t^{(j)} = f_t^{(i)} + \left(\mathrm{rf}_t^{(i,j)} - y_t^{(i,j)}\right) \frac{M_t^{(j)} - M_t^{(i)}}{365}, \tag{4.1}$$

where $f_t^{(i)}$ and $f_t^{(j)}$ are logarithmic prices of the i^{th} and j^{th} nearby futures contract at time t, $M_t^{(i)}$ and $M_t^{(j)}$ are the days to expiry for the respective contracts, $\mathrm{rf}_t^{(i,j)}$ is the risk-free rate, and $y_t^{(i,j)}$ is the convenience yield at time t for the period from the expiration date of the i^{th} to the j^{th} contract. We calculate the above risk free rate by bootstrapping from the overnight, 1-, 2-, 3-, and 6-month as well as 1-, 2-, and 3-year constant maturity rates obtained from the Federal Reserve Economic Data (FRED) database.

Our approach is deliberately non-parametric as opposed to approaches which model convenience yield as a continuous-time stochastic process (Schwartz, 1997; Sørensen, 2002; Prokopczuk and Wu, 2013). Apart from avoiding restrictive assumptions, our approach has the benefit that it allows us to obtain the convenience yield for any pair of maturities which is our main objective.

Descriptive statistics for the convenience yield from the first and second nearby, i.e., $y^{(1,2)}$ are presented in Table 4.1. In line with the prior literature (Gorton et al., 2013; Prokopczuk and Wu, 2013), we find strong cross-sectional variation in the standard deviation of convenience yields. For instance, the volatility of natural gas is 173.35%, while that of gold is only 1.47%. This cross-sectional variation in the standard deviation is strongly influenced by seasonal patterns in demand and supply cycles, e.g., energy con-

Table 4.1: Summary Statistics for the Convenience Yield

This table reports summary statistics on the nearest convenience yield, $y^{(1,2)}$, for 27 commodities at the monthly frequency. The sample period is from July 1959 to December 2018, covering 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs, each one separated by a horizontal line. The mean and standard deviation are reported in percentage points.

Commodity	Mean	Std. Dev.	AR(1)	Skew	Kurt	Obs
WTI Crude	7.26	25.03	0.76	1.16	6.32	428
Heating Oil	8.26	51.82	0.35	9.51	129.77	390
Natural Gas	10.45	173.35	0.18	10.79	147.84	345
Gasoil	6.68	28.69	0.59	4.98	40.40	351
Gasoline	18.65	50.14	0.41	2.23	12.25	385
Corn	-0.88	21.98	0.62	7.40	88.85	714
Oats	1.97	24.51	0.73	3.36	22.93	713
Rough Rice	-4.25	23.16	0.52	4.30	27.98	359
Chicago Wheat	2.44	26.88	0.64	5.94	60.92	714
Feeder Cattle	6.85	14.66	0.62	0.34	4.92	562
Live Cattle	7.94	21.44	0.61	1.00	4.56	649
Lean Hogs	13.39	62.81	0.60	1.26	5.72	392
Copper	6.95	12.00	0.84	2.24	10.14	361
Gold	0.53	1.47	0.58	2.18	22.87	527
Palladium	3.99	6.48	0.67	4.78	49.25	381
Platinum	3.75	4.24	0.89	2.06	9.97	392
Silver	0.06	1.93	0.41	-5.03	94.48	527
Soybean Oil	6.32	22.38	0.74	3.77	24.82	714
Canola	-1.52	8.64	0.60	2.61	12.21	442
Soybeans	8.37	39.60	0.34	9.31	125.64	714
Soybean Meal	10.65	30.63	0.56	4.20	26.77	714
Cotton	6.43	61.04	0.46	17.81	363.24	710
Lumber	-1.44	23.95	0.73	0.90	5.04	390
Cocoa	2.72	16.72	0.86	2.79	12.34	713
Orange Juice	4.82	31.11	0.60	10.07	158.96	621
Coffee	3.49	22.74	0.84	2.57	12.34	556
Sugar	4.01	23.03	0.79	1.81	9.09	694

sumption in winter or harvest seasons in the case of agricultural commodities. Reported autocorrelations are of similar magnitude as in Gu et al. (2019). To provide more formal evidence to this, in Table 4.2 we report the results from regressions of the average convenience yield per month for each commodity on monthly dummy variables. The F-statistic from testing the hypothesis that all dummy variables are jointly equal to zero is rejected for all but seven commodities.[2]

Drawing on the above evidence, we measure the volatility of the convenience yield at the monthly frequency to capture the seasonal variation in the mean. In particular, we define the series of monthly volatilities as

$$\sigma_t(y^{(i,j)}) = \sqrt{\frac{1}{N_t - 1}\sum_{\tau=1}^{N_t}(y_\tau^{(i,j)} - \overline{y_t^{(i,j)}})^2}, \tag{4.2}$$

where N_t is the number of daily observations in month t, and $\overline{y_t^{(i,j)}}$ is the average convenience yield in month t computed from the prices of the i^{th} and j^{th} nearest futures contracts.

Our proposed measure is based on the relative changes in convenience yield volatility across different points of the futures curve. In order for this measure to be meaningful, there should be sufficient variation in convenience yield volatility across the futures term structure. In Table C.3 of Appendix C, we report the volatility of the first six convenience yields, i.e., $\sigma(y^{(1,2)})$ to $\sigma(y^{(6,7)})$. We find that the volatility of the first convenience yield, $\sigma(y^{(1,2)})$, is higher than the volatility of the second convenience yield, $\sigma(y^{(2,3)})$, in most markets.

Our newly proposed convenience yield risk (CYR) measure is defined as follows:

$$\text{CYR}_t = \frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \sigma_{t-i}(y^{(2,3)})\right], \tag{4.3}$$

where $\sigma_t(y^{(1,2)})$ and $\sigma_t(y^{(2,3)})$ are the monthly volatilities of the first and second nearest convenience yield, respectively, defined in Equation (4.2).

[2]Furthermore, Schneider and Tavin (2020) document a seasonal behaviour of the volatility in agricultural commodity markets that needs to be addressed when measuring convenience yield risk.

Table 4.2: Seasonality in the Convenience Yield

This table reports the average convenience yield for each calendar month (columns 'Jan' to 'Dec'). The last two columns show the R^2 and the p-value from the F-test that the coefficient estimates of a regression of monthly convenience yield on 12 monthly dummies are jointly zero. The sample period spans from July 1959 to December 2018, covering 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs, each one separated by a horizontal line.

Commodity	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	$\mathbf{R^2}$	**F-stat**
WTI Crude	-1.96	1.34	0.16	0.81	1.07	-0.20	1.17	3.12	-0.84	0.65	6.89	0.32	0.01	0.990
Heating Oil	-29.64	-27.28	-7.54	3.99	13.39	16.43	17.96	14.66	13.69	12.00	1.49	-39.44	0.15	0.000
Natural Gas	-67.90	-81.34	14.92	19.06	16.89	10.52	21.40	53.12	58.52	34.58	-48.82	-84.49	0.08	0.004
Gasoil	-11.82	-7.24	0.46	3.18	11.05	10.26	11.50	3.54	0.08	1.46	-4.02	-17.66	0.10	0.000
Gasoline	51.28	4.39	-6.82	-15.39	-24.30	-17.07	-86.23	-39.18	-16.79	-9.26	9.02	14.73	0.41	0.000
Corn	17.02	14.25	13.78	-5.77	-6.86	4.73	6.15	18.49	18.97	18.36	17.37	17.90	0.17	0.000
Oats	4.47	-4.86	-1.88	4.66	2.56	16.46	17.53	17.03	15.30	14.96	8.15	5.88	0.09	0.000
Rough Rice	16.83	15.32	16.53	-16.60	-6.68	11.04	13.26	16.95	18.27	17.27	17.64	15.68	0.21	0.000
Chicago Wheat	1.38	-11.71	-11.78	15.74	16.88	18.43	18.66	15.02	15.07	13.96	1.39	1.69	0.16	0.000
Feeder Cattle	7.11	3.01	8.60	1.45	-0.79	-1.00	3.12	10.36	6.36	-0.04	0.89	5.51	0.07	0.000
Live Cattle	-9.89	-11.74	-4.48	-3.83	5.26	5.95	10.06	9.83	6.40	6.65	8.21	10.39	0.13	0.000
Lean Hogs	56.22	60.11	-0.86	-13.04	-102.15	-102.05	-19.32	-10.49	19.02	28.57	7.17	12.99	0.63	0.000
Copper	0.29	-0.20	0.14	0.23	0.44	0.25	0.98	-0.44	1.14	1.95	0.47	-1.21	0.01	0.998
Gold	9.97	10.11	9.83	9.66	10.19	10.06	10.24	9.99	10.17	9.59	9.94	9.78	0.00	1.000
Palladium	3.18	3.99	4.50	2.78	4.80	3.80	3.79	4.41	4.27	4.55	4.67	3.65	0.01	0.989
Platinum	3.62	3.88	4.23	3.86	4.02	4.48	4.11	4.17	4.90	4.23	4.10	4.95	0.01	0.999
Silver	10.19	10.33	10.53	10.34	10.51	10.59	10.52	10.68	11.24	10.35	10.39	10.16	0.00	1.000
Soybean Oil	7.99	7.05	6.11	-1.00	0.39	0.72	-8.34	4.34	8.97	4.72	7.25	8.47	0.05	0.000
Canola	8.04	11.03	11.26	4.32	5.87	13.64	13.64	13.92	14.09	13.17	12.85	7.95	0.10	0.000
Soybeans	10.63	9.20	9.15	-8.56	-9.00	-50.92	-0.41	12.64	13.72	12.33	11.76	11.10	0.19	0.000
Soybean Meal	6.62	9.36	9.77	-1.51	-5.44	-29.32	-23.99	4.24	9.24	3.48	5.79	6.40	0.15	0.000
Cotton	12.30	7.23	8.29	-17.97	-26.86	2.35	6.23	8.17	12.14	11.23	11.23	11.37	0.04	0.004
Lumber	9.84	6.86	10.83	4.34	5.11	-10.66	-3.51	15.41	24.95	18.56	18.63	8.92	0.17	0.000
Cocoa	6.59	8.39	6.17	8.70	8.24	7.18	8.08	8.92	7.57	7.24	7.65	7.02	0.00	1.000
Orange Juice	12.66	9.36	7.72	8.45	7.75	0.74	-0.49	-3.92	-8.67	10.82	12.34	13.97	0.05	0.001
Coffee	9.76	8.52	7.85	7.70	7.93	5.30	5.52	6.82	7.00	4.60	8.32	7.93	0.00	0.997
Sugar	2.72	0.81	0.15	7.63	6.82	11.87	11.94	14.47	6.29	4.75	4.04	5.50	0.03	0.033

The reasons for CYR providing the most comprehensive view of the risk associated with the convenience yield are threefold. First, we use the monthly frequency to allow for a varying mean convenience yield due to seasonal behaviour. Second, we incorporate the term structure of convenience yields by effectively measuring the slope of volatilities between two points on the term structure. Third, we use a 12-months window to control for seasonality in the volatility. Additionally, in the light of Gu et al. (2019), CYR can be interpreted as a relative measure between short- and medium-term risks of the convenience yield.

We perform several checks to establish the robustness of our findings in Section 4.5. Descriptive statistics for the CYR of each commodity market are provided in Table C.4 of Appendix C.

4.3 Predicting Commodity Returns

4.3.1 Portfolio Sorts

We move on to explore whether CYR predicts commodity returns in the time series and the cross-section. Investors with a long position in commodity futures would require a premium for bearing the risk associated with variations in the convenience yield. Conversely, investors with short positions in commodity futures are willing to pay a premium to avoid the risk associated with variations in the convenience yield. Although the convenience yield accrues to the owner of the physical commodity, the uncertainty will affect both spot and futures markets through arbitrage. However, the strength of the effect is expected to be decrease for further deferred contracts as the volatility of short-term contracts is more reactive (Ng and Pirrong, 1994). Thus, the spread return, $(F^{(1)} - F^{(2)})$, should be higher in commodity markets with high CYR, and vice versa.

