Three Essays on the Dynamics of Commodity Markets

Timm Frederik Schmich

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Accounting and Finance Division
Stirling Management School
University of Stirling
Scotland, United Kingdom

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To Mehtap

ABSTRACT

This thesis examines the effect of weather events, monetary policy, and financialization on changes in global inventory, futures prices, spot prices, futures returns, and producers' equity returns of exchange-traded commodities. First, I investigate the relationship between temperature and precipitation anomalies on aluminium futures returns. Prior research only examines the effects of weather anomalies on soft commodities, although flooding, drought and temperature are also identified as disrupters to mining operations in both regulatory filings and media reports. However, I find no evidence of weather effects on aluminium futures returns. Instead, the evidence suggests that inventories provide enough buffer for weather events and that trading around such events is unlikely to yield abnormal returns.

Second, I investigate the relationships between metal futures returns and global monetary policy and demonstrate that a multiplier ratio created to proxy for market liquidity and the effectiveness of unconventional monetary policy is positively related to the price of industrial metals. Contrary to prior research, there is little evidence of a relationship between real interest rates and industrial metals futures returns. These findings will enhance the ability of policymakers and other agents to determine whether the intended effects of quantitative easing are being transmitted to the markets.

Third, I investigate the role of financialization in shaping the relationship between non-commercial speculation (hereinafter, speculation), trader concentration, and commodity futures returns. While prior studies variously find evidence of stabilising, reinforcing and destabilising effects of speculation upon returns, I show that speculation does not Granger-cause futures returns but that there is evidence of reverse causality from futures returns to speculation. Additionally, commodity futures returns respond to the publication of open interest information. Overall, financialization reduces the power of individual traders to set futures prices in a concentrated commodity market. These findings support a policy approach aimed at enhancing transparency rather than adding regulatory controls.

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GLOSSARY OF ACRONYMS AND TERMS

Acronym	*Term*
BDI	Baltic Dry Index
BR	Brazil, Federative Republic of
CBA	Central Bank Assets
CFR	Commodity Futures Returns
CFTC	US Commodity Futures Trading Commission
CL	Commercial Long Open Interest
CME	Chicago Mercantile Exchange
CN	China, People's Republic of
COT	Commitment of Traders
CPI	Consumer Price Index
CRU	Climate Research Unit
CS	Commercial Short Open Interest
CSI	Cubic Spline Interpolation
DCOT	Disaggregated Commitment of Traders
EDC	European Debt Crisis
ESV	Excess Net Long Non-Commercial Speculation Variable
EU	European Union
FCOJ	Frozen Concentrated Orange Juice
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GSCI	Goldman Sachs Commodity Index
HL	Hedging Long
HS	Hedging Short
IN	India, Republic of
JP	Japan
LME	London Metal Exchange
LTC	Long Trader Concentration
LTCC	Long Trader Concentration – Commercial
LTCNC	Long Trader Concentration – Non-Commercial
MaU	Mine-specific and USGS information
M2	M2 Money Supply
MR	Multiplier Ratio
NCL	Non-Commercial Long Open Interest
NCS	Non-Commercial Short Open Interest
NOAA	National Oceanic and Atmospheric Administration
NRL	Non-Reportable Long
NRS	Non-Reportable Short
OI	Open Interest
OLS	Ordinary Least Squares
PSR	Producer Stock Returns
QE	Quantitative Easing
QR	Quantile Regression
RIR	Real Interest Rate
SL	Speculation Long
SP500	S&P 500 index

SPIMSI	Standard & Poor's GSCI Industrial Metals Spot Index
SPGSI	Standard & Poor's GSCI Gold Spot Index
SS	Speculation Short
STC	Short Trader Concentration
STCC	Short Trader Concentration – Commercial
STCNC	Short Trader Concentration – Non-Commercial
TWI	Trade-Weighted USD Index
UK	United Kingdom
US	United States of America
USD	United States Dollar
USGS	Unite States Geological Survey
TWI	Trade-weighted USD index
VIX	CBOE Volatility Index on the S&P 500
WTI	Working T-Index

"One of the funny things about the […] market is that every time one person buys, another sells, and both think they are astute."

– William Feather

CHAPTER 1 THESIS INTRODUCTION

1.1 MOTIVATION

The history of commodity trading is as old as the civilisation of humankind. Clay tablets found by archaeologists in the region of ancient Mesopotamia suggest that derivative contracts on commodities were present during the reign of the Babylonian King Hammurabi around 1,780 BC (Nagarajan, 2011). Since then, global commodity markets have experienced ups and downs: some slow and steady, some fast and heavy. A prominent example of an early commodity speculation bubble is the boom and bust of the Dutch tulip mania in the 1630s (Shiller, 2005).

While contracts for future delivery of commodities have long been available, the contracts were unstructured and trading the contracts was difficult. This changed with the establishment of the Dōjima Rice Exchange in the 18th century in Osaka, Japan, which became the world's first modern organised futures exchange (Hamori et al., 2001). Despite facing difficulties during its early years of trading[1], the Dōjima Rice Exchange introduced a standardised form of trading – the futures contract was born. Today, futures exchanges are the preferred choice to trade commodities.[2] Because of the liquidity and transparency present on futures markets, futures serve as guidance for commodity-related businesses such as producers, consumers, and merchants (Black, 1976) and are a crucial tool for financial risk management for industries that are affected by commodity price fluctuations.

Characteristics such as perishability, the need for physical storage and delivery, restricted or localised availability, and the lack of dividend or interest yields distinguish commodities from asset classes such as stocks, bonds, and real estate. Since the rapid increase in the financialization of commodity markets since the early 2000's, exchange-traded commodities

[1] During its early years, the Japanese government, represented by the governor of Osaka, prohibited this form of trading as it was considered as form of gambling and price manipulation (Moss and Kintgen, 2009).
[2] For example, the Chicago Mercantile Exchange (CME) Group handles well over 4 million commodity-related contracts worth billions of USD daily (CME Group, 2017a) or the London Metal Exchange (LME) with an annual trading volume of 12 trillion USD or 40 times global production (LME, 2016).

have experienced a drastic increase in financial demand and supply. As well as satisfying consumption demand, commodity investments are also used for diversifying portfolio risk (Sari et al., 2010; Roache and Rossi, 2010)[3] and as an inflation hedge (Gorton and Rouwenhorst, 2006; Bampinas and Panagiotidis, 2015). Whereas the valuation of a company's stock can be related to its expected future cash-flows, the equilibrium price of a commodity reflects current and future expectations regarding supply and demand. Ultimately, it is perceptions of the relative scarcity of the commodity in future that determines its monetary value today.

The evaluation of commodity markets has long been a cornerstone of academic research. The seminal work on the economics of exhaustible commodities and their relationship with real interest rates by Hotelling (1931), also known as Hotelling's rule, is among the first to show that producers' can increase revenue by delaying the extraction of exhaustible goods if interest rates are low. Subsequent research by Working (1949) and Brennan (1958) evaluates and develops the theory on the supply of commodity storage and its relationship with the associated costs. Later, Working (1960), Johnson (1960), and Ederington (1979) measure and evaluate the performance of hedging and speculation on commodity markets to show that futures markets are useful to mitigate commodity price risk for hedgers. Black (1976) and Cox et al. (1981) investigate the relationship between forward and futures and formulate valuation models for commodities and other assets. Gibson and Schwartz (1990), Schwartz (1997; 1998), and Schwartz and Smith (2000) present quantitative one- and two-factor models to estimate commodity prices and, among others, Cortazar et al. (2013; 2015; 2016) provide improved versions of these earlier models. These estimation models typically assume that commodities follow the law of one price at the global level. Richardson (1978), Ardeni (1989), and Rogoff (1996) test the appropriateness of the law of one price and the purchasing power parity on commodity markets and show that the same commodities exhibit different prices in various locations and that there are limits to arbitrage.

Generally, global and particularly US-related macroeconomic variables are used to estimate commodity prices. Among others, Dornbusch (1987) examines the relationship

[3] While several studies highlight that commodities are a useful tool to mitigate portfolio risk (Sari et al., 2010; Roache and Rossi, 2010), Olson et al. (2017) argue that commodities do not sufficiently hedge risk associated with the S&P 500 composite index, i.e. stock market risk.

between exchange rates and commodity prices. Frankel (1979) links exchange rates, monetary policy, and money supply and builds on the overshooting model by Dornbusch (1976) to show that commodity prices tend to overshoot beyond the long-term equilibrium (Frankel and Hardouvelis, 1985; Frankel, 1986) and are negatively correlated to money announcements (Frankel and Hardouvelis, 1985) and real interest rates (Frankel, 2006; 2014)[4]. Global demand and supply also play a key role for the determination of commodity prices. Kilian (2009), Kilian and Murphy (2014), and Stuermer (2014) identify strong co-movements between global demand and the global market prices of commodities and conclude that commodity prices are demand-driven in the long run.

1.2 THESIS OBJECTIVES

Although the research on commodity markets is constantly developing, important questions are still left unanswered. Changes in the volatility of global commodity prices because of increasingly integrated global commodity markets (Huchet-Bourdon, 2011), political instability in producing countries (Blas and Blair, 2011), and the increasing trade and consumption of commodities worldwide (Trade Map, 2016) are recent and important trends. These point to the need for an evaluation of these newly observed market phenomena, the identification and assessment of influential factors that have experienced less attention before[5], and re-evaluation of existing studies. Thus, this thesis examines the effect of weather events, monetary policy, and financialization on changes in global inventory, futures prices, spot prices, futures returns, and producers' equity returns of exchange-traded commodities. It sheds further light upon the factors that correlate with and drive commodity markets.

First, I examine the role of weather anomalies, based on both temperature and precipitation, on changes in global aluminium inventory and futures returns as well as on the equity returns of bauxite mining and aluminium producing companies. While it is known that climate change significantly affects agriculture in the US (Adams et al., 1990) and that the prices of agricultural goods, such as frozen concentrated orange juice, depend on weather events in production areas (Roll, 1984; Boudoukh et al., 2007), little is known about the

[4] The significant negative relationship between real interest rates and annual log real commodity prices mostly applies to agricultural commodities. Most annual metals and crude oil prices are not significantly affected by the US real interest rate.

[5] This includes the relationship between weather anomalies and mining operations or the interactions between monetary policy, both conventional and unconventional, and global commodity prices.

relationship between weather events, their impact on the excavation and production of non-ferrous metals, and thus their inventory and price. This is surprising, as non-ferrous metals provide a crucial underpinning of economic activity. For example, aluminium is a non-ferrous metal that is widely used for construction, and its distinctive characteristics such as its light weight and easy usability make it an irreplaceable component in the automotive industry. With annual world aluminium production of around 57,500,000 metric tonnes in 2015 (USGS, 2017), aluminium is one of the most diverse and widely used metals. Moreover, metal-producing corporations (BHP Billiton, 2015:236; Rio Tinto, 2016:14-15) and the media (Fogarty, 2011; Wallop, 2011; Hack, 2013; Platts Metals Daily, 2013; Sharma, 2014; Keenan and Stringer, 2016) highlight that weather events affect the excavation of bauxite, the main source of aluminium. Due to its economic significance, I contribute to closing this gap in the literature and evaluate the relationship between weather anomalies, i.e. abnormal temperature and precipitation, and changes in global aluminium inventory, futures returns, and the equity returns of bauxite mining and aluminium producing companies. In Chapter 2, I develop daily global weather anomaly indices to track weather anomalies based on data from weather stations with the shortest possible distance to the individual bauxite mines that are spread around the globe. Afterwards, I test whether or not these weather anomalies significantly impact changes in global aluminium inventory, aluminium futures returns, and miners' equity returns.

Second, I investigate the relationship between monetary policy and metal prices. This includes both conventional and unconventional monetary policy. While it is known that increases in real interest rates, particularly US real interest rates, significantly reduce real commodity prices (Frankel, 2006), it remains unclear how global real interest rates affect commodity prices in both in the long- and the short-term and if the magnitude of this impact depends on the market interventions introduced by central banks following the global financial crisis in 2008[6]. Particularly for industrial metals and gold, a global approach might

[6] As a response to the global financial crisis, central banks of economies such as the US and the Eurozone reduced their interest rates to counteract the economic downturn and support economic growth. Since then, nominal interest rates in those economies have been considerably low, with values ranging around zero percent and below. This led to an abundance of liquidity that may have altered the mechanism that underlies the inventory transmission channel and explains the transmission from real interest rates to commodity prices (please refer to Chapter 3 for a thorough discussion of monetary policy, transmission channels, interest rates, and market liquidity). It remains unclear whether this increase in economy-specific central bank induced liquidity has altered the mechanisms on global commodity markets and how markets may react once the central bank liquidity will be reduced.

be more fruitful than the focus on US markets in prior research. Although the US is still the largest single economy as of 2016, the arrival of Asian consumers led by China as the largest importer of coal and non-ferrous metals, with a share well above 40 percent (World Bank, 2015; IMF, 2016) may alter the leading impact of the US on commodity market dynamics towards a more balanced global interaction. Paired with the global expansion in unconventional monetary policy and the reduction in nominal interest rates during the recent decade as a response to the GFC in 2008, I investigate the interaction of global industrial metal and gold prices, global monetary policy, and global trade in Chapter 3. I introduce a measure which uses information on central bank assets to proxy for global central bank market interventions and unconventional monetary policy, to measure the effectiveness of the latter, i.e. the absorption of unconventional monetary policy into the economy of the seven scrutinised economic areas. Moreover, I introduce a measure of global real interest rates, defined as the GDP-weighted real interest rate of the seven evaluated economies that account for 70 percent of world's central bank assets or almost 24 percent of world GDP (Kuntz, 2016), to evaluate their effects on the prices of global industrial metals and gold.

Third, I scrutinise the interaction between non-commercial speculation, trader concentration, and commodity futures returns. While prior literature has investigated this relationship, the results are unclear. To identify a link between speculation and futures returns, prior research often uses direct measures of speculation paired with commodity futures open interest. It concentrates on the conditional mean and neglects the heterogeneity in the impact of non-commercial speculative open interest between quantiles of the commodity return distribution (e.g. Irwin and Sanders, 2010; Etienne et al., 2016). However, the mean analysis might hide valuable information that is crucial to understand the relationship between the main variables. First, commodity futures returns experience fat tails (Han et al., 2015; Nagayev et al., 2016). Thus, outliers disproportionally affect the mean. Second, the mean models assume that the relationship between commodity prices or returns and speculative open interest is constant. If speculative open interest provides reinforcing (e.g., Haase et al., 2016) or increasing (Basak and Pavlova, 2016) effects, one should be able to observe constant coefficients at the lower and upper quantiles of the return structure. However, if speculative open interest has a destabilising effect, as shown by Bosch and Pradkhan (2015) for precious metals prior to June 2006, one may observe negative coefficients on the left tail and positive coefficients on the right tail of commodity futures returns. These effects may even accelerate at the extremes when momentum or predatory trading is present in the market.[7] However, if speculative open interest has a stabilising effect (e.g., Kim, 2015; Brunetti et al., 2016) the coefficient should be positive on the left tail and negative on the right tail of commodity futures returns. Either way, the mean analysis conceals the real impact of the regressors on different quantiles of the dependent variable. Extreme events in financial markets have led to drastic price fluctuations during the last two decades. In Chapter 4, I contribute towards closing this gap by evaluating the interactions and Granger-causal relationships of excess non-commercial speculation, trader concentration, and a panel of ten commodity futures returns. Moreover, I investigate the transmission of these effects to futures returns via different transmission channels to shed further light on the difference between trading and information about trading and the transmission of such to commodity futures returns.

1.3 THESIS OUTCOME

The thesis begins with the evaluation of the role of global weather anomalies and their effect on bauxite mining operations to identify the response of global aluminium futures returns and inventory changes to weather anomalies, i.e. deviations from the normal value. Despite being one of the leading metals in construction, telecommunications, and the automotive industry, and having an annual production of around 57,500,000 metric tonnes of primary aluminium in 2015 (USGS, 2017) worth well above 100 billion USD[8], aluminium has received relatively little attention in prior research. I close this gap by showing that precipitation anomalies, defined as the deviation from normal values over a span of 14 years and measured with a newly created weather anomaly index that combines global weather station data, significantly reduce global aluminium inventory. Moreover, I show that abnormal stock price returns of bauxite mining and aluminium producing companies are

[7] While Bessembinder et al. (2014) find little significant evidence for predatory strategies present in the crude oil futures market but rather liquidity-supporting effects, research on momentum trading, i.e. trading on existing trends, indicates a tendency of overreaction in asset markets at long horizons (e.g. Hong and Stein, 1999). Building on Moskowitz et al. (2012), I create a dummy that illustrates a 12-week time-series momentum strategy with a 1-week holding period, i.e. if the average return of the last 12 weeks is positive or zero, the dummy is 1 and if the average return of the last 12 weeks is negative, the dummy is set to 0. While the momentum dummy is negative and highly significant, i.e. at the 1 percent level, which suggests strong impact of momentum on the estimation of commodity futures returns, all variables of interest remain significant and with their respective signs as highlighted in the main analysis.

[8] This calculation is based on an annual production of 57,500,000 metric tonnes multiplied by an average price of 1,800 USD per metric tonne on the LME.

driven by temperature anomalies that are observed on the same day as the abnormal returns, temperature anomalies that have been captured during non-trading days, and multi-day temperature anomaly events. The implications and contributions to the literature are twofold. First, the limited significance of the findings on weather anomaly effects on aluminium futures returns and inventory changes suggest that, despite the high costs that weather events can impose on mining operations (cf. BHP Billiton, 2015), there is only a limited effect if any on exchange-traded aluminium futures returns. Thus, practitioners should not be overly concerned about the short-term effects of weather events on the global aluminium price as inventories seem to sufficiently buffer for these effects. Second, the novel method of combining global weather station-specific data equips other academics and practitioners with a means of evaluating weather effects for different applications. For example, one may think about calculating precipitation and temperature anomaly indices for large cities with high demand for industrial metals to estimate the effect of weather anomalies on the demand for these goods.

Second, I investigate the relationship between global monetary policy, both conventional and unconventional, market liquidity, and exchange-traded metal prices. Since the outbreak of the GFC in 2008, quantitative easing has gained substantial popularity among leading central banks. Because of these market interventions, the four largest central banks (PBOC, FED, BoJ, ECB) hold assets of more than 17.8 trillion USD which translates to roughly 70 percent of world's central bank assets or almost 24 percent of world GDP (Kuntz, 2016). Despite this considerable share of the global financial markets, little research evaluates the impact of the monetary policy induced distortion in global liquidity on the price of gold and non-ferrous metals. Thus, I scrutinise the effects of monetary policy and the change in liquidity on exchange-traded base metal and gold prices. The evaluation goes beyond prior research and introduces a new measure, the global multiplier ratio, to proxy for global central bank market interventions and unconventional monetary policy. The multiplier ratio is calculated by dividing M2 by central bank assets for each economy. In a second step, the ratios for each economy are weighted by the size of the central bank assets to create a global measure. The global multiplier ratio has a positive and significant effect on the prices of industrial metals during the period surrounding the GFC and particularly on the price of copper. These findings are complemented by a newly created global real interest rates index which is not limited to US interest rates but also includes rates from other major economies. While I find little significant evidence in favour of real interest rates affecting the estimation of non-ferrous metals prices, the findings for the gold price indicate otherwise and are in line with prior research for the US. The findings also suggest that the market's ability to absorb central bank liquidity and translate it into economic growth appears to be more important than the level of global real interest rates for the estimation of industrial metal prices. Despite the limited significance of the results, the global multiplier ratio allows investors and academics to quickly and efficiently quantify the impact of global central bank market interventions and consider the associated effects on commodity prices in their models. With this measure, it is possible to investigate the extent to which the intended effects of quantitative easing, i.e. an increase in lending and thus market liquidity is transmitted to the markets. Moreover, the findings indicate that the global approach provides better estimates than the focus on US measures in prior research. For example, I show that the correlation of China's real interest rate with industrial metal prices is stronger compared to the US real interest rate. These findings are fruitful for other academics who are interested in the analysis of monetary policy, as they highlight that future research should shift the focus from US markets towards a global approach. Although the US is still the largest single economy as of 2016, the arrival of Asian consumers led by China as the largest importer of coal and non-ferrous metals with a share well above 40 percent (World Bank, 2015; IMF, 2016) may alter the leading impact of the US on commodity market dynamics towards a more balanced global interaction. Furthermore, researchers may gain from further use of the trade data employed in this study, which explains a considerable share of variations of the price of industrial metals and gold. These data are freely available and offered by the International Trade Centre, a joint agency of the World Trade Organization and the United Nations. Given that monetary policy, and particularly unconventional monetary policy since the GFC, deserves considerable attention, these results serve as a fresh reminder of the consequences of market interventions by central banks and their impact on areas that experience less attention in an inflation-targeting environment.

Third, I examine non-commercial speculation, trader concentration, and their explanatory power for the futures returns of a basket of ten commodities. Not only do I evaluate the mean impact of speculation and trader concentration but further extend prior research by analysing the varying impact of the regressors on different quantiles of the commodity futures return distribution. With this approach, it is possible to thoroughly scrutinise the quantiles of commodity futures returns, including the extremes, to identify the nonlinear explanatory power of speculation and trader concentration. The quantile evaluation indicates that at the upper and lower quantiles of the distribution, speculation seems to stabilise the futures returns of a panel of ten commodities, by dampening them. Furthermore, when evaluating the commodities individually, the findings suggest that speculation has a stronger stabilising, i.e. positive, effect on the left tail of the futures return distribution, i.e. 5^{th} to 50^{th} quantile, only for soybeans and gold. For most other commodities, the results indicate a reinforcing relationship between speculation and futures returns, for both the mean and quantile regressions. Prior research is further extended by applying the Dumitrescu and Hurlin (2012) adjusted Granger causality test to the heterogenous panel data. At this point, prior results are confounded by the finding that, in fact, futures returns Granger-cause non-commercial speculation. This is consistent with the idea that, beyond a certain point in the lower return quantiles, negative returns induce non-commercial speculators to buy futures, which thus dampens subsequent negative returns. Conversely, when prices rise beyond a certain point, i.e. in the upper return quantiles, non-commercial speculators sell their positions, which again dampens subsequent positive returns. In addition, the findings for the signalling effect, i.e. the effect of the information content of the US Commodity Futures Trading Commission (CFTC) Commitment of Traders report, show that market participants use information on changes in non-commercial open interest once it is available and adjust their exposures accordingly. This effect is particularly evident when non-commercial speculation deviates from its expected value. In the end, the answer to the question of whether non-commercial speculation improves the estimation of commodity futures returns, would appear to be yes. The findings, however, also reveal that non-commercial speculation is unlikely to Granger-cause commodity futures returns. The implications and contributions to the literature that can be drawn from the fourth chapter are threefold. First, the obtained coefficients suggest that the impact of changes in open interest on futures returns is miniscule. For example, I show that for each 100,000 short contracts open interest by traders allocated to the managed money group (i.e. speculators), returns decrease by only 0.0034 percent. While still tiny, the impact of merchants' open interest, i.e. traders who are primarily concerned with producing or consuming the commodities, is comparably much stronger (approximately four times[9]). Thus, the effect of

[9] Please refer to Chapter 4.4.3 for more details.

non-commercial, i.e. speculative trading on futures returns is smaller than the effects stemming from commercial trading. Second, on a weekly basis, excess non-commercial speculation does not Granger-cause returns. That is, while changes in the futures price (i.e. returns) lead to changes in non-commercial open interest, there is no significant lagged impact of speculative trading on any of the ten tested commodity futures returns. These findings are important for regulators, investors, and other parties that are interested in the factors that influence commodity prices. Investors gain from these findings by realising that their actions, on a weekly basis, do not drive returns. Moreover, the results suggest that the poor reputation of speculation that has been painted by the popular media, and is deeply rooted in society, might be exaggerated and should be reviewed to draw a more accurate picture. That is, the negative connotation about the effect of speculation on society and its negative impact on economic health arguably overshadow its positive effects, such as the provision of liquidity, assisting the price discovery mechanism, reducing hedging costs, and better integrating commodity markets with other financial markets (Fattouh et al., 2012; Irwin and Sanders, 2012). Third, the findings suggest that futures markets react to information related to open interest once it becomes public. In particular, when excess non-commercial speculation deviates from its expected value, one can observe a highly significant impact on futures returns. Instead of imposing new regulations on trading and position limits, regulators may consider adopting a more transparent, market-oriented approach. This could involve publishing daily reports of trading volumes and open interest and including the names of the trading parties. If more information is available, the impact of each publication is likely to be less.

1.4 OUTLINE OF THESIS

Chapter 2 evaluates the effect of weather events on the primary aluminium market. Chapter 3 investigates global monetary policy, market liquidity, and their impact on exchange-traded metals. In Chapter 4, the relationship between non-commercial speculation, measured by the excess net long non-commercial open interest in US futures markets, and a range of agricultural, energy, and metal commodities is examined. Chapter 5 concludes, highlights limitations, and presents areas for future research.

CHAPTER 2 WEATHER EVENTS AND THE PRIMARY ALUMINIUM MARKET

2.1 INTRODUCTION

Global economic growth and the urbanisation of developing countries during the last century have fuelled the demand for commodities, including the growing thirst for non-ferrous metals. For construction, telecommunication, the automotive industry, electricity, or any other industry that relies on the distinctive characteristics of non-ferrous metals such as their light weight, easy usability, and high electrical conductivity, these metals are an irreplaceable component[10]. With an annual world aluminium production of around 57,500,000 metric tonnes in 2015 (USGS, 2017), aluminium is one of the most diverse and widely used metals. While only a fraction of this production is eventually sold on commodity exchanges for physically delivery[11], the price that results from exchange trading serves as a benchmark for producers, merchants, and consumers. Thus, a relatively minor change in the price of the underlying commodity traded on an exchange can lead to severe implications for all financial and other business transactions linked to the commodity.

Despite their importance for the economy, little is known about the impact of environmental factors on the global inventory and price of exchange-traded aluminium. This is surprising, as metal-producing corporations (BHP Billiton, 2015:236; Rio Tinto, 2016:14-15) and the media (Fogarty, 2011; Wallop, 2011; Hack, 2013; Platts Metals Daily, 2013; Sharma, 2014; Keenan and Stringer, 2016) highlight that weather events affect the excavation of bauxite, the main source of aluminium. Although research on soft commodities (e.g. Roll, 1984; Boudoukh et al., 2007) has identified a significant link between weather events and futures returns, these results arguably do not generalise to base metals. While weather extremes can destroy crops and thus harm the seasonal yield, mining operations are only affected during weather extremes.

[10] Contrary to agricultural commodities, metals are non-perishable and can therefore be stored for an unlimited time and relatively cheaply (unlike agricultural commodities, which may have to be cooled or require other specific storage conditions). This allows consumers, producers, and other market participants to store metals relatively cheaply whenever they expect prices to change in future to avoid unforeseeable price changes. Despite differences in the storability of commodities, I still expect metal prices to react to unexpected effects such as unpredicted or unpredictable weather events. That is, while the event itself might be predictable, the real impact on operations and thus output is not foreseeable. Thus, while I appreciate the difference in the storability of metals compared to agricultural commodities which can lead to a reduction in price volatility, I expect the price of both commodity groups to react to unexpected weather anomalies.

[11] For example, the LME states that 6 million tonnes of all commodities traded on the exchange have been delivered in and out in 2015 (LME, 2016).

Evaluating the impact of weather anomalies on base metals is challenging because mines are often located in remote locations and the weather stations that measure temperature and precipitation are scarce. However, the global distribution of bauxite mines makes it possible to mitigate this bias as Australia, a country with accurate weather reporting, produces approximately 35 percent of global bauxite, which makes it the world's largest producer of bauxite. Hence, in this study, I use aluminium as a representative of non-ferrous metals and evaluate the impact of temperature and precipitation anomalies on changes in the global inventory and the futures price. The study is complemented by an evaluation of weather anomalies on the equity price returns of major aluminium producing companies that operate some of the mines in the sample. The reason for this is twofold. First, prices are widely believed to incorporate all market forces including changes in inventory and global mine production. Likewise, commodity prices are often assumed to capture available market information, thus embodying the equilibrium between demand and supply. This study enables consumers to better understand the specific role played by extreme weather events on changes in aluminium inventory and price, allowing investors to better value their investments and financial institutions to create products to mitigate weather risks. To the best of my knowledge, this study is the first that evaluates the impact of temperature and precipitation anomalies on changes in the global futures price and the inventory of exchange-traded aluminium.