We begin by sorting the 27 commodities on CYR and build a 'High' portfolio containing half of the commodities with the highest CYR and a 'Low' portfolio containing half of the commodities with the lowest CYR. We hold these portfolios for one month and repeat the sorting. Table 4.3 reports the annualized average return, t-statistic of the average return, and Sharpe ratio for the 'High', 'Low' and 'High-Low' portfolios. We find a highly significant average nearby futures return of 7.56% per annum (t-stat = 3.63) for the 'High-Low' portfolio (Panel A). The average spread return is also significant (t-stat = 2.25) but lower. We also see that in the case of nearby returns, it is the 'High' portfolio that contributes to the positive and significant 'High-Low' return, as opposed to the spreading returns of the 'High-Low' portfolio which is driven by the 'Low' leg.

Table 4.3: Performance of Convenenience Yield Risk Portfolios

This table reports the average returns, t-statistic of the average return (in parentheses) using Newey and West (1987) standard errors with 2 lags, and Sharpe ratio for portfolios sorted by convenience yield risk. We sort the 27 commodities by their CYR and form a 'High' portfolio containing the commodities with the highest CYR and a 'Low' portfolio containing the commodities with the lowest CYR. We also report the returns on the 'High-Low' spread portfolio. The commodities in each portfolio are equally-weighted. The sample period ranges from July 1959 to December 2018. Panel A reports the first nearby returns, while Panel B shows the spread returns using the first and second nearby contract.

Panel A: First Nearby Returns

	High	Low	High–Low
Av. Return	7.41	-0.15	7.56
(t-stat)	(3.24)	(-0.07)	(3.63)
Sharpe Ratio	0.47	-0.01	0.51

Panel B: Spread Returns

	High	Low	High–Low
Av. Return	-0.28	-1.14	0.87
(t-stat)	(-0.84)	(-4.22)	(2.25)
Sharpe Ratio	-0.12	-0.62	0.32

4.3.2 Time Series Tests

We start by testing whether the CYR factor provides independent information for commodity futures returns. To this end, we perform spanning regressions of the returns on the 'High-Low' portfolio on a constant and the various well-established commodity factors, i.e.,

$$r^{\text{CYR}} = \alpha + \beta_1 r^{\text{MRKT}} + \beta_2 r^{\text{BAS}} + \beta_3 r^{\text{MOM}} + \beta_4 r^{\text{BASMOM}} + \beta_5 r^{\text{IVOL}} + \epsilon, \tag{4.4}$$

where α is the risk-adjusted excess return, r^{CYR} is the return on the long-short convenience yield risk portfolio, r^{MRKT} is the market factor, i.e., the return on an equally-weighted portfolio of all commodities, r^{BAS} is the basis factor, i.e., the return on a long-short portfolio formed by sorting on the basis, r^{MOM} is the momentum factor, i.e., the return on a long-short portfolio sorted on momentum (Bakshi et al., 2019), r^{BASMOM} is the basis-momentum factor, i.e., the return on a long-short portfolio sorted on basis-momentum (Boons and Prado, 2019), and r^{IVOL} is the idiosyncratic volatility factor, i.e. the return on a long-short portfolio sorted on idiosyncratic volatility (Fernandez-Perez et al., 2016). Finally, $\beta_1, \ldots, \beta_5$ are the slope parameters of the above factors and ϵ is the residual. Below we provide information on the construction of the above factors.

The four factors in Equation (4.4) correspond to zero-cost long-short portfolios constructed through sorting the commodities by basis (BAS), momentum (MOM), basis-momentum (BASMOM), and idiosyncratic volatility (IVOL). These signals are constructed as follows:

$$\text{BAS}_t = \left(f_t^{(i)} - f_t^{(j)}\right) \frac{365}{M_t^{(j)} - M_t^{(i)}}, \tag{4.5}$$

$$\text{MOM}_t = \sum_{j=1}^{12} r_{t-j}^{(1)}, \tag{4.6}$$

$$\text{BASMOM}_t = \sum_{j=1}^{12} r_{t-j}^{(1)} - \sum_{j=1}^{12} r_{t-j}^{(2)}, \tag{4.7}$$

$$\text{IVOL}_t = \sigma_t(\epsilon), \tag{4.8}$$

where $\sigma_t(\epsilon)$ corresponds to the monthly standard deviation on the residuals of a regression of daily returns on the daily factors, BAS, MOM, BASMOM, and a constant for each month t. We provide summary statistics on the factor returns in Table C.5 in Appendix C. The correlations reported in Table 4.4 show that the returns on CYR have low correlations with the other four factors.

Tables C.6 and C.7 of Appendix C show the results from the the regressions of Equation (4.4) for the nearby and spreading futures returns, respectively. An insignificant regression α is taken as evidence that the CYR factors is not spanned by the other factors. The intercept is statistically significant in all regressions for both the nearby and spreading returns. Therefore, the CYR factor is not spanned by the other four commodity factors.[3]

Table 4.4: Correlation of Commodity Factor Returns

This table reports the time series average of correlations between the return on the market portfolio (MRKT), and the returns on long-short portfolios created by sorting on basis (BAS), momentum (MOM), basis-momentum (BASMOM), idiosyncratic volatility (IVOL), and convenience yield risk (CYR). The sample includes 27 commodity markets for the period from July 1959 to December 2018. The top-right part of the table presents the correlation for nearby futures returns and the lower-left part those for spread returns.

Nearby / Spread	MRKT	BAS	MOM	BASMOM	IVOL	CYR
MRKT		0.03	0.19	0.11	0.44	0.04
BAS	0.36		0.37	0.44	-0.05	0.06
MOM	0.27	0.60		0.27	0.22	0.07
BASMOM	0.13	0.57	0.57		-0.03	0.14
IVOL	0.48	0.29	0.32	0.19		0.15
CYR	0.21	0.03	-0.02	0.05	0.11	

[3]For further robustness, we also perform independent double sorts in Table C.8 of Appendix C.

4.3.3 Cross-Sectional Tests

We showed above that the returns on CYR are not spanned by other factors, thus the predictive power of CYR cannot be explained by passive exposure to other known factors. We move to explore whether the CYR can predict cross-sectional variations in commodity futures returns. Thus, we estimate pooled predictive regressions of the form

$$r_{i,t+1} = \gamma_0 + \gamma_1 \mathrm{CYR}_{i,t} + \gamma_2' X_{i,t} + \theta_t + \kappa_i + \eta_{i,t+1}, \tag{4.9}$$

where $r_{i,t+1}$ is the return on commodity i in month $t+1$, γ_0 is the intercept, γ_1 is the coefficient of the convenience yield risk measure, $\mathrm{CYR}_{i,t}$, and γ_2 is the vector of parameters for the MRKT, BAS, BASMOM, and IVOL factors, represented by the vector $X_{i,t}$. Also, θ_t denotes indicator variables for each month (time fixed effects), κ_i are indicator variables for each commodity (commodity fixed effects), and $\eta_{i,t+1}$ is the error term. All variables are standardized to obtain interpretable coefficient estimates.

The results presented in Table 4.5 show that CYR significantly predicts commodity returns in the cross-section. This result holds regardless of including time or commodity fixed effects to the regressions.

When we consider time and commodity fixed effects (column (4)), a one standard deviation increase in CYR predicts an increase in annual returns of 5.16% (t-stat = 2.79). This effect stems solely from variation in the CYR as return variations across time and markets have been accounted for through fixed effects. Our evidence remains robust, if we control for the other commodity return predictors, i.e., basis, momentum, basis-momentum, and idiosyncratic volatility (column (5)).

Table 4.5: Cross-Sectional Predictive Regressions

This table reports the results from panel regressions of future commodity returns on predictive signals as in Equation (4.9)

$$r_{i,t+1} = \gamma_0 + \gamma_1 CYR_{i,t} + \gamma_2' X_{i,t} + \theta_t + \kappa_i + \eta_{i,t+1}, \tag{4.9}$$

where $r_{i,t+1}$ is the return on commodity i in month $t+1$, $\mathrm{CYR}_{i,t}$ is the convenience yield risk measure, $X_{i,t}$ is the vector of control variables including the basis, momentum, basis-momentum, and idiosyncratic volatility, θ_t are indicator variables for each month (time fixed effects), κ_i are indicator variables for each commodity (commodity fixed effects), and $\eta_{i,t+1}$ is the commodity- and time-specific error term. Only the coefficient γ_1 is reported with the associated t-statistic using standard errors clustered by time. The 'Time FE' and 'Commodity FE' rows indicate whether time or commodity fixed effects are employed in the panel estimation.

	(1)	(2)	(3)	(4)	(5)
CYR	3.94	5.64	3.53	5.16	4.20
(t-stat)	(2.26)	(2.74)	(2.18)	(2.79)	(2.21)
X	No	No	No	No	Yes
Time FE	No	No	Yes	Yes	Yes
Commodity FE	No	Yes	No	Yes	Yes
R^2	0.002	0.006	0.186	0.191	0.195

4.3.4 Convenience Yield Risk Timing Strategy

In the previous section, we have shown that convenience yield risk is a significant predictor of commodity futures returns both in the time series and the cross-section. This new factor is also not spanned by established commodity factors, such as basis, momentum, basis momentum, and idiosyncratic volatility. From an investor's perspective, an important question is whether a profit can be achieved by following a trading strategy that employs CYR as a signal. We, thus, implement a trading rule which takes a long position in commodities if their CYR today is higher than 12 months ago. Our strategy is long only since the analysis of Subsection 4.3.1 suggests that the significant return of the long-short CYR portfolio comes from its long leg. As a benchmark for comparison, we employ a time series momentum (TSMOM) strategy similar to Moskowitz et al. (2012).

The returns of the two strategies can be written as follows:

$$r_{k,t}^{\text{CYR}} = \begin{cases} r_{k,t}, & \text{if } \text{CYR}_{k,t-1} > \text{CYR}_{k,t-13} \\ 0, & \text{else,} \end{cases} \qquad r_{k,t}^{\text{TSMOM}} = \begin{cases} r_{k,t}, & \text{if } \sum_{i=1}^{12} r_{k,t-i} > 0 \\ 0, & \text{else,} \end{cases} \tag{4.10}$$

where $r_{k,t}^{\text{CYR}}$ is the return on the CYR timing strategy and $r_{k,t}^{\text{TSMOM}}$ is the return on the TSMOM strategy for each commodity market k and month t, respectively.

Table C.9 in Appendix C reports the returns on the CYR timing strategy compared to the benchmark TSMOM strategy. For 17 out of 27 markets the timing strategy provides positive returns as compared to 20 markets for the TSMOM benchmark. Although the time series momentum strategy performs slightly better, there is no significant difference as seen from the last column of the table which shows the difference in the average annualized returns of the two strategies (TSMOM-CYR) and the t-statistic from testing its significance (in parentheses). In Table C.10 of Appendix C, we implement the same strategy at the sector level, i.e., we build equally-weighted sector portfolios and the sector convenience yield risk.[4] The results indicate that for 5 out of 6 sectors the CYR timing strategy generates positive returns. Furthermore, a diversified strategy across all sectors achieves an annual return of 3.24% (t-stat = 2.68). Although the difference is not statistically significant, the CYR strategy generates more than 50% larger returns than the benchmark time series momentum strategy for sectors.

In sum, a long-only CYR timing strategy achieves a profit especially at the aggregate portfolio level. This profit is comparable to that of the established time series momentum strategy.

[4]Note, that while we use equal weights for comparibility, Moskowitz et al. (2012) employ weights that fix the ex-ante volatility at 40%.

4.4 Economic Explanations

In this section, we aim to explore the economic channels driving the time and term structure variation of convenience yield risk. Further, we disentangle the channels through which convenience yield risk and convenience yield are connected and investigate how the returns on the sorted CYR portfolio are related to financial market conditions.

4.4.1 Dissecting Convenience Yield Risk

We can decompose convenience yield risk in a similar spirit to Koijen et al. (2018) who analyze carry. We assume that the volatility of the convenience yield does not change with the time to maturity of the contract. In other words, the convenience yield volatility only varies across contracts but stays constant for a given contract. Under this condition, the volatility of the nearest convenience yield at time $t+1$, $\sigma_{t+1}(y^{(1,2)})$, is equal to the volatility of the second nearest convenience yield at time t, $\sigma_t(y^{(2,3)})$, because $y_{t+1}^{(1,2)}$ and $y_t^{(2,3)}$ belong to the same pair of underlying futures contracts.[5]

More formally, we can define the difference as excess volatility, $\xi_{t,t+1}$, i.e.,

$$\xi_{t,t+1}(y^{(1,2)}) := \sigma_{t+1}(y^{(1,2)}) - \sigma_t(y^{(2,3)}), \tag{4.11}$$

and express convenience yield risk in the following way:

$$\begin{aligned}
\mathrm{CYR}_t = \quad & \frac{1}{12}\sum_{i=1}^{12} \sigma_{t-i}(y^{(1,2)}) - \sigma_{t-i}(y^{(2,3)}) \\
= \quad & \frac{1}{12}\sum_{i=1}^{11} \sigma_{t-i}(y^{(1,2)}) - \sigma_{t-i-1}(y^{(2,3)}) \quad + \quad \frac{1}{12}\left[\sigma_{t-12}(y^{(1,2)}) - \sigma_{t-1}(y^{(2,3)})\right] \\
\overset{(4.11)}{=} \quad & \frac{1}{12}\sum_{i=1}^{11} \xi_{t-i-1,t-i}(y^{(1,2)}) \quad - \quad \frac{1}{12}\left[\sigma_{t-1}(y^{(2,3)}) - \sigma_{t-12}(y^{(1,2)})\right] \\
\overset{(4.11)}{=} \quad & \underbrace{\frac{1}{12}\sum_{i=1}^{12} \xi_{t-i-1,t-i}(y^{(1,2)})}_{\textbf{Average Excess Volatility}} \quad - \quad \frac{1}{12}\underbrace{\left[\sigma_{t-1}(y^{(2,3)}) - \sigma_{t-13}(y^{(2,3)})\right]}_{\textbf{Annual Change in Volatility}}.
\end{aligned}$$

[5] In fact, this holds true only if the underlying commodity contracts have monthly expiry schedules. If the schedule is bimonthly or quarterly, an adjustment explained in Appendix C is necessary.

Hence, if the volatility of the convenience yield did not change with the time to maturity of the contract, i.e., $\xi_{t-i-1,t-i} = 0$ for all i, CYR would only be driven by the variations of the annual change in the volatility of the second nearest convenience yield.

We can abbreviate the above decomposition and write:

$$\text{Average Excess Volatility} = \text{CYR} + \tfrac{1}{12}\Delta_{t-13,t-1}\sigma\left(y^{(2,3)}\right), \tag{4.12}$$

where $\Delta_{t-13,t-1}\sigma(y^{(2,3)})$ is the annual change in the volatility of the second nearby convenience yield.

Table 4.6 reports the results of the decomposition of the average excess volatility for each commodity market. The comparison shows that almost all of the variation in the average excess volatility is attributed to convenience yield risk. On the contrary, the annual change in the volatility of the second nearest convenience yield contributes only little to the average excess volatility (rough rice and platinum are the only exceptions). The correlation between the average excess volatility and convenience yield risk, as well as between average excess volatility and the annual change in the volatility of the second nearest convenience yield, reported in the last two columns of Table 4.6, documents the strong relationship between average excess volatility and CYR (average correlation of 0.94), while average excess volatility and annual change in the volatility of the second nearest convenience yield are comoving much less (average correation of 0.29).[6]

The above decomposition emphasizes the importance of the term structure dimension of the convenience yield. While the excess volatility is measured from two convenience yields of different maturities, the annual change in volatility is measured using the convenience yield of contracts with fixed maturities , i.e., the second and third nearby futures. Therefore, the decomposition shows that the term structure variation of convenience yields is the driving force of convenience yield risk.

[6] Figure C.1 in Appendix C depicts the close relationship graphically.

Table 4.6: Decomposition of Convenience Yield Risk

This table reports the decomposition of the average excess volatility into the convenience yield risk (CYR) and the annual change in the volatility of the second convenience yield ($\Delta\sigma(y^{(2,3)})$) as presented in Equation (4.12). The first and second columns report the decomposition of the mean and add up to 100%. The third and fourth columns show the proportion of the standard deviation from the standard deviation of the average excess volatility. The fifth (sixth) column reports the correlation between average excess volatility and CYR (the annual change of volatility in the second convenience yield).

Commodity	Mean		Std. Dev.		Correlation	
	CYR	$\Delta\sigma(y^{(2,3)})$	CYR	$\Delta\sigma(y^{(2,3)})$	CYR	$\Delta\sigma(y^{(2,3)})$
WTI Crude	100.0%	0.0%	98.8%	21.0%	0.98	0.16
Heating Oil	101.1%	-1.1%	95.5%	24.0%	0.97	0.30
Natural Gas	100.2%	-0.2%	98.2%	36.6%	0.93	0.23
Gasoil	102.2%	-2.2%	95.3%	40.8%	0.91	0.32
Gasoline	100.4%	-0.4%	94.3%	31.9%	0.95	0.33
Corn	100.2%	-0.2%	97.9%	19.8%	0.98	0.21
Oats	99.3%	0.7%	89.7%	28.5%	0.96	0.49
Rough Rice	92.5%	7.5%	97.0%	34.4%	0.94	0.26
Chicago Wheat	100.0%	-0.0%	96.9%	26.1%	0.97	0.25
Feeder Cattle	102.0%	-2.0%	92.7%	36.4%	0.93	0.38
Live Cattle	100.1%	-0.1%	95.2%	22.7%	0.97	0.32
Lean Hogs	99.4%	0.6%	92.4%	33.8%	0.94	0.39
Copper	103.3%	-3.3%	103.9%	17.8%	0.99	-0.13
Gold	96.3%	3.7%	72.1%	66.5%	0.75	0.69
Palladium	102.2%	-2.2%	99.7%	15.2%	0.99	0.10
Platinum	132.4%	-32.4%	93.5%	28.9%	0.96	0.36
Silver	96.5%	3.5%	85.9%	50.6%	0.86	0.51
Soybean Oil	103.3%	-3.3%	105.5%	38.2%	0.93	0.04
Canola	96.1%	3.9%	94.7%	21.3%	0.98	0.35
Soybeans	99.6%	0.4%	102.6%	52.1%	0.87	0.21
Soybean Meal	100.2%	-0.2%	101.0%	32.3%	0.95	0.13
Cotton	99.5%	0.5%	96.8%	32.9%	0.94	0.26
Lumber	99.9%	0.1%	97.9%	24.7%	0.97	0.21
Cocoa	100.2%	-0.2%	94.8%	23.4%	0.97	0.34
Orange Juice	100.6%	-0.6%	93.3%	35.1%	0.94	0.36
Coffee	100.7%	-0.7%	94.6%	14.6%	0.99	0.43
Sugar	100.4%	-0.4%	93.9%	24.4%	0.97	0.36

4.4.2 The Samuelson Effect

The Samuelson (1965) effect describes the empirical observation that the volatility of a commodity futures contract increases as it approaches expiration. At the heart of our convenience yield risk measure is the differential between the volatilities of two convenience yields with different pairs of maturities. Therefore, it is an interesting question how these two concepts relate to each other.

Before we analyze the relationship between convenience yield risk and the Samuelson effect, let us make three assumptions. First, since the risk-free rate does not vary theoretically and the variance of interest rates is much smaller than the variance of the basis, we assume

$$\sigma^2(\mathrm{rf}) \approx 0. \tag{4.13}$$

Second, although there are agricultural markets with large gaps in the expiry schedule, most commodities expiry schedules are evenly distributed, i.e., we assume

$$M^{(2)} - M^{(1)} \approx M^{(3)} - M^{(2)}. \tag{4.14}$$

Third, as the work of Schneider and Tavin (2018) has shown, pairs of neighboring futures prices have equal covariances, i.e., we assume

$$\mathrm{Cov}(f^{(1)}, f^{(2)}) \approx \mathrm{Cov}(f^{(2)}, f^{(3)}). \tag{4.15}$$

If we now consider the variances of convenience yields, we can write

$$\begin{aligned}
\sigma^2(y^{(1,2)}) - \sigma^2(y^{(2,3)}) &= \sigma^2(b^{(1,2)} + \mathrm{rf}^{(1,2)}) - \sigma^2(b^{(2,3)} + \mathrm{rf}^{(2,3)}) \\
&\overset{(4.13)}{=} \left[\tfrac{365}{M^{(2)}-M^{(1)}}\right]^2 \sigma^2(f^{(1)} - f^{(2)}) - \left[\tfrac{365}{M^{(3)}-M^{(2)}}\right]^2 \sigma^2(f^{(2)} - f^{(3)}) \\
&\overset{(4.14)}{=} C^2 \cdot \left[\sigma^2(f^{(1)}) - \sigma^2(f^{(3)}) + 2\left(\mathrm{Cov}(f^{(1)}, f^{(2)}) - \mathrm{Cov}(f^{(2)}, f^{(3)})\right)\right] \\
&\overset{(4.15)}{=} C^2 \cdot \left[\sigma^2(f^{(1)}) - \sigma^2(f^{(3)})\right],
\end{aligned} \tag{4.16}$$

where $C := \frac{365}{M^{(2)}-M^{(1)}} = \frac{365}{M^{(3)}-M^{(2)}}$ is a constant. Thus, we show that the spread in the variance of convenience yields, which is the main driver of convenience yield risk, is linearly related to the spread between the variances of the first and third futures contract, which can be interpreted as a measure for the strength of the Samuelson effect. In other words, markets that evidence a stronger Samuelson effect, experience higher magnitudes of convenience yield risk. This theoretical result is confirmed when comparing our results with the literature on the Samuelson effect (Bessembinder et al., 1996; Duong and Kalev, 2008).

4.4.3 Convenience Yield Risk and Convenience Yield

A natural question is how convenience yield risk is related to the convenience yield. Regressing the time series average of our measure on the time series average of convenience yield for each commodity yields an R^2 of 44%. This relationship is depicted in Figure 4.1 and shows that higher convenience yield is related to higher CYR. Figure 4.2 depicts the five-year rolling correlation average across all 27 commodities and the 95% confidence bands (dotted lines). The correlation stays close to zero over the whole sample. We see that the correlation exhibits some time variation but for most of the time it is quite low.

The question remains how we can reconcile these two observations. One explanation could be the positive skew of commodity returns due to more positive price shocks that are rather short-lived, e.g., weather conditions. Therefore, commodities that exhibit higher convenience yield risk are more often backwardated, i.e., have positive convenience yields. On the other hand, while positive and negative price shocks at the front end of the commodity futures curve have opposite effects on the convenience yield, both will increase convenience yield risk due to increasing volatility of the convenience yield. [7]

[7] This is also illustrated in Figure C.2 of Appendix C which shows that the relative frequency with which commodities are in the 'High' basis or 'High' CYR portfolio is quite different. In a robustness check in Table C.15 of Appendix C, we also document that the part of convenience yield risk that is orthogonal to basis still has predictive power for commodity futures returns.