It is found that precipitation anomalies significantly affect changes in the global inventory of exchange-traded aluminium. Particularly when precipitation anomalies occur on multiple days, the reducing effect on inventory changes is significant. In addition, on days when weather data are unavailable (for example, due to extreme weather), a significant reduction in inventory levels is observed. However, since 2009 there has been an oversupply of aluminium (Sanderson et al., 2016), and during this period the association of precipitation events with inventory levels has diminished. The effect of temperature anomalies is found to be non-significant for both aluminium inventory changes and futures returns. Moreover, mostly non-significant coefficients are found for the volatility of the two dependent variables. Unlike aluminium futures returns, the abnormal returns of an equally-weighted portfolio of bauxite mining and aluminium producing companies are found to be significantly driven by both temperature and precipitation anomalies. These findings confirm that the operators of mines in tropical and sub-tropical areas studied in this research benefit from temperatures and rainfall below the usual levels but are negatively affected by anomalies higher than the expected levels.

The remainder of Chapter 2 is organised as follows. Section 2.2 provides a review of prior research and highlights the motivation for this study. Subsequently, Section 2.3 discusses the data collection and variable definition which is supplemented by the research methodology in Section 2.4. The empirical results are discussed and reported in Section 2.5 and the study closes with the conclusion, a critical review of the findings, and potential areas for future research presented in Section 2.6.

2.2 LITERATURE REVIEW

It is well known that unpredictable weather conditions influence the yield and thus market price of agricultural goods (Rankin, 2014). Weather risk, however, does not only impact agricultural production but impacts all commodity producing companies. Oil and gas (Yang et al., 2009) and mining companies (Locke et al., 2011; BHP Billiton, 2015) are affected by unpredictable weather disruptions and their impact is expected to increase in future (Mendelsohn et al., 2006; Wang et al., 2013). The inaccessibility of mining sites has a financial impact on commodity producing companies of several hundred million USD yearly (BHP Billiton, 2015:236) and therefore influences the value of these companies as well as the market price and market price volatility of the affected metals.

Prior literature offers extensive research on the relationships between weather, agricultural and energy commodity prices, and the stock market performance of the producers of such goods. Yet, little research examines the impact of weather on base metals. This is surprising, as researchers examining the climate impact on mining companies provide convincing evidence for the demand of such research (e.g. Hodgkinson et al., 2010; Loechel et al., 2013), as adverse weather events can severely influence mining operations. Besides the obvious consequences of extreme temperature and precipitation (e.g. droughts, floods, landslip, or overflowing of waste ponds (Hodgkinson et al., 2010) and bushfires (Garnaut, 2011)), weather can lead to more complex problems. Garnaut (2011) argues that long-term hot temperatures lead to sub-tropical conditions that may cause a spread of tropical diseases. This increases the cost of maintaining a healthy and efficient labour force. Moreover, droughts can lead to adverse policy decisions such as limited access to fresh water or forced investment in desalinating seawater for their operations (Craze, 2015). This limits the accessibility to fresh water and thus increases the production costs for mining companies. Anaman and Lellyett (1997) and Colls (1993) support these claims by providing evidence for the relationship of adverse weather events and mining operations and highlight the necessity of further research in this field. Finally, major mining companies such as BHP Billiton (2015), Rio Tinto (2015), and Norsk Hydro (2015) report the potential financial and operational impact of weather disruptions in their annual reports[12]. Although weather clearly increases the financial and operational risk of those companies[13], they refrain from using weather derivatives due to several reasons. As little research on the hedging performance of weather derivatives for mining companies is available, prior findings related to agricultural commodities might partially explain this behaviour.

Despite the positive effect of weather derivatives on the financial performance of agricultural producers (Miranda and Glauber, 1997; Duncan and Myers, 2000; Brown and Kshirsagar, 2015) only few companies use weather derivatives. The reasons for this are fourfold. First, producers usually do not possess the financial knowledge to efficiently use financial products or are simply not familiar with them. Second, weather derivatives typically have a basis risk as the weather stations used for the measurement are not on the premises of the insurant but are stationed in a city nearby. Hence, a farmer might face strong rainfall, but the nearest weather station is not affected by it, which leads to uninsured production cuts. Third, weather derivatives, especially exchange-traded ones, only insure against general weather phenomena but do not cover producer-specific risks. Odening et al. (2007) find that

[12] For example, BHP Billiton (2015) highlight in their annual report for the financial year of 2014 that *"During 2008, extreme weather across the central Queensland coalfields affected production from the BHP Billiton Mitsubishi Alliance (BMA) and BHP Billiton Mitsui Coal (BMC) operations. The Group settled insurance claims in respect of the lost production and insurance claim income of US$210 million (after tax expense) was recognised in the year ended 30 June 2012."* Moreover, Rio Tinto (2015) highlight in their annual report for the financial year of 2014 that *"In January 2014, all Pilbara coastal and some mine operations were suspended as a result of tropical cyclone Christine and heavy rainfall that continued into February. North America's extreme weather in Q1 also significantly affected IOC's production and shipments in the first half of 2014."* Lastly, Norsk Hydro (2015) highlight in their annual report for the financial year of 2014 that *"Costs associated with operating a mine may increase rapidly as a result of, among others, production interruptions or delays, […] and weather and other natural phenomena […]."* and that *"Some of our operations are located in close proximity to sizable communities. Major accidents due to human error, […] extreme weather or other natural disasters, could result in loss of life or extensive damage to the environment or communities. Such events could result in major claims, fines, penalties and significant damage to Hydro's reputation"*.

[13] According to Anaman and Lellyett (1997), 85 percent of mining companies in Queensland, Australia use public weather data from the Bureau of Meteorology for their operational planning. This confirms that mining companies are well aware of the impact of weather on their operations. Furthermore, Hennessy et al. (2007) argue that the temperature in Australia has risen almost 1º Celsius during the last century. Moreover, the level of precipitation declined. Hennessy et al. (2007) show that these changes match with climate projections for the future. This indicates a supply risk on water for mining companies in the severely affected areas, as sufficient water supply is crucial for their operations.

less than 25 percent of wheat yields in Germany are explained by cumulative rainfall. Thus, producers' yields are more likely to be affected by an individual mix of weather phenomena instead of the amount of sunshine, rainfall, or temperature. Fourth, while relatively higher risk can lead to higher risk premiums on weather derivatives, which partially explains the low acceptance of those products (Mahul, 1999; Duncan and Myers, 2000), regional separation, i.e. personalised or highly segregated areas, can help to reduce the risk and thus risk premiums on weather derivatives. This decreases the cost and threshold for producers to use such insurance products. However, due to the geographical concentration of mineral resources in often remote areas, this might not be possible for mining. Compared to farming and energy production, the locations of metal ores are limited and often remote. Mining companies must accept the given weather conditions in metal ore-rich areas instead of choosing the mining site. Based on the yearly production output of 2014 (USGS, 2015), Australia, Brazil, Guinea, India, and China represent primary mining countries for aluminium ores, i.e. bauxite. Overall, prior research highlights several reasons why commodity producers may stay away from weather derivatives to hedge their exposure to adverse weather. Although these products can reduce the financial distress for producers, the net effect of weather anomalies on the supply remains unchanged. That is, if weather events negatively affect the production and reduce the output, the supply will be reduced. This leads to a new equilibrium price on the market that may be partially compensated by existing inventory. Thus, one should still be able to observe the effect of weather anomalies on both inventory and price of the underlying commodity, regardless of whether or not weather events are hedged.

However, other factors can influence the observability of the effect of weather anomalies on the price of aluminium. First, one cannot obtain primary aluminium directly from the ground. Instead of mining the traded metal directly, the excavated ore needs chemical processing. The process begins with the extraction of bauxite from the mine which then passes through several refining steps that include storage and transportation, and finally ends with the storage of short-term supply in privately held or partially monitored warehouses by global exchanges such as the LME. These warehouses provide buffer stocks that may offset short-term losses in production. Thus, the supply of primary aluminium to the market might not be affected. Likewise, consumers may build private stocks to cater for short-term supply shocks. Second, secondary aluminium obtained from scrap can also be used for consumption as aluminium is a fully recyclable metal (The Aluminium Association, 2016a). This allows consumers and traders to switch between primary and secondary supply. Indeed, the secondary base metal market contributes 20 percent to the overall aluminium market (Bain 2013). Thus, environmental influences on the operations of miners may only partially influence market prices, as the demand for metals can be satisfied by secondary sources. A more efficient recycling policy of metals over time may reduce the dependence and demand for primary base metals. For now, this is not possible as the share of secondary aluminium is still comparably low and an increase in recycling needs new policies which must be implemented. As I am investigating the short-term, i.e. daily relationship between the variables, it is unlikely that changes in policy have any short-term effect. Moreover, although base metals are generally recyclable, one should bear in mind that these metals can only be recycled if they are no longer in use. As aluminium is vastly used for construction and telecommunication, the recyclable material may only be available after many years. According to The Aluminium Association (2016a), three-quarters of all aluminium produced is still in use. With a growing worldwide population and demand for faster telecommunication networks and housing, the demand for primary base metals will remain high (Bain, 2013). Third, the unlimited storability of base metals – with respect to the affiliated costs of storage – acts as a buffer for short-term disruptions in supply or demand. Compared to agricultural commodities, metals are not perishable. During times of low real interest rates, storing base metals becomes cheaper for investors (e.g. Frankel, 2006; Frankel and Rose, 2010). Hence, holding safety stocks can compensate for the potential risk of weather-influenced shortages in supply as consumers and traders can hold a specific equivalent of the required material and mitigate their price risk. However, this requires that the investor or buyer holds sufficient funds to trade and store the goods today, a strategy that has its own risk due to the unpredictability of both weather and prices. Investors might only realise the increase in prices once the mining output is affected and prices have been adjusted. Fourth, weather forecasts may significantly affect the commodity price before the actual event happens.[14] According to the Met Office UK (2016), weather forecasts provide a relatively accurate short-term prediction which diminishes as the forecast horizon increases. Although weather itself cannot be mitigated, it is possible to increase resilience

[14] The effect on the price might not be linked to the weather event itself but the deviation of the actual temperature or precipitation from its expected, i.e. forecasted value. As appropriate historical weather forecast information is scarce, it is not possible to calculate this deviation.

against likely but unpredictable adverse events. Dorfleitner and Wimmer (2010) show that weather forecasts significantly impact the price of temperature derivatives traded on the Chicago Mercantile Exchange up to eleven days ahead. Although one might be tempted to expect a comparable impact on commodity prices, it must be borne in mind that reliable forecasts require adequate data. With limited accessibility and availability of weather station information near mining sites, a reliable weather forecast for these areas is difficult. Overall, one should not forget that markets continuously price in the influences of both expectations and the actual event. Thus, an unforeseeable impact on the supply should impact the price and inventory accordingly.

To the best of my knowledge, little research examines the influence of weather anomalies on the price and inventory of exchange-traded aluminium and the stock returns of aluminium producers. Weather events represent risk that is hard to diversify.[15] While mine locations around the globe can help to minimise the risk for a company, it is not possible to fully mitigate the risk for the interruption-free supply of commodities. Only if one fully understands the impact of weather anomalies on the price and inventory of an exchange-traded commodity, it is possible to mitigate investor-individual financial risk. The indispensable characteristics of aluminium for the transport, construction, or food processing industry paired with its economic impact of employing more than 155,000 workers and generating more than 65 billion USD annually only in the US qualifies it as a crucial commodity for almost every consumer (The Aluminium Association, 2016a).

It is expected that absolute weather anomalies are inversely related to production output. Weather anomalies decrease the global supply, which reduces inventory and increases the market price. This study allows consumers to better understand changes in aluminium market prices and inventory and their causing factors, enables investors to adequately incorporate weather anomalies into their investment decisions, provides a basis for insurers and financial institutions to create financial products to mitigate potential risks, and helps policy makers to evaluate the correlation between climate change, market behaviour, and financial products available on the market to protect participants from potential fraud. With respect to the increasing influence of climate change on weather and

[15] For example, bauxite mines are geographically concentrated in few locations globally. Australia, a country with accurate weather reporting, produces approximately 35 percent of global bauxite, which makes it the world's largest producer of bauxite.

mining operations (Hodgkinson et al., 2010), the study provides new insight on the interaction of weather anomalies and the price and inventory of exchange-traded aluminium and tests the hypotheses:

H_1: Weather anomalies are inversely related to inventory.

H_2: Weather anomalies are positively related to aluminium futures prices.

By testing these two hypotheses, this study attempts to answer the research question: Do weather anomalies affect the returns and inventory of exchange-traded aluminium?

2.3 DATA COLLECTION AND VARIABLE DEFINITION

2.3.1 DATA

The analysis uses five primary sources of information: the Thomson Reuters database for financial and economic data (Datastream), the Federal Reserve Bank of St. Louis, the National Oceanic and Atmospheric Administration National Climate Data Center (NOAA), the US Geological Survey (USGS), and the annual reports of the bauxite mining and aluminium producing companies that operate the mines studied. First, I extract the London Metal Exchange (LME) 3-months aluminium futures daily price for the research period from 1st January 2001 to 31st December 2014 from Datastream. Seventy-six percent of the global non-ferrous futures are transacted on the LME (2016). Following Frankel and Rose (2010), the United States Gross Domestic Product (US GDP) is used to deflate the market prices. Unlike other deflators such as the consumer price index (Svedberg and Tilton, 2006), the US GDP includes all consumption and investment from all individuals of a country and does not limit itself to a fixed basket of goods. As the total inventory of aluminium held by companies, investors, and countries is not publicly available, LME warehouse stocks are added to the dataset to proxy for global inventory. The LME organises, supervises, and regulates warehouses operated by subcontractors. Changes in aluminium stored in these warehouses illustrate a short-term change in supply and demand as market participants can sell or buy aluminium on the exchange that is stored in these warehouses. Due to the leading position of the LME in the non-ferrous market, the reported warehouse stocks are a reasonable proxy for global inventory.

Second, I add variables to control for influential factors on the market price and inventory. Overall, both are driven by four forces: the current supply, the expected future supply, the current demand, and the expected future demand. All changes in the price will ultimately be the result of changes in at least one of these main factors. They, on the other side, are influenced by changes in various micro- and macroeconomic, technological, environmental, and other factors. I follow prior research and consider different proxies to incorporate those effects into the model. Contrary to Frankel and Rose (2010), I do not use the real global GDP to proxy for global demand or economic activity but the Baltic Dry index (BDI). While aluminium is widely used for construction, transport, and the electronics industry (Norsk Hydro, 2016), global GDP not only represents metals and metal-related raw materials but includes all goods traded globally. Furthermore, the World Bank reports global GDP only on a yearly basis. Instead, I follow Kilian (2009) and Kuralbayeva and Malone (2012) and consider an index that uses global shipping rates to proxy for global demand. This index, the BDI, focuses on raw materials shipped by sea, excludes other factors influencing global GDP, and is available daily. The BDI is provided by the Baltic Exchange in London and the data are captured from Datastream.

Additionally, the real interest rate, a measure of conventional monetary policy (Frankel and Rose, 2010), controls for cheap money in the market. Low real interest rates allow investors to physically store metals at a cheaper rate, which increases the inventory demand for aluminium.[16] Furthermore, low real interest rates allow consumers of base metals to invest in their business, which will also increase the demand for those goods. Following Akram (2009), I use the USD 3-month deposit rate and the year-on-year US consumer price index (CPI) change to calculate the real interest rate. The source for these data is Datastream. The trade-weighted USD index, which measures the relative value of the USD compared to other currencies, controls for the foreign exchange (FX) impact. Most of the global exchange-traded commodities, including aluminium, are traded in USD. Therefore, the demand for raw materials not only depends on the USD price but also the converted price in the buyers' currency. An increase in the relative value of the USD will therefore lead to a decrease in demand from countries with relatively weaker currency compared to the USD (Roache, 2008). As the daily data provided by the Federal Reserve Bank of St. Louis show gaps throughout the research period, the arithmetic average of the preceding and succeeding trading day is used for days with missing data. Lastly, I add the S&P 500 composite index to

[16] This transmission channel of conventional monetary policy is called inventory channel and is thoroughly discussed in Section 3.2.2.

control for equity market risk. I extract this data from Datastream. Except for a brief period during the global financial crisis in 2007-2008, Creti et al. (2013) find evidence for a positive correlation between the S&P 500 and aluminium returns.

Table 2.2 provides information on the financial and weather anomaly index variables used in this study. The 3,653 daily observations represent the research period between 1st January 2001 and 31st December 2014. The parameters in Table 2.2 are defined as: FP as the deflated 3-month futures aluminium price, IL as the LME inventory stocks that proxy for global inventory, EA as the Baltic Dry Index that proxies for global demand, RIR as the real interest rate, TWI as the trade-weighted USD index, SP500 as the S&P 500 composite index, P for precipitation, T for temperature, WAI as the weather anomaly index, DoA for daily only Australia (i.e. only weather anomalies for Australian mines), mean for the arithmetic mean, median for the median, std. dev. for standard deviation, min for the minimum value of the time-series, max for the maximum value of the time-series, skew for skewness, kurt for kurtosis, and the test statistics of the augmented Dickey-Fuller test (ADF) for unit-roots. PP test results are reported where deviations from the statistical significance of the ADF test statistic can be observed (in parentheses). The test statistics indicate unit roots for most of the variables except for the weather anomaly indices. Thus, I use the periodical logarithmic change, or first difference, to transform the data[17]. I use logarithmic changes when the time-series does not include negative numbers (e.g. futures time-series) and use first differences when negative and positive values are present in the time-series (e.g. real interest rate, which experiences positive and negative values thorough the research period). The extensions _r for log returns and _f for first differences indicate if and how the data are transformed to achieve stationarity of the time-series. Moreover, the distributions of the futures returns and changes in inventory indicate that the data are not normally distributed. However, as the data sample consists of 3,653 observations for each of the variables, I can reasonably assume that the central limit theorem applies (Brooks, 2008). The temperature anomaly index values are denoted in tenths of a degree Celsius and the precipitation anomaly index values are denoted in tenths of a mm. All other variables are in 100's of a percent, except for skewness, kurtosis, and ADF.

[17] $R_t = \ln(P_t / P_{t-1})$ for logarithmic change and $R_t = P_t - P_{t-1}$ for first difference.

In addition to the control variables in the model, other factors may influence the price and inventory of exchange-traded aluminium. This includes secondary aluminium, which requires only ten percent of the energy used to produce primary aluminium (The Aluminium Association, 2016b). Hence, an increase in energy costs may lead to a growing demand for secondary aluminium. Also, the price of a substitute of aluminium may incentivise consumers to change for cheaper industrial metals. However, this requires that the substitute provides comparable chemical characteristics and usability. I believe that these factors do not change the price in the short-term but may lead to a change in a mid- to long-term perspective and can therefore be neglected for this study. Third, I collect daily weather information from the NOAA. The NOAA provides the information per weather station. In this study, I focus on the average temperature and precipitation reported by weather stations with the nearest proximity to the eleven mines examined. The evaluation includes some of the largest bauxite mines and represent a total share of more than 40 percent of global bauxite excavation in 2014. As some weather stations report incomplete data for the overall research period, I use the available information from the nearest weather station that reports partial temperature or precipitation data and substitute missing values with the second nearest station data. If this information is not available, I use the next nearest station. Following New et al. (2000) and Harris et al. (2014), this procedure considers all mines up to a maximum distance of 1,200 kilometres for temperature and 450 kilometres for precipitation. I apply this algorithm until all necessary information is obtained, i.e. temperature and precipitation per individual mine throughout the whole research period.[18] This algorithm analyses, formats, and structures the data and substitutes missing values by weather information from the nearest weather station with available data for each individual day. This approach accounts for missing data and provides a more complete basis for the research. Table 2.1 lists the individual mines and the availability of the nearest weather station and presents the adjusted availability in percent after the calculations. The results in Table 2.1 show that the algorithm helps to close gaps and drastically reduces the percentage of missing weather data.

[18] It must be highlighted that this decision might potentially bias the study. As harsh weather can be the reason for missing data, the missing information itself incorporates valuable information. However, this cannot be scrutinised, as the information is not available. In the robustness exercise, the potential impact of missing data is evaluated.

Based on the data obtained from the NOAA, it is possible to build a weather index that allows me to evaluate the impact of weather. To do so, I transform the weather information into anomalies, i.e. calculate the daily deviation per mine from its normal value. Contrary to the method by the NOAA, which suggests using the 30-year average (NOAA, 2016a), I limit the calculation to the research period, i.e. the 14-year average to account for the mine-specific weather measurements. As the availability of weather information per station changes each day, the 30-year average would draw on data from different weather stations to the 14-year average. Ultimately, I do not expect a significant difference between both periods. As I focus on strong deviations from the normal value, minor differences in the normal value are unlikely to influence the result. Following the calculation of the normal values, I calculate the absolute deviation to the actual measurement each day to determine anomalies. It is expected that strong deviations equally influence the production, regardless whether they are positive or negative. Moreover, using absolute deviations reduces the potential offset of positive and negative deviations among the eleven examined mines.

Table 2.1: Substitution of Missing Daily NOAA Weather Information

Mine Name	*Before substitution - temperature*	*After substitution – temperature*	*Distance to farthest weather station*	*Before substitution - precipitation*	*After substitution – precipitation*	*Distance to farthest weather station*	*Global share of production (in 2014)*
Boddington	0.00	100.00	32.0 km	82.38	100.00	18.3 km	8.12
Huntly	0.00	100.00	45.1 km	77.72	100.00	16.3 km	9.83
Willowdale	0.00	100.00	32.6 km	56.15	100.00	16.8 km	4.27
Gove	99.98	100.00	139.4 km	99.86	100.00	9.3 km	2.79
Weipa	0.00	100.00	157.2 km	99.34	100.00	9.4 km	11.22
Trombetas	99.28	99.98	879.1 km	0.27	2.39	297.4 km	7.69
Paragominas	98.57	99.98	780.8 km	63.15	71.31	296.9 km	4.36
Juruti	99.28	99.98	887.1 km	0.27	2.39	277.3 km	2.05
Boke	3.56	100.00	572.1 km	1.43	54.61	420.6 km	6.75
Kindia	15.53	100.00	718.1 km	5.89	49.09	435.7 km	1.45
Panchpatmali	98.85	99.97	227.8 km	41.95	50.60	227.8 km	2.92
Average	46.82	99.99	406.5 km	48.04	66.40	184.2 km	61.45

Notes: The table illustrates the availability of data in percent before and after I substitute missing values from the nearest available weather station by further distant data. All figures are shown in percentage if not stated otherwise. The figures represent the overall availability of data for the research period from 1st January 2001 to 31st December 2014.

2.3.2 WEATHER INDEX CREATION

To combine the information of the mines studied, I build an index that weights the anomalies per day. Weighting the anomalies is necessary, as each mine has a different impact on the market supply. Mines with relatively higher supply to the market are expected to have a bigger impact on the dependent variables. To incorporate the relative strength of each mine, the yearly mine output in metric tonnes is used to calculate the weights w_{it} for each mine i at time t. The annual reports from the mining companies that operate the mines provide this information on a yearly basis.[19] In some cases, changing ownership of mines or inconsistent reporting leads to incomplete mine-specific data. Thus, the yearly gapless country-specific production output information for bauxite provided by the USGS (2015) is used to fill the gaps. The yearly country-specific production output information is allocated by using the reported mine-specific information from previous and succeeding years to calculate each individual mine's share of the total production output for the country in which the mine is located. In a second step, the weather anomalies and weights are combined and form the weather anomaly indices for temperature and precipitation. The anomaly indices are calculated as:

$$WAI_t = \sum_{i=1}^{n} (|m_{it} - n_{it}| * w_{it-1}) \tag{2.1}$$

with WAI_t as weather anomaly index, m_{it} as the mine-specific temperature or precipitation observation each day, n_{it} as the normal temperature or precipitation for each mine, and w_{it-1} as mine-specific weight for each mine i at time $t-1$ with $\sum w_{it} = 1$ for each year.

Table 2.2: Key Statistics

	Mean	*Std. Dev.*	*Min*	*Max*	*Kurt*	*Skew*	*ADF*
FP_r	-0.0030	1.3559	-8.2575	5.9153	5.5570	-0.2921	-63.312***
IL_r	0.0704	0.6206	-1.6041	10.9929	66.5107	5.5980	-40.752***
EA_r	-0.0196	1.9681	-12.0718	13.6576	8.5791	0.0000	-20.780***
RIR_f	-0.0007	0.0950	-0.8070	1.3234	34.1788	1.7566	-82.587***
TWI_r	-0.0026	0.3022	-2.2975	1.7340	7.6776	-0.0006	-58.766***
SP500_r	0.0122	1.2519	-9.4695	10.9572	12.1134	-0.2016	-66.310***
P_WAI	54.6030	43.1645	1.8083	718.0309	36.8064	4.1596	-52.526***
T_WAI	15.0304	7.9139	1.3291	53.7853	5.0691	1.2785	-38.029***
P_WAI_DoA	40.0482	43.5311	1.0225	597.1161	27.5390	3.9641	-49.524***
T_WAI_DoA	18.0675	12.1938	0.4773	85.2049	5.5110	1.3897	-38.623***

Notes: This table provides information on the financial and weather anomaly index variables used in this study. With 3,653 daily observations representing the research period of between 1st January 2001 and 31st December 2014. In addition, the table provides information whether the data are stationary and needs transformation before I can use it for the study. I use the augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP) to test for a unit root. As all variables except the weather anomaly indices are non-stationary, the transformed variables are reported. With _r for log returns and _f for first differences. The parameters are defined as: FP as the deflated 3-month futures aluminium price, IL as LME inventory stocks that proxy global inventory, EA as Baltic Dry Index that proxies global demand, RIR as real interest rate, TWI as the trade-weighted USD index, SP500 as the S&P 500 composite index, P for precipitation, T for temperature, WAI as weather anomaly index, and DoA for daily only Australia. With the arithmetic mean (mean), the median, standard deviation (std. dev.), minimum value (min), maximum value (max), the skewness (skew), kurtosis (kurt), and the test statistics of the augmented Dickey-Fuller test (ADF) for unit-roots. PP test results are reported where deviations from the statistical significance of the ADF test statistic can be observed (in parentheses). The temperature anomaly index values are denoted in tenths of a degree Celsius and the precipitation anomaly index values are denoted in tenths of a mm. All other variables are in 100's of a percent, except for skewness, kurtosis, and ADF. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

[19] The yearly output is taken as no daily, weekly, or monthly output information on mine level is available.

In total, four weather anomaly indices are created. Two indices each for temperature and precipitation anomalies that either consider all eleven global bauxite mines or only the five mines located in Australia, which is the largest bauxite producing country (USGS, 2015). Table 2.2 provides information on the key statistics of the weather indices and other variables used in this study. For all weather indices at levels, the null hypothesis of a unit root at the 1 percent significance level can be rejected.

2.4 RESEARCH METHODOLOGY

This section describes the econometric framework to evaluate the consequences of weather anomalies on the inventory and returns of exchange-traded aluminium. Roll (1984), who presents one of the seminal papers examining the impact of weather on frozen orange juice concentrate (FCOJ), uses a simple linear regression. Boudoukh et al. (2007), who revaluate the findings by Roll (1984), use a nonlinear regression model and provide evidence for a stronger relationship between similar variables. Boudoukh et al. (2007) further add that temperature only impacts the production of FCOJ once it reaches a specific threshold, which is 32 degree Fahrenheit (i.e. 0 degree Celsius). Temperature above this threshold, however, does not significantly influence the yield of FCOJ. Furthermore, the researchers argue that the intensity of temperature changes is not constant, i.e. a change of 5 degrees near the freezing point has a stronger impact on the yield than a change from 40 to 45 degrees Fahrenheit. Compared to Roll (1984), who suggests that weather has little influence on the price of FCOJ, Boudoukh et al.'s (2007) approach explains almost 50 percent of the return variation on days with temperature below the freezing point. While the 32 degree Fahrenheit threshold is suitable for agricultural products that are affected by freezing temperatures (Boudoukh et al., 2007), the question of a specific threshold temperature and precipitation for mining arises. Contrary to agricultural commodities, mining is less prone to weather influences. Yet, they are not immune, as history shows that persistent hot temperature or strong precipitation forces production stops (Hodgkinson et al., 2010). The challenging question is to determine the threshold temperature and precipitation as prior research gives little advice on such levels. Instead of a fixed threshold at a specific temperature or above a set level of rainfall, the deviation from the normal value that is used to calculate the weather anomaly indices provides a better approximation. With this approach, one can easily determine whether temperature and precipitation events are strongly deviating from their normal values. The stronger the deviation, the more likely it is that the weather anomaly has a detrimental effect on the mining process.[20] Building on Roll (1984), Hirshleifer and Shumway (2003), and Boudoukh et al. (2007), the ordinary least squares regression model can be written as:

$$R_t = \alpha + \beta_m WAI_t + \beta_n X_t + \varepsilon_t \tag{2.2}$$

with R_t as close-to-close log change of FP_t as futures price and IL_t as inventory, α as intercept, β as coefficients, WAI_t as vector of weather anomaly index values for temperature or precipitation, X_t as vector of controls with $X_t = [IL_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of FP_t and $X_t = [FP_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of IL_t, EA_t as economic activity (global demand), RIR_t as real interest rate, TWI_t as the relative value of the USD compared to other currencies, $SP500_t$ as control for equity market risk, and ε_t as error term. All variables are at time t. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.[21]

Furthermore, prior research argues that weather can influence the market price volatility of commodities (Fleming et al., 2006). In addition to changes in global inventory and price, their volatility is being evaluated. A GARCH (1,1) model as in Richards et al. (2004) and Shu and Hung (2009) is used. Although previous studies argue that alternative models to the GARCH (1,1) model provide more accurate estimates (McMillan and Speight, 2007), others argue that the GARCH (1,1) has good statistical power as it controls for time-varying volatility and incorporates heteroscedasticity (Hansen and Lunde, 2005). As I am mainly interested in the results for the coefficient τ_m and whether weather anomalies influence the volatility of inventory changes and aluminium futures returns, the standard GARCH model is sufficient for this exercise. The model can be written as:

$$R_t = \alpha + \tau_m WAI_t + \beta_n X_t + \varepsilon_t \tag{2.3}$$

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[20] In addition, I add threshold dummy variables that measure the 90th and 95th quantile of anomalies to concentrate on the largest weather anomalies. While the significance of the weather anomaly indices diminishes in this scenario, the statistical significance of some dummy threshold variables can be observed. However, as the findings and significance are weak, I refrain from reporting these robustness evaluations separately.