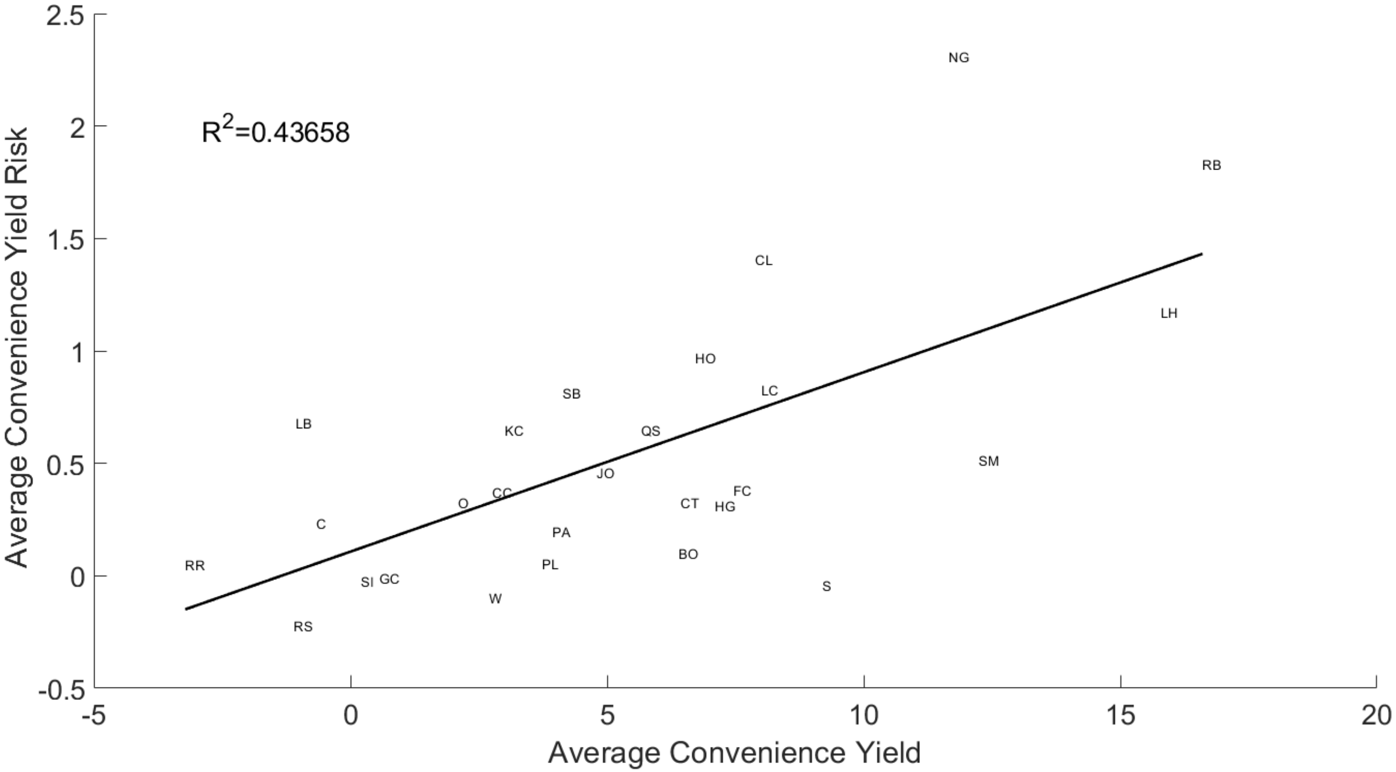


Figure 4.1: Average Convenience Yield Risk vs. Average Convenience Yield

This figure plots the time series averages of the first convenience yield against the time series averages of convenience yield risk (CYR) *for 27 commodity markets over the period from July 1959 to December 2018. The commodities are marked with their Bloomberg ticker (see Table C.1). The black line corresponds to a cross-sectional linear regression of the time series averages of convenience yield risk on the time series average of the convenience yield.*

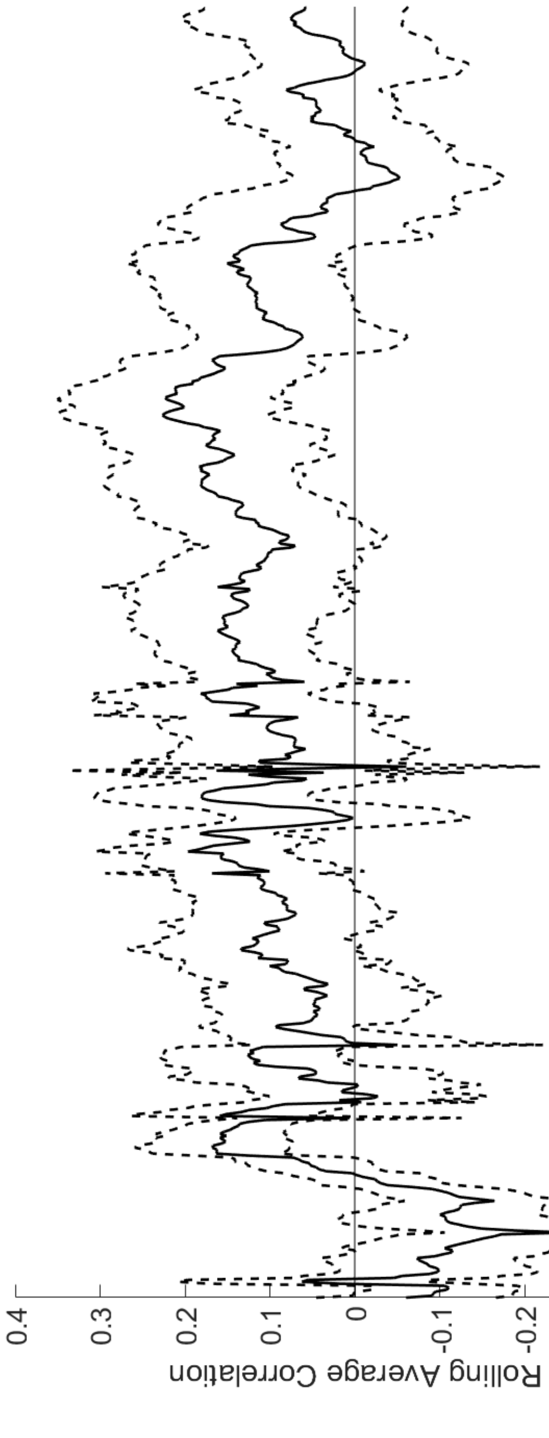


Figure 4.2: Rolling Correlation Between Convenience Yield and Convenience Yield Risk

This figure shows the average 5-year rolling correlations between the convenience yield and the convenience yield risk. The sample consists of 27 commodity markets covering the period from July 1959 to December 2018. The dotted lines are the 95% confidence bands.

4.4.4 Relationship to Financial Variables

We next investigate whether the returns of the long-short CYR portfolio can be explained by variables related to financial liquidity, credit risk, and financial market stress. We regress the return of the 'High-Low' CYR portfolio on the term spread, i.e., the difference between the yield on the 10-year U.S. Treasury bond and the 3-month U.S. Treasury bill, and the return on the S&P500. Furthermore, we use the past 30-day realized volatility of the S&P500 as a proxy for realized volatility, the VIX option-implied volatility which is often used as a proxy for general equity market stress, the TED spread, i.e., the difference between the 3-month LIBOR and the 3-month U.S. Treasury bill rate, as a proxy for funding liquidity, and the default spread defined as the difference between the Moody's Aaa and Baa corporate bond yields, as a measure of credit risk. The results of the above regressions are summarized in Table C.11 of Appendix C. Most variables do not have a significant effect on the CYR portfolio return in univariate regression, therefore we focus on the multivariate regression in column (6). Interestingly, although interest rates enter the convenience yield directly, we find the term spread to be insignificant. We find stock market variables, i.e., stock return, realized, and implied volatility to have a negative effect on CYR portfolio returns. In the general context, correlations between equity and commodity returns were found to be low to negative (Gorton and Rouwenhorst, 2006; Bhardwaj et al., 2015), however Christoffersen et al. (2019) find a common factor in commodity volatility related to stock market volatility. While funding liquidity does not influence the CYR return, we find a significantly negative relationship with credit risk, i.e., higher credit risk leads to lower returns on the portfolio sorted by CYR.

Overall, none of the above variables are able to fully explain the excess return on the sorted convenience yield risk portfolios as the intercept stays significant in any variation of variables.

4.5 Robustness Checks

In this section, we conduct several checks to establish the robustness of our findings. We first investigate the impact of alternative definitions of the convenience yield risk. We then analyze the returns of the long-short CYR portfolio over various formation and holding periods. Finally, we explore the returns of an alternative long-short portfolio which sorts commodities by the convenience yield risk orthogonalized with respect to the basis.

4.5.1 Signal and Portfolio Construction

We begin by employing alternative definitions of convenience yield risk. We first address the fact that expiration schedules differ across commodity markets, i.e., the second nearby contract may be expiring a month after the first nearby contract, e.g., in energy markets, or up to three months after the first nearby contract, e.g., in agricultural markets.

To make our convenience yield measure more comparable across commodity futures with different maturities we define four alternative CYR measures. In the first one, we choose the nearbys contracts for each market, such that the average difference between the first and the chosen nearby contract is as close as possible to 90 days (Fixed90Days). In the second one, we use an average over the next five available convenience yields (Next5Average).[8] In the third one, we use all convenience yields, for which the front contract has on average less than one year to expiry (Max1Year). Lastly, we control for liquidity by taking an average over all convenience yields, $y^{(i,i+1)}$, for which the i^{th} nearby contract exhibits at least 10% of the trading volume of the first nearby contract

[8] The choice to use the next 5 convenience yields is maximal in the sense that all markets provide at least 6 nearby convenience yields.

(Min10Volume). The formal definitions are as follows:

$$\textbf{Fixed90Days:} \quad \frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \sigma_{t-i}(y^{(j^*,j^*+1)})\right], \qquad \text{s.t. } j^* = \underset{j>1}{\arg\min}\,|(\bar{M}^{(j)} - \bar{M}^{(1)}) - 90|, \tag{4.17}$$

$$\textbf{Next5Average:} \quad \frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \frac{1}{5}\sum_{j=2}^{6}\sigma_{t-i}(y^{(j,j+1)})\right], \tag{4.18}$$

$$\textbf{Max1Year:} \quad \frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \frac{1}{\#N_{365}}\sum_{j\in N_{365}}\sigma_{t-i}(y^{(j,j+1)})\right], \qquad \text{s.t. } N_{365} = \{i > 1 : \bar{M}^{(i)} < 365\} \tag{4.19}$$

$$\textbf{Min10Volume:} \quad \frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \frac{1}{\#N_V}\sum_{j\in N_V}\sigma_{t-i}(y^{(j,j+1)})\right], \qquad \text{s.t. } N_V = \{j > 1 : \bar{V}^{(j)} > 0.1\bar{V}^{(1)}\} \tag{4.20}$$

where $\sigma_t(y^{(j,j+1)})$ is the monthly volatility of the j^{th} convenience yield, $\bar{M}^{(j)}$ is the average time to maturity in days of the j^{th} nearby, and $\bar{V^{(j)}}$ is the average trading volume of the j^{th} nearby.

One may also wonder about whether the portfolio returns are affected by the specific sorting procedure followed to create long-short portfolios and by the equal weighting of the commodities in these portfolios. To this end, we analyze the portfolio returns for our core CYR measure of Equation (4.3) and the four alternative measures above under alternative considerations. In particular, we create the long-short CYR portfolio by sorting the commodities by a specific CYR measure and then take the spread in the returns of the top and bottom terciles. As an additional check, we employ a rank-based weighting instead of an equal weighting scheme for the commodities. Lastly, we lag the CYR signal by one month and repeat the analysis. The results presented in Table C.12 of Appendix C show that the results are robust to these considerations. Table C.13 of Appendix C documents that the return of the CYR spread portfolio remains economically and statistically significant when we use the 21 commodities of Szymanowska et al. (2014), only cover the period from 1990-2018, or when we omit one of the six sectors.

4.5.2 Formation and Holding Period

Our measure is effectively an average of the volatility differentials over 12 months, that is rebalanced every month. Thus, it is interesting to see how the returns on the portfolios sorted on CYR behave across various formation and holding periods.

We report returns for formation and holding periods of 1, 6, and 12 months in Table C.14 of Appendix C. Three main conclusions can be derived from these results. First, changing the formation and holding period is affecting spread returns (Panel B) more than nearby returns (Panel A). Second, nearby returns, and less so spread returns, are robust against altering either the formation or holding period. Third, when the formation period is reduced to 1 month and the holding period is extended to 12 months, we find negative returns indicating a weak reversal effect.

4.5.3 Convenience Yield Risk Orthogonal to the Basis

To robustify the argument that the returns on CYR are different from the returns on the basis, we remove the influence of the basis on CYR. We run time series regressions of CYR on the basis for each commodity and only use the convenience yield risk that is orthogonal to basis as an alternative measure, i.e.,

$$\mathrm{CYR}_k = \alpha_k + \beta_k \mathrm{BAS}_k + \epsilon_k, \tag{4.21}$$

$$\mathrm{CYR}_k^{\top} = \mathrm{CYR}_k - \beta_k \mathrm{BAS}_k \tag{4.22}$$

where $\mathrm{CYR}_k^{\top}$ is the convenience yield risk of commodity k orthogonal to the basis, i.e., the residual from the regression in Equation (4.21), BAS_k, α_k is the intercept, β_k is the slope, and ϵ_k is the error term for commodity market k.

If our measure only captures information that is already contained in the basis, the return on long-short portfolios with respect to $\mathrm{CYR}^{\top}$ should not provide significant excess return. The results in Table C.15 of Appendix C confirm slightly smaller, but still significant excess returns for all alternative signals that are orthogonal to the basis.

4.6 Conclusion

We conclude that convenience yield risk (CYR) is a robust predictor of commodity returns. Its predictive power for commodity futures returns reaches beyond known commodity predictors and does not originate from the cross-sectional or time series variation in the returns themselves. CYR is mainly driven by the excess volatility of the short-term slope over the long-term slope of the term structure of commodities, and therefore influenced by the strength of the Samuelson effect. On average, convenience yield risk is high for commodities with high convenience yield, but is uncorrelated at higher frequencies. Linking CYR to global financial characteristics, does provide plausible channels, but cannot serve as a comprehensive explanation for its predictive power.

C Appendix

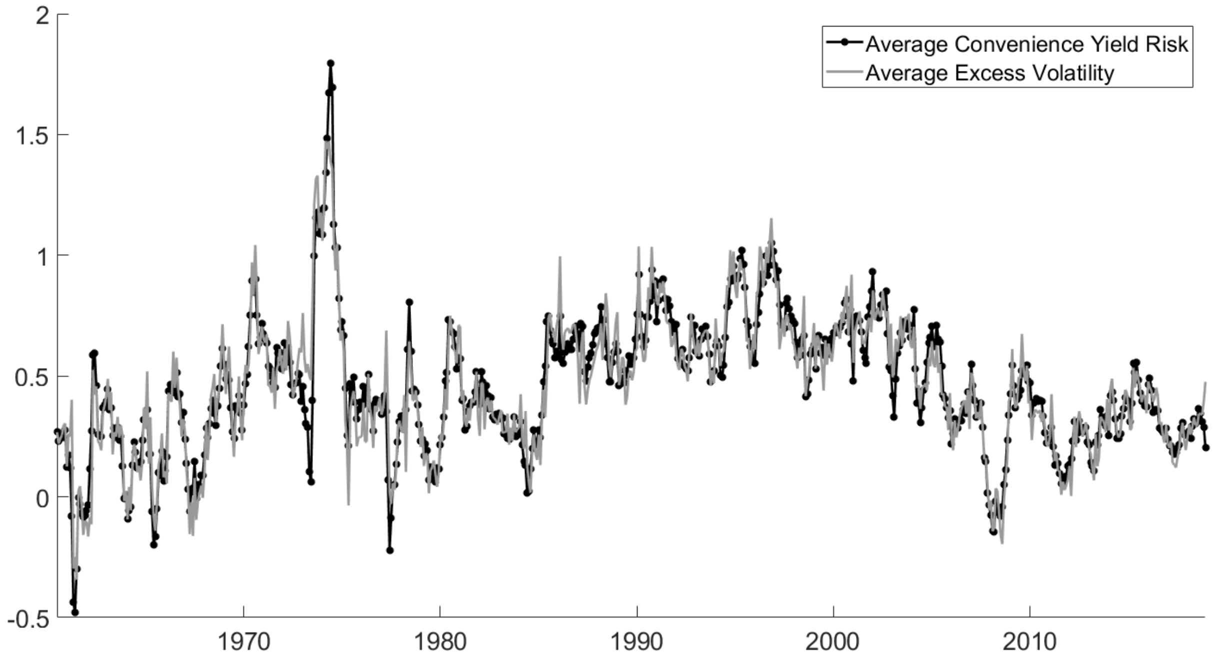


Figure C.1: Average Convenience Yield Risk and Average Excess Volatility

This figure shows the time series of cross-sectional average convenience yield risk and cross-sectional average excess volatility for the 27 commodity markets under consideration. The sample period ranges from July 1959 to December 2018. The average excess volatility for a single commodity is the sum of convenience yield risk and the annual change in the volatility of the second nearest convenience yield as defined in Equation (4.12).

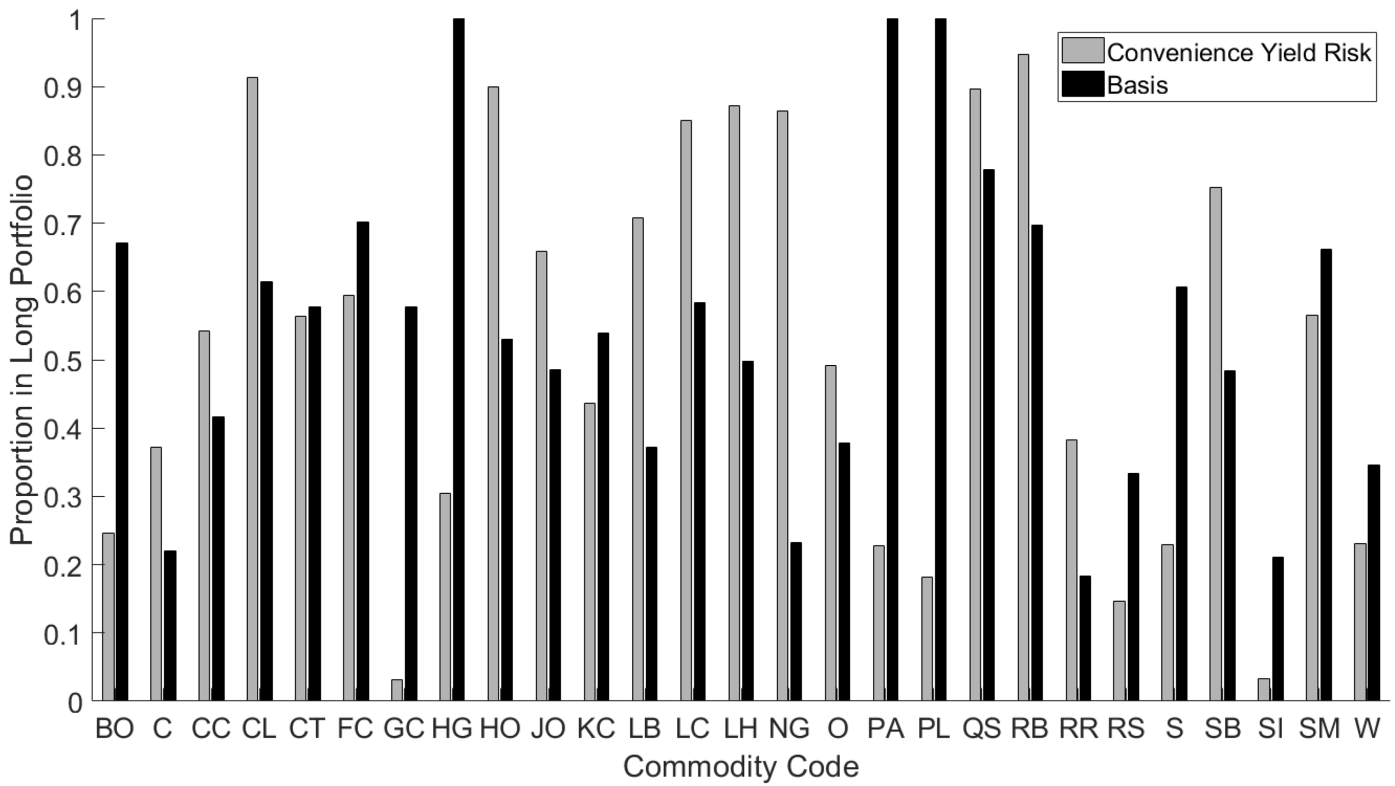


Figure C.2: Relative Frequency of Commodity in 'High' Portfolio

This figure shows the percentage of months a particular commodity is included in the 'High' convenience yield risk portfolio (grey bars) and 'High' basis portfolio (black bars). The commodities are sorted either on the convenience yield risk (basis) to form two portfolios, a 'High' portfolio including those commodities with the highest convenience yield risk (basis) and a 'Low' portfolios including the commodities with the lowest convenience yield risk (basis). The remaining percentage on the plot corresponds to the 'Low' portfolio. The different commodity markets are indicated by their Bloomberg ticker, see Table C.1 in Appendix C.

Table C.1: Bloomberg Commodity Futures Data

This table lists the commodity futures price series obtained from Bloomberg. The second column lists the Bloomberg ticker, the third column the commodity sector. The fourth column reports the exchange on which the contracts is traded using abbreviations for the Intercontinental Exchange (ICE), the New York Mercantile Exchange (NYMEX), the Commodity Exchange (COMEX), the Chicago Board of Trade (CBOT), and the Chicago Mercantile Exchange (CME). The fifth column reports the expiry month and the sixth column reports the size of one contract.

Commodity	Ticker	Sector	Exchange	Expiry Month	Contract Size
WTI Crude Oil	CL	Energy	NYMEX	Jan-Dec	1,000 Barrels
Heating Oil	HO	Energy	NYMEX	Jan-Dec	42,000 Gallons
Natural Gas	NG	Energy	NYMEX	Jan-Dec	10,000 Million Btu
Gasoil	QS	Energy	NYMEX	Jan-Dec	100 Tonnes
Gasoline	HU/XB	Energy	NYMEX	Jan-Dec	42,000 Gallons
Corn	C	Grains	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
Oats	O	Grains	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
Rough Rice	RR	Grains	CBOT	Jan,Mar,May,Jul,Sep,Nov	2,000 Hundredweights
Wheat (Chicago)	W	Grains	CBOT	Mar,May,Jul,Sep,Dec	5,000 Bushels
Copper	HG	Metals	COMEX	Mar,May,Jul,Sep,Dec	25,000 Pounds
Gold	GC	Metals	COMEX	Feb,Apr,Jun,Aug,Oct,Dec	100 Troy Ounces
Palladium	PA	Metals	NYMEX	Mar,Jun,Sep,Dec	100 Troy Ounces
Platinum	PL	Metals	NYMEX	Jan, Apr, Jul, Oct	50 Troy Ounces
Silver	SI	Metals	COMEX	Mar,May,Jul,Sep,Dec	5,000 Troy Ounces
Feeder Cattle	FC	Livestock	CME	Jan,Mar,Apr,May,Aug,Sep,Oct,Nov	50,000 Pounds
Lean Hogs	LH	Livestock	CME	Feb,Apr,May,Jun,Jul,Aug,Oct,Dec	40,000 Pounds
Live Cattle	LC	Livestock	CME	Feb,Apr,Jun,Aug,Oct,Dec	40,000 Pounds
Canola	RS	Oilseeds	ICE	Jan,Mar,May,Jul,Nov	20 Metric Tonnes
Soybeans	S	Oilseeds	CBOT	Jan,Mar,May,Jul,Aug,Sep,Nov	5,000 Bushels
Soybean Meal	SM	Oilseeds	CBOT	Jan,Mar,May,Jul,Aug,Sep,Oct,Dec	100 Short Tons
Soybean Oil	BO	Oilseeds	CBOT	Jan,Mar,May,Jul,Aug,Sep,Oct,Dec	60,000 Pounds
Cotton	CT	Softs	ICE	Mar,May,Jul,Oct,Dec	50,000 Pounds
Lumber	LB	Softs	CME	Jan,Mar,May,Jul,Sep,Nov	110,000 Feet
Cocoa	CC	Softs	ICE	Mar,May,Jul,Sep,Dec	10 Metric Tonnes
Coffee	KC	Softs	ICE	Mar,May,Jul,Sep,Dec	37,500 Pounds
Orange Juice	JO	Softs	ICE	Jan,Mar,May,Jul,Sep,Nov	15,000 Pounds
Sugar	SB	Softs	ICE	Mar,May,Jul,Oct	112,000 Pounds

Table C.2: Summary Statistics for First Nearby Returns

This table reports summary statistics for the first nearby futures return series for 27 commodities covering 6 sectors, Energy, Grains, Livestock, Metals, Oilseeds, and Softs, each one separated by a horizontal line. We report mean, standard deviation (Std. Dev.), first order autocorrelation (AR(1)), skewness (Skew), kurtosis (Kurt), and the number of observations (Obs). Mean and standard deviations are annualized and in percentage points. The sample period ranges from July 1959 to December 2018.