[21] I also use Newey-West standard errors to further account for autocorrelation. The significance of the focus variables remains comparable to the results obtained with robust standard errors.

$$h_t^2 = \gamma_0 + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1}^2 + \tau_m WAI_t \quad (2.4)$$

with R_t as close-to-close log change of FP_t as futures price and IL_t as inventory, α as intercept, β as coefficients, X_t as vector of controls as in equation (2.2), WAI_t as weather anomaly index for temperature or precipitation, and h_t^2 as the conditional variance of R_t.

2.5 EMPIRICAL RESULTS

A key advantage of the daily analysis is the ability to evaluate the short-term relationships between the chosen variables. To estimate the effect of weather anomalies on changes in the aluminium futures price and inventory, I begin with the evaluation of the OLS estimations which are reported in Table 2.3.

Table 2.3: Ordinary Least Squares Regression

	Aluminium Futures Returns		*Inventory Changes*	
	All Mines	Australian Mines	All Mines	Australian Mines
P_WAI	1.30e-06	2.05e-06	-4.44e-06**	-1.63e-06
	(4.53e-06)	(4.15e-06)	(1.94e-06)	(1.86e-06)
T_WAI	9.78e-06	1.91e-06	9.91e-06	1.08e-06
	(2.64e-05)	(1.70e-05)	(1.42e-05)	(9.35e-06)
IL_r	-0.0879**	-0.0879**		
	(0.0348)	(0.0348)		
FP_r			-0.0225**	-0.0225**
			(0.00946)	(0.00947)
EA_r	-0.00431	-0.00440	0.00316	0.00264
	(0.0117)	(0.0117)	(0.00482)	(0.00484)
RIR_f	0.00127	0.00127	-0.00160	-0.00161
	(0.00219)	(0.00219)	(0.00167)	(0.00167)
TWI_r	-1.631***	-1.631***	0.00350	0.00250
	(0.0820)	(0.0820)	(0.0498)	(0.0499)
SP500_r	0.174***	0.174***	-0.00211	-0.00239
	(0.0194)	(0.0194)	(0.0120)	(0.0120)
Constant	-0.000249	-0.000148	0.000796***	0.000748***
	(0.000522)	(0.000405)	(0.000282)	(0.000230)
Observations	3,653	3,653	3,653	3,653
Adjusted R^2	0.182	0.182	0.003	0.001

Notes: This table provides information about the results of the regression examining all mines in this study. The dataset consists of 3,653 trading days between 1st January 2001 and 31st December 2014. The temperature anomaly values WAI are in tenths of degree Celsius and precipitation is in tenths of mm. The parameters are defined as: WAI as the anomaly weather index value with P_ for precipitation and T_ for temperature, IL_r as LME inventory, FP_r as aluminium futures price returns, EA_r as Baltic Dry Index, RIR_r as real interest rate, TWI_r as the trade-weighted USD index, and SP500_r as the S&P 500 index. With robust standard errors (Huber/White/sandwich estimator) in parentheses. If the ADF test suggests a unit root, log changes or first difference are used to transform the time-series (_r indicating log returns, _f indicating first difference). * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

The model is defined as:

$$R_t = \alpha + \beta_m WAI_t + \beta_n X_t + \varepsilon_t$$

with α as intercept, $\beta_{m\ to\ n}$ as coefficients, R_t as close-to-close log change of FP_t as futures price and IL_t as inventory, WAI_t as vector of weather anomaly index values for temperature or precipitation, X_t as vector of controls with $X_t = [IL_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of FP_t and $X_t = [FP_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of IL_t, EA_t as economic activity represented by the Baltic Exchange Dry Index, RIR_t as real interest rate, TWI_t as the relative value of the USD, $SP500_t$ as parameter controlling for equity market risk, and ε_t as error term. All variables are at time t. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.

While precipitation anomalies are negatively associated with inventory changes at the 5 percent significance level, the magnitude of the coefficient is very small and there is no evidence that futures returns are affected by precipitation anomalies. Moreover, temperature anomalies are non-significant for both inventory changes and futures returns. In a succeeding step, I reduce the number of examined mines from eleven to five key mines all located in two areas in Australia. As these five mines account for approximately 35 percent of global bauxite output in 2014, the evaluation of weather events in these areas limits the focus to a few locations that significantly contribute to the global output of the raw material bauxite and may help to reduce the potential bias stemming from global weather events. The columns named Australian mines in Table 2.3 illustrate the results. Weather anomalies appear to have no significant impact on futures returns and inventory changes. Despite reports by mining companies (Rio Tinto, 2016:14-15) and newspaper articles about production cuts (Wallop, 2011; Platts Metals Daily, 2013), the analysis cannot identify an observable impact of weather anomalies on futures returns. However, as the inventory changes are significantly affected by precipitation anomalies, the findings indicate that inventory stocks might buffer short-term production cuts so that these are not channelled through to prices.

A potential bias that may arise because of the chosen methodology is simultaneity bias. This bias describes an endogeneity issue in which an explanatory variable is correlated with the error term of the regression. More precisely, one may not be able to treat the independent variable as fully exogenous but must accept that the independent variable is endogenous. Instead of a unidirectional relationship from the independent variable to the dependent variable, the evaluated variables may indeed have a bidirectional relationship, which must be accounted for. As a result, the estimated coefficients are biased (Brooks, 2008). Particularly for the estimation of aluminium futures returns and inventory changes, which are both used as dependent and independent variables in the regression models, this bias might occur as price changes could trigger market participants to change their inventory holdings. Likewise, changes in inventory may lead to changes in the price. For example, increases in inventory demand may lead to an increase in demand overall. If the supply remains constant, this will increase the price of the underlying. To deal with simultaneity bias, I first drop the potentially affected variables to test if the other coefficient estimates, particularly the weather anomaly indices, remain constant. The results suggest that the effect of both precipitation and temperature anomalies on aluminium futures returns remain non-significant. Likewise, the results for inventory changes remain comparable to those reported in Table 2.3. Second, I treat aluminium futures returns and inventory changes as endogenous variables and run a two-stage least squares regression (cf. Floyd, 2013). Building on Aldieri and Vinci (2017) and Boumparis et al. (2017), I use lagged versions of aluminium futures returns (for the estimation of inventory changes) and inventory changes (for the estimation of aluminium futures returns) at t-1 and t-2 as instrumental variables. While the Durbin score and the Wu-Hausman test (H_0 = variables are exogenous) are significant at the 1 percent significance level in all tested scenarios[22], which suggests that it is appropriate to treat inventory changes and aluminium futures returns as endogenous variables, the coefficients for both weather anomaly indices remain non-significant for the estimation of aluminium futures returns. Moreover, while the coefficient of precipitation weather anomalies for the estimation of inventory changes slightly increases (from -4.44e-06 to -5.09e-06), its statistical significance reduces and only holds at the 10 percent level. Thus, after controlling for simultaneity bias, all weather anomaly index coefficients are not significant at the 5 percent level, which suggests that the estimation power of the weather anomaly indices is still non-significant for the estimation of both aluminium futures returns and inventory changes[23].

2.5.1 THE LAGGED AND GROWING EFFECT OF WEATHER ANOMALIES

Contrary to agricultural commodities, where freezing temperature can strongly harm the seasonal harvest, the effect of short-term weather anomalies on futures returns and inventory changes can only be observed if a) the weather anomalies are severe b) occur on the same day as the weather anomaly and c) mining operators are not able to compensate for short-term production cuts immediately after the weather event. Only if the production cuts remain for a longer period, i.e. comprise of multi-day events instead of single day occurrences[24], it is expected that output targets are no met, which eventually affects the supply, inventory, and price of aluminium. Moreover, weather anomalies, and the bauxite

[22] The Durbin score and the Wu-Hausman tests suggest that treating inventory changes and aluminium futures returns as endogenous variables is appropriate. The four tested scenarios are in line with Table 2.3, i.e. I test the effects of weather anomalies for all mines and Australian mines only on both aluminium futures returns and inventory changes.

[23] The OLS regression results without the inventory changes (for the estimation of aluminium futures returns) and aluminium futures returns (for the estimation of inventory changes) as independent variables and the two-stage least squares results are available upon request.

[24] I further test the potential impact of the direction the weather anomaly, i.e. if it is a positive or negative deviation from the normal value. For both weather variables, the direction of the deviation, proxied by a dummy for the direction and a recalculation of the weather indices with positive and negative deviations, does not change the results.

mines studied, are spread throughout the globe. Thus, weather events in a certain area might occur during non-trading times and might not be reflected in the price on the same day. To test the potential impact of multi-day and time-varying effects of weather anomalies on the dependent variables, lags and leads of the weather variables and other new variables for the growing impact of weather anomalies, weather anomalies occurring during non-trading days, and the potential impact of missing weather information are added to the model. I begin with the introduction of two lags[25], i.e. two trading days, of the dependent variable reported in Table 2.4, which tests whether the adjustment of the market price and inventory requires several days. For example, this might be due to different time zones or a time delay in the availability of information on the impact of the weather event on the production. Likewise, the leads of weather anomalies test whether upcoming weather anomalies (i.e. forecasts) have been incorporated into the price in advance of the event. With non-significant results for all lagged and lead weather variables, the introduction of lags and leads for the estimation of changes in the global price and inventory provides little additional support for both the overall sample of weather anomalies for all eleven and the five Australian mines. The reason for these findings might be twofold. First, since the GFC in 2008, global aluminium stocks rose drastically. Thus, the existing stocks might be sufficient to account for short-term losses in production. In support of this hypothesis, the results in Table 2.4 show that precipitation anomalies appear to significantly impact changes in global inventory. It must be noted that OLS and other linear regressions may show multicollinearity among the independent variables. According to Brooks (2008), an underlying assumption of OLS regression is that all independent variables are not correlated with each other. In this perfect scenario, adding or removing an explanatory variable from a model would not cause any changes in the coefficients of the other regressors. However, as most explanatory variables experience some sort of correlation with each other, it is necessary to assess how much they are correlated and to what extent this multicollinearity affects the estimated coefficients. To measure the degree of collinearity (cf. Fahrmeir et al., 2013), I follow Chen et al. (2014c) and use the variance inflation factor (vif)[26]. For all estimated models in Table 2.4, the mean vif is well below 1.2 with the highest values for the lagged temperature anomaly indices below 1.5. These results suggest that little multicollinearity is present in the estimated models.

[25] As the accuracy of weather forecasts decreases over time (Met Office UK, 2016), I limit the analysis to two lags.

[26] I use this test for possible collinearity for all other linear regressions in this thesis, too.

Moreover, to reduce the potential multicollinearity, I run the regressions with the individual lagged variables, i.e. I test for weather anomaly effects at each lag individually. Again, all coefficients and their respective significance remain as in Table 2.4. More importantly, the predominant non-significance of the weather anomaly indices remains after testing the estimation power of the lagged weather anomaly indices individually.

Table 2.4: Lags and Leads of the Weather Variables

	Aluminium Futures Returns				*Inventory Changes*			
	Lags	Leads	Lags–AUS	Leads–AUS	Lags	Leads	Lags–AUS	Leads–AUS
P_WAI	1.16e-06	8.11e-07	1.78e-06	2.01e-06	-4.01e-06**	-4.03e-06**	-2.21e-06	-2.44e-06
	(4.62e-06)	(4.58e-06)	(4.29e-06)	(4.17e-06)	(1.89e-06)	(1.94e-06)	(1.85e-06)	(1.92e-06)
L1.P_WAI	8.99e-07	1.20e-06	2.33e-06	-1.44e-06	-1.91e-06	-1.27e-06	2.51e-06	4.07e-06
	(4.78e-06)	(4.46e-06)	(4.59e-06)	(4.49e-06)	(2.04e-06)	(2.08e-06)	(2.26e-06)	(2.69e-06)
L2.P_WAI	1.60e-06	1.55e-06	-4.17e-06	4.34e-06	-5.47e-07	-1.72e-06	9.79e-07	6.83e-07
	(4.86e-06)	(4.44e-06)	(4.54e-06)	(3.95e-06)	(2.20e-06)	(2.80e-06)	(2.23e-06)	(2.46e-06)
T_WAI	2.54e-06	1.43e-05	-2.16e-06	3.65e-06	2.72e-06	2.06e-06	-1.28e-06	-2.79e-06
	(2.94e-05)	(2.98e-05)	(1.88e-05)	(1.92e-05)	(1.46e-05)	(1.39e-05)	(9.25e-06)	(9.22e-06)
L1.T_WAI	1.10e-05	4.19e-06	7.31e-06	4.14e-06	7.00e-06	1.45e-05	1.81e-06	8.27e-06
	(3.10e-05)	(3.01e-05)	(2.00e-05)	(1.92e-05)	(1.56e-05)	(1.72e-05)	(9.51e-06)	(1.11e-05)
L2.T_WAI	1.57e-05	-3.05e-05	5.65e-06	-2.06e-05	2.09e-05	7.02e-06	1.14e-05	-6.11e-07
	(2.79e-05)	(2.90e-05)	(1.80e-05)	(1.85e-05)	(1.40e-05)	(1.48e-05)	(8.93e-06)	(9.63e-06)
IL_r	-0.0881**	-0.0872**	-0.0878**	-0.0878**				
	(0.0349)	(0.0349)	(0.0349)	(0.0348)				
FP_r					-0.0224**	-0.0223**	-0.0224**	-0.0224**
					(0.00945)	(0.00948)	(0.00947)	(0.00948)
EA_r	-0.00419	-0.00483	-0.00418	-0.00468	0.00347	0.00352	0.00281	0.00311
	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.00482)	(0.00484)	(0.00484)	(0.00490)
RIR_f	0.00121	0.00121	0.00128	0.00125	-0.00157	-0.00159	-0.00159	-0.00163
	(0.00219)	(0.00219)	(0.00219)	(0.00218)	(0.00167)	(0.00167)	(0.00167)	(0.00167)
TWI_r	-1.633***	-1.630***	-1.631***	-1.630***	0.00442	0.00177	0.00176	0.00346
	(0.0822)	(0.0818)	(0.0822)	(0.0817)	(0.0497)	(0.0498)	(0.0497)	(0.0499)
SP500_r	0.174***	0.174***	0.174***	0.174***	-0.000969	-0.00256	-0.00107	-0.00267
	(0.0194)	(0.0194)	(0.0194)	(0.0194)	(0.0120)	(0.0120)	(0.0119)	(0.0120)
Constant	-0.000671	-4.58e-05	-0.000223	5.00e-06	0.000591	0.000734*	0.000432	0.000523
	(0.000710)	(0.000697)	(0.000531)	(0.000520)	(0.000392)	(0.000438)	(0.000299)	(0.000324)
Observations	3,651	3,651	3,651	3,651	3,651	3,651	3,651	3,651
Adjusted R^2	0.181	0.181	0.181	0.182	0.002	0.002	0.001	0.001

Notes: This table provides information about the results of the regression examining all mines in this study. The dataset consists of 3,653 trading days between 1st January 2001 and 31st December 2014. The temperature anomaly values WAI are in tenths of degree Celsius and precipitation is in tenths of mm. The parameters are defined as: WAI as the anomaly weather index value with P_ for precipitation and T_ for temperature, L1. and L2. for lags at time t-1 and t-2 or leads at t+1 and t+2, AUS for Australia which limits the weather variables to the five Australian mines in this study, IL_r as LME inventory, FP_r as aluminium futures price returns, EA_r as Baltic Dry Index, RIR_r as real interest rate, TWI_r as the trade-weighted USD index, and SP500_r as the S&P 500 index. With robust standard errors (Huber/White/sandwich estimator) in parentheses. If the ADF test suggests a unit root, log changes or first difference are used to transform the time-series (_r indicating log returns, _f indicating first difference). * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

The model is defined as:

$$R_t = \alpha + \beta_{m.0} WAI_t + \beta_{m.1} WAI_{t-1} + \beta_{m.2} WAI_{t-2} + \beta_n X_t + \varepsilon_t$$

with α as intercept, $\beta_{m\ to\ n}$ as coefficients, R_t as close-to-close log change of FP_t as futures price and IL_t as inventory, WAI_t as vector of weather anomaly index values for temperature or precipitation, X_t as vector of controls with $X_t = [IL_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of FP_t and $X_t = [FP_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of IL_t, EA_t as economic activity represented by the Baltic Exchange Dry Index, RIR_t as real interest rate, TWI_t as the relative value of the USD, $SP500_t$ as parameter controlling for equity market risk, and ε_t as error term. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.

Second, a one-day observation of the weather anomalies might not be sufficient to evaluate their impact on the dependent variables as multi-day weather anomalies are necessary to significantly affect the mining. Therefore, four new variables that address these issues are added. First, a dummy variable that indicates whether 20 percent or more weather data on each trading day are missing is added. As strong weather events might be the reason for the missing information, the variable reveals details on the relationship between missing weather information and the dependent variables. Second, a variable that shifts weather events on non-trading days within the 90th percentile of weather anomalies to the following trading day is added. Third, I calculate a variable that cumulates the strongest weather anomaly values in the 90th percentile of weather anomalies during times of multi-day events. Once the anomaly is below the 90th quantile threshold of weather anomalies, the calculation restarts at 0. Moreover, weather phenomena occur throughout the whole time, regardless of the trading hours of an exchange. As weekends and other non-trading days might influence returns once the exchange starts trading again, I accumulate the weather index values on non-trading days and shift them to the following trading day. With this approach, I test if returns react to strong weather anomalies that occur on non-trading days. Fourth, I calculate the moving average of anomaly index values of the trading day and the previous four days, which may include both trading and no-trading days. This variable combines the impact of a growing effect of weather anomalies and the effect of all weather anomalies throughout the research period on trading and non-trading days.

In Table 2.5, the numerical findings for the four new variables are presented. First, the missing weather data variable, which measures the availability of weather data throughout the research period, is only available for precipitation as temperature data are sufficiently available during the research period. The findings reveal a significant positive, i.e. increasing effect of missing precipitation data on both futures returns (10 percent significance level) and changes in inventory (1 percent significance level). Thus, not the data that is available but the data that is missing tells us that weather anomalies have, in fact, a significant positive association with the dependent variables. Second, weekend data, i.e. the evaluation of weather anomalies that are reported during non-trading days and are shifted to the following trading day, indicate a highly significant positive effect of temperature anomalies on changes in inventory. Third, the results for the growing anomaly index, i.e. an index that accumulates weather anomalies above a set threshold and is reset to zero once a value is below the threshold, and the growing anomaly index only for trading days add limited new insight to the previous findings as the coefficients for futures returns and inventory changes are non-significant. The threshold defined as severe weather anomalies is set to the 90th percentile of weather anomalies. This follows the definition of the NOAA (2016b), which defines climate extremes as the most unusual ten percent of weather events. In contrast, the fourth variable, which measures the average of the anomalies on the trading day and its four preceding days, indicates a significant negative association between precipitation anomalies and inventory changes. The significant coefficient confirms that multi-day precipitation anomalies are associated with declines in aluminium inventory stocks and that the effect is stronger than single-day precipitation anomalies.

Table 2.5: New Variables

	Aluminium Futures Returns				*Aluminium Inventory*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
P_Missing	0.00142*				0.00231***			
Weather	(0.000741)				(0.000417)			
T_Missing								
Weather	-				-			
P_Weekend		-4.86e-06				-2.03e-06		
Data		(3.19e-06)				(1.29e-06)		
T_Weekend		-1.38e-05				2.32e-05***		
Data		(1.65e-05)				(8.75e-06)		
P_Growing			-1.26e-06				-5.61e-07	
Index			(3.12e-06)				(1.11e-06)	
T_Growing			-9.70e-06				7.07e-06	
Index			(8.38e-06)				(4.44e-06)	
P_Average of 5				-2.05e-06				-1.10e-05**
Days				(8.91e-06)				(4.27e-06)
T_Average of 5				1.54e-05				2.40e-05
Days				(3.93e-05)				(1.82e-05)
Observations	3,653	3,653	3,653	3,653	3,653	3,653	3,653	3,653
Adjusted R^2	0.183	0.183	0.182	0.182	0.014	0.004	0.002	0.003

Notes: This table provides information about the results of the regression examining all mines in this study. The dataset consists of 3,653 trading days between 1st January 2001 and 31st December 2014. The temperature anomaly values are in tenths of degree Celsius whereas precipitation is in tenths of mm. The parameters are defined as: P_ for precipitation and T_ for temperature, Missing Weather as dummy variable that indicates whether more than 20 percent of weather anomalies are missing throughout the research period, Weekend Data as weather anomaly within the 90th percentile that is reported during a non-trading day and then shifted to the following trading day, Growing Index as index value that accumulates weather anomalies that exceed the 90th percentile of anomalies and is reset to 0 once a value is outside the 90th percentile, and Average of 5 Days as a variable that measures the average weather anomaly index of the trading day itself and the four preceding trading and non-trading days. With robust standard errors (Huber/White/sandwich estimator) in parentheses. If the ADF test suggests a unit root, log changes or first difference are used to transform the time-series (_r indicating log returns, _f indicating first difference). * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. While the controls are included in the model, I refrain from reporting the controls coefficients.

The model is defined as:

$$R_t = \alpha + \beta_m NewVar_t + \beta_n X_t + \varepsilon_t$$

with α as intercept, $\beta_{m\ to\ n}$ as coefficients, R_t as close-to-close log change of FP_t as futures price and IL_t as inventory, $NewVar_t$ as one of the four new variables Missing Weather, Weekend Data, Growing Index, and Average of 5 Days, X_t as vector of controls with $X_t = [IL_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of FP_t and $X_t = [FP_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of IL_t, EA_t as economic activity represented by the Baltic Exchange Dry Index, RIR_t as real interest rate, TWI_t as the relative value of the USD, $SP500_t$ as parameter controlling for equity market risk, and ε_t as error term. All variables are at time t. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.

2.5.2 STRUCTURAL BREAK AND OVERSUPPLY

Since the year 2009, the aluminium market experiences an ongoing oversupply (Sanderson et al., 2016). Thus, short-term influences on the supply of bauxite might be satisfied by the supply glut. To test this assumption, I apply the Chow break test (Chow, 1960) to equation (2.2), set the break to 30th June 2009, and concentrate on changes in inventory as the dependent variable. With a test statistic of 4.70 and a p-value of 0.00, the null hypothesis of no structural change can be rejected. Once I drop the control variables from the model, the test statistic increases to 11.60 (p-value = 0.00).

Table 2.6: Structural Break

	Aluminium Futures Returns		*Aluminium Inventory*	
	01/01/2001 – 30/6/2009	01/07/2009 – 31/12/2014	01/01/2001 – 30/6/2009	01/07/2009 – 31/12/2014
P_WAI	-4.62e-07	3.90e-06	-5.78e-06**	-2.02e-07
	(5.65e-06)	(7.11e-06)	(2.90e-06)	(1.46e-06)
T_WAI	-2.60e-06	3.60e-05	1.11e-05	-1.73e-05
	(3.22e-05)	(4.53e-05)	(1.97e-05)	(1.21e-05)
IL_r	-0.0998***	-0.00968		
	(0.0371)	(0.0749)		
FP_r			-0.0345**	-0.000802
			(0.0138)	(0.00618)
EA_r	-0.00295	-0.00291	-0.00167	0.00512
	(0.0187)	(0.0144)	(0.00897)	(0.00384)
RIR_f	0.00237	-0.00219	-0.00216	-0.000689
	(0.00287)	(0.00322)	(0.00253)	(0.00104)
TWI_r	-1.388***	-1.959***	-0.00699	0.0888*
	(0.108)	(0.128)	(0.0726)	(0.0466)
SP500_r	0.139***	0.246***	-0.00786	0.0252
	(0.0229)	(0.0358)	(0.0143)	(0.0212)
Constant	4.77e-05	-0.000776	0.00131***	0.000212
	(0.000668)	(0.000817)	(0.000425)	(0.000228)
Observations	2,217	1,436	2,217	1,436
Adjusted R^2	0.128	0.284	0.003	0.005

Notes: This table provides information about the results of the structural break regression examining all mines in this study. The dataset consists of 3,653 trading days between 1st January 2001 and 31st December 2014. The temperature anomaly values WAI are in tenths of a degree Celsius whereas precipitation is in tenths of a mm. The parameters are defined as: WAI as the anomaly weather index value with P_ for precipitation and T_ for temperature, IL_r as LME inventory, FP_r as aluminium futures price returns, EA_r as Baltic Dry Index, RIR_r as real interest rate, TWI_r as the trade-weighted USD index, and SP500_r as the S&P 500 index. With robust standard errors (Huber/White/sandwich estimator) in parentheses. If the ADF test suggests a unit root, log changes or first difference are used to transform the time-series (_r indicating log returns, _f indicating first difference). * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

The model is defined as:

$$R_t = \alpha + \beta_m WAI_t + \beta_n X_t + \varepsilon_t$$

with α as intercept, $\beta_{m\ to\ n}$ as coefficients, R_t as close-to-close log change of FP_t as futures price and IL_t as inventory, WAI_t as vector of weather anomaly index values for temperature or precipitation, X_t as vector of controls with $X_t = [IL_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of FP_t and $X_t = [FP_t + EA_t + RIR_t + TWI_t + SP500_t]$ for the analysis of IL_t, EA_t as economic activity represented by the Baltic Exchange Dry Index, RIR_t as real interest rate, TWI_t as the relative value of the USD, $SP500_t$ as parameter controlling for equity market risk, and ε_t as error term. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.

In a second step, I limit the research period from 1st January 2001 to 30th June 2009 to focus on the pre-supply glut period and rerun the OLS regression model as in equation (2.2) for futures returns and changes in inventory. The results suggest that prior to mid-2009, precipitation significantly (5 percent level) reduced inventory. However, during the second sub-sample research period from 1st July 2009 to 31st December 2014, the significance of this effect diminishes. Thus, it is likely that the supply glut present in the aluminium market sufficiently compensates for short-term production cuts. Moreover, the interaction of inventory changes and futures returns switches with the growing supply glut in the market. While the relationship in the first subsample from 1st January 2001 to 30th June 2009 is highly significant (up to 1 percent level), it gets non-significant afterwards. Thus, the oversupply of the market may not only have altered the interaction between weather anomalies and the dependent variables but also the interaction between the dependent variables.[27]

2.5.3 THE IMPACT OF NEWS

To test the impact of reported weather phenomena during the research period (e.g. Wallop, 2011; Sharma, 2014), I draw on the approach by Core et al. (2008) and Brutti and Sauré (2015) and search for news and articles available online by the Financial Times (ft.com) and Reuters (reuters.com) which are related to weather and bauxite mining. This analysis returns mixed results. Although various reports and articles examine the interaction between mining production and the weather, society, and the environment, only a few articles report specific news of weather and bauxite mines. In a second step, I extend the search for bauxite and weather-related news to local and specialist newspapers globally. In contrast to the first approach, this method produces far more results for the chosen search terms. However, the obtained articles are partially unrewarding. Although the search terms are mentioned in the articles, they are often not in context with the impact of weather phenomena on bauxite mining. To mitigate this bias, I take advantage of the options provided by the news search engine Nexis.com which enables limiting of the spacing between the words within the search term. Thus, it is possible to exclude articles that mention the search terms but are out of context. This search leads to a total of 103 articles published on 71 dates throughout the research period. While this restriction of the search might bias the analysis as it excludes potentially valuable information, the trade-off is necessary to ensure a target-oriented result. The publication dates of the articles show that most of the news articles are published during quarter two of each year (40 percent). Furthermore, most articles are published from 2011 onwards (56 percent). The publication dates of the obtained news articles are set as event days. For changes in global inventory and futures returns the results indicate some statistically significant T-values throughout the research period. As the significant event days are limited for all three variables (i.e. only two to four significant event days), the results are

[27] Another possible explanation for this behaviour is the decrease in interest rates after the global financial crisis in 2008. Since then, interest rates are at low levels. Low real interest rates increase the inventory demand for commodities (Frankel, 2006), which provide larger buffer stocks for short-term production losses. Moreover, low interest rates and regulation changes by the LME (Desai, 2016) allow market participants to shift to private warehouses that may offer cheaper and less regulated storage than the warehouses monitored by the LME.

rather random and should be taken with care. The findings remain comparable when the event window is extended to ±1 day.