Commodity	Mean	Std. Dev.	AR(1)	Skew	Kurt	Obs
WTI Crude	6.87	32.62	0.19	0.34	5.61	430
Heating Oil	8.93	30.81	0.11	0.42	4.45	390
Natural Gas	-7.78	47.83	0.08	0.59	4.45	345
Gasoil	9.43	30.60	0.19	0.29	4.89	354
Gasoline	14.26	32.10	0.16	0.40	5.52	385
Corn	-2.13	23.68	0.00	1.20	9.71	714
Oats	-0.43	29.01	-0.03	2.22	23.22	712
Rough Rice	-7.25	25.33	0.01	0.94	7.93	360
Chicago Wheat	-1.61	25.13	0.05	0.78	6.84	714
Feeder Cattle	3.35	16.49	-0.02	-0.37	5.32	565
Live Cattle	4.71	16.17	-0.01	-0.19	5.17	649
Lean Hogs	-2.97	23.64	-0.04	-0.18	3.42	393
Copper	7.42	24.96	0.07	-0.00	5.66	361
Gold	1.25	18.97	-0.00	0.49	6.35	528
Palladium	12.12	31.24	-0.01	0.37	6.41	393
Platinum	4.12	21.68	0.01	-0.02	6.77	393
Silver	2.34	31.59	0.05	0.58	8.65	528
Soybean Oil	5.40	28.38	-0.03	1.25	9.20	714
Canola	-0.78	19.52	-0.00	0.02	5.47	444
Soybeans	5.18	25.47	0.03	1.45	13.21	712
Soybean Meal	9.34	28.97	0.05	1.96	18.37	714
Cotton	2.12	23.46	0.06	0.62	6.17	712
Lumber	-5.35	27.22	0.06	0.11	3.49	393
Cocoa	3.03	30.44	0.00	0.65	4.30	712
Orange Juice	4.92	32.45	-0.04	1.59	11.18	623
Coffee	4.29	36.41	-0.01	1.21	6.71	557
Sugar	4.76	41.66	0.17	1.17	6.65	696

Table C.3: Volatility of Convenience Yield along the Term Structure

This table reports the volatility of the first to sixth convenience yield, $y^{(1,2)}, \ldots, y^{(6,7)}$, *for 27 commodities covering 6 sectors: Energy, Grains, Livestock, Metals, Oilseeds, and Softs, each one separated by a horizontal line. The sample period spans from July 1959 to December 2018. Nearby series with more than 50% missing values are left blank.*

Commodity	$\sigma(y^{(1,2)})$	$\sigma(y^{(2,3)})$	$\sigma(y^{(3,4)})$	$\sigma(y^{(4,5)})$	$\sigma(y^{(5,6)})$	$\sigma(y^{(6,7)})$
WTI Crude	4.17	2.47	1.80	1.55	1.32	1.13
Heating Oil	3.98	2.70	2.05	1.64	1.43	1.19
Natural Gas	12.01	10.29	9.94	4.99	5.62	3.53
Gasoil	3.04	2.43	2.05	2.44	3.02	3.15
Gasoline	4.80	3.12	2.27	2.18	1.76	1.50
Corn	2.16	1.21	1.20	1.70	2.48	2.27
Oats	3.23	3.09	5.60	6.44	4.41	4.88
Rough Rice	3.21	3.08	3.13	4.94		
Chicago Wheat	1.80	2.39	2.38	2.16	3.07	2.98
Feeder Cattle	1.84	1.51	1.49	1.14	1.59	2.73
Live Cattle	1.60	1.08	0.89	0.85	1.05	1.19
Lean Hogs	4.46	3.38	3.29	2.93	6.40	6.60
Copper	1.14	0.79	0.69	0.67	0.58	0.57
Gold	0.11	0.09	0.10	0.10	0.12	0.14
Palladium	1.14	0.61	0.56			
Platinum	0.69	0.67	0.62			
Silver	0.29	0.31	0.20	0.17	0.18	0.22
Soybean Oil	1.87	1.74	1.21	1.45	1.45	1.57
Canola	1.00	0.83	0.99	1.30	1.63	1.43
Soybeans	2.53	2.27	2.21	1.75	1.80	4.08
Soybean Meal	4.24	2.75	3.13	2.61	2.39	2.23
Cotton	2.31	1.87	1.68	2.14	1.72	1.50
Lumber	3.20	2.44	5.99	4.10	6.65	
Cocoa	0.91	0.66	0.54	0.52	0.46	0.54
Orange Juice	1.97	1.48	1.14	1.36	1.66	1.49
Coffee	2.65	1.39	1.00	1.15	1.40	1.69
Sugar	2.22	1.76	1.27	1.06	1.24	

Table C.4: Summary Statistics for Convenience Yield Risk

This table reports summary statistics on convenience yield risk for 27 commodities covering 6 sectors, Energy, Grains, Livestock, Metals, Oilseeds, and Softs, each one separated by a horizontal line. Convenience yield risk is measured according to Equation (4.3). *We report for each commodity the mean, standard deviation (Std. Dev.), first order autocorrelation coefficient (AR(1)), skewness (Skew), kurtosis (Kurt) and number of observations (Obs.). The sample period from July 1959 to December 2018.*

Commodity	Mean	Std. Dev.	AR(1)	Skew	Kurt	Obs.
WTI Crude	1.41	1.29	0.97	1.72	6.40	430
Heating Oil	0.97	0.97	0.94	1.65	6.16	390
Natural Gas	2.31	2.43	0.88	0.47	3.42	345
Gasoil	0.65	0.61	0.81	-1.08	17.24	354
Gasoline	1.83	1.16	0.91	0.80	4.52	385
Corn	0.23	0.58	0.95	1.84	7.41	703
Oats	0.35	0.80	0.93	0.37	4.22	703
Rough Rice	0.06	0.84	0.90	0.54	5.58	361
Chicago Wheat	-0.09	0.75	0.96	-2.61	17.23	703
Feeder Cattle	0.38	0.54	0.85	-0.23	4.09	565
Live Cattle	0.83	0.68	0.95	0.25	3.17	649
Lean Hogs	1.17	0.95	0.90	0.86	3.94	391
Copper	0.32	0.56	0.95	2.62	10.19	361
Gold	-0.01	0.19	0.85	-0.80	15.44	528
Palladium	0.21	0.55	0.97	3.13	15.51	375
Platinum	0.07	0.29	0.93	0.84	6.04	392
Silver	-0.01	0.14	0.89	-2.55	19.27	528
Soybean Oil	0.09	0.73	0.94	1.90	13.29	703
Canola	-0.22	0.54	0.94	-1.74	8.12	441
Soybeans	-0.05	0.61	0.84	0.18	9.04	703
Soybean Meal	0.53	1.32	0.94	1.49	10.20	703
Cotton	0.34	0.76	0.94	-0.99	9.19	703
Lumber	0.69	0.96	0.95	0.26	3.74	389
Cocoa	0.38	0.51	0.95	1.63	6.83	703
Orange Juice	0.46	0.52	0.89	0.70	3.97	623
Coffee	0.65	1.07	0.96	1.97	6.87	557
Sugar	0.81	0.85	0.93	1.52	7.72	694

Table C.5: Summary Statistics for Commodity Factor Returns

This table reports summary statistics on the factor returns for an equally-weighted market portfolio, as well as for long-short portfolios created by sorting the 27 commodities on the basis, momentum, basis-momentum, and idiosyncratic volatility. the sample period ranges from July 1959 to December 2018. We report the mean, standard deviation (Std. Dev.), Sharpe ratio (SR), skewness (Skew), and kurtosis (Kurt). The mean and standard deviations are annualized and reported in percentage points.

Commodity	Mean	Std. Dev.	SR	Skew	Kurt
Market	3.93	13.28	0.30	0.61	8.25
Carry	7.20	14.20	0.51	-0.04	4.27
Momentum	9.89	15.57	0.64	0.14	4.70
Basis-Momentum	14.74	14.61	1.01	0.25	6.29
Idiosyncratic Volatility	2.93	15.38	0.19	0.38	5.16

Table C.6: Spanning Regressions for First Nearby Returns

This table reports the results from the spanning regressions of Equation (4.4). *We regress the return of the long-short convenience yield risk portfolio on the return of an equally-weighted commodity market portfolio, the return of the portfolios sorted by the basis (BAS), momentum (MOM), basis-momentum (BASMOM), and idiosyncratic volatility (IVOL). The sample includes 27 commodities over the period from July 1959 to December 2018. Returns are annualized and expressed in percentage points. t-statistics using Newey and West (1987) standard errors (with two lags) are reported in parentheses below the estimated coefficients.*

Variable	(1)	(2)	(3)	(4)	(5)	(6)
α	7.31	7.20	6.74	5.83	7.07	5.20
	(3.78)	(3.47)	(3.37)	(2.87)	(3.63)	(2.70)
MRKT	0.07					-0.05
	(0.73)					(-0.37)
BAS		0.05				-0.00
		(0.89)				(-0.03)
MOM			0.08			0.02
			(1.58)			(0.37)
BASMOM				0.12		0.12
				(2.35)		(2.10)
IVOL					0.17	0.18
					(2.97)	(2.44)
R^2	0.00	0.00	0.01	0.01	0.03	0.05
Obs	713	713	713	713	714	713

Table C.7: Spanning Regressions for Spread Returns

This table reports the results from the spanning regressions of Equation (4.4)*. We regress the spreading return of the long-short convenience yield risk portfolio on the spreading return of an equally-weighted commodity market portfolio, the spreading return of the portfolios sorted by the basis (BAS), momentum (MOM), basis-momentum (BASMOM), and idiosyncratic volatility (IVOL). The sample includes 27 commodities over the period from July 1959 to December 2018. Returns are annualized and expressed in percentage points. t-statistics using Newey and West (1987) standard errors (with two lags) are reported in parentheses below the estimated coefficients.*

Variable	(1)	(2)	(3)	(4)	(5)	(6)
α	1.09	0.86	0.87	0.75	0.87	0.91
	(3.01)	(2.24)	(2.29)	(1.90)	(2.29)	(2.48)
MRKT	0.37					0.40
	(2.91)					(3.79)
BAS		0.03				-0.05
		(0.41)				(-0.87)
MOM			-0.01			-0.10
			(-0.13)			(-1.65)
BASMOM				0.05		0.10
				(0.72)		(1.60)
IVOL					0.11	0.04
					(1.54)	(0.71)
R^2	0.04	0.00	0.00	0.00	0.01	0.06
Obs	713	713	713	713	714	713

Table C.8: Independent Double Portfolio Sorts

This table presents average monthly returns for portfolios formed from independent sorts by convenience yield risk and basis, momentum, basis-momentum, idiosyncratic volatility, hedging pressure, or speculative pressure. Hedging (Speculative) pressure is computed as the fraction of long minus short positions over the total open interest of commercial (non-commercial) traders from the Commitment of Traders report. The groups are formed from the intersection of the two convenience yield risk groups and the two groups of each control variable based on the median rank. The 'High' ('Low') portfolio includes the commodities above (below) the median. The 'High–Low' portfolio corresponds to the long-short zero cost portfolio that buys the commodities in the top group and sells those in the bottom group. The left panel reports the returns on the single sorts with respect to each signal. The sample covers 27 commodities for the period from July 1959 to December 2018. Returns are annualized and in percentage points. t-statistics based on Newey and West (1987) standard errors with two lags are reported in parentheses.

Signal		Single Sort	Double Sort on Signal and CYR		
			High	Low	High–Low
Basis	High	7.60 (3.77)	11.32 (4.62)	3.95 (1.53)	7.30 (2.60)
	Low	0.41 (0.21)	4.14 (1.45)	-2.05 (-0.93)	6.37 (2.18)
	High–Low	7.19 (3.91)	7.11 (2.32)	6.04 (2.46)	
Momentum	High	8.94 (4.09)	13.17 (5.09)	3.86 (1.41)	9.63 (3.31)
	Low	-0.93 (-0.51)	0.66 (0.25)	-2.63 (-1.28)	3.26 (1.15)
	High–Low	9.87 (4.90)	12.09 (3.80)	6.14 (2.34)	
Basis-Momentum	High	11.25 (5.43)	14.41 (5.72)	7.32 (2.76)	6.30 (2.16)
	Low	-3.47 (-1.86)	-0.76 (-0.27)	-4.76 (-2.27)	4.30 (1.41)
	High–Low	14.72 (7.78)	14.57 (4.45)	12.60 (4.84)	
Idiosync. Volatility	High	5.37 (2.27)	9.34 (3.13)	-1.89 (-0.67)	11.15 (3.40)
	Low	2.42 (1.56)	2.92 (1.46)	0.81 (0.47)	2.02 (1.03)
	High–Low	2.95 (1.48)	6.43 (2.12)	-2.72 (-1.11)	
Hedging Pressure	High	4.51 (1.84)	7.87 (2.48)	1.18 (0.44)	6.69 (2.20)
	Low	-0.89 (-0.41)	2.85 (1.03)	-5.56 (-2.03)	8.41 (2.61)
	High–Low	5.40 (2.44)	5.02 (1.42)	6.73 (2.47)	
Speculative Pressure	High	0.00 (0.00)	2.26 (0.84)	-4.38 (-1.67)	6.64 (2.25)
	Low	4.17 (1.66)	6.98 (2.12)	0.70 (0.26)	6.28 (2.00)
	High–Low	-4.17 (-1.80)	-4.72 (-1.32)	-5.08 (-1.87)	

Table C.9: CYR Timing Strategy – Individual Commodities

This table reports for each commodity market the average returns on the long-only time series momentum strategy (Moskowitz et al., 2012) and those of the timing strategy based on convenience yield risk. The long-only returns for each period are based on the criteria outlined in Equation (4.10). *Sectors are separated by horizontal lines. The last row reports the return on a diversified strategy combining all commodity markets. The third column reports the return difference between the returns of the TSMOM and CYR strategies (TSMOM-CYR). Returns are annualized and in percentage points. Newey and West (1987) t-statistics with two lads are reported in parentheses.*

Sector	TSMOM Strategy	CYR Strategy	Difference
WTI Crude	9.31 (2.25)	2.36 (0.56)	-6.95 (-1.59)
Heating Oil	10.07 (2.54)	2.12 (0.62)	-7.95 (-2.14)
Natural Gas	4.03 (0.57)	-0.91 (-0.15)	-4.94 (-0.74)
Gasoil	11.18 (2.77)	4.86 (1.18)	-6.33 (-1.64)
Gasoline	12.77 (2.72)	6.69 (1.57)	-6.08 (-1.32)
Corn	-0.90 (-0.27)	1.14 (0.35)	2.04 (0.62)
Oats	2.00 (0.50)	7.84 (1.75)	5.84 (1.44)
Rough Rice	-1.97 (-0.62)	-0.71 (-0.19)	1.27 (0.35)
Chicago Wheat	-0.20 (-0.06)	-1.28 (-0.36)	-1.08 (-0.25)
Feeder Cattle	2.81 (1.51)	-0.40 (-0.22)	-3.21 (-1.56)
Live Cattle	0.70 (0.38)	-0.81 (-0.44)	-1.51 (-0.98)
Lean Hogs	-2.20 (-0.83)	-3.19 (-0.98)	-0.99 (-0.30)
Copper	6.33 (1.83)	6.29 (2.20)	-0.04 (-0.02)
Gold	4.61 (1.95)	-0.40 (-0.21)	-5.01 (-2.19)
Palladium	11.60 (2.24)	10.61 (2.98)	-0.99 (-0.21)
Platinum	3.02 (0.99)	0.40 (0.15)	-2.62 (-0.95)
Silver	3.52 (0.82)	0.02 (0.00)	-3.51 (-0.86)
Soybean Oil	0.22 (0.06)	4.22 (1.45)	4.01 (1.18)
Canola	1.07 (0.37)	-2.20 (-0.76)	-3.27 (-1.36)
Soybeans	0.92 (0.25)	4.77 (1.64)	3.85 (1.09)
Soybean Meal	6.07 (1.40)	6.74 (2.10)	0.67 (0.18)
Cotton	1.28 (0.37)	2.32 (0.71)	1.04 (0.30)
Lumber	1.02 (0.28)	-2.24 (-0.55)	-3.26 (-1.06)
Cocoa	-1.08 (-0.25)	1.00 (0.24)	2.08 (0.54)
Orange Juice	-2.98 (-0.84)	3.45 (0.75)	6.44 (1.47)
Coffee	-0.59 (-0.12)	-0.56 (-0.12)	0.03 (0.01)
Sugar	5.78 (1.29)	7.69 (1.98)	1.91 (0.44)
Diversified	3.28 (2.14)	2.22 (1.87)	-1.06 (-0.89)

Table C.10: CYR Timing Strategy – Sectors

This table reports for each commodity sector the average returns on the long-only time series momentum strategy (Moskowitz et al., 2012) and those of the timing strategy based on convenience yield risk. The long-only returns for each period are based on the criteria outlined in Equation (4.10)*. Sector portfolios are equally-weighted, and the sector convenience yield risk is based on the average convenience yields across a sector. The last row reports the return on a diversified strategy combining all commodity markets. The third column reports the return difference between the returns of the TSMOM and CYR strategies (TSMOM-CYR). Returns are annualized and in percentage points. Newey and West (1987) t-statistics with two lads are reported in parentheses.*

Sector	TSMOM Benchmark	CYR Strategy	Difference
Energy	8.50 (2.14)	10.61 (2.77)	2.11 (0.56)
Grains	-0.69 (-0.26)	1.61 (0.61)	2.30 (0.77)
Live Stock	1.08 (0.63)	0.72 (0.38)	-0.36 (-0.17)
Metals	5.68 (2.03)	3.53 (1.58)	-2.15 (-0.82)
Oilseeds	-1.12 (-0.35)	3.78 (1.51)	4.89 (1.75)
Softs	-1.64 (-0.78)	-0.82 (-0.40)	0.82 (0.39)
Diversified	1.97 (1.28)	3.24 (2.68)	1.27 (0.97)

Table C.11: Relationship to Financial Variables

This table reports the results from time series regressions of the return on long-short convenience yield risk portfolios on the term spread (TERM), the return on the S&P500, r_{SP500}, the change in stock market volatility $\Delta\sigma_{SP500}$, the change in the CBOE Volatility Index (ΔVIX), the TED spread (TED), and the default spread (DEF). The sample covers the period from July 1959 to December 2018. Returns are annualized and in percentage terms, t-statistics based on Newey and West (1987) standard errors with two lags are reported in parentheses below the estimated coefficients.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	11.40	5.99	6.09	4.56	13.02	26.86
	(2.43)	(2.29)	(2.30)	(1.26)	(2.23)	(3.40)
TERM	-2.61					-0.14
	(-1.19)					(-0.05)
r_{SP500}	-3.63					-8.54
	(-1.32)					(-2.44)
$\Delta\sigma_{\mathrm{SP500}}$		-4.98				-10.19
		(-1.38)				(-2.56)
ΔVIX		-1.35				-1.32
		(-1.96)				(-2.37)
$\Delta(\sigma_{\mathrm{SP500}}-\mathrm{VIX})$			0.03			
			(0.08)			
TED				3.82		6.62
				(0.64)		(0.73)
DEF					-6.04	-23.86
					(-1.08)	(-3.27)
R^2	0.01	0.02	0.00	0.00	0.00	0.08
Obs	444	344	341	396	714	344

Table C.12: Robustness Check for Signal and Portfolio Construction

This table reports the returns on long-short portfolios sorted by convenience yield risk (CYR) using the four alternative measures of Equation (4.17) – (4.20)*:*

Fixed90Days: $\frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \sigma_{t-i}(y^{(j^*,j^*+1)})\right]$ *s.t.* $j^* = \arg\min_{j>1} |(\bar{M}^{(j)} - \bar{M}_{(1)}) - 90|$,

Next5Average: $\frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \frac{1}{5}\sum_{j=2}^{6}\sigma_{t-i}(y^{(j,j+1)})\right]$,

Max1Year: $\frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \frac{1}{\#N_{365}}\sum_{j\in N_{365}}\sigma_{t-i}(y^{(j,j+1)})\right]$, *s.t.* $N_{365} = \{i{>}1{:}\bar{M}^{(i)}{<}365\}$,

Min10Volume: $\frac{1}{12}\sum_{i=1}^{12}\left[\sigma_{t-i}(y^{(1,2)}) - \frac{1}{\#N_V}\sum_{j\in N_V}\sigma_{t-i}(y^{(j,j+1)})\right]$, *s.t.* $N_V = \{j{>}1{:}\bar{V}^{(j)}{>}0.1\bar{V}^{(1)}\}$,

where $\sigma_t(y^{(j,j+1)})$ *is the monthly volatility of the* j^{th} *convenience yield,* $\bar{M}^{(j)}$ *is the average time to maturity in days of the* j^{th} *nearby, and* $\bar{V}^{(j)}$ *is the average trading volume of the* j^{th} *nearby. Panel A uses the top and bottom tertiles for the long-short portfolio, Panel B uses rank-weights for the commodities in each portfolio, and Panel C allows for 1-month lag of one month between measuring the signal and investing. The sample consists of 27 commodities covering the period from July 1959 to December 2018. We report annualized monthly returns in percentage points, t-statistics based on Newey and West (1987) standard errors with two lags, and annualized Sharpe ratios.*

Panel A: Tertiles

	CYR	Fixed90Days	Next5Average	Max1Year	Min10Volume
Av. Return	8.47	7.78	7.04	7.07	7.06
(t-stat)	(3.06)	(2.92)	(2.72)	(2.64)	(2.55)
Sharpe Ratio	0.44	0.41	0.38	0.37	0.36

Panel B: Rank-Weighting

	CYR	Fixed90Days	Next5Average	Max1Year	Min10Volume
Av. Return	8.10	7.02	6.39	6.52	6.77
(t-stat)	(3.09)	(2.79)	(2.52)	(2.51)	(2.54)
Sharpe Ratio	0.44	0.39	0.36	0.35	0.36

Panel C: Lagged Signal by 1 Month

	CYR	Fixed90Days	Next5Average	Max1Year	Min10Volume
Av. Return	7.30	6.71	6.00	5.81	5.85
(t-stat)	(3.49)	(3.31)	(2.93)	(2.80)	(2.92)
Sharpe Ratio	0.50	0.47	0.41	0.39	0.40