2.5.4 WEATHER ANOMALIES AND THE REALISED VOLATILITY

As a final exercise, I shift the focus from changes in global inventory and price to the volatility of such.

Table 2.7: GARCH (1,1) Model

		Aluminium Futures Returns			*Aluminium Inventory*		
		(1)	(2)	(3)	(4)	(5)	(6)
Mean Equation	P_WAI	3.68e-06			2.78e-06		
		(3.91e-06)			(2.43e-06)		
	T_WAI	2.42e-05			-4.72e-06		
		(2.28e-05)			(1.73e-05)		
	P_Missing Weather		0.00132**			0.000925	
			(0.000671)			(0.000841)	
	P_Average of 5 Days			5.27e-07			6.21e-06
				(7.77e-06)			(5.84e-06)
	T_Average of 5 Days			3.14e-05			0.000109*
				(3.45e-05)			(5.80e-05)
	IL_r	-0.0726**	-0.0796**	-0.0737**			
		(0.0310)	(0.0311)	(0.0309)			
	FP_r				0.0228*	0.00638	0.0112
					(0.0118)	(0.0150)	(0.0113)
	EA_r	-0.000424	-0.000181	-0.000346	-0.00467	0.00700	0.00432
		(0.0111)	(0.0112)	(0.0111)	(0.00777)	(0.0109)	(0.00815)
	RIR_f	0.000456	0.000542	0.000500	-0.00174	0.000117	0.000943
		(0.00240)	(0.00240)	(0.00241)	(0.00139)	(0.00159)	(0.00159)
	TWI_r	-1.461***	-1.462***	-1.462***	0.0920*	0.0361	0.0784
		(0.0887)	(0.0897)	(0.0888)	(0.0513)	(0.0638)	(0.0511)
	SP500_r	0.181***	0.181***	0.180***	-0.0310***	-0.0249	-0.0207
		(0.0175)	(0.0174)	(0.0175)	(0.0119)	(0.0179)	(0.0149)
	Constant	-0.000711	-0.000258	-0.000645	2.56e-06	0.000139	-0.00181**
		(0.000464)	(0.000199)	(0.000715)	(0.000354)	(0.000189)	(0.000739)
Variance Equation	P_WAI	0.000763			-0.0116		
		(0.00481)			(0.0105)		
	T_WAI	0.0248			-0.140		
		(0.0255)			(0.0977)		
	P_Missing Weather		0.662			1.046	
			(0.437)			(0.906)	
	P_Average of 5 Days			0.00316			0.00994*
				(0.00748)			(0.00558)
	T_Average of 5 Days			0.0449			-0.0342
				(0.0325)			(0.0804)
	Constant	-13.75***	-13.28***	-14.21***	-10.76***	-12.81***	-13.03***
		(0.834)	(0.473)	(1.052)	(1.008)	(0.337)	(1.011)
ARCH Terms	L.Arch	0.0402***	0.0407***	0.0395***	0.827***	0.598**	0.674***
		(0.0113)	(0.0108)	(0.0115)	(0.318)	(0.255)	(0.212)
	L.Garch	0.949***	0.947***	0.950***	0.571***	0.599***	0.596***
		(0.0154)	(0.0155)	(0.0157)	(0.0609)	(0.0738)	(0.0541)

Notes: This table provides information about the results of a GARCH (1,1) model examining all eleven mines in the study. The dataset consists of 3,653 trading days between 1st January 2001 and 31st December 2014. The data source is the NOAA daily dataset. The temperature anomaly values WAI are in tenths of a degree Celsius whereas precipitation is in tenths of a mm. The parameters are defined as: WAI as the anomaly weather index value with P_ for precipitation and T_ for temperature, Missing Weather as dummy variable that indicates whether more than 20 percent of weather anomalies are missing throughout the research period, Average of 5 Days as a variable that measures the average weather anomaly index of the trading day itself and the four preceding trading and non-trading days, IL_r as LME inventory, FP_r as aluminium futures price returns, EA_r as Baltic Dry Index, RIR_r as real interest rate, TWI_r as the trade-weighted USD index, and SP500_r as the S&P 500 index. With robust standard errors (Huber/White/sandwich estimator) in parentheses. If the ADF test suggests a unit root, log changes or first difference are used to transform the time-series (_r indicating log returns, _f indicating first difference). * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

I begin with the evaluation of the volatility of changes in global inventory reported in Table 2.7. Contrary to the multi-day findings for precipitation on changes in global inventory, the effect on the volatility of inventory changes is non-significant. This equally applies to the missing weather data dummy and both weather anomaly indices.

2.5.5 ABNORMAL PRODUCER STOCK RETURNS

The aluminium market is globally interconnected and thus represents the global equilibrium of all supply and demand to and from this market. While, it is expected that a local weather anomaly only slightly affects the global supply, the effect on the output and thus profit of the company that operates the mine is expected to be stronger. Thus, I shift the focus from the commodity itself to major aluminium mining and producing companies to evaluate the potential impact on their profit, which is proxied by their stock market performance. The share price of four major mining companies with substantial exposure in the examined locations build the basis for an equally-weighted abnormal log return index. Next, the potential impact of both weather anomaly indices and all other weather-related variables created for this study are tested. I use two different approaches to test for a potential impact of temperature and precipitation anomalies on the abnormal stock returns: an OLS regression model and the rank test. The research period runs from 1st January 2001 to 31st December 2014. I use daily close-to-close returns for Alcoa (now Arconic), Norsk Hydro, Rio Tinto, and BHP Billiton. The stock information is obtained from the following stock exchanges: Alcoa (New York Stock Exchange, NYSE), Norsk Hydro (Oslo Stock Exchange, Oslo Bors), Rio Tinto and BHP Billiton (Australian Securities Exchange, ASX). As market return, general stock indices on each market are chosen. That is, NYSE composite for Alcoa, OBX for Norsk Hydro, and ASX 200 for Rio Tinto and BHP Billiton. The 10-year US treasury bills rate is used as a proxy for the risk-free rate. All financial information is obtained from Datastream. The abnormal stock returns are calculated by deducting the estimated returns from the real returns of each individually stock. I manually calculate the time-varying betas $B_{i,t}$ for the Capital Asset Pricing Model (CAPM) on a rolling 250-day basis.[28] The OLS regression model is defined as:

[28] In addition to the CAPM model, I estimate a market model using OLS regression. The results for both techniques are comparable but the significance of the weather anomaly coefficients is lower for the market model.

$$S_t = \alpha + \beta_1 WV_t + \beta_n X_t + \varepsilon_t \tag{2.5}$$

$$S_t = \frac{1}{N}\sum_{i=1}^{N}\left[R_{i,t} - \mathrm{E}R_{i,t}\right] \tag{2.6}$$

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{2.7}$$

$$ER_{i,t} = rf_t + B_{i,t}(R_{M.t} - rf_t) \tag{2.8}$$

$$B_{i,t} = \frac{\sum_{t=-250}^{0}(R_{i,t} - E(R_i))(R_{m,t} - E(R_m))}{\sum_{t=-250}^{0}(R_{m,t} - E(R_m))^2} \tag{2.9}$$

with S_t as close-to-close equally-weighted abnormal stock returns, α as intercept, β as coefficients, WV_t with $WV_t = WAI_t$ or $WV_t = NewVar_t$ that represents the precipitation or temperature anomaly index $WAI_t = [P\_WAI_t + T\_WAI_t]$, the weather variables that either represent the growing interaction term, the shift of weather events on non-trading days to the following trading day, a dummy variable for missing weather information, or the average index value of the trading day itself and its four preceding days denoted as $NewVar_t = [P\_Missing\ Weather_t + P\_Weekend\ Data_t + T\_Weekend\ Data_t + P\_Growing\ Index_t + T\_Growing\ Index_t + P\_Average\ Of\ 5\ Days_t + P\_Average\ Of\ 5\ Days_t]$, X_t as vector of controls with $X_t = [FP_t + IL_t + EA_t + RIR_t + TWI_t]$ with FP_t as aluminium futures returns, IL_t as global aluminium inventory, EA_t as economic activity represented by the Baltic Exchange Dry Index, RIR_t as real interest rate, TWI_t as the relative value of the USD, ε_t as error term, $ER_{i,t}$ as estimated return, $R_{M.t}$ as market return, $R_{i,t}$ as real return, rf_t as risk-free interest rate proxied by the 10-year US treasury bills[29], and $B_{i,t}$ as 250-day beta of stock i. All variables are at time t. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.

The descriptive statistics in Table 2.8 indicate positive abnormal returns during times of commodity price surges. Beginning with the financialization of commodity markets in the early 2000s and particularly from 2005 to mid-2006, the equally-weighted abnormal returns

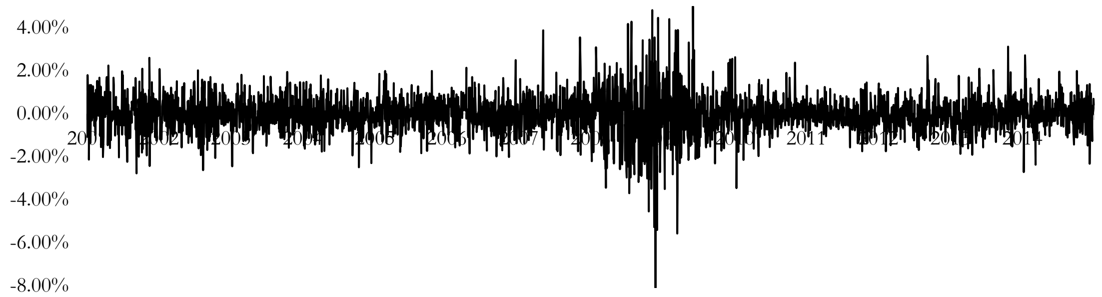
[29] In addition to the US interest rate, I use economy-specific, i.e. Norwegian and Australian, interest rate information to calculate the expected returns based on the CAPM. The results are comparable to those based on the US interest rate.

portfolio reports high abnormal returns that last until the outbreak of the GFC in 2008. Shortly after, i.e. mid-2009, the abnormal returns portfolio again reports positive abnormal returns that last until the second surge in commodity prices which ended in 2011.

Table 2.8: Descriptive Statistics for Abnormal Stock Returns

	Obs	*Mean*	*Std. Dev.*	*Min*	*Max*	*Skewness*	*Kurtosis*	*ADF*
Alcoa	3653	-0.0004	0.0172	-0.1377	0.1676	0.0257	10.8819	-60.714***
Norsk Hydro	3653	-0.0001	0.0136	-0.1625	0.1503	-0.0071	18.0791	-64.811***
Rio Tinto	3653	0.0000	0.0162	-0.3839	0.1386	-3.4173	93.7072	-56.177***
BHP Billiton	3653	0.0001	0.0123	-0.0688	0.0712	0.0877	6.5239	-58.257***
Equally-Weighted Portfolio	3653	-0.0001	0.0088	-0.0815	0.0500	-0.2114	8.8620	-54.237***

Equally-weighted Abnormal Returns, CAPM



Notes: This table presents the descriptive statistics of the equally-weighted abnormal aluminium producer stock returns portfolio and its components between 1st January 2001 and 31st December 2014. With Obs as observations, Mean as average value, Std. Dev. As standard deviation, Min as minimum value, Max as maximum value, and ADF as augmented Dickey-Fuller test statistic. To test the robustness of the ADF test, I use the Phillips-Perron test. For all variables, the test statistic for both tests suggest sufficient stationarity of the time-series. The graph illustrates the portfolio values of the equally-weighted abnormal aluminium producer stock returns portfolio between 1st January 2001 and 31st December 2014. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

Next, I shift to the results of the OLS regression as in equation (2.5) reported in Table 2.9. Contrary to aluminium futures returns, the equally-weighted abnormal returns portfolio is significantly influenced by both anomaly indices. Only for temperature anomalies does the estimation identify a weakly significant positive effect (10 percent significance level) on the abnormal equity returns portfolio of aluminium miners. The significance of the coefficient strengthens if one focuses on the anomaly indices, for Australia only. This is expected as three out of four mine operators (Alcoa, Rio Tinto, BHP Billiton) within the portfolio have extensive exposure in Australia.[30] Splitting the sample into periods before and after the supply glut in 2009 confirms these findings and indicates a non-significant effect of precipitation anomalies. For temperature anomalies, the effect appears to happen during the first sub-sample period, i.e. between 1st January 2001 and 30th June 2009. However, it must be noted that these results only hold at the 10 percent significance level. This coincides with

[30] I've also evaluated the effects of the weather anomaly indices on the abnormal equity returns for each firm individually. The results are comparable to those obtained for the equally-weighted portfolio. The results are available upon request.

most of the news articles linked to weather and bauxite mining, where the majority are published from 2011 onwards.

Table 2.9: Abnormal Stock Returns Portfolio

	Equally-Weighted Abnormal Returns Portfolio					
	All Mines			Australian Mines Only		
	Total	01/01/2001 – 30/06/2009	01/07/2009 – 31/12/2014	Total	01/01/2001 – 30/06/2009	01/07/2009 – 31/12/2014
P_WAI	-4.66e-06	-4.63e-06	-5.61e-06	-3.17e-06	-4.20e-06	-3.05e-06
	(3.21e-06)	(4.43e-06)	(3.86e-06)	(2.82e-06)	(4.33e-06)	(3.12e-06)
T_WAI	3.36e-05*	3.52e-05	3.14e-05	2.42e-05**	2.62e-05*	2.07e-05
	(1.82e-05)	(2.40e-05)	(2.40e-05)	(1.18e-05)	(1.55e-05)	(1.56e-05)
IL_r	-0.0103	-0.0116	0.00180	-0.00905	-0.0105	0.00276
	(0.0264)	(0.0287)	(0.0432)	(0.0264)	(0.0287)	(0.0431)
FP_r	0.0921***	0.0957***	0.0934***	0.0921***	0.0959***	0.0933***
	(0.0132)	(0.0183)	(0.0171)	(0.0132)	(0.0183)	(0.0171)
EA_r	0.0248**	0.0610***	-0.0112	0.0245**	0.0609***	-0.0116
	(0.0105)	(0.0189)	(0.00907)	(0.0105)	(0.0188)	(0.00908)
RIR_f	-0.000594	0.00126	-0.00316	-0.000616	0.00122	-0.00316
	(0.00283)	(0.00427)	(0.00197)	(0.00283)	(0.00427)	(0.00197)
TWI_r	-0.0340	-0.110	0.121	-0.0342	-0.109	0.120
	(0.0665)	(0.0926)	(0.0761)	(0.0665)	(0.0925)	(0.0763)
Constant	-0.000326	-0.000281	-0.000431	-0.000388	-0.000307	-0.000530
	(0.000356)	(0.000507)	(0.000425)	(0.000280)	(0.000404)	(0.000339)
Observations	3,653	2,217	1,436	3,653	2,217	1,436
Adjusted R^2	0.025	0.032	0.029	0.024	0.032	0.028

Notes: This table illustrates the results of the OLS and structural break regression examining all mines and the five Australian mines only. The dataset consists of 3,653 trading days between 1st January 2001 and 31st December 2014. The temperature anomaly values WAI are in tenths of a degree Celsius and precipitation anomalies are in tenths of a mm. The structural break is set to end-June 2009 and is based on the growing supply glut in the global aluminium market since then. The parameters are defined as: WAI as the anomaly weather index value with P_ for precipitation and T_ for temperature, IL_r as LME aluminium inventory, FP_r as aluminium futures price returns, EA_r as Baltic Dry Index, RIR_r as real interest rate, and TWI_r as the trade-weighted USD index. With robust standard errors (Huber/White/sandwich estimator) in parentheses. If the ADF test suggests a unit root, log changes or first difference are used to transform the time-series (_r indicating log returns, _f indicating first difference). * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

The model is defined as:

$$R_t = \alpha + \beta_m WAI_t + \beta_n X_t + \varepsilon_t$$

with α as intercept, $\beta_{m\ to\ n}$ as coefficients, R_t as the Equally-Weighted Abnormal Returns Portfolio, WAI_t as vector of weather anomaly index values for temperature or precipitation, X_t as vector of controls with $X_t = [FP_t + IL_t + EA_t + RIR_t + TWI_t]$, FP_t as aluminium futures returns, IL_t as inventory, EA_t as economic activity represented by the Baltic Exchange Dry Index, RIR_t as real interest rate, TWI_t as the relative value of the USD, and ε_t as error term. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.

Lastly, the additional weather variables that build on the anomaly indices and their interaction with the equally-weighted abnormal returns portfolio are tested. Table 2.10 reports the results. While weather events that happen on a weekend and the growing weather anomaly index estimates confirm a significant effect of weather anomalies on the equally-weighted abnormal returns portfolio, that holds at the 10 percent level for precipitation and at the 5 and 1 percent significance level for temperature anomalies, missing precipitation weather information[31] appears to have a significant effect on the portfolio, which holds at the 5 percent significance level. However, while the results are partially statistically significant, the magnitude of the effect on the abnormal stock returns portfolio, much like

[31] As the availability of temperature data throughout the research period is sufficient, no missing temperature variable is tested.

the effect on futures returns, is small. That is, if precipitation weather information is missing, the abnormal stock returns portfolio is increased by only 0.127 percent.

Table 2.10: Abnormal Stock Returns Portfolio with Additional Weather Variables

	Equally-Weighted Abnormal Returns Portfolio			
	(1)	(2)	(3)	(4)
P_Missing Weather	0.00127**			
	(0.000548)			
P_Weekend Data		-4.07e-06*		
		(2.30e-06)		
T_Weekend Data		3.34e-05***		
		(1.10e-05)		
P_Growing Index			-4.30e-06*	
			(2.52e-06)	
T_Growing Index			1.11e-05**	
			(5.53e-06)	
P_Average of 5 Days				-1.80e-06
				(6.25e-06)
T_Average of 5 Days				3.53e-05
				(2.92e-05)
Observations	3,653	3,653	3,653	3,653
Adjusted R^2	0.025	0.026	0.025	0.024

Notes: This table provides information about the results of the regression examining all mines in this study. The dataset consists of 3,653 trading days between 1st January 2001 and 31st December 2014. The temperature anomaly values are in tenths of a degree Celsius whereas precipitation is in tenths of a mm. The parameters are defined as: P_ for precipitation and T_ for temperature, Missing Weather as dummy variable that indicates whether more than 20 percent of weather anomalies are missing throughout the research period, Weekend Data as weather anomaly within the 90th percentile that is reported during a non-trading day and then shifted to the following trading day, Growing Index as index value that accumulates weather anomalies that exceed the 90th percentile of anomalies and is reset to 0 once a value is outside the 90th percentile of weather anomalies, and Average of 5 Days as a variable that measures the average weather anomaly index of the trading day itself and the four preceding trading and non-trading days, IL_r as LME aluminium inventory, FP_r as aluminium futures price returns, EA_r as Baltic Dry Index, RIR_r as real interest rate, and TWI_r as the trade-weighted USD index. With robust standard errors (Huber/White/sandwich estimator) in parentheses. If the ADF test suggests a unit root, log changes or first difference are used to transform the time-series (_r indicating log returns, _f indicating first difference). * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. While the controls are included in the model, I refrain from reporting the controls coefficients.

The model is defined as:

$$R_t = \alpha + \beta_m NewVar_t + \beta_n X_t + \varepsilon_t$$

with α as intercept, $\beta_{m\ to\ n}$ as coefficients, R_t as the Equally-Weighted Abnormal Returns Portfolio, $NewVar_t$ as one of the four new variables Missing Weather, Weekend Data, Growing Index, and Average of 5 Days, X_t as vector of controls with $X_t = [FP_t + IL_t + EA_t + RIR_t + TWI_t]$, FP_t as aluminium futures returns, IL_t as inventory, EA_t as economic activity represented by the Baltic Exchange Dry Index, RIR_t as real interest rate, TWI_t as the relative value of the USD, and ε_t as error term. All variables are at time t. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.

Another observation which is present among all significant coefficients concerned with the equally-weighted abnormal returns portfolio evaluation and weather anomalies, is the sign of the temperature anomaly index coefficients. While missing precipitation data reduces the equally-weighted abnormal returns portfolio, temperature anomalies show a consistently positive effect on the portfolio. This is unexpected, as I initially projected both indices to have a negative effect on the abnormal stock returns portfolio. The positive relationship between temperature anomalies and the equally-weighted abnormal stock returns portfolio suggests that high temperature anomalies lead to positive abnormal returns. One potential explanation is that temperature anomalies during the research period are not as severe as they must be to significantly affect the production. Throughout the research period, the highest temperature anomaly index value is 53.79, which translates to a deviation from the normal temperature by 5.379 degrees Celsius. As a result, one may conclude that the observed temperature anomalies have not been detrimental for the production process but are favourable instead. Moreover, the temperature anomaly index shows a pattern of recurring high values during the summer months of the southern hemisphere. Paired with the locations of the mines operated by the companies in the equally-weighted abnormal returns portfolio[32], this may simply reflect the correlation of higher production during summer months with usually less precipitation (that might negatively affect production) and the higher observed temperature anomalies of up to 5.4 degrees Celsius. For precipitation anomalies, this pattern cannot be observed and the values are instead spread more equally throughout the year. Lastly, the effect of temperature anomalies might be less clear than hypothesised. Initially, I expected that the effect of weather anomalies is equally detrimental for the dependent variables, regardless whether the deviation from the normal temperature or precipitation is positive or negative. However, as most of the mines operated by the companies in the equally-weighted abnormal returns portfolio are in tropical and sub-tropical areas, negative temperature anomalies, i.e. colder weather than usual, might be desired.

Table 2.11: Abnormal Stock Returns with Opposing Weather Anomalies

	Equally-Weighted Abnormal Returns Portfolio
P_WAI_Opposites	6.52e-07
	(2.52e-06)
T_WAI_ Opposites	-8.38e-06
	(1.20e-05)
Observations	3,653
Adjusted R^2	0.023

Notes: This table provides information about the result of the regression examining the effect of the opposing weather anomaly indices on the equally-weighted abnormal returns portfolio. The dataset consists of 3,653 trading days between 1st January 2001 and 31st December 2014. The temperature anomaly values are in tenths of a degree Celsius whereas precipitation is in tenths of a mm. The parameters are defined as: P_ for precipitation and T_ for temperature, WAI as Weather Anomaly Index, Opposites indicating that the index can take negative and positive values, IL_r as LME aluminium inventory, FP_r as aluminium futures price returns, EA_r as Baltic Dry Index, RIR_r as real interest rate, and TWI_r as the trade-weighted USD index. With robust standard errors (Huber/White/sandwich estimator) in parentheses. If the ADF test suggests a unit root, log changes or first difference are used to transform the time-series (_r indicating log returns, _f indicating first difference). * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. While the controls are included in the model, I refrain from reporting the controls coefficients.

The model is defined as:

$$R_t = \alpha + \beta_m WAI\_opposites_t + \beta_n X_t + \varepsilon_t$$

with α as intercept, $\beta_{m\ to\ n}$ as coefficients, R_t as the Equally-Weighted Abnormal Returns Portfolio, $WAI\_opposites_t$ as vector of weather anomaly index values for temperature or precipitation with both negative and positive index values, X_t as vector of controls with $X_t = [FP_t + IL_t + EA_t + RIR_t + TWI_t]$, FP_t as aluminium futures returns, IL_t as inventory, EA_t as economic activity represented by the Baltic Exchange Dry Index, RIR_t as real interest rate, TWI_t as the relative value of the USD, and ε_t as error term. Robust standard errors (Huber/White/sandwich estimator) are used to control for heteroscedasticity.

Thus, instead of using absolute weather anomaly indices, I rerun the OLS regression model but use an index that can take both positive and negative values. Positive index values

[32] Alcoa: Huntly and Willowdale in Australia; Rio Tinto: Weipa and Gove in Australia; BHP Billiton: Boddington in Australia; Norsk Hydro: Paragominas in Brazil.

represent temperature and precipitation that is higher or stronger than the normal value, i.e. hotter temperature or more rainfall than usual. Negative index values represent temperature or precipitation that is colder or less than the normal. For both indices with opposite values, the regression results in Table 2.11 indicate no significant relationship between weather anomalies and the equally-weighted abnormal returns portfolio.[33] These findings suggest that the direction of anomalies does not influence the outcome of the estimations.

As a last exercise, I use a nonparametric test for abnormal returns, the rank test, to avoid the preconditions of parametric tests for event studies such as normality of the underlying time-series. Event days are defined as the strongest ten percent of anomalies within the temperature and precipitation anomaly indices. As highlighted earlier, the single-day event test might not be appropriate to examine weather events, as they usually occur as multi-day events rather than single-day events before they significantly harm the operations. Thus, the methodology presented by Corrado (1989) is extended by a multi-day test that considers the two preceding and succeeding days surrounding the event day. The rank test by Corrado (1989) and the multi-day extension model are defined as:

Single-Day

$$T_0 = \frac{1}{N}\sum_{i=1}^{N}\frac{\left(K_{i,0} - 125.5\right)}{S(K)} \tag{2.10}$$

Multi-Day

$$T_1 = \frac{1}{N}\sum_{i=1}^{N}\frac{\left(\left(\frac{1}{5}\sum_{t=-2}^{+2} K_{i,t}\right) - 125.5\right)}{S(K)} \tag{2.11}$$

$$K_{i,t} = rank(A_{i,t}) \tag{2.12}$$

$$S(K) = \sqrt{\frac{1}{250}\sum_{t=-244}^{+5}\left(\frac{1}{N}\sum_{i=1}^{N}(K_{i,t} - 125.5)\right)^2} \tag{2.13}$$

with T_0 and T_1 as test statistic on the event day, $K_{i,t}$ as the rank of the abnormal stock return $A_{i,t}$ between time t = -244 to +5, and $S(K)$ as standard deviation of the rank for stock i at time t. Naturally, the average of rank 1 to 250 equals 125.5. Furthermore, higher abnormal

[33] For aluminium futures returns and aluminium inventory changes, both anomaly indices with opposite values are non-significant when used for the estimation of the dependent variables.

returns represent a lower rank, i.e. the highest returns are at rank 1 and the lowest are at rank 250. For both precipitation and temperature, the rank test statistic for the ten largest absolute anomalies suggests no statistical significance for any of the examined event dates. All values of test statistic T_0 range between -1.59 and 1.61, which is below the 95 percent significance level z-score of 1.96. For T_1, i.e. the multi-day test statistic, the obtained values range between -0.47 and 1.58, which suggests that the multi-day approach does not improve the test results.

2.6 CONCLUSION

This study extends prior research by providing insight on the effect of weather anomalies on changes in the inventory and price of exchange-traded aluminium. The analysis uses a self-defined algorithm to combine weather information from various bauxite mines spread throughout the globe. It also evaluates the impact of temperature and precipitation anomalies on changes in the global inventory and futures returns of exchange-traded aluminium. Lastly, it examines the effect on the abnormal returns of major aluminium mining and producing companies. Positive precipitation anomalies are found to reduce the global inventory of exchange-traded aluminium. This is particularly evident when weather data are unavailable and when precipitation anomalies occur on multiple days. However, this effect diminishes after the aluminium market became oversupplied in 2009. Temperature anomalies do not appear to influence inventory changes, or futures returns. Moreover, most of the independent variables are not related to the volatility of the two dependent variables. Multi-day temperature anomalies are the exception and positively affect the volatility of inventory changes. Moreover, a portfolio of abnormal stock returns of aluminium producing companies is found to be influenced by temperature anomalies.

Despite using the most accurate data for this study, the limited availability of weather information may bias the results. For remote locations where the mines are often located information is scarce. Thus, the individual weather anomaly indices for some mines use distant weather station information. In addition, the weather anomaly index calculation approach itself might introduce bias as I use a novel method to combine the information from mine locations spread throughout the globe. Lastly, the study covers a combined share of 50 percent of global mine production. Large mining countries such as China are excluded from this study due to the inaccessibility of reliable information. This could potentially introduce a sample selection bias. While these factors might reduce the validity of the research, I believe that the evaluation of both futures returns and inventory changes, the examination of the abnormal stock returns of major aluminium producers, and the robust research model in this study sufficiently mitigate the above risks.

Future research may apply the algorithm presented here to combine the information from different mine locations to calculate precipitation and temperature anomaly indices for large cities with high demand for industrial metals to estimate the effect of weather anomalies on demand. Moreover, future research may focus on the relationship between earlier steps in the process chain and further retest the findings for other metals such as gold and copper. Especially for commodities with lower inventory stocks, or perishable commodities, the results may vary significantly.

CHAPTER 3 GLOBAL MONETARY POLICY AND METAL PRICES

3.1 INTRODUCTION

To overcome a liquidity crisis, the often-cited advice by Bagehot (Goodhart, 1999) suggests that central banks should lend freely, at a high rate of interest, and against good collateral. As in the case of the Mexican debt crisis bailout by the United States and others in 1995[34], history provides examples of the success of this theory. Since the GFC in 2008 and the subsequent monetary policy measures introduced by central banks globally, the requirements for liquidity have changed. Money has been freely available since then, despite low penalty rates and the inferior quality of acceptable collateral.

One of the main goals of all conventional and unconventional monetary policies is to ensure price stability. By increasing bank lending to non-financial corporations and households, quantitative easing (QE) aims to increase private expenditure and accelerate consumption and investment (Ryan-Collins et al., 2016). For this process to work, it is assumed that financial institutions provide effective credit intermediation and that debtors use those funds to consume. Prior research examines the impact of conventional monetary policy on different asset classes including commodities (e.g. Frankel, 2006, 2014; Calvo, 2008; Akram, 2009; Vansteenkiste, 2009; Ma et al., 2015) and further scrutinises the response of commodity markets to announcements of unconventional monetary policy (Scrimgeour, 2014). Leading financial writers also highlight the necessity for research in this area and illustrate the influence and potential risk of unconventional monetary policy on commodity prices (e.g. Kemp, 2010; Reddy, 2010; Campbell, 2014). Notwithstanding this, little research focuses on the precise impact on global industrial commodities and the longer-term interaction with global conventional and unconventional monetary policy. Although central banks are generally more concerned with domestic economic growth and less with global market conditions, one might expect that prices are driven by global supply and demand changes instead of individual economy-specific monetary policy. The implementation of announced measures, the resulting changes in global liquidity, and the ability of an economy to successfully incorporate the resulting liquidity changes into the market, are likely to be

[34] In 1995, the United States coordinated a bailout of 50 billion USD to help Mexico overcome the debt crisis. The contract for Mexico included penalty rates and compelled the Mexican government to pledge oil exports as a collateral for the deal. The subsequent recovery of the Mexican economy suggests that the financial intervention by external bodies can solve a sovereign debt crisis (cf. Conesa and Kehoe, 2014).

more influential than the individual policy announcements. This study focuses on the medium to long-term impact of monetary policy measures by introducing a global multiplier ratio to proxy for global market liquidity and global unconventional monetary policy.

Investments in metals, both industrial and precious, may provide advantages for investors and other market participants. These advantages include (a) a hedge against inflation (Gorton and Rouwenhorst, 2005; Bampinas and Panagiotidis, 2015), (b) a hedge against future USD demand, and (c) the ability of gold to serve as a safe haven asset (Roache and Rossi, 2010; Sari et al., 2010). Furthermore, metals and other storable commodities, as a primary contributor to production, immediately represent changes in future expected demand (e.g. Krugman, 2008; Kilian, 2009). As supply-increasing investments usually take several years to implement, changes in future growth expectations trigger future demand and drive today's demand for inventory and ultimately prices. Thus, changes in industrial metal prices may serve as an early predictor of future changes in inflation. For example, Chen et al. (2014b) find evidence that commodities have predictive power on the consumer price index (CPI) and producer price index (PPI) of small commodity exporting countries. However, the gradual decline in commodity prices, particularly industrial metal prices, since the beginning of 2011 raises concerns about whether interventions by the central banks distort financial markets. In fact, the focus on USD prices may be misleading for exchange-traded metals. Fluctuations of the USD triggered by relative changes in US (foreign) monetary stimulus influence the associated costs and revenue of commodity exporting and importing countries and may ultimately drive commodity prices (e.g. Portes, 2012).

Therefore, this study scrutinises the impact of changes in the balance sheets of major central banks, i.e. the monetary base, on exchange-traded non-ferrous metals and gold. To measure the effectiveness of central bank interventions, I create the multiplier ratio by dividing market liquidity (proxied by M2) by the chosen proxy for unconventional monetary policy (central bank assets) for each of the examined seven economies. In a second step, the economy-individual multiplier ratios are weighted by the size of their central bank assets and summarised to create the global multiplier ratio. Moreover, the study incorporates trade-specific data of commodity exporting and importing countries and links this information with industrial commodities and monetary policy. This leads to the research question: how does global conventional and unconventional monetary policy influence the price of exchange-traded metals? The contributions of the study are: (1) I introduce a new measure, the global multiplier ratio, which uses information on central banks assets to proxy for global central bank market interventions and unconventional monetary policy, to measure the effectiveness of the latter, i.e. the absorption of such into their economies. When central banks engage in unconventional monetary policy, they buy government and corporate debt securities in the secondary market, which increases their balance sheet assets. Thus, by using this information and by assuming that the other asset positions remain relatively constant over time, it is possible to circumvent the lack of availability of precise unconventional monetary policy data for all of the examined seven economies. This variable allows investors and policy makers to quickly and efficiently quantify the impact of global central bank market interventions and consider the associated effects on commodity prices in their models. More precisely, this measure provides a quick indication as to whether the intended unconventional monetary policy measures function as intended and are used to improve lending and eventually spending; (2) Unlike prior studies (e.g. Frankel, 2006; 2014), I do not limit the study to US interest rates but include other major economies; (3) I use global import information to complement the study with real demand measures instead of using proxies (e.g. Kuralbayeva and Malone, 2012); (4) I extend prior research and include commodities that have experienced little attention in prior studies; (5) I approach the potential endogeneity bias stemming from monetary policy and provide evidence that the model is robust. Overall, I find evidence that the global multiplier ratio, which measures the ratio between market liquidity and unconventional monetary policy[35], is positively associated with the price of industrial metals. Moreover, prior research on the relationship between global real interest rates and commodity prices is confirmed for a few non-ferrous metals and gold. By adding unconventional monetary policy, market liquidity, and real interest rates to the equation, it is possible to distinguish between the effects of the different influential factors.

The remainder of Chapter 3 is organised as follows. Section 3.2 discusses prior research, the state of the literature, and how monetary policy can impact commodities. Subsequently,

[35] Whereas unconventional monetary policy represents the root of the fresh liquidity that is induced by the actions of the central banks into the economy, the market liquidity (here: M2 money measure), which can be used to scrutinise the impact of money on the economy (Mankiw, 2016), provides a measure of all money and near money assets that circulate within an economy (Abel et al., 2011). When central banks engage in unconventional monetary policy, they buy government and corporate debt securities in the secondary market, which increases their balance sheet assets. By doing so, the central banks aim to encourage lenders to give out more money at lower rates, which should eventually translate into higher M2, if the measure works as intended. Thus, the global multiplier ratio provides a quick indication on whether the unconventional monetary policy measures function as intended and are used by the economy to improve lending and eventually spending.

I consolidate the data and conceive the methodology in Section 3.3 and present the empirical results of the study in Section 3.4. The study concludes with Section 3.5, which consolidates the findings and presents potential areas for future research.

3.2 LITERATURE REVIEW

3.2.1 MONETARY POLICY AND COMMODITY MARKETS

While most prior research scrutinises the relationships between conventional monetary policies and various forms of asset classes, the number of papers concerned with unconventional monetary policy is continuously increasing. For example, a common approach is to use the event study method of Kuttner (2001) to evaluate the immediate response of exchange-traded commodities to monetary policy announcements (Glick and Leduc, 2012; Joyce and Tong, 2012; Georgiadis and Gräb, 2015; Eser and Schwaab, 2016; Haitsma et al., 2016). The main advantage of this technique lies in its ability to evaluate the impact of the announcement, but it relies upon the implicit assumption that the announcement contains all the price sensitive information. However, although the announcements are important, details of the exact procedure of the market operation are not known at the announcement date (Fratzscher et al., 2013) and the market operation itself provides further information that should not be left out. In fact, the influence of monetary policy on prices resulting from the portfolio rebalancing channel may occur over a longer period than the typical event window used in these studies (Ueda, 2013). The evaluation of announcement reactions may not only withhold valuable information but further bias the real impact, as it only represents the first reaction to a shock. To account for these effects, other studies draw on lower frequency data and rely on techniques like the "identification through heteroscedasticity" approach by Rigobon and Sack (2004) or variations of vector autoregression (VAR) models that define non-announcement and announcement periods to test the impact of announcements on commodities and to confirm findings for higher frequency data (Kapetanios et al., 2012; Claus et al., 2014; Gambacorta et al., 2014; Unalmis and Unalmis, 2015; Haitsma et al., 2016; Tillmann, 2016).

Overall, the above studies present mixed results. For example, Glick and Leduc (2012) argue that the announcement of large-scale asset purchase programmes implies lower expected future economic growth, which leads to less future demand and therefore lower commodity prices. While this is a logical argument for an economy subjected to asset purchases, it may not always generalise with respect to global commodity demand. In fact, global trade of raw materials such as copper ore and concentrates remained high throughout the years studied (Trade Map, 2016). Even if demand decreases due to lower expected future economic growth, the quantitative impact of such an influence on global commodity prices remains unclear. Second, if stock prices increase because of QE (Haitsma et al., 2016), investors and companies experience a growth in wealth, which enables them to consume more in the future. Again, higher future consumption would trigger higher future demand which causes higher demand for inventory today and thus higher commodity prices. Moreover, the support of central banks in meeting future economic growth expectations should drive commodity prices upwards as uncertainty about the future recedes. However, the effectiveness of QE is disputed. Although QE has evidently reduced interest rates (Girardin and Moussa, 2011), the impact on macroeconomic variables differs globally. While Ueda (2012) suggests a minor impact of QE on the Japanese CPI, Bowman et al. (2015) add that the improvement in lending by banks could not sufficiently stimulate demand in Japan, which ultimately led the researchers to the conclusion that QE did not sufficiently help to overcome deflation. The findings for the UK, however, are rather ambiguous. Whereas Lyonnet and Werner (2012) find little evidence for a positive effect of UK QE on UK GDP, Kapetanios et al. (2012) identify a peak impact of UK QE of 1.5 percent on real UK GDP and 1.25 percent on CPI. Moreover, Weale and Wieladek (2016) suggest an increase of 0.25 percent for GDP and 0.32 percent for inflation for the UK and an increase of 0.58 percent for GDP and 0.62 percent for inflation for the US based on data from 2009 to mid-2014. Likewise, Le et al. (2016) present evidence for a positive impact of QE on real GDP and real economic growth for US data. The results suggest that announcement effects have a weaker influence on the UK economy than they do on the US economy. As US unconventional monetary policy is larger in dollar terms, the overall surplus in global liquidity may dictate the magnitude of the impact. Moreover, the difference in results between the QE measures of the US, UK, and Japan may also be influenced by the individual approach used. Whereas pure QE is less concerned with the composition of the assets purchased, targeted QE, also known as credit easing, evaluates each asset before it is purchased to ensure that the mix held by the central bank is not negatively affecting the market (Bernanke, 2009). While the effectiveness of the former is potentially limited, the latter can be more beneficial (Curdia and Woodford, 2011).

Furthermore, Goodhart and Ashworth (2012) highlight that prior studies often underestimate the impact of UK QE1 on GDP as they do not fully account for beneficial effects on the credit spread and the relative value of a currency. Moreover, Martin and Milas (2012) show that the impact of QE diminished throughout time and for each batch. Whereas QE was apparently effective in 2008 and 2009, later measures show less impact. As literature examining the precise impact and interaction of QE, conventional monetary policy, global liquidity, and individual commodity prices is scarce, it remains unclear how QE influences commodity prices over time and whether such effects are different from the growth in global liquidity. Apart from the primarily positive impact of QE on real GDP and inflation, little is known about the recent impact on industrial metal prices.[36] While central banks focus on economic growth and inflation (Clarida, 2012), commodity price changes immediately impact future growth and inflation. Hence, it is crucial to understand the consequences of all central bank actions and the potential implications for their primary target.

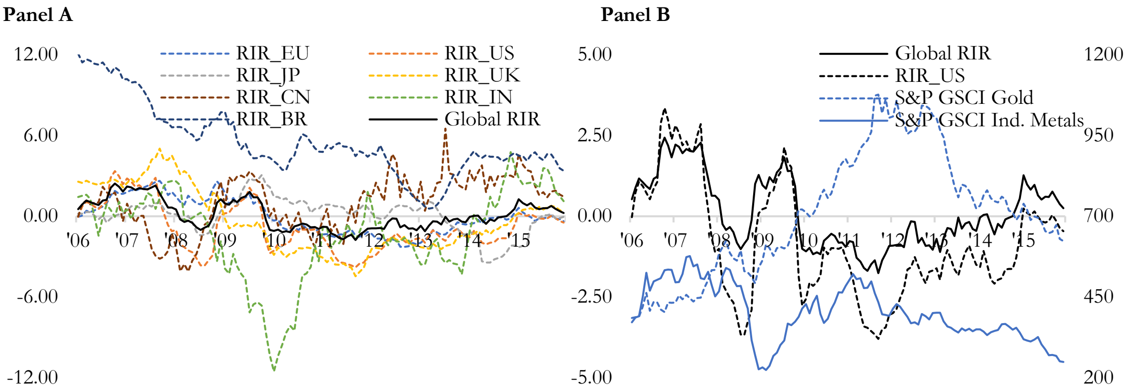
3.2.2 TRANSMISSION CHANNELS OF MONETARY POLICY

Unlike unconventional monetary policy, economies around the globe use conventional measures to achieve price stability, stimulate economic growth, and currency control. Following Frankel (2006) and Anzuini et al. (2013), conventional monetary policy stimulates economic activity via three transmission channels: the inventory channel, the supply channel, and the financial channel. The inventory channel arises because lower real interest rates increase the demand for storable commodities. When real interest rates decrease, either via conventional monetary policy changes, i.e. changes in the main refinancing rate charged by a central bank, or because of unconventional monetary policy, i.e. QE (Glick and Leduc, 2012), the cost of storage decreases. Thus, the demand for inventory increases, which increases the demand for commodities and ultimately puts upward pressure on the price (Akram, 2009; Frankel, 2014; Kilian and Murphy, 2014). For example, Scrimgeour (2014) finds that an increase in the interest rate by 0.1 percent leads to a decrease in commodity prices by 0.6 percent on average, with metals showing the largest impact. Figure 3.1 illustrates the development of the GDP-weighted[37] daily real 3-month interbank interest

[36] Although prior research suggests an impact of QE on commodity prices (e.g. Claus et al., 2014; Barroso et al., 2015), none of the scrutinised studies includes recent quantitative measures by major central banks.
[37] The calculation of the GDP-weighted index is explained thoroughly in Section 3.3.2.

rates and the Standard & Poor's GSCI Industrial Metals (SPIMSI) and Gold (SPGSI) spot indices from January 2006 to December 2015.

Figure 3.1: Real Interest Rates and Commodity Prices



Notes: These figures illustrate the development of the GDP-weighted real 3-month interbank interest rates of the United States (US), the Eurozone (EU), Japan (JP), China (CN), the United Kingdom (UK), India (IN), and Brazil(BR), the Standard & Poor's (S&P) GSCI Gold index (SPGSI), and the Standard & Poor's (S&P) GSCI Industrial Metals index (SPIMSI) from January 2006 to December 2015. The interest rates are realised by subtracting the year-on-year change of the CPI from the nominal interest rates. The primary axis in both panels show the real interest rates in 100's of percent, whereas the secondary axis in panel B illustrates the index value in USD per point. The SPGSI and SPIMSI are deflated by the US CPI (2015=100). With RIR for real interest rates.

Following times of decreasing interest rates, commodity prices tend to show a delayed increasing trend. Especially after the GFC of 2007-2008, where nominal interest rates have decreased drastically, commodity prices increased rapidly. In line with prior research[38], Figure 3.1 indicates a negative correlation between commodity prices and real interest rates. Particularly panel B in Figure 3.1 suggests that the US real interest rate has experienced stronger fluctuations than the measurement of global real interest rates. For example, the correlation coefficients for the changes in the quarterly real interest rate and commodity prices in the EU (gold: -0.493) and China (industrial metals: -0.407) between the second quarter of 2006 and the fourth quarter of 2015[39] are stronger than those measures for the US (gold: -0.389, industrial metals: -0.306)[40]. Moreover, the correlation coefficients for the global multiplier ratio and global real interest rate are often stronger than the correlation coefficients for the individual economy measures. Although the US is still the largest single economy as of 2016, the arrival of Asian consumers led by China as the largest importer of coal and non-ferrous metals, with a share well above 40 percent (World Bank, 2015; IMF,

[38] Harvey et al. (2016) present a comprehensive analysis of the relationship of commodity prices and UK interest rates since the 17th century. The researchers show that increasing interest rates cause a decrease in commodity prices.
[39] Due to the use of first differences, the sample runs from February or the second quarter of 2006 to December or the fourth quarter of 2015.
[40] In the data section of this chapter, I present and further discuss the quarterly and monthly correlation coefficients of global real interest rates, the global multiplier ratio, and commodity prices.

2016) may dilute the leading impact of the US on commodity market dynamics towards a more balanced global interaction. For example, Klotz et al. (2014) show a negative correlation between commodity prices and the real interest rate of China, which ranges from negative 0.52 for precious metals to negative 0.74 for energy commodities. Moreover, Le and Chang (2016) present a positive correlation (0.18) between interest rates and the oil price for Japan, which is a major importer of oil. Both studies, however, limit their focus to one country and fail to evaluate the combined impact of major economies. Thus, one should not generalise findings in prior research that focuses on US or other single economy real interest rates to global markets such as commodities. The growing interconnection of global trade and financial markets justifies a re-evaluation of the latest market changes and particularly the growing market interventions by central banks.

The supply channel, much like the inventory channel, transmits the impact of the interest rate. A reduction in the interest rate lowers the incentive for producers to extract the exhaustible commodity, which makes it more attractive to leave it underground instead. This ultimately reduces the supply of commodities and increases the market price. Thus, changes in interest rates do not only affect the market price via the increase in inventory demand (inventory channel) but also reduce the supply of the commodity to the market (supply channel).

The financial channel theory argues that investors and speculators shift into commodity contracts to compensate for the diminishing yields on bonds and other assets resulting from the decrease in interest rates. This shift increases the demand for commodities and drives the price. More precisely, the financial channel consists of three sub-channels: the signalling, the portfolio rebalancing[41], and the liquidity premium channel. The signalling channel arises from latest information about future expected growth 'signals' implicit within central banks' monetary policy announcements. Glick and Leduc (2012) argue that announcements of further asset purchases negatively impact investors' future expectations, as they are introduced to improve market conditions. The portfolio rebalancing channel arises when investors seek to reallocate funds released when their portfolio holdings are purchased by central banks. Central bank purchases increase the demand and hence price of certain portfolio holdings, which reduces the yield of treasury bills and other relatively safe assets

[41] Both the signalling and the portfolio rebalancing channel might also be triggered by other transmission channels and are not limited to the financial channel.

and motivates investors to sell their holdings. The newly available funds directly impact commodity prices via the portfolio rebalancing and the liquidity premium channel. The liquidity premium channel reflects the desire of investors to be compensated for liquidity risk that is associated with a market. Instead of investing in commodities, equities represent a suitable alternative. By shifting funds from fixed income to equities, the price of the latter increases, which increases both the market value of the company and the wealth of equity holders. The increase in the market value of companies provides several advantages. According to Mishkin (1996), the increase in firm value increases Tobin's q (Tobin, 1969), which positively increases the investment spending affinity of companies. Moreover, the increase in firm value reduces the moral hazard and default risk of the company, which ultimately reduces the liquidity premium on debt and eases the access to fresh funds. Besides, equity holders experience an increase in wealth following the increase in equity prices. Thus, they can increase their consumption, which leads to higher demand for consumer goods and eventually higher commodity prices. Whereas conventional monetary policy does not influence the existence of asset price bubbles (Gali, 2014), loose monetary policy can fuel them (Hu and Rocheteau, 2015).

3.2.3 THE FOREIGN EXCHANGE EFFECT OF MONETARY POLICY

Unlike other asset classes, commodities are primarily traded in USD. By increasing the money supply, central banks effectively dilute the value of their currency. Furthermore, one must differentiate between domestic measures and global prices. Whereas central banks are concerned with domestic growth and are unlikely to consider the financial conditions of other countries as key decision criteria, commodity prices are influenced by world demand and supply, which may be partially driven by individual central bank decisions and partially driven by other global market conditions. Thus, a monetary measure in one economy might have a different impact on commodity prices compared to another. To coherently explain this issue, let's have a look at the following three examples:

1. The United States of America, a major importer and consumer of commodities, introduces monetary policy that increases the supply of money. Following the increase in money supply and thus currency in circulation, the value of the USD decreases compared to other currencies. Thus, the demand for commodities from other currencies increases,

which lifts the price of a commodity to its new equilibrium. Result: The USD price of commodities increases.

2. The Eurozone, another major importer of commodities, follows the United States and introduces money supply increasing measures. As a result, the value of the Euro decreases compared to the USD and other currencies. Hence, buying commodities at market price becomes more expensive for Eurozone economies, which in turn reduces the demand. Result: The price in USD of a commodity decreases. Yet, it must be highlighted that the decrease in the value of a currency also contributes to an increase in exports and relative attractiveness for foreign investors. Thus, the negative impact on commodity prices might be short-lasting and will be offset by an increase in exports and foreign investment in the long-term. This may contribute to an increase in demand and price.
3. Chile, as the major exporter of copper, increases the money supply as the result of monetary policy. As in the other two examples, this decreases the value of the Chilean Peso (CLP) compared to the USD and other currencies. Consequently, the revenues of Chilean copper producers increase as the sale of copper in USD accumulates more CLP. Hence, this may lead to a slight decrease in (or at least stable) USD prices, as the exporting company requires less USD to maintain its operations at an equal level. In the mid-to long-term, producers' incentive to increase supply rise due to the higher returns in CLP. Thus, the supply on the global market increases, which leads to a reduction in price.

Besides the impact on the USD market price, however, the relative decrease in currency value in the third example may lead to an influx of foreign investments as it encourages investors to shift funds to countries that provide higher expected yields. In return, these countries must cope with the impact of the liquidity influx and other related effects such as the appreciation of their currency, which eventually contributes to the so-called currency wars (Portes, 2012; Hanson and Stein, 2015). For commodity producing countries, the passive appreciation of their currency due to the escalating US monetary policy may disproportionally impact exports and returns. Especially for commodity-rich countries, this situation may lead to the highly unfavourable situation of a so-called Dutch disease (Oomes and Kalcheva, 2007). As a large influx of foreign investment leads to a currency appreciation, other exports of commodity-rich countries become less competitive on the global market, which eventually leads to an economic slowdown. As the exchange rates of major exporting countries such as Chile for copper or Australia for aluminium ores, and Japan and Europe as major importers, are managed on a freely floating basis, these countries must cope with the adverse effect of a relative currency appreciation compared to the USD following a monetary measure by the US. In contrast, other large importers (China) or exporters (US) are less or not affected by the appreciation of their currency compared to the USD as they are either manage the exchange rate with the USD (China) or experience the benefit of being the currency of legal tender (US). This gives producers and consumers from those markets a competitive advantage as they do not have to bear an exchange rate risk associated with the sale or purchase of the commodities. This may influence producer and consumer decisions and ultimately impact the supply, demand, and price of the underlying good.[42] Barroso et al. (2015) evaluate the impact of the influx of foreign currency because of US monetary policy into Brazil. The researchers find that this influx contributed to the drastic increase in the Brazilian Real from 2000 to 2012 and they argue that this eventually contributed to increasing the inflation in Brazil. Albeit the nominal positive impact of a weaker USD on commodity prices is established (Akram, 2009; Chen et al., 2014a), little is known about the real impact on the flow of commodities and particularly industrial metals.

3.2.4 CENTRAL BANK LIQUIDITY

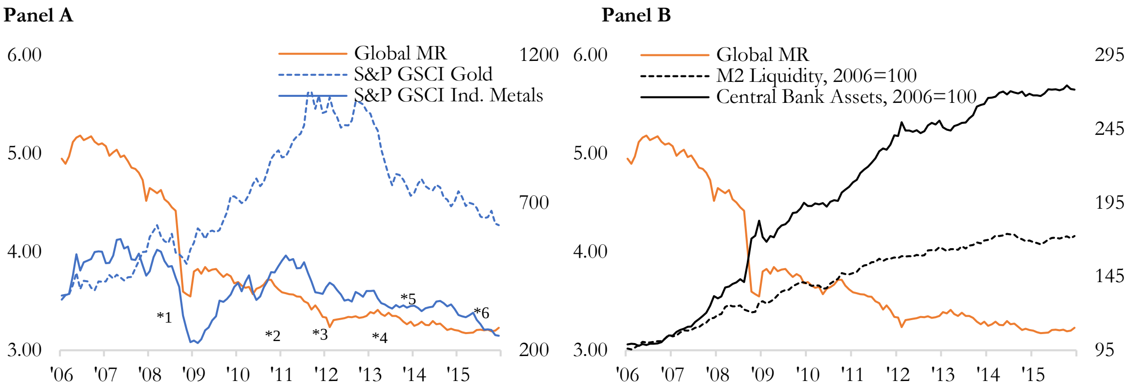
Unconventional monetary policy has been extensively used by the US, the Eurozone, Japan, and the UK since the outbreak of the GFC in 2008. In contrast to a change in real interest rates, the asset purchase programmes by central banks infuse the market with fresh liquidity which is transmitted via different transmission channels. As a result, commodity prices are expected to react to the increase in money supply. For example, Wang et al. (2016), who evaluate monthly data until December 2011, illustrate the gradual impact of escalating foreign liquidity and increases in the domestic monetary base on Chinese asset prices. Moreover, Beckmann et al. (2014) and Ratti and Vespignani (2015) highlight the impact of BRIC and G3 liquidity shocks on monthly commodity prices and Ratti and Vespignani (2015) confirm Granger causality from broad market liquidity (M2) to commodity prices.

A primary target of quantitative easing is the active reduction of long-term interest rates, which shall lead to an increase in lending by commercial banks and eventually increase

[42] Fratzschler et al. (2013) note that little evidence in favour of pegged exchange rates is available in prior literature. In fact, the researchers highlight that such measures might have exacerbated the impact of Fed's monetary policy.

consumption. However, to ensure that this mechanism works, central banks rely on both commercial banks and their willingness to lend money and not to use it otherwise and borrowers to use the fresh capital to consume. The multiplier ratio, i.e. a measure of market liquidity and quantitative easing efforts by central banks, is an economic indicator that illustrates the ability of an economy to utilise fresh capital stemming from unconventional central bank measures and introduce it to the economy by lending and eventually spending. Figure 3.2 illustrates the time series of the four variables which are either directly or indirectly related to unconventional monetary policy: (1) global M2, a monetary aggregate I use to proxy for market liquidity[43], (2) central bank assets, which act as a proxy for global quantitative easing or unconventional monetary policy, (3) the global multiplier ratio, which is derived from (1) and (2), and (4) the real prices of industrial metals and gold.

Figure 3.2: Multiplier Ratio, Liquidity, and Commodity Prices



Notes: Panel A illustrates the development of the global multiplier ratio (MR), defined as the central bank asset-weighted ratio of M2 over central bank assets of each of the seven central banks, and the index values of the Standard & Poor's (S&P) GSCI Industrial Metals (SPIMSI) and Gold Spot (SPGSI) indices, which are deflated by the individual CPI, from January 2006 to December 2015. Panel B illustrates the global multiplier ratio, the sum of the total assets of the balance sheets of the Federal Reserve, the European Central Bank, the Bank of Japan, the People's Bank of China, the Bank of England, the Reserve Bank of India, and the Central Bank of Brazil and the sum of M2 measures for each of the seven central banks. All deflators are re-indexed to 2015=100. The sum of the central bank assets and M2 are re-indexed to 2006 = 100. Monthly arithmetic averages for the exchange rates are used to convert to USD. In both panels, the primary axis shows the multiplier ratio. In panel A, the secondary axis illustrates the index value in USD per point. In panel B, the secondary axis shows the indexed values of M2 and the central bank assets. *1: QE1 by the FED; *2: QE2 by the FED; *3: BoJ increases the commercial account balance and expands QE; *4: QE3 by the FED; *5: Japan extends QE; *6: ECB launches the expanded asset purchase programme (QE).

Figure 3.2 suggests that commercial banks do not sufficiently pass through the new liquidity to consumers by equivalently increasing their lending. This is shown by a stronger increase of central bank assets (indexed) compared to M2. Put simply, the money multiplier effect of one USD in central bank induced liquidity decreases over time suggesting that the global economy no longer uses fresh central bank liquidity as efficiently as it did prior to the GFC.

[43] I follow prior research (e.g. Ratti and Vespignani, 2015) and use M2 as proxy for market liquidity.

3.3 METHODOLOGY AND DATA

3.3.1 METHODOLOGY

Index Measurements

To evaluate the impact of monetary measures and global liquidity on commodity prices, some adjustments to raw data are necessary. The global multiplier ratio calculates the central bank asset weighted ratio of M2 over the central bank assets. Whereas prior studies estimate the immediate reaction to the central bank announcements or purely focus on absolute monetary aggregates, this approach tests the longer-term reaction of the commodity price index to the markets' ability to utilise the fresh liquidity. In other words, the global multiplier ratio diverts from the prior 'shock' or 'QE on/off' evaluation of unconventional monetary policy and generalises the ability of an economy to utilise the fresh liquidity and translate it into economic growth. Thus, one can link commodity price changes and economic activity and extend this relationship by the ability of an economy to adapt to higher levels of central bank induced market liquidity. Put simply, every monetary unit a central bank introduces to a market increases the available liquidity in that market. Market participants can use this fresh capital to borrow, lend, or invest. Because of the fractional reserve banking common in most world economies, banks only hold a fraction of their customers' deposits in reserve and earn interest by lending the remainder. Hence, the overall liquidity in the market is increased via the multiplier effect.[44] The more often a monetary unit is traded among the market participants, the higher the broad market liquidity measure (i.e. M2) gets. Therefore, a change in lending leads to a change in the ratio of market liquidity (here proxied by M2) to central bank assets. The higher the ratio, the higher the lending among market participants, which ultimately translates to a higher market liquidity. There are three potential risks that can prevent central banks from achieving their aims: excess capital, future expectations, and alternative use of the eased access to fresh funds. First, financial institutions can hold excess capital that exceeds the daily required transaction levels due to limited demand by debtors, controlled supply by the banks itself because of insufficient collateral by existing and new debtors, or delayed intermediation due to other reasons[45]. Second, financial intermediates may interpret the market interventions of central banks as a

[44] Please refer to Abel et al. (2011:526-527) for a more detailed explanation on fractional reserve banking.
[45] Benmelech and Bergman (2012) argue that during times of monetary expansions, banks tend to hoard liquidity instead of lending it.

signal for lower expected future economic growth, which may ultimately lower their incentive to issue loans and build reserves instead. Third, investments are usually not geographically restricted. Whereas central banks focus on the stimulation of their own economy, market participants can use the newly available funds to invest in other markets with potentially higher expected returns. Thus, the multiplier ratio measures the effectiveness of central banks' efforts to increase their domestic money supply on a global scale, i.e. for the seven evaluated economies. This measure allows market participants to evaluate whether the unconventional monetary policy efforts by major central banks have been converted into market liquidity, i.e. whether the markets use the freshly available funds provided by the central banks to increase lending. More precisely, the measure provides a quick indication as to whether the increase in liquidity stemming from unconventional monetary policy is used to increase lending, thus eventually increasing M2. As a response to unconventional monetary policy, the global multiplier ratio should first decrease (as M2 remains relatively stable and central bank assets increase) but should, over the mid- to long-term horizon, increase, as M2 increases due to the multiplier effect. Thus, the global multiplier ratio allows market participants to quickly identify whether, to what extent, and how fast unconventional central bank measures are absorbed by the markets and translated into general market liquidity. The global multiplier ratio provides an easily reproduceable measure that quantifies the time an economy requires to convert new central bank liquidity into market liquidity and the extent to which an economy is able to multiply this new liquidity. The global multiplier ratio is calculated as:

$$MR_t = \sum_{k=1}^{n} \frac{M2_{k,t}}{CBA_{k,t}} * \rho_{k,t} \tag{3.1}$$

$$\rho_{k,t} = \frac{CBA_{k,t}}{\sum_{k=1}^{n} CBA_{k,t}} \tag{3.2}$$

with MR_t as global multiplier ratio, $CBA_{k,t}$ as central bank assets, $M2_{k,t}$ as money supply that measures the amount of cash, checking and savings deposits, money market securities, and other time deposits within an economy, $\rho_{k,t}$ as individual central bank asset weight for each economy k at time t.

Whereas simple summation of the data is sufficient for some variables, others require an economy-specific weighting to incorporate their relative economic strength. Despite the availability of pre-defined indices such as the trade-weighted USD index, no base metal specific index is available that fits the specifications of this study. Motivated by the approach underlying the trade-weighted USD index, I adopt a simplified version for the commodity trade-weighted USD index (Board of Governors of the Federal Reserve System (US), 2016). This index has been proven to deliver reliable results in predicting commodity prices in prior research (Kuralbayeva and Malone, 2012; Chen et al., 2014a) and is calculated as:

$$FX_t = FX_{t-1} * \prod_{j=1}^{n} \left(\frac{e_{j,t}}{e_{j,t-1}} \right)^{cw_{j,t}} \tag{3.3}$$

$$cw_{j,t} = \frac{X_{j,t-1}}{\sum_{j=1}^{n} X_{j,t-1}} \tag{3.4}$$

where FX_t and FX_{t-1} are the nominal USD exchange rate index, $e_{j,t}$ and $e_{j,t-1}$ are the price of the USD for foreign currency j, $N(t)$ is the number of countries in the index, $cw_{j,t}$ is the weight of currency j with $\sum cw_{j,t} = 1$, and $X_{l,t-1}$ represents the sum of the commodity exports and imports of economy l = [Eurozone, United Kingdom, Japan, USA, China, Brazil, India], all at time t or $t - 1$. The weight is based on previous years' trade and is adjusted once yearly at the turn of the year. Only yearly exports and imports declared as unwrought metal and converted to USD of the five commodities aluminium, copper, lead, nickel, and zinc are considered. I specifically do not include gold, as this commodity is highly traded, i.e. imported and exported, by countries that do neither produce nor consume the commodity but simply act as a merchant. This would disproportionally overvalue the importance of those currencies in the index. Furthermore, the weighting only considers countries with a share on global trade of more than five percent for the individual year, which allows me to concentrate on the major global trading countries.

Whereas the base metal trade-weighted USD index computes the product of periodical geometric-weighted changes, the real interest rate index follows a simpler approach and multiplies the real interest rate with the country-specific GDP-weight[46] for each year. Following Akram (2009), I use 3-month interbank rates deflated by the economy-specific year-on-year changes in consumer price indices to calculate the real interest rates. I chose real interest rates over nominal interest rates as a change in real interest rates represent a change in the cost of holding inventory. In contrast, this only holds true for nominal interest rates if inflation remains constant. The global real interest rate is calculated as:

$$RIR_t = \sum_{j=1}^{n} ri_{j,t} * ew_{j,t} \tag{3.5}$$

$$ri_{j,t} = i_{j,t} - \pi_{j,t} \tag{3.6}$$

$$ew_{j,t} = \frac{GDP_{j,t-1}}{\sum_{j=1}^{n} GDP_{j,t-1}} \tag{3.7}$$

with RIR_t as the real interest rate index, $ri_{j,t}$ as the real interest rate, $i_{j,t}$ as the nominal interest rate, $\pi_{j,t}$ as the year-on-year CPI change, and $ew_{j,t}$ as the economy-specific weight with $\sum ew_{j,t} = 1$, and $GDP_{j,t-1}$ as the GDP in USD of economy j at time t and $t-1$. The GDP in local currency is converted using average daily exchange rates for each period. Note that the year-on-year CPI change is a monthly measure that remains constant throughout each month.

Regression Model

In the literature review, I discuss various techniques to evaluate the interaction between monetary policy and asset prices. The primary approach underlying most of these studies follows a simple logic – it distinguishes whether a monetary policy measure is in place or not and defines them as monetary shocks. In contrast, the model in this study uses OLS regression and new measures to estimate the mid-to long-term impact of central bank policies and commodity prices. The model is defined as:

[46] Following Desroches and Francis (2010) and Rachel and Smith (2015), I use the GDP to weight global interest rates. I compare both nominal and real GDP and do not find a significant difference in the results. Thus, I concentrate on the nominal GDP weighting.

$$CI_t = \alpha + \beta_1 MR_t + \beta_2 RIR_t + \beta_3 FX_t + \beta_4 CFS_t + \beta_5 IBM_t + \beta_6 SP500_t + \beta_7 VIX_t + \varepsilon_t \tag{3.8}$$

with CI_t as the commodity index, α as the intercept, β as coefficients, MR_t as the global multiplier ratio, RIR_t as the global real interest rate, FX_t as the global base metal trade-weighted USD index, and the control variables CFS_t as the cash-forward spread, to capture supply-demand imbalances (Kuralbayeva and Malone, 2012), IBM_t as the imports of ores and unwrought base metals, to control for global physical supply and demand, $SP500_t$ as the S&P 500 composite index, to control for equity market risk, VIX_t as the S&P 500 volatility index, to control for the equity market volatility, and ε_t as the error term, all at time t. Depending on the stationarity of each time-series, I either use data at levels or first differences.

It must be highlighted that the OLS model contains methodological caveats. It is likely that commodity price changes affect central bank decisions. While their primary focus is on consumer prices, increases in commodity prices certainly compromise future economic growth and impact consumer prices to a certain extent.[47] Therefore, it is fair to assume that central bank interventions are not fully exogenous but endogenous to changes in commodity prices. However, in the OLS model they are defined as fully exogenous variables. As monetary measures are mostly announced ex ante and are usually not adjusted mid-term (Lo Duca et al., 2016), monetary policy is more concerned with consumer price stability than producer (base metal) prices, and inflation is stickier than commodity market prices, I believe that the potential endogeneity is small. Although it is not possible to eliminate it, I seek to mitigate the potential endogeneity by adding instrumental variables in the robustness tests.

3.3.2 DATA

The analysis draws on three main data sources. Thomson Reuters Datastream, the trade map created by the International Trade Centre, a joint agency of the World Trade Organization and the United Nations, for country-specific export and import information, and

[47] For example, changes in the oil prices often have an immediate effect on consumer petrol prices and energy costs, both part of consumer price indices. The impact, however, is not linear and often smaller than the actual change in commodity prices.

information provided by seven central banks. The central banks are: the European Central Bank (ECB), the Bank of England (BOE), the US Federal Reserve (FED), the Bank of Japan (BOJ), the People's Bank of China (PBOC), the Reserve Bank of India (RBI) and Banco Central de Brazil (BCB). The economies and respective central banks are chosen based on their data availability throughout the research period and their importance for the global economy. More precisely, these seven economies are the seven largest economies according to the World Bank as of 2017 (World Bank, 2017). Moreover, while all seven central banks actively manage their interest rates and have adjusted them in response to market turbulences, four out of the seven central banks (ECB, BOE, FED, BOJ) have additionally engaged in quantitative easing measures. These four central banks (PBOC, FED, BOJ, ECB) hold assets of more than 17.8 trillion USD which translates to roughly 70 percent of the World's central bank assets, or almost 24 percent of world GDP (Kuntz, 2016). Therefore, unlike prior research (e.g. Glick and Leduc, 2012; Haitsma et al., 2016), I do not limit the study to either the individual or total of the four major economies that had implemented quantitative easing measures as of 2016. The research period starts in January 2006 and ends in December 2015, totalling 120 (119) monthly and 40 (39) quarterly observations at level (first difference), which is limited by the availability of the trade data. As the primary source of the global commodity price data, I choose the daily S&P GSCI Industrial Metals Spot index (SPIMSI), comprising aluminium, copper, lead, nickel, and zinc, and the S&P GSCI Gold Spot index (SPGSI) in USD. Both the SPIMSI and the SPGSI are constructed using the nearest dated futures prices weighted by production data (S&P Dow Jones Indices, 2017). The reason I choose the S&P GSCI indices is twofold. First, the S&P GSCI main and sub-indices have proven reliable in prior research (e.g. Chen et al., 2014b; Kang et al., 2016). Second, the indices provide a measure of global market prices which is weighted by the production output of the individual index components. This approach considers the relative importance of each commodity for the global economy. Moreover, I obtain spot price data of the five commodities included in the SPIMSI provided by the LME for the robustness exercise.

In addition to commodity price data, I obtain monetary aggregate M2 data from Datastream, which is commonly referred to as market liquidity or broad money in prior research (e.g. Ratti and Vespignani, 2015). Moreover, I extract central bank asset information directly from the individual central banks to calculate the global multiplier ratio. It must be noted that central bank assets do not only include assets that have been purchased for quantitative easing purposes but also include other assets that are in the possession of central banks. For example, the ECB (2018) holds other assets such as gold and gold reserves and tangible and intangible fixed assets[48]. However, as information on quantitative easing is often either not publicly available or is limited, I must assume that the other assets besides those held for monetary purposes do not greatly change over time and thus do not affect the outcome of the analysis.

Furthermore, I obtain data to calculate the base metal specific trade-weighted USD index based on equation (3.3) and (3.4), the real interest rate index based on equations (3.5) to (3.7), and other financial data to control for market interactions. This includes trade-specific monthly import and export information in USD offered by the ITC and exchange-rate information provided by Datastream, the nominal 3-month interbank rates deflated by the individual economy-specific year-on-year changes in the consumer price index from Datastream, spot and 3-month commodity futures prices from Datastream to calculate the spot-futures-spread (as spot minus futures prices), and information on the S&P 500 composite index and the CBOE VIX to proxy for equity market risk and volatility.[49] While the information on global trade (imports and exports), central bank assets, the consumer price index, and M2 are available at monthly frequencies, commodity price information, nominal interest rates, and equity market data are available at daily frequencies. I calculate the monthly (quarterly) averages for all variables which are available at a higher frequency. Table 3.1 provides descriptive statistics of all of the variables used for this study and the pairwise correlation of industrial metal and gold prices, the global multiplier ratio, and global real interest rates. All prices and volumes in Table 3.1 are in USD or converted to USD for each period using average exchange rates. Where data at a lower frequency is available, the

[48] The assets of the ECB include gold and gold receivables, claims on non-euro area residents denominated in foreign currency, claims on euro area residents denominated in foreign currency, other claims on euro area credit institutions denominated in euros, securities of euro area residents denominated in euros (which are securities that are held for monetary purposes), intra-Eurosystem claims, and other assets (ECB, 2018).

[49] In this study, I do not include inventory data. As discussed earlier in this paper, the inventory transmission channel suggests that a decrease in real interest rates lowers the costs to hold inventory and thus increases the demand for commodities (Anzuini et al., 2013). As the increased demand is not consummative, it increases the stocks held in warehouses. Therefore, real interest rates and inventory are expected to comparably affect commodity prices. As I am interested in the analysis of real interest rates, I focus on such to avoid ambiguity in the results. I find that once inventory data are added, the coefficients for real interest rates become non-significant. This indicates that the hypothesised transmission of real interest rates to gold price changes might be sufficiently explained by either real interest rates itself or actual inventory data.

arithmetic average is calculated to obtain monthly values. The abbreviations are defined as: Vol for volume, ADF for augmented Dickey-Fuller, MON for monthly, QTR for quarterly, FD as first difference, S&P for Standard and Poor's, TR as Thomson Reuters Datastream, CB for central bank, ITC for International Trade Centre, USD pp as USD per points, Mt as metric tonnes, and tsd. USD as thousands of USD, Unconv. as unconventional, Conv. as conventional, MP as monetary policy, ML as market liquidity, MR as global multiplier ratio, RIR as real interest rate, EU as Eurozone, US as United States, JP as Japan, UK as United Kingdom, CN as China, IN as India, and BR as Brazil. Time-series in italics are deflated by the US implicit price deflator of the Gross Domestic Product provided by the Energy Information Administration (EIA, 2009 = 100). Underlined variables indicate an index or combination of various rates, prices, or sources. Numbers in bold indicate whether data at levels or first differences for each variable are used. The Phillips-Perron (PP) test mostly confirms the findings of the augmented Dickey-Fuller (ADF) for both the monthly and quarterly time-series.

Panel D in Table 3.1 reports the pairwise correlation coefficients between changes in commodity prices and both the global multiplier ratio and global real interest rates and indicates that a more global approach, i.e. combining the seven evaluated economies, might provide additional advantage compared to examining only the multiplier ratios and real interest rates of the individual economies. While the favoured US interest rate and liquidity data in prior research (e.g. Frankel, 2014; Hammoudeh et al., 2015) significantly correlates with commodity prices in my sample, other economies are in no way inferior. For example, both multiplier ratios for the Eurozone and Japan, i.e. two economies that have implemented extensive quantitative easing measures during the recent decade, show comparable correlation to commodity prices. In fact, the correlation coefficients for the quarterly real interest rate and commodity prices in the EU (gold, -0.493) and China (industrial metals, -0.407) are stronger than those measures for the US (gold: -0.389, industrial metals: -0.306). Moreover, the combined global multiplier ratio and real interest rate are often stronger than for the individual economy measures. Although the US is still the largest single economy as of 2016, the arrival of Asian consumers led by China as the largest importer of coal and non-ferrous metals with a share well above 40 percent (World Bank, 2015; IMF, 2016) may alter the leading impact of the US on commodity market dynamics towards a more balanced global interaction.

Table 3.1: Overview of Variables and Descriptive Statistics

Panel A: Overview Variable	*Source*	*Original Frequency*	*Unit*	*Type*	*Proxy for*	*ADF – MON* Level	*ADF – MON* FD	*ADF – QTR* Level	*ADF – QTR* FD
S&P Ind. Metals Spot	TR	Daily	USD pp	Index	Industrial Metal Prices	-1.13	**-8.02*****	-1.34	**-4.96*****
S&P Gold Spot	TR	Daily	USD pp	Index	Gold Price	-1.62	**-9.39*****	-1.45	**-4.32*****
Multiplier Ratio	TR/CB	Monthly	-	Index	Unconv. MP and ML	-1.36	**-8.26*****	-2.10	**-6.05*****
Real Interest Rate	TR	Daily	100's %	Index	Conv. MP	-1.56	**-7.36*****	-1.72	**-4.29*****
Trade-Weighted USD	TR/ITC	Daily	-	Index	Exchange Rate Impact	0.92	**-6.52*****	0.38	**-3.86*****
Cash-Forward Spread	TR	Daily	USD pp	Index	Implied Return on Inventory	**-2.81***	-12.2***	-2.45	**-5.73*****
CFS – Gold	TR	Daily	USD	Index	Holdings	**-6.60*****	-24.6***	-2.20	**-9.65*****
Imports Base Metals	ITC	Monthly	Tsd. USD	Vol	Global Trade and Demand	**-3.42****	-15.9***	-1.96	**-4.21*****
Imports Gold	ITC	Monthly	Tsd. USD	Vol		-2.53	**-13.0*****	-1.67	**-8.23*****
S&P 500 Index	TR	Daily	-	Index	Equity Risk	-0.20	**-8.75*****	-0.23	**-3.92*****
CBOE VIX	TR	Daily	-	Index	Equity Volatility	-2.79*	**-9.43*****	-2.68*	**-6.46*****

Panel B: Descriptive Statistics – Monthly	*Mean*	*Median*	*StDev*	*Obs*	*Kurtosis*	*Skew*
S&P Ind. Metals Spot	-0.0090	0.0032	0.2331	119	4.7424	-0.3429
S&P Gold Spot	0.0183	-0.0017	0.2697	119	3.8543	0.2140
Global Multiplier Ratio	-0.0144	-0.0097	0.0727	119	18.0476	-2.3748
Global Real Interest Rate	-0.0028	0.0002	0.2936	119	5.3376	-0.3170
Trade-Weighted USD	0.1064	0.0133	1.1248	119	5.6184	0.9053
Cash-Forward Spread – Industrial Metals	-0.9056	-1.5239	2.2558	119	5.541	1.5777
Cash-Forward Spread – Gold	-2.4068	-2.2213	2.5272	119	2.3364	-0.398
Imports Ores + Unwrought Metal	166486.7	171862.3	27853.69	119	3.8099	-0.9031
Imports Gold	1,068.25	-20.8927	27,806.85	119	5.4470	-0.3198
S&P 500 Index	0.0414	0.1557	0.4855	119	8.5288	-1.6537
CBOE VIX	0.0498	-0.2961	4.6611	119	20.1990	3.0156

Panel C: Descriptive Statistics – Quarterly	*Mean*	*Median*	*StDev*	*Obs*	*Kurtosis*	*Skew*
S&P Ind. Metals Spot	-0.0283	-0.0014	0.4431	39	6.9970	-1.0555
S&P Gold Spot	0.0603	0.0683	0.4478	39	3.4554	-0.0878
Global Multiplier Ratio	-0.0443	-0.0265	0.1399	39	15.8198	-2.7584
Global Real Interest Rate	-0.0126	0.0266	0.5576	39	4.4608	-0.7026
Trade-Weighted USD	0.3062	-0.1481	2.3906	39	4.8555	1.1689
Cash-Forward Spread – Industrial Metals	-0.0462	0.0349	1.4305	39	4.2395	-0.2681
Cash-Forward Spread – Gold	0.1474	0.2032	1.3759	39	6.6563	-1.0939
Imports Ores + Unwrought Metal	761.4243	1,864.037	16,315.96	39	4.1532	-0.8217
Imports Gold	2,565.160	6,280.595	26,724.25	39	6.2195	-0.5288
S&P 500 Index	0.1257	0.2389	0.8776	39	8.3331	-1.9989
CBOE VIX	0.1271	-0.4738	7.4433	39	11.6702	2.1299

Panel D: Correlation MR – FD	*MR*	*MR-EU*	*MR-US*	*MR-JP*	*MR-UK*	*MR-CN*	*MR-IN*	*MR-BR*
S&P Ind. Metals Spot – Monthly	0.399***	0.277***	0.342***	0.197**	-0.134	-0.088	0.141	0.209**
S&P Ind. Metals Spot – Quarterly	0.631***	0.500***	0.614***	0.504***	-0.186	-0.140	0.044	0.268*
S&P Gold Spot – Monthly	0.048	0.020	0.079	-0.100	0.013	-0.069	-0.026	0.114
S&P Gold Spot – Quarterly	0.172	0.001	0.257	0.274	-0.055	-0.249	-0.118	0.162

Panel E: Correlation RIR – FD	*RIR*	*RIR-EU*	*RIR-US*	*RIR-JP*	*RIR-UK*	*RIR-CN*	*RIR-IN*	*RIR-BR*
S&P Ind. Metals Spot – Monthly	-0.305***	-0.247***	-0.262***	-0.159*	-0.160*	-0.181**	0.041	-0.076
S&P Ind. Metals Spot – Quarterly	-0.342**	-0.175	-0.306*	-0.189	0.020	-0.407**	0.046	-0.215
S&P Gold Spot – Monthly	-0.276***	-0.273***	-0.260***	-0.030	-0.112	-0.049	-0.117	-0.085
S&P Gold Spot – Quarterly	-0.456***	-0.493***	-0.389**	-0.085	-0.328**	-0.256	0.013	-0.253

Notes: All prices and volumes are denoted in USD or converted to USD for each period using monthly average exchange rates. Where information at lower frequency is available, the arithmetic average is calculated. With Vol for volume, ADF for augmented Dickey-Fuller, MON for monthly, QTR for quarterly, FD as first difference, S&P for Standard and Poor's, TR as Thomson Reuters Datastream, CB for central bank, ITC for International Trade Centre, USD pp as USD per points, Mt as metric tonnes, and tsd. USD as thousands of USD, Unconv. as unconventional, Conv. as conventional, MP as monetary policy, as ML as market liquidity, MR as global multiplier ratio, RIR as real interest rate, EU as Eurozone, US as United States, JP as Japan, UK as United Kingdom, CN as China, IN as India, and BR as Brazil. The research period stretches from January (February due to first differences) 2006 to December 2015 with 119 monthly and 39 quarterly observations. Time-series in italic are deflated by the US implicit price deflator of the Gross Domestic Product provided by the Energy Information Administration (EIA, 2009 = 100). Underlined variables indicate an index or combination of various rates, prices, or sources. Numbers in bold indicate whether level data or first difference of each variable is used. The Phillips-Perron (PP) test mostly confirms the findings of the augmented Dickey-Fuller (ADF) for both the monthly and quarterly time-series. Panel D and E illustrate the monthly and quarterly pairwise correlation of first differences of the MR and RIR indices for each evaluated economy and the S&P Industrial Metals Spot index. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

For example, Klotz et al. (2014) show a negative correlation between commodity prices and the real interest rate of China, which ranges from negative 0.52 for precious metals to negative 0.74 for energy commodities. Moreover, Le and Chang (2016) show a positive correlation (0.18) of interest rates and the oil price in Japan, which is a major importer of oil. Both studies, however, limit their focus to one country and do not evaluate the potential combined impact of major economies. Compared to the evaluation of industrial metals, gold-specific indicators are obtained for the evaluation of the SPGSI. This includes global gold imports and the spot-futures spread.[50]

3.4 EMPIRICAL RESULTS

3.4.1 INDUSTRIAL METALS SPOT INDEX

Let us begin with the OLS results for the industrial metals. Table 3.2 reports the results for the monthly and quarterly time-series. The results for both the monthly and quarterly analysis indicate a positive impact of the global multiplier ratio changes on industrial metal index changes significant at the 5 percent level. Moreover, the estimates reveal that global central banks assets and global M2 separately and jointly provide weaker explanation power for industrial metal price changes compared to the multiplier ratio. Thus, the global multiplier ratio provides a better measurement of market and central bank induced liquidity than its individual components and shows that an increase in the ability of an economy to utilise fresh central bank liquidity has a positive effect on the development of industrial metal prices. The global real interest rate provides low negative explanatory power for changes in the industrial metals price index. Earlier research finds a significant negative impact of the real US interest rate on the aluminium price (e.g. Frankel, 2006, 2014), but the current study indicates that the effect of real interest rates is subsumed by the addition of the multiplier ratio indicating that this is a more important determinant of commodity prices than real interest rates. The unwrought base metal trade-weighted USD index significantly and negatively influences industrial commodity price index changes in the monthly dataset and confirms prior findings by Kuralbayeva and Malone (2012) for daily copper prices. These findings suggest that, despite the massive increase in liquidity by the FED since 2008, the exchange rate impact of the USD remains significant. In contrast, the analysis for the quarterly data shows that the estimation power of the base metal trade-weighted USD index diminishes. Thus, exchange rates seem to strongly influence monthly price changes for industrial metals but have limited impact on longer time horizons.

[50] London Bullion gold price minus the third continuous COMEX futures contract price.

Overall, the global multiplier ratio, a measure of global market liquidity and central bank assets, investigates the ability of an economy to utilise fresh capital provided by central banks; particularly during times of unconventional monetary policy. I show that this measure is superior to simply using its components. Furthermore, I extend prior research on the estimation power of the real interest rate by considering additional economies to the US. The individual rates are combined to form an easily testable GDP-weighted global real interest rate index.

Table 3.2: OLS Regression Results – Industrial Metals Spot Index

	Industrial Metals Spot Index							
	Monthly				Quarterly			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Multiplier Ratio	0.581**				0.735**			
	(0.261)				(0.308)			
CBA		-2.11e-05*		-1.75e-05*		-1.51e-05		-2.08e-05
		(1.11e-05)		(9.79e-06)		(1.21e-05)		(1.26e-05)
M2			-9.75e-06	-6.32e-06			6.52e-06	1.19e-05
			(6.51e-06)	(5.51e-06)			(6.56e-06)	(7.36e-06)
Real Interest Rate	-0.0731	-0.0560	-0.0522	-0.0439	0.0491	0.0651	0.0506	0.0487
	(0.0616)	(0.0614)	(0.0596)	(0.0613)	(0.0595)	(0.0688)	(0.0687)	(0.0668)
Trade-Weighted USD	-0.103***	-0.123***	-0.141***	-0.141***	-0.0171	-0.0288	0.00321	0.00715
	(0.0168)	(0.0188)	(0.0266)	(0.0258)	(0.0158)	(0.0191)	(0.0263)	(0.0252)
Cash-Forward Spread	0.0119	0.00983	0.0108	0.00905	-0.0484	-0.0381	-0.0427	-0.0485
	(0.00806)	(0.00816)	(0.00867)	(0.00837)	(0.0290)	(0.0332)	(0.0337)	(0.0325)
Imports	-1.15e-06**	-1.18e-06**	-1.32e-06**	-1.25e-06**	1.92e-05***	1.92e-05***	2.10e-05***	2.09e-05***
	(5.73e-07)	(5.62e-07)	(5.50e-07)	(5.44e-07)	(2.86e-06)	(3.39e-06)	(4.03e-06)	(3.58e-06)
S&P 500	0.179***	0.163***	0.132**	0.144**	0.000980	-0.00436	0.0130	0.0207
	(0.0636)	(0.0589)	(0.0556)	(0.0556)	(0.0450)	(0.0523)	(0.0521)	(0.0487)
CBOE VIX	0.0102	0.00975	0.00501	0.00894	-0.0110	-0.0152*	-0.0199***	-0.0138*
	(0.00793)	(0.00821)	(0.00651)	(0.00778)	(0.00648)	(0.00754)	(0.00631)	(0.00769)
Constant	0.204**	0.220**	0.248**	0.243**	-0.00544	0.00600	-0.0828	-0.0634
	(0.100)	(0.0974)	(0.0974)	(0.0958)	(0.0309)	(0.0489)	(0.0494)	(0.0596)
Observations	119	119	119	119	39	39	39	39
Adj. R^2	0.531	0.528	0.520	0.529	0.866	0.845	0.840	0.849
Root MSE	0.160	0.160	0.162	0.160	0.162	0.174	0.177	0.172

Notes: This table illustrates the monthly and quarterly OLS regression results for the SPIMSI. The research period runs from January (February due to first differences) 2006 to December 2015. This leads to 119 observations for the monthly and 39 for the quarterly data. Normality of the residuals cannot be rejected at the 5 percent level for all models using the skewness-kurtosis and Shapiro-Wilk tests. The augmented Dickey-Fuller test suggests stationarity for all residuals at the 1 percent level. For all models, I use robust standard errors (Huber/White/sandwich estimator) to control for heteroscedasticity. The correlogram with 95 percent confidence bands suggests some autocorrelation for higher lags (> 16) in the monthly time-series. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Robust standard errors (Huber/White/sandwich estimator) in parentheses.

The models are defined as:

(1): $\Delta CI_t = \alpha + \beta_1 \Delta MR_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(2): $\Delta CI_t = \alpha + \beta_1 \Delta CBA_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(3): $\Delta CI_t = \alpha + \beta_1 \Delta M2_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(4): $\Delta CI_t = \alpha + \beta_{1a} \Delta CBA_t + \beta_{1b} \Delta M2_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(5): $\Delta CI_t = \alpha + \beta_1 \Delta MR_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 \Delta CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(6): $\Delta CI_t = \alpha + \beta_1 \Delta CBA_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 \Delta CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(7): $\Delta CI_t = \alpha + \beta_1 \Delta M2_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 \Delta CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(8): $\Delta CI_t = \alpha + \beta_{1a} \Delta CBA_t + \beta_{1b} \Delta M2_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 \Delta CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$

With α as intercept, CI as commodity index changes, MR as multiplier ratio, CBA as the sum of central bank assets, M2 as the sum of M2 market liquidity, RIR as real interest rate, FX as global base metal trade-weighted USD index, CFS as cash-forward spread, IBM as imports of ores of and unwrought base metals in USD, SP500 as S&P 500 composite index, VIX as S&P 500 volatility index, and ε as error term.

The findings indicate that the interest rate index itself might not be the determining factor for industrial metal prices. Instead, the ability of an economy to multiply central bank induced liquidity is more important. Likewise, the global trade in base metals, proxied by the imports of ores and unwrought base metals, significantly complements the model and increases its explanation power. Global imports, the trade-weighted USD index, and the multiplier ratio provide an adjusted R^2 of 85 percent in the quarterly series and well above 46 percent in the monthly series.[51]

3.4.2 GOLD SPOT INDEX

Unlike industrial metals, gold is often used as a safe haven commodity which experiences high demand during times of uncertainty. Thus, one might expect that the effects of monetary policy transmitted via the transmission channels presented in Section 3.2.2 might differ for gold compared to industrial metals. While I expect that the inventory channel and the liquidity premium channel play a minor role for the transmission of monetary policy effects to the price of gold, the signalling channel and the portfolio rebalancing channel are important vehicles for the transmission of monetary policy effects. However, it is expected that these effects are different for gold compared to industrial metals, as investors and other market participants shift to gold from other assets if they feel uncertain about future economic growth. Whereas industrial metal prices are expected to act as an early indicator for economic growth, i.e. they experience a positive correlation with economic growth, the relationship between the price of gold and economic growth is expected to be inverse. While Glick and Leduc (2012) argue that the announcement of large-scale asset purchase programmes implies lower expected future economic growth, which leads to less future demand and therefore lower commodity prices, I argue that such announcements have the opposite effect for gold, as investors shift to safe haven assets during times of uncertainty, which increases the demand for gold and thus the price. Likewise, the effects stemming from the portfolio rebalancing channel might differ for gold compared to industrial metal prices due to the safe haven aspect that accompanies gold. That is, while the funds might be used by investors to invest in commodities such as copper and corn to profit from future price gains that are the result of market intervention by the central banks, gold prices might decline if investors expect that the market interventions are effective, which eventually leads to less uncertainty and thus lower demand for gold. Therefore, the effects from the portfolio

[51] In addition to OLS regression, I test for the impact of the global multiplier ratio on the volatility of industrial metals index changes. While the GARCH (1,1) suggests significant impact of the global multiplier ratio, the ARCH-LM test results indicate no ARCH effects in the mean model for the quarterly time-series. For the monthly time-series, ARCH effects can be found. I report the GARCH (1,1) model results in Appendix A3.2.

rebalancing channel may have the opposite effect on the price of gold compared to the price of industrial metals.

Table 3.3: OLS Regression Results – Gold Spot Index

	Gold Spot Index							
	Monthly				Quarterly			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Multiplier Ratio	0.102				0.564			
	(0.329)				(0.501)			
CBA		6.58e-06		3.09e-06		1.40e-07		-1.22e-05
		(1.47e-05)		(1.57e-05)		(1.86e-05)		(2.13e-05)
M2			6.66e-06	6.04e-06			1.81e-05	2.14e-05
			(8.42e-06)	(9.17e-06)			(1.62e-05)	(1.83e-05)
Real Interest Rate	-0.0699	-0.0747	-0.0848	-0.0856	-0.146*	-0.136	-0.170**	-0.172**
	(0.0669)	(0.0641)	(0.0657)	(0.0649)	(0.0816)	(0.0817)	(0.0745)	(0.0788)
Trade-Weighted USD	-0.128***	-0.126***	-0.108***	-0.108***	-0.0991**	-0.102**	-0.0550	-0.0521
	(0.0301)	(0.0293)	(0.0391)	(0.0395)	(0.0431)	(0.0412)	(0.0658)	(0.0694)
Cash-Forward Spread	-0.00707	-0.00676	-0.00734	-0.00731	-0.0340	-0.0411	-0.0390	-0.0352
	(0.00857)	(0.00852)	(0.00861)	(0.00868)	(0.0356)	(0.0364)	(0.0338)	(0.0354)
Imports	1.00e-06	1.04e-06	1.10e-06	1.11e-06	4.69e-06**	4.59e-06**	4.93e-06**	5.02e-06**
	(1.00e-06)	(9.92e-07)	(9.68e-07)	(9.72e-07)	(1.77e-06)	(1.81e-06)	(1.85e-06)	(1.95e-06)
S&P 500	-0.130	-0.134*	-0.111	-0.113	-0.221*	-0.221*	-0.152	-0.146
	(0.0800)	(0.0791)	(0.0820)	(0.0832)	(0.112)	(0.116)	(0.135)	(0.139)
CBOE VIX	0.0121	0.00982	0.0116	0.0109	0.00536	-0.00157	0.00105	0.00477
	(0.0109)	(0.0109)	(0.00986)	(0.0109)	(0.0152)	(0.0151)	(0.0129)	(0.0153)
Constant	0.0200	0.0137	0.00227	0.00106	0.134**	0.112	-0.0157	-0.00615
	(0.0332)	(0.0358)	(0.0375)	(0.0383)	(0.0568)	(0.0782)	(0.121)	(0.122)
Observations	119	119	119	119	39	39	39	39
Adj. R^2	0.284	0.285	0.288	0.282	0.387	0.370	0.395	0.379
Root MSE	0.228	0.228	0.228	0.228	0.351	0.356	0.348	0.353

Notes: This table illustrates the monthly and quarterly OLS regression results for the SPGSI. The research period runs from January (February due to first differences) 2006 to December 2015. This leads to 119 observations for the monthly and 39 for the quarterly data. Normality of the residuals is rejected at the 5 percent level for model 1 using the skewness-kurtosis and Shapiro-Wilk tests. The augmented Dickey-Fuller test suggests stationarity for all residuals at the 1 percent level. For all models, I use robust standard errors (Huber/White/sandwich estimator) to control for heteroscedasticity. The correlogram with 95 percent confidence bands suggests some autocorrelation and partial autocorrelation for higher lags. Yet, the Box-Pierce' Q statistic tests are non-significant at the 5 percent level. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Robust standard errors (Huber/White/sandwich estimator) in parentheses.

The models are defined as:

(1): $\Delta CI_t = \alpha + \beta_1 \Delta MR_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(2): $\Delta CI_t = \alpha + \beta_1 \Delta CBA_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(3): $\Delta CI_t = \alpha + \beta_1 \Delta M2_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(4): $\Delta CI_t = \alpha + \beta_{1a} \Delta CBA_t + \beta_{1b} \Delta M2_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(5): $\Delta CI_t = \alpha + \beta_1 \Delta MR_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 \Delta CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(6): $\Delta CI_t = \alpha + \beta_1 \Delta CBA_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 \Delta CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(7): $\Delta CI_t = \alpha + \beta_1 \Delta M2_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 \Delta CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$;
(8): $\Delta CI_t = \alpha + \beta_{1a} \Delta CBA_t + \beta_{1b} \Delta M2_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 \Delta CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$

With α as intercept, CI as commodity index changes, MR as multiplier ratio, CBA as the sum of central bank assets, M2 as the sum of M2 market liquidity, RIR as real interest rate, FX as global base metal trade-weighted USD index, CFS as cash-forward spread, IBM as imports of ores of and unwrought base metals in USD, SP500 as S&P 500 composite index, VIX as S&P 500 volatility index, and ε as error term.

As a result, one may expect an opposite effect of changes in the global multiplier ratio on changes in the gold price index. However, the results reported in Table 3.3 do not show evidence of a statistically significant relationship between the multiplier ratio and the gold price. In contrast to industrial metals, the explanatory power of the global real interest rate index on changes in the gold price is negative and significant at the 5 percent level when quarterly data are used. These findings complement prior research (Frankel, 2006) and show that the gold price is influenced by the global real interest rate. Contrary to the evaluation of industrial metals, global imports are only associated with the gold price in the quarterly time-series but do not provide any significant impact at the monthly frequency. Overall, the results suggest that the real interest rate appears to be more important for the estimation of the gold price, whereas the global multiplier ratio provides better explanation power for industrial metals prices.

3.4.3 ENDOGENEITY

This section takes a closer look at the potential endogeneity bias between monetary policy and industrial commodity prices. To control for endogeneity in the regression model, appropriate instrumental variables for the conventional (real interest rate index) and unconventional (global multiplier ratio) monetary policy must be identified. Such instrumental variables must affect the dependent variable only through the potentially endogenous variables of interest, i.e. without being correlated with the error term. Applied to this study's framework, one must find instruments that impact the industrial metal price changes via the individual monetary policy measures without directly influencing the price development. This is challenging, as the almost immediate absorption of latest information on the financial markets complicates the unambiguous distinction between cause and effect. Therefore, I compare the effectiveness of several instrumental variables to mitigate a potential variable selection bias. The first instrumental variable for the global multiplier ratio is the consumer price index (CPI). Central banks, and thus monetary policy, are primarily concerned with consumer prices (e.g. ECB, 2017). Industrial metal prices, on the other side, are expected to contribute little to consumer price changes. However, as the CPI is a key decision criterion for central banks' market interventions, i.e. it can influence central bankers to adjust their unconventional monetary policy measures to achieve their targeted inflation rate, it has a direct impact on both the global multiplier ratio and the real interest rate index[52]. The US, G7, and world CPI are obtained for this analysis. Second, the St. Louis Fed Financial Stress Index (STLFSI) provides a compact risk measure which includes, among other financial indicators, several interest rate series and yield spread data to identify financial distress in the markets. In addition, the Chicago Fed National Financial Conditions Risk Index (NFCIRISK), a measure that helps to focus on financial conditions in money, debt,

[52] CPI year-on-year changes are used to calculate the real interest rate and central banks use CPI information to adjust the nominal interest rate. Moreover, as the effects of unconventional monetary policy and inflation are expected to be sticky, I believe that inflation, measured by the CPI, acts as a good instrumental variable for monetary policy.

and equity markets, and its sub-indices for credit (NFCICREDIT), risk (NFCIRISK), and leverage (NFCILEVERAGE) are added.

Table 3.4: IV Regression – Industrial Metals

	Consumer Price Index (CPI)			*Financial Conditions*		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Monthly	MR	RIR	MR+RIR	MR	RIR	MR+RIR
Multiplier Ratio	2.706*	0.573**	2.603	0.746*	0.618*	0.862
	(1.446)	(0.242)	(1.604)	(0.448)	(0.328)	(0.557)
Real Interest Rate	-0.0617	-0.158	-0.0812	-0.0722	0.313	0.334
	(0.0756)	(0.103)	(0.117)	(0.0602)	(0.305)	(0.307)
Trade-Weighted USD	-0.0820***	-0.0927***	-0.0806***	-0.102***	-0.152***	-0.152***
	(0.0218)	(0.0207)	(0.0224)	(0.0169)	(0.0437)	(0.0441)
Cash-Forward Spread	0.00845	0.0133	0.00892	0.0116	0.00555	0.00485
	(0.00889)	(0.00806)	(0.00940)	(0.00781)	(0.00984)	(0.00989)
Imports	-8.83e-07	-1.21e-06**	-9.09e-07	-1.13e-06**	-8.79e-07	-8.35e-07
	(7.47e-07)	(5.36e-07)	(7.54e-07)	(5.51e-07)	(7.74e-07)	(7.60e-07)
S&P 500	0.247***	0.175***	0.243***	0.184***	0.199**	0.208**
	(0.0753)	(0.0582)	(0.0816)	(0.0641)	(0.0781)	(0.0833)
CBOE VIX	0.0289**	0.00878	0.0277*	0.0116	0.0165	0.0189
	(0.0142)	(0.00702)	(0.0164)	(0.00851)	(0.0105)	(0.0119)
Constant	0.182	0.214**	0.185	0.202**	0.159	0.154
	(0.125)	(0.0946)	(0.125)	(0.0965)	(0.133)	(0.131)
Observations	119	119	119	119	119	119
R^2	0.239	0.550	0.268	0.557	0.371	0.347
Durbin Score	4.68**	1.21	4.73*	0.25	3.20*	3.72
Wu-Hausman	4.50**	1.13	2.25	0.23	3.04*	1.76
First-Stage statistics						
Partial R^2	0.05	0.33	0.04/0.28	0.32	0.06	0.31/0.06
Robust F-Value	1.57	23.13***	-	6.24***	1.19	-
Over-Identification tests						
Sargan Score	0.32	3.45	0.00	7.46*	3.18	2.71
Basmann	0.30	3.26	0.00	7.23*	2.97	2.54
Panel B: Quarterly	(7)	(8)	(9)	(10)	(11)	(12)
Multiplier Ratio	-0.684	0.717***	-1.947	0.644	0.744***	0.617
	(2.467)	(0.261)	(3.645)	(0.682)	(0.283)	(0.686)
Real Interest Rate	0.0712	0.0979	0.204	0.0505	0.0261	0.0250
	(0.0661)	(0.102)	(0.265)	(0.0578)	(0.0960)	(0.0974)
Trade-Weighted USD	-0.0199	-0.0224	-0.0348	-0.0173	-0.0146	-0.0145
	(0.0199)	(0.0189)	(0.0397)	(0.0143)	(0.0152)	(0.0156)
Cash-Forward Spread	-0.0268	-0.0506**	-0.0135	-0.0470	-0.0473*	-0.0452
	(0.0533)	(0.0258)	(0.0709)	(0.0290)	(0.0265)	(0.0305)
Imports	2.06e-05***	1.96e-05***	2.27e-05***	1.93e-05***	1.90e-05***	1.91e-05***
	(3.36e-06)	(2.74e-06)	(5.60e-06)	(2.80e-06)	(2.73e-06)	(2.95e-06)
S&P 500	-0.00352	-0.00651	-0.0249	0.000692	0.00451	0.00458
	(0.0597)	(0.0438)	(0.109)	(0.0409)	(0.0416)	(0.0426)
CBOE VIX	-0.0277	-0.0115*	-0.0433	-0.0121	-0.0108*	-0.0122
	(0.0297)	(0.00587)	(0.0440)	(0.00918)	(0.00586)	(0.00884)
Constant	-0.0646	-0.00342	-0.111	-0.00924	-0.00639	-0.0119
	(0.127)	(0.0282)	(0.178)	(0.0346)	(0.0279)	(0.0349)
Observations	39	39	39	39	39	39
R^2	0.803	0.888	0.563	0.890	0.890	0.889
Durbin Score	0.70	0.36	2.13	0.02	0.08	0.11
Wu-Hausman	0.55	0.28	0.84	0.02	0.06	0.04
First-Stage statistics						
Partial R^2	0.02	0.28	0.02/0.17	0.13	0.27	0.13/0.27
Robust F-Value	0.23	8.17***	-	1.35	5.36***	-
Over-Identification tests						
Sargan Score	0.87	1.87	0.04	2.18	2.12	2.07
Basmann	0.66	1.46	0.03	1.66	1.61	1.62

Notes: This table illustrates the monthly and quarterly IV regression results for the SPIMSI. The research period runs from January (February due to first differences) 2006 to December 2015. This leads to 119 observations for the monthly and 39 for the quarterly data. With MR as global multiplier ratio and RIR as real interest rate index. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Robust standard errors (Huber/White/sandwich estimator) in parentheses. With 5 percent or lower as most desirable. All variables are at time t.

All measures are expected to directly impact the lending and thus the global multiplier ratio via M2 as well as the real interest rate index but do not directly affect industrial commodity prices. The instrumental variable regression for both the CPI and the risk measures in Table 3.4 suggest no significant endogeneity present in the models. The Durbin score and the Wu-Hausman test (H_0 = variables are exogenous) are non-significant at the 5 percent significance level in most tested scenarios. Only for the multiplier ratio and CPI, I obtain coefficients that are significant at the 5 percent level, which indicates that the variables are not exogenous. The first-stage regression statistics report partial R^2 of up to 33 percent for the risk measures and thus provide a good instrumental variable analysis. In addition to CPI and risk, I test other instrumental variables. Yet, none of these variables provide a better fit than CPI or risk.

3.4.4 ROBUSTNESS EXERCISE

Structural Changes

During the research period, which spans from January 2006 to December 2015, the world economy experienced two major crises. The US mortgage crisis, which began emerging in 2007, was heavily fuelled by the collapse of Lehman Brothers in September 2008, and eventually led to the GFC. The impact of this crisis spilled over to the European market and led to the second major crisis during the research period known as the European debt crisis, which started in 2009 and is still not fully resolved at the end of the research period in 2015.

To test for potential breaks, I begin with the addition of dummy variables to the main regression model and extend the base model by six dummy variables that capture the US mortgage and subsequent GFC (US1: January 2007 to December 2011, US2: January 2007 to December 2009, and US3: January 2008 to December 2009) and the European debt crisis (EU1: January 2009 to December 2015, EU2: January 2009 to December 2013, and EU3: January 2010 to December 2012). The results in Table 3.5 suggest that the GFC in 2008-2009 significantly affects the industrial metal index at the 1 percent level. Moreover, the significance of the monthly global multiplier ratio coefficient becomes non-significant after adding the dummy variables. In contrast, gold prices are stronger affected by the European debt crisis.[53] It must be noted that the overlapping dummy variables may cause

[53] In addition, I use the CBOE VIX index to define crises thresholds (cf. Fatum and Yamamoto, 2016). I test the significance of a dummy variable that indicates the 90th percentile and the 95th percentile of VIX values

multicollinearity. Much like Table 2.4, where I test for multicollinearity among lagged and lead variables, it is necessary to also test for multicollinearity here to ensure the accuracy of the estimated coefficients reported in Table 3.5.

Table 3.5: OLS Regression – Extended by Dummy Variables

	Industrial Metals		*Gold*	
	Monthly	Quarterly	Monthly	Quarterly
Multiplier Ratio	0.371	1.088***	0.160	1.050
	(0.271)	(0.377)	(0.395)	(0.732)
Real Interest Rate	-0.0813	0.0428	-0.0338	-0.0602
	(0.0661)	(0.0483)	(0.0626)	(0.109)
Trade-Weighted USD	-0.116***	-0.0302	-0.133***	-0.0951
	(0.0193)	(0.0232)	(0.0314)	(0.0578)
Cash-Forward Spread	0.0266**	-0.0613***	-0.0219*	0.00435
	(0.0102)	(0.0204)	(0.0125)	(0.0513)
Imports	-1.05e-06	1.63e-05***	9.14e-07	3.46e-06
	(6.69e-07)	(3.13e-06)	(9.53e-07)	(2.65e-06)
S&P 500	0.156**	0.123*	-0.0820	-0.116
	(0.0653)	(0.0700)	(0.0947)	(0.169)
CBOE VIX	0.00921	6.51e-05	0.0177	0.0128
	(0.00784)	(0.00804)	(0.0118)	(0.0166)
US1	0.0175	-0.0371	0.130	0.359
	(0.0415)	(0.113)	(0.0916)	(0.214)
US2	-0.159*	-0.200	-0.0962	-0.0384
	(0.0927)	(0.159)	(0.120)	(0.310)
US3	0.166**	0.426***	0.104	0.134
	(0.0694)	(0.102)	(0.0703)	(0.277)
EU1	0.0619	-0.0538	0.207**	0.298
	(0.0680)	(0.100)	(0.0818)	(0.220)
EU2	-0.0156	-0.158*	-0.171**	-0.385
	(0.0480)	(0.0909)	(0.0845)	(0.292)
EU3	-0.00253	0.125	0.0521	0.278
	(0.0467)	(0.108)	(0.103)	(0.342)
Constant	0.171	0.0737	-0.150*	-0.163
	(0.141)	(0.0760)	(0.0768)	(0.158)
Observations	119	39	119	39
Adjusted R^2	0.552	0.885	0.319	0.444

Notes: This table illustrates the monthly and quarterly OLS regression results for the SPIMSI. The research period runs from January (February due to first differences) 2006 to December 2015. This leads to 119 observations for the monthly and 39 for the quarterly data. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. Robust standard errors (Huber/White/sandwich estimator) in parentheses.

The models are defined as:

Industrial Metals – Monthly: $\Delta CI_t = \alpha + \beta_1\Delta MR_t + \beta_2\Delta RIR_t + \beta_3\Delta FX_t + \beta_4 CFS_t + \beta_5 IBM_t + \beta_6\Delta SP500_t + \beta_7\Delta VIXt + \beta_8 US1_t + \beta_9 US2_t + \beta_{10} US3_t + \beta_{11} EU1_t + \beta_{12} EU2_t + \beta_{13} EU4_t + \varepsilon_t$

Industrial Metals – Quarterly: $\Delta CI_t = \alpha + \beta_1\Delta MR_t + \beta_2\Delta RIR_t + \beta_3\Delta FX_t + \beta_4\Delta CFS_t + \beta_5\Delta IBM_t + \beta_6\Delta SP500_t + \beta_7\Delta VIXt + \beta_8 US1_t + \beta_9 US2_t + \beta_{10} US3_t + \beta_{11} EU1_t + \beta_{12} EU2_t + \beta_{13} EU4_t + \varepsilon_t$

Gold – Monthly: $\Delta CI_t = \alpha + \beta_1\Delta MR_t + \beta_2\Delta RIR_t + \beta_3\Delta FX_t + \beta_4 CFS_t + \beta_5\Delta IBM_t + \beta_6\Delta SP500_t + \beta_7\Delta VIXt + \beta_8 US1_t + \beta_9 US2_t + \beta_{10} US3_t + \beta_{11} EU1_t + \beta_{12} EU2_t + \beta_{13} EU4_t + \varepsilon_t$

Gold – Quarterly: $\Delta CI_t = \alpha + \beta_1\Delta MR_t + \beta_2\Delta RIR_t + \beta_3\Delta FX_t + \beta_4\Delta CFS_t + \beta_5\Delta IBM_t + \beta_6\Delta SP500_t + \beta_7\Delta VIXt + \beta_8 US1_t + \beta_9 US2_t + \beta_{10} US3_t + \beta_{11} EU1_t + \beta_{12} EU2_t + \beta_{13} EU4_t + \varepsilon_t$

With α as intercept, CI as commodity index changes (industrial metals or gold), MR as multiplier ratio, RIR as real interest rate, FX as global base metal trade-weighted USD index, CFS as cash-forward spread, IBM as imports of ores of and unwrought base metals, SP500 as S&P 500 composite index, VIX as S&P 500 volatility index, US1 as dummy variable indicating the period between the years 2007 and 2011, US2 as dummy variable indicating the period between the years 2007 and 2009, US3 as dummy variable indicating the period between the years 2008 and 2009, EU1 as dummy variable for the period between 2009 and 2015, EU2 as dummy variable for the period between 2009 and 2013, EU3 as dummy variable for the period between 2010 and 2012, and ε as error term. All variables are at time t.

Thus, I first run the regression with non-overlapping dummy variables. Compared to the findings reported in Table 3.5, the results remain comparable, i.e. the significance of the

during the research period. As both percentile ranges simply cover the period between 2008 and 2009, this analysis does not provide additional value to the existing dummy variables and is thus not reported.

estimated coefficients for the variables of interest, the global multiplier ratio and global real interest rate, are comparable to those presented in Table 3.5. Second, I use the variance inflation factor (vif) to test for multicollinearity in the model. All vif values are well below 10[54]. Moreover, as the dummy variables are primarily used as controls and are not variables of interest, potential collinearity among them does not affect the estimates of the variables of interest (Allison, 2012). According to Allison (2012), multicollinearity only increases the standard errors for the collinear variables and not the others. As long as these variables are not collinear with the variables of interest, their function as control variables is not weakened by potential multicollinearity among them (Allison, 2012).

While adding dummy variables to account for crisis periods can partially explain differences in the explanatory power of regressors throughout the research period, a statistical approach to identify breaks within the sample may be more appropriate. Thus, the second structural break evaluation relies on the Bai and Perron (2003a, 2003b) test and uses a least squares regression with breaks.

Table 3.6: OLS with Bai-Perron Structural Breaks

	Industrial Metals				***Gold***			
Panel A: Monthly	2006M02 - 2008M01	2008M02 - 2009M08	2009M09 - 2011M02	2011M03 - 2015M12	2006M02 - 2008M12	2009M01 - 2011M09	2011M10 - 2013M06	2013M07 - 2015M12
Multiplier Ratio	0.0648	1.0185***	0.5741	-0.6835	-0.5534	1.4614**	-0.4023	1.0032
	(0.2524)	(0.2883)	(0.6967)	(0.4209)	(0.3955)	(0.6195)	(1.2321)	(1.4083)
Real Interest Rate	0.3190**	-0.5310***	-0.0977	0.0544	0.0630	-0.1615***	0.2709	0.4000***
	(0.1236)	(0.0668)	(0.0883)	(0.0814)	(0.0971)	(0.0842)	(0.2345)	(0.1466)
Trade-Weighted USD	-0.4185***	-0.0466*	-0.0642	-0.0984***	-0.1717***	-0.0761**	-0.0761**	-0.0381
	(0.0660)	(0.0244)	(0.0553)	(0.0179)	(0.0500)	(0.0372)	(0.0372)	(0.0280)
Cash-Forward Spread	0.0249***	-0.0861***	-0.0124	0.0188	-0.0294**	-0.0029	-0.0029	-0.0618**
	(0.0075)	(0.0253)	(0.0226)	(0.0139)	(0.0140)	(0.0164)	(0.0164)	(0.0242)
Imports	-2.77e-06**	-9.70e-07	3.32e-06*	-2.17e-06**	4.41e-08	2.85e-06***	2.85e-06***	-2.3e-06***
	(1.17e-06)	(1.49e-06)	(1.89e-06)	(8.45e-07)	(1.95e-06)	(1.03e-06)	(1.03e-06)	(7.25e-07)
S&P 500	-0.1784*	0.1070	0.2088	0.0853*	-0.2498***	-0.0186	-0.0186	-0.2869**
	(0.0993)	(0.0897)	(0.1354)	(0.0512)	(0.0537)	(0.1404)	(0.1404)	(0.1405)
CBOE VIX	-0.0237*	0.0117	-0.0148**	0.0014	-0.0045	0.0358**	0.0358**	-0.0406*
	(0.0138)	(0.0105)	(0.0072)	(0.0059)	(0.0072)	(0.0138)	(0.0138)	(0.0224)
Constant	0.3142*	0.1860	-0.5716*	0.3947**	-0.1536**	0.1288***	0.1288***	-0.0222
	(0.1865)	(0.2569)	(0.3422)	(0.1587)	(0.0688)	(0.0419)	(0.0419)	(0.0343)
Observations	24	19	18	58	35	33	21	30
Adj. R^2	0.776				0.550			

Notes: This table illustrates the monthly OLS regression Bai-Perron Structural Breaks and Newey-West Standard Errors results for the price of industrial metals and gold. The research period runs from January (February due to first differences) 2006 to December 2015. This leads to 119 observations for the monthly data. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Newey-West standard errors in parentheses.

Due to the limited number of observations, I limit the potential breaks to three to ensure sufficient observations for each of the four sub-samples and further limit this exercise to monthly data. The results of the OLS model with Bai-Perron structural breaks reported in Table 3.6 show that the relationship between changes in commodity prices, the global

54 Chatterjee and Hadi (2012) argue that a vif value greater than 10 indicates collinearity issues.

multiplier ratio, and real interest rates is far from being constant. The results suggest that the positive effect of the multiplier ratio on monthly changes in the price of industrial metals is only significant between February 2008 and August 2009 in the monthly sample. This also applies to changes in the price of gold. Moreover, the results suggest a negative impact of real interest rates on monthly changes in the price of industrial metals that is significant between February 2006 and August 2009. This indicates that real interest rates had a significant positive effect on industrial metal price changes prior to the GFC, which indicates that the effect stemming from real interest rates, most notably the inventory channel[55], has not been in line with theory during this time. Instead, other market forces appear to have had a stronger effect during this period. However, since September 2009, the significance of both variables diminishes.

These findings allow me to draw three conclusions. First, the impact of both the global multiplier ratio and real interest rates on industrial metal prices changes over time. Thus, linear models might not fully explain the true relationship between commodity prices and real interest rates. Second, while early QE measures may have lifted industrial metal prices, latest measures, i.e. after 2011, seem to have a non-significant impact on industrial metal prices. Third, while the impact of global real interest rates is non-significant for the overall research period, sub-sample results suggest that the impact can be significant during shorter periods. The findings indicate that the price of gold is significantly and positively affected by the multiplier ratio between January 2009 and the September 2011. Moreover, like industrial metals, the price of gold is both positively and negatively affected by the global real interest rate during different sub-periods. Industrial metals and gold prices are similarly, i.e. positively, affected by the multiplier ratio. The assumption that gold, as a safe haven asset that experiences higher demand during times of uncertainty, has an inverse relationship with the multiplier ratio and real interest rates compared to industrial metals cannot be confirmed.

Individual Industrial Metals

The findings for the SPIMSI indicate that the global multiplier ratio has significant positive estimation power at the 5 percent significance level on the industrial metals index. Yet, it remains unclear whether this effect applies to all industrial metals equally. In this section, I split the analysis by each of the five individual industrial metals. Compared to the evaluation

[55] Low real interest rates lead to an increase in inventory demand and thus raise in prices.

of the industrial metals index, commodity-specific indicators are used for imports and the spot-futures spread. The results in Table 3.7 show a significant positive impact of the global multiplier ratio on the price of copper at the 5 percent significance level in both the monthly and quarterly time-series.

Table 3.7: OLS Regression – Individual Industrial Metals

Panel A: Monthly	***Aluminium Spot***	***Copper Spot***	***Lead Spot***	***Nickel Spot***	***Zinc Spot***
Multiplier Ratio	1.807	13.55**	4.066	41.36*	1.643
	(1.438)	(5.374)	(4.074)	(24.79)	(2.606)
Real Interest Rate	-0.811*	-0.871	0.119	-9.147	0.201
	(0.416)	(1.382)	(0.587)	(7.886)	(0.599)
Trade-Weighted USD	-0.489***	-2.228***	-0.622***	-4.549**	-0.804***
	(0.103)	(0.395)	(0.167)	(1.837)	(0.149)
Cash-Forward Spread	0.0121***	0.0205**	0.0156**	0.0176***	0.0283**
	(0.00409)	(0.00812)	(0.00713)	(0.00262)	(0.0140)
Imports	-1.14e-05	-1.23e-05	-0.000105*	-0.00212***	-0.000223***
	(1.35e-05)	(2.30e-05)	(5.58e-05)	(0.000682)	(6.81e-05)
S&P 500	0.746*	2.960**	1.478**	13.87**	1.973***
	(0.438)	(1.329)	(0.609)	(5.459)	(0.443)
CBOE VIX	0.0586	0.103	0.130	0.579	0.152***
	(0.0532)	(0.152)	(0.0919)	(0.549)	(0.0578)
Constant	0.812	0.949	1.070**	32.88***	3.605***
	(0.625)	(2.037)	(0.480)	(10.39)	(1.087)
Observations	119	119	119	119	119
Adjusted R^2	0.421	0.490	0.261	0.448	0.349
Panel B: Quarterly	***Aluminium Spot***	***Copper Spot***	***Lead Spot***	***Nickel Spot***	***Zinc Spot***
Multiplier Ratio	0.364	19.86**	2.852	-5.967	4.577
	(1.344)	(7.750)	(3.216)	(43.51)	(4.793)
Real Interest Rate	-0.366	0.852	1.158	-12.05	0.725
	(0.310)	(1.358)	(0.689)	(8.723)	(1.007)
Trade-Weighted USD	-0.183*	-1.246***	-0.296	5.415	-0.153
	(0.0904)	(0.338)	(0.182)	(4.149)	(0.234)
Cash-Forward Spread	0.0120	0.0558***	0.0469	0.0195***	0.0117
	(0.0150)	(0.0143)	(0.0285)	(0.00633)	(0.0388)
Imports	0.000268***	0.000482***	0.00107***	0.0109***	0.000938***
	(4.75e-05)	(9.88e-05)	(0.000294)	(0.00362)	(0.000309)
S&P 500	0.115	1.672*	1.094**	-4.576	0.0376
	(0.397)	(0.877)	(0.471)	(6.458)	(0.573)
CBOE VIX	-0.0693**	-0.0115	0.0407	-2.263	-0.0332
	(0.0307)	(0.161)	(0.0868)	(1.379)	(0.0871)
Constant	0.134	-0.193	0.339	-6.824	0.126
	(0.521)	(0.774)	(0.497)	(5.077)	(0.857)
Observations	39	39	39	39	39
Adjusted R^2	0.814	0.810	0.609	0.729	0.435

Notes: This table illustrates the monthly and quarterly OLS regression results for the individual industrial metal spot prices. The research period runs from January (February due to first differences) 2006 to December 2015. This leads to 119 observations for the monthly and 39 for the quarterly data. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Robust standard errors (Huber/White/sandwich estimator) in parentheses.

The model is defined as:

$$\Delta CI_t = \alpha + \beta_1 \Delta MR_t + \beta_2 \Delta RIR_t + \beta_3 \Delta FX_t + \beta_4 CFS_t + \beta_5 \Delta IBM_t + \beta_6 \Delta SP500_t + \beta_7 \Delta VIXt + \varepsilon_t$$

With α as intercept, CI as commodity index changes, MR as multiplier ratio, RIR as real interest rate, FX as global base metal trade-weighted USD index, CFS as cash-forward spread, IBM as imports of ores of and unwrought base metals, SP500 as S&P 500 composite index, VIX as S&P 500 volatility index, and ε as error term. All variables are at time t.

However, the real interest rate index provides mostly non-significant estimation power on the price of the individual commodities. Once I drop the primarily non-significant stock market related controls from the model, the global multiplier ratio is significant for aluminium, copper, lead, and nickel in the quarterly time-series.[56] Overall, the individual commodity results only confirm the findings obtained for the SPIMSI for copper, the most-traded industrial metal on the market.[57] Contrary to the industrial metals index, the cash-forward (spot-futures) spread provides significant positive estimation power at the 1 percent level in the quarterly time-series and extends findings in prior research. Both Frankel and Rose (2010) and Frankel (2014) report a non-significant impact of the spot-futures spread on annual real copper prices. Moreover, Sun et al. (2013) report non-significant estimation power of log returns of the LME aluminium futures-spot spread on the returns of the LME futures and Chinese Shanghai Metals Market spot price of aluminium. I, however, show that the LME spot-futures spread significantly and positively affects aluminium price changes.

Variable Selection Bias

The last section of the robustness exercise deals with the potential variable selection bias underlying the dataset. First, the SPIMSI is swapped by the LMEX, a comparable index provided by the London Metal Exchange that consists of futures data of six non-ferrous metals (SPIMSI plus tin) that is, like the SPIMSI, weighted by the preceding five-year production data. As expected, all results for the OLS regression are comparable and the global multiplier ratio remains significant for both the monthly and quarterly data. Second, individual commodity currencies are added to the dataset to test their estimation power compared to the self-created trade-weighted base metal USD index. The Australian Dollar, Chilean Peso, Norwegian Krone, and Peruvian Sol are floating currencies of countries with major non-ferrous metal operations.[58] The addition of several individual currencies provides little extra value. Compared to the OLS results, the individual currencies indicate a minor advantage based on slightly higher R^2. However, the adjusted R^2 and root-mean-square error (RMSE) suggest superiority of the trade-weighted base metal USD index in the quarterly analysis. The trade-weighted base metal USD index does not only provide better results than the individual currencies, it further offers a pooling of various base metal-related currencies

[56] These results are not included in this study but are available upon request.
[57] In addition to industrial metals and gold, I extend the analysis to crude oil (WTI, NYMEX), natural gas (NYMEX), and wheat (No. 2). The findings suggest a significant positive effect of the global multiplier ratio and a significant negative effect of the real interest rate on crude oil in the reduced-form model, both at the 1 percent significance level. Once I add further controls such as global imports, the significance of the global multiplier ratio diminishes. Moreover, the models suggest little significant estimation power for both focus variables on the price of natural gas and wheat. Results are stored in Table A3.3 in the appendix.
[58] Currencies, in the context of this study, are defined as the currency pair local currency to USD.

and their joint movement throughout time. This equips researchers with a convenient and accurate measure to track movements in base metal currencies.[59]

3.5 CONCLUSION

Changes in nominal refinancing interest rates and the implementation of comprehensive asset purchase programmes are two approaches used by major inflation-targeting central banks to maintain price stability. Since the outbreak of the GFC in 2008, asset purchase programmes have been used by leading central banks. The combination of nominal near-zero interest rates and the purchase of significant quantities of government and corporate debt has equipped market participants with access to plentiful cheap capital. Because of these market interventions, the four largest central banks (PBOC, FED, BoJ, ECB) hold assets of more than 17.8 trillion USD which translates to roughly 70 percent of the World's central bank assets, or almost 24 percent of world GDP (Kuntz, 2016). Consequently, the reduction in the availability of government debt on the secondary market has forced investors to find alternatives for the newly accessible funds.

Despite the considerable share of global financial markets accounted for by central bank assets, little research evaluates the impact of the monetary policy induced distortion of global liquidity on the price of non-ferrous metals and gold. This study closes the gap in the literature and scrutinises the effects of monetary policy and changes in liquidity on exchange-traded base metal and gold prices. It goes beyond prior research and introduces a new measure, the global multiplier ratio, to proxy for global central bank market interventions and unconventional monetary policy measures. This variable indicates whether the freshly induced money by central banks is translated into broad market liquidity (by measuring the relationship with M2) and whether this transmission influences industrial metal and gold prices. The significance of the positive effect of the global multiplier ratio on the price of industrial metals is limited in time and specific to one commodity, i.e. the effect appears to be only significant during the period surrounding the GFC for an index of industrial metals and gold and is found to only significantly influence the price of copper if the industrial

[59] In addition to the presented robustness tests, I further evaluate linear interdependencies of the monthly time-series. Due to few quarterly observations, this analysis is limited to monthly data. The linear interdependency analysis suggests long-run causality from the independent variables to the real interest rate index and from the independent variables to global imports in the monthly data at the 5 percent significance level. The results for short-run causality indicate a significant impact of the lagged global multiplier ratio on all but global imports in the monthly time-series.

metals are evaluated individually. Despite the limited statistical significance of the results, the global multiplier ratio allows investors and policy makers to quickly and efficiently quantify the impact of global central bank market interventions and to consider the associated effects on commodity prices in their models. The findings reported here suggest that the increase in central bank induced liquidity had a limited influence on both industrial metals and gold prices. This is contrary to the initial expectation that industrial metal prices respond to monetary policy measures. That is, if the effects of monetary policy work as intended, one should be able to observe an increase in investment and consumption, which should increase industrial metal prices. However, as the results suggest a non-significant relationship between monetary policy and metal prices, it remains arguable whether the examined monetary measures during the research period sufficiently fulfil their purpose.

The global multiplier ratio is complemented by a newly created global real interest rates index, which is not limited to US interest rates but also includes the interest rates of other major economies. The results provide little evidence that real interest rates influence non-ferrous metal prices. In line with prior research for the US, I do find evidence that real interest rates are associated with the gold price. In addition, I evaluate commodities that have experienced little attention in prior studies and show that the explanatory variables have different estimation power for individual commodities. In fact, the price of copper is the only industrial metal that is influenced by the global multiplier ratio in both the monthly and quarterly sample. However, as copper is also the most traded industrial metal among those evaluated, the findings suggest that most market participants may use this metal to trade and participate in the speculative industrial metal markets (i.e. without the intention to hedge risk linked to physical metals or use the goods). That is, by engaging in copper trading, market participants may try to benefit from future economic growth changes, as prior literature has found significant links between global copper prices and economic activity (e.g. Guo, 2018) and copper consumption and economic growth (Jaunky, 2013).

Overall, this study provides new insights into the interaction of money supply, monetary policy, and global base metal and gold prices. The increasing normalisation and persistence of asset purchases within the central bank toolkit motivates greater attention by researchers. The results presented in this chapter serve as a fresh reminder of the consequences of market interventions by central banks and their impact on areas that experience less attention in an inflation-target environment.

CHAPTER 4 FINANCIALIZATION AND COMMODITY FUTURES RETURNS

4.1 INTRODUCTION

Since the early 2000s, commodities have increasingly been regarded as an asset class in their own right. The expanded supply of futures contracts facilitating trading in commodities is a process known as the financialization of commodity markets (Basak and Pavlova, 2016). Since the onset of financialization, sharp surges and subsequent corrections in commodity prices have fuelled a debate about the effects of commodity market financialization, and particularly financial non-commercial speculation, among policy makers, academics, and the media. While some prominent figures advocate that *"[…] both trend-following speculation and institutional commodity index buying reinforce the upward pressure on prices."* (Soros, 2008:2) and *"Index speculators have driven futures and spot prices higher."* (Masters, 2008:5), agreement about the impact of speculation remains elusive in the academic literature. Rather than financial speculation increasing volatility, some find evidence for a lowering effect (Bohl and Stephan, 2013; Kim, 2015), no impact on price levels (Buyuksahin and Harris, 2011; Fattouh et al., 2012), or no evidence of speculative bubbles for a range of commodities (Brooks et al., 2015). Others argue that spot prices go up with financialization (Basak and Pavlova, 2016), have been particularly driven by speculative shocks between 2004 and 2008 and the subsequent correction of prices (Juvenal and Petrella, 2015), and are not solely driven by their physical supply and demand anymore but also by financial supply and demand due to index investment (Tang and Xiong, 2012).

Motivated by recent regulatory changes in the US and the EU[60] and inconsistent findings in the academic literature on the impact of commodity market financialization, this study examines the effectiveness of variables linked to financialization for explaining the returns of ten commodities comprising softs, copper, three precious metals, crude oil, and natural gas. I separate the evaluation of the effects of commodity financialization on commodity futures returns, particularly at the extremes, into excess net long non-

[60] Recent regulatory changes such as the Dodd-Frank act in the US and the MiFID II directive in the EU aim to stabilise the asset markets and limit speculative trading activity by non-commercial commodity investors. According to article 58 paragraph 2 of MiFID II (Directive 2014/65/EU), traders must report precise holding positions at least daily to avoid trading beyond the set limits (cf. European Parliament, 2014). Article 69 paragraph 1 and 2 grant supervisory powers to EU member states' financial authorities, "*(o) request any person to take steps to reduce the size of the position or exposure;*" and "*(p) limit the ability of any person from entering into a commodity derivative, including by introducing limits on the size of a position any person can hold at all times in accordance with Article 57 of this Directive;*" (European Parliament, 2014: 107).

commercial speculation and trader concentration[61]. I further show that these effects are transmitted via two channels denoted as the financial channel and the signalling channel. This approach assesses the growing participation of commercial and non-commercial traders on US commodity markets since the early-2000s and whether this has influenced prices during boom-and-bust cycles over the last two decades. I find that speculation, on average, has a reinforcing effect on returns. However, when examining the whole distribution of returns using a quantile regression, I find that speculation seems to stabilise returns for a panel of ten commodities, by dampening them at the upper and lower quantiles of the distribution. However, the commodity-specific findings suggest that ESV only has a stronger stabilising, i.e. positive effect on the left tail of the return distribution, i.e. the 5^{th} to 50^{th} quantiles for soybeans and gold. For most other individual commodities, the results rather indicate a reinforcing relationship between ESV and returns, for both the mean and quantile regressions. Moreover, for all commodities, the effect of non-commercial speculation on returns, indicated by the magnitude of the coefficients, is small. Further analysis using Granger causality tests reveals reverse causality[62], i.e. returns Granger-cause non-commercial speculation. This contradicts the common belief that non-commercial speculation drives commodity prices. The stabilising effect observed for the panel of ten commodities, i.e. support at the lower tail and reduction at the upper tail, of speculation on returns is rather the reaction of non-commercial traders to changes in the futures price. When prices fall, non-commercial traders increase their positions, which leads to an increase in non-commercial open interest. Conversely, traders reduce their open interest by taking profits when prices increase. This might be due to traders who calculate expected prices of the commodities and use short-term market fluctuations, i.e. variations from their expected price, to profit. However, another possible explanation for the observed interaction might be grounded in the frequency of the data, i.e. the weekly observations. The observed unidirectional Granger causality from returns to non-commercial speculation might be part of an interaction between returns and speculation, where the Granger causal effects from

[61] In this study, I synonymously use the terms market concentration and trader concentration, as both describe the concentration of market participants, i.e. traders, on commodity futures markets.

[62] In this study, I define causality as causal effects from non-commercial speculation to returns and reverse causality as causality from returns to non-commercial speculation, to easily distinguish between the two forms of potential causality. If causality exists both ways, it is denoted as bidirectional causality. I chose this definition due to the common perception in the media that speculation has influenced the price of commodities.

speculation to returns is not observable with weekly data[63]. In addition to the financial effect, I identify a second transmission channel of speculation, denoted as the signalling effect, which suggests that the information content of the US Commodity Futures Trading Commission (CFTC) Commitment of Traders report significantly affects returns once the information becomes public. These results are robust to a range of commodity-specific and macroeconomic controls. The findings help investors, regulators, and policymakers to better understand the role of commodity financialization in shaping the relationship between non-commercial speculation, trader concentration, and the futures returns of exchange-traded commodities.

The remainder of Chapter 4 is organised as follows. Section 4.2 discusses the transmission from speculation to returns and provides a review of prior research. Subsequently, Section 4.3 introduces the data and methodology, which is followed by the empirical results of the study in Section 4.4 and the conclusion in Section 4.5.

4.2 THEORETICAL BACKGROUND AND LITERATURE

Financialization describes the phenomenon of the increasing importance of the financial sector relative to the real sector of the economy (Palley, 2013) and the increasing significance of financial markets, actors, and institutions for the world economy (Epstein, 2005). The financialization of commodity markets offers market participants an alternative to physical hedging and speculation, as it does not require them to buy, store, and hold goods until consumption or (re)sale. Likewise, market participants who are interested in selling commodities can do so by taking short positions. With the financialization of exchange-traded commodities and the increase in the number of products available, the trading of commodities has become easier. Smaller producers or consumers and traders who are less interested in the production or consumption of the goods can profit from the advantages of a financialized market such as accessibility, competition, open pricing, liquidity, and leverage. Thus, the financialization of commodity markets provides more opportunities for traders to participate in financial hedging and speculation. While producers offer their products on a market and use the short position of futures contracts to mitigate their downside price risk, consumers of those goods usually take the long position to insure themselves against rising

[63] As data at higher frequency is not available, the validation of this assumption is not possible.

prices. Similarly, financial speculators take either short or long positions to gain from future price movements and, in return, provide an obligation to either sell or buy the underlying goods in future.[64] Therefore, both commercial (producers and consumers) and non-commercial (speculators) traders enter into an obligation to either sell or buy a commodity once the futures contract expires. Despite their different intentions, the impact of their involvement in futures markets on the underlying commodity is similar: both affect the (expected) demand and supply (for either consumption or speculation) and thus the price.[65] In addition to lower costs, easier tradability, and leverage, financial hedging and speculation provides another advantage over physical hedging and speculation: measurability. Unlike its physical counterpart, where one may buy goods and store them in private warehouses that are not monitored or even known by any authority, the traceability of financial hedging and speculation is relatively clear.

Particularly since the beginning of the early 2000s, commodity markets received increasing attention from investors and researchers. Growing demand from developing countries, an increasing global population, and the absence of alternative investment opportunities following the dot-com bubble burst attracted index fund investors to commodity markets. In March 2003, the first exchange traded fund (ETF) backed by physical gold launched (Saefong, 2013). Since then, the daily open interest (and trade volume) in major commodity markets such as gold, corn, and crude oil futures on average tripled from 324 thousand (68 thousand) contracts in 1996 to 1.2 million (555 thousand) contracts in 2016. As this development may have fuelled the two most prominent commodity peaks since the turn of the millennium in 2008 and 2011, it has encouraged researchers to scrutinise the link between the volume and structure of the commodity futures market and the time-series characteristics of commodity prices.

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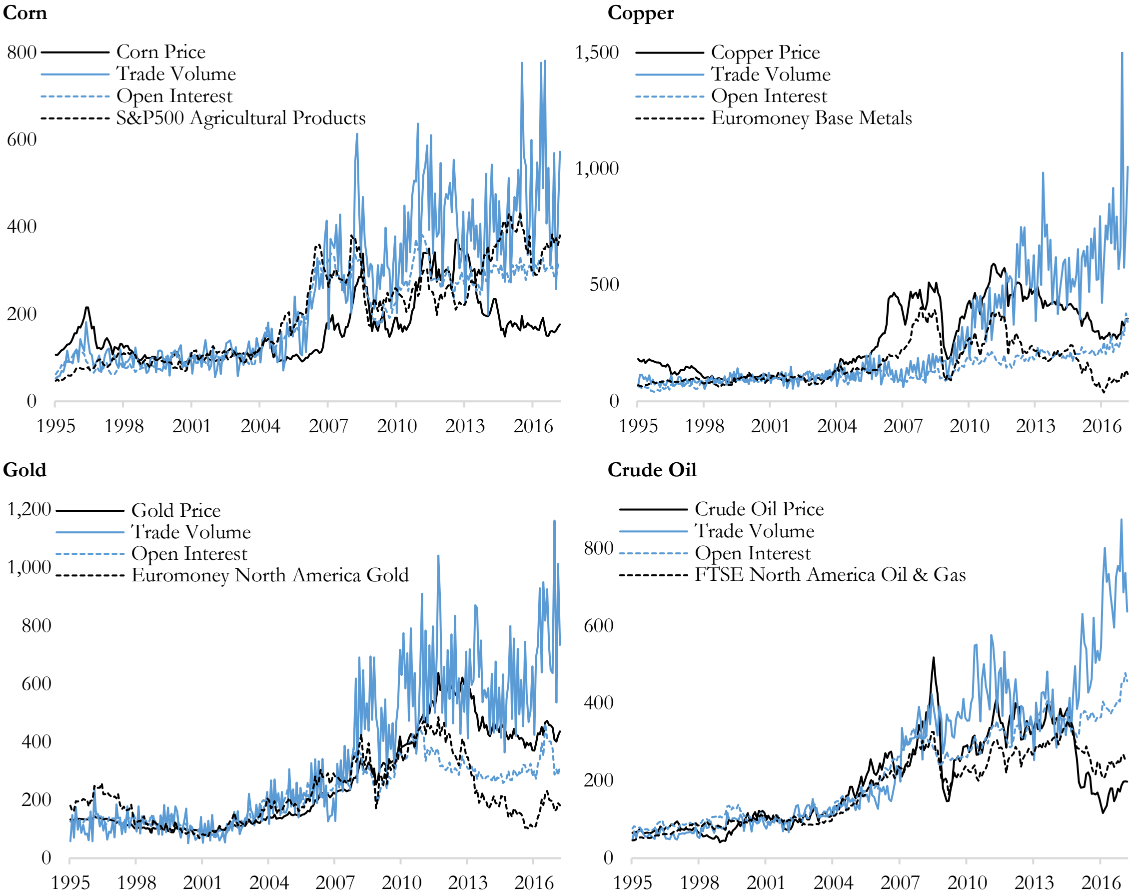
[64] Unlike stocks and bonds, commodities do not pay dividends or accrue value via interest and retained earnings but can be either consumed or used to produce other goods. Thus, commodity investors solely profit from price changes arising due to changes in (expected) supply and demand.

[65] One might imagine a situation where a producer that has sold future produce on the futures market and is not able to fulfil the contract obligation at maturity. Likewise, a consumer that secures expected future demand with a futures contract might not need the full quantity at maturity. As both can sell all or parts of their obligation, it remains unclear whether this initial hedge is, in fact, a speculative trade at a later point in time. Moreover, one might be unclear as to whether a wholesaler is defined as a hedger or speculator. Consequently, the question arises as to whether speculation has a different impact on commodities to hedging and if its impact is measurable.

To identify a link between speculation and returns, prior research often uses direct measures of speculation paired with commodity futures open interest. It concentrates on the conditional mean and neglects the heterogeneity in the impact of non-commercial speculative open interest between quantiles of the commodity return distribution (e.g. Irwin and Sanders, 2010; Etienne et al., 2016).

Figure 4.1: Trading Volume, Open Interest, Commodity Prices, and Equity Indices



Notes: This figure illustrates the monthly development of the price, open interest (in contracts), and trade volume (in contracts) of gold, copper, crude oil (light sweet), and corn continuous futures traded on the New York Mercantile Exchange (NYMEX), Commodities Exchange (COMEX), and the Chicago Board of Trade (CBOT), the S&P 500 Agricultural Products index, the Euromoney North America Base Metals and Gold indices, and the FTSE North America Oil & Gas index from January 1995 to March 2017. All price time-series are nominal and indexed to 2002-2004 = 100.

However, the mean analysis might hide valuable information that is crucial to understand the relationship between the main variables. First, commodity futures returns experience fat tails (Han et al., 2015; Nagayev et al., 2016). Thus, outliers disproportionally affect the mean. Second, the mean models assume that the relationship between commodity prices or returns and speculative open interest is constant. If speculative open interest provides reinforcing (e.g., Haase et al., 2016) or increasing (Basak and Pavlova, 2016) effects, one should be able to observe constant coefficients at the lower and upper quantiles of the return structure.

However, if speculative open interest has a destabilising effect, as shown by Bosch and Pradkhan (2015) for precious metals prior to June 2006, one may observe negative coefficients on the left tail and positive coefficients on the right tail of commodity returns. These effects may even accelerate at the extremes when momentum or predatory trading is present in the market.[66] However, if speculative open interest has a stabilising effect (e.g., Kim, 2015; Brunetti et al., 2016) the coefficient should be positive on the left tail and negative on the right tail of commodity returns. Either way, the mean analysis conceals the real impact of the regressors on different quantiles of the dependent variable. Extreme events in financial markets have led to drastic price fluctuations during the last two decades. Yet, little is known about the effects of non-commercial speculation and its impact on the returns formation, particularly in the extremes.

Moreover, despite the usefulness of linear regression where all observations are captured at the same time, past values of the regressors may hold valuable information to improve the estimation of the dependent variable. While this sort of causality, commonly referred to as Granger causality, may not identify