Table C.13: Robustness Check for Sample Choice

This table reports the returns on long-short portfolios sorted by convenience yield risk (CYR), and the four alternative signals defined in Equation (4.17) – (4.20)*. Panel A uses the same sample as Szymanowska et al. (2014), Panel B uses only the second half of the sample 1990–2018, and Panel C excludes the commodities of a specific sector. The sample consists of 27 commodities covering the period from July 1959 to December 2018. We report annualized monthly returns in percentage points, and t-statistics based on Newey and West (1987) standard errors with two lags. Panel A and B include annualized Sharpe ratios.*

Panel A: Dataset Szymanowska et al. (2014)

	CYR	Fixed90Days	Next5Average	Max1Year	Min10Volume
Av. Return	6.33	5.93	5.50	6.11	5.59
(t-stat)	(3.25)	(3.11)	(2.92)	(3.25)	(2.91)
Sharpe Ratio	0.45	0.42	0.40	0.44	0.40

Panel B: Sample 1990–2018

	CYR	Fixed90Days	Next5Average	Max1Year	Min10Volume
Av. Return	6.03	5.72	5.82	6.32	6.32
(t-stat)	(2.27)	(2.11)	(2.17)	(2.29)	(2.17)
Sharpe Ratio	0.46	0.42	0.42	0.46	0.44

Panel C: Average Returns excluding Sectors

	CYR	Fixed90Days	Next5Average	Max1Year	Min10Volume
Energy	7.61 (3.21)	6.81 (3.16)	6.10 (2.76)	6.49 (2.92)	6.19 (2.73)
Grains	6.13 (2.12)	4.89 (1.77)	4.71 (1.67)	5.04 (1.72)	5.37 (1.82)
Livestock	8.77 (3.12)	7.39 (2.74)	6.15 (2.25)	6.47 (2.32)	6.79 (2.35)
Metals	8.06 (2.91)	7.17 (2.63)	6.83 (2.52)	7.21 (2.57)	7.20 (2.59)
Oilseeds	7.42 (2.71)	7.58 (2.68)	7.12 (2.53)	6.91 (2.39)	8.24 (2.76)
Softs	8.92 (3.46)	7.00 (2.77)	6.55 (2.51)	6.03 (2.28)	5.77 (2.12)

Table C.14: Robustness Check for Formation and Holding Period

This table reports the returns on long-short portfolios sorted by convenience yield risk (CYR) for formation and holding periods of 1, 6, and 12 months. The original signal is measured over 12 months, and updated at the end of each month, i.e., FP=12, HP=1. Panel A and B report the first nearby and spread returns on the long-short portfolio, respectively. The sample consists of 27 commodities over the period from July 1959 to December 2018. We report annualized average monthly returns and t-statistics for Newey and West (1987) with HP+1 lags.

Panel A: First Nearby Returns

Holding Period (HP)	Formation Period (FP)		
	1 Month	6 Months	12 Months
1 Months	4.29 (2.36)	5.38 (2.70)	6.93 (3.28)
6 Months	0.90 (0.41)	7.55 (2.26)	6.09 (2.26)
12 Months	-2.72 (-0.85)	1.61 (0.81)	3.91 (1.58)

Panel B: Spread Returns

Holding Period (HP)	Formation Period (FP)		
	1 Month	6 Months	12 Months
1 Months	0.03 (0.07)	0.87 (1.99)	0.81 (2.12)
6 Months	-0.15 (-0.43)	0.68 (1.64)	0.19 (0.48)
12 Months	-1.30 (-1.66)	-0.13 (-0.22)	-0.06 (-0.15)

Table C.15: Convenience Yield Risk Orthogonal to Basis

This table reports the returns on long-short portfolios sorted by the convenience yield risk that is orthogonal to the basis, and the counterparts for the four alternative signals from Equation (4.17) – (4.20)*. The influence of basis is removed by regressing the original signal on the basis and subtracting the linear part from the original signal as in Equation* (4.21)*. The sample consists of 27 commodities over the period from July 1959 to December 2018. We report annualized average monthly returns, t-statistics for Newey and West (1987) with two lags, and the annualized Sharpe ratios.*

	$\text{CYR}^\top$	$\text{Fixed90Days}^\top$	$\text{Next5Average}^\top$	$\text{Max1Year}^\top$	$\text{Min10Volume}^\top$
Av. Return	4.74	5.41	4.04	4.73	3.42
(t-stat)	(2.38)	(2.75)	(2.19)	(2.56)	(1.76)
Sharpe Ratio	0.33	0.37	0.29	0.34	0.24

Maturity Adjustment

The derivation of the decomposition of the convenience yield risk measure in Section 4.4 is based on a monthly expiry schedule for the underlying commodity, such that $y_t^{(1,2)}$ and $y_{t-1}^{(2,3)}$ refer to the same contract. However, many commodities do not have monthly, but bimonthly or even quarterly expiration schedules. The decomposition has to be adjusted slightly, to incorporate this lag.

Assume, that the contracts of the commodity under investigation expire every K month. Further, recall the definition of excess volatility from Equation (4.11)

$$\xi_{t,t+K}(y^{(1,2)}) := \sigma_{t+K}(y^{(1,2)}) - \sigma_t(y^{(2,3)}), \tag{4.11}$$

where $\sigma_t(y^{(1,2)})$ and $\sigma_t(y^{(2,3)})$ are the monthly volatilities of the first and second nearest convenience yield, respectively. The decomposition works in the same way, but the latter part becomes a sum of annual volatility changes of the second convenience yield, i.e.,

$$\begin{aligned}
\mathrm{CYR}_t = {} & \frac{1}{12}\sum_{i=1}^{12} \sigma_{t-i}(y^{(1,2)}) - \sigma_{t-i}(y^{(2,3)}) \\
= {} & \frac{1}{12}\sum_{i=1}^{12-K} \sigma_{t-i}(y^{(1,2)}) - \sigma_{t-i-K}(y^{(2,3)}) + \frac{1}{12}\sum_{j=1}^{K} \sigma_{t-13+j}(y^{(1,2)}) - \sigma_{t-j}(y^{(2,3)}) \\
\overset{(4.11)}{=} {} & \frac{1}{12}\sum_{i=1}^{12-K} \xi_{t-i-K,t-i}(y^{(1,2)}) - \frac{1}{12}\sum_{j=1}^{K} \sigma_{t-j}(y^{(2,3)}) - \sigma_{t-13+j}(y^{(1,2)}) \\
\overset{(4.11)}{=} {} & \frac{1}{12}\sum_{i=1}^{12} \xi_{t-i-K,t-i}(y^{(1,2)}) - \frac{1}{12}\sum_{j=1}^{K} \sigma_{t-j}(y^{(2,3)}) - \sigma_{t-12-j}(y^{(2,3)}).
\end{aligned}$$

Chapter 5

Conclusion

5.1 Summary

This thesis investigates comovements, inventory news, and convenience yield risk in commodity futures markets. The three essays discuss three important mechanisms in commodity futures markets; first, the interconnection of commodity returns and the evolution of their dynamics within the changing environment of the 21^{st} century; second, the reaction of commodity prices to the release of inventory information conditional on expectations; and third, the predictive power of convenience yield risk along the term structure of commodity futures.

In the first essay, we show that the comovement of commodity futures returns is best described with a simple factor model based on tradable long-short portfolio returns. The excess comovement, which cannot be explained by the model, is negligible, while macro factor models leave large excess comovements (Pindyck and Rotemberg, 1990; Le Pen and Sévi, 2017).

Decomposing the comovement reveals that the dynamics are driven by intersectoral rather than intrasectoral comovements, and that the changes in factor exposures only play a minor role in the time variation of the comovement. The increase of comovements during the financialization period is mainly driven by an increase of factor covariances casting doubt on a persistent effect.

The second essay has shown that inventory news affect natural gas markets such that unexpected increases of stock holdings have a negative price effect. Moreover, the news on such storage announcement days accounts for more than half of the annual return on natural gas markets. While the study confirms the role of inventory as an important figure for supply and demand expectations, it is puzzling that the significant return cannot be fully explained by the announcement surprise.

The intraday analysis of this announcement effect reveals that instead of being realized past the announcement, we find a price drift already up to 90 minutes ahead of the publication. However, the drift is not in line with a story of informed trading as it only amounts to half of the total announcement return. Therefore, the results pose a challenge to the understanding of how the information on storage news is facilitated by natural gas markets.

In the third essay, we propose a measure of convenience yield risk that predicts commodity futures returns in the cross-section. The measure incorporates seasonalities and the term structure dimension of convenience yields. It is mainly driven by the variation of risk along the slope rather than across time and can be interpreted as measure of the Samuelson effect under certain conditions.

Portfolios sorted by convenience yield risk generate an excess return that is statistically significant after controlling for common commodity risk factors. Further, convenience yield risk predicts commodity returns in the cross-section even after controlling for commodity and time fixed effects.

We show that convenience yield risk is on average higher for commodity markets with higher average convenience yields, but this relationship breaks down at the short horizon emphasizing that times of high convenience yield do not necessarily coincide with times of high convenience yield risk. Lastly, the returns on sorted convenience yield risk portfolios cannot be reconciled with exposure to financial stress, credit risk, or funding liquidity.

5.2 Suggestions for Further Research

The results of this thesis build the foundation for a number of research questions to be answered in further studies. In Chapter 2, we compare the ability of two models based on either macroeconomic factors or traded long-short portfolio returns to fit the covariance structure of commodity returns. While, from a global perspective, traded portfolio returns outperform the macro factors, this might be different for single sectors or commodities. A study at the sector level adds to the discussion about whether all commodity markets should be treated as one asset class and along which lines a classification is sensible (Greer, 1997). Perhaps, thinking of market integration between specific local sectors will reveal more than at a global horizon (Büyükşahin et al., 2010).

In the light of Fattouh et al. (2013), assuming a stronger relationship between macroeconomic fundamentals and commodity prices, it could be insightful to reverse the perspective and to investigate the effect of commodity returns on the comovements of macroeconomic variables. As a result, this might motivate a joint approach allowing for feedback effects from both sides.

In reference to the work of Christoffersen et al. (2019), a further extension could deal with the comovements of volatilities, as our work suggests that they follow a different dynamic. Many ways of comparing the volatility models can be explored. While one could obtain the volatilities from the modelled returns, it is also interesting to see whether the same variables that explain return comovements can also explain volatility comovements.

For Chapter 3, the EIA storage report provides a unique opportunity to study the effect of storage news on commodity markets. Although other markets provide similar reports, they are blended with other information. Nonetheless, a natural extension of the analysis is to investigate news events on other commodity markets. Although evidence has been provided for sectors, such as energy (Kilian and Vega, 2011), metals (Elder et al., 2012), or agricultural markets (Adjemian, 2012), the literature is missing a comprehensive study of all commodity markets to identify which news affect every market, and how they differ from sector-specific or even commodity-specific events such as the EIA report. Furthermore, studies at the intraday level are scarce. Studying pre- and post-announcement effects can provide additional information on the speed and structure of information flow in commodity markets.

From a theoretical point of view, the negative sign of the risk premium on EIA announcement days motivates the development of a model that can internalize and explain the effect. The work of Ai and Bansal (2018) provides such a characterization theorem for the set of intertemporal preferences that generates a non-negative announcement premium, but does not cover a negative risk premium.

The convenience yield risk studied in Chapter 4 is a concept that can easily be expanded to other asset classes, such as currencies, stock indices, or bond markets. The literature has shown that the concept of momentum (Asness et al., 2013) or carry (Koijen et al., 2018) can be applied in different asset classes and can therefore be seen as a global factor. Similarly, one might ask whether the variation in the slope of the term structure is a common factor that affects returns or whether it is specific to commodity markets. Within an intraday dataset the information content of the signal could be tested at a higher frequency. The literature has provided evidence that other strategies also work at higher frequencies, e.g. intraday momentum (Gao et al., 2018).

Another interesting feature of the commodity futures term structure is the possibility to form constant maturity futures, i.e., daily rebalanced linear combinations of multiple nearby futures to obtain a constant time to maturity. With respect to many sorting and weighting algorithms, the timing for rolling over futures positions or measuring signals is decisive. Therefore, an analysis of constant maturity futures reveals how much of an observed effect can be addressed to the maturity effect.

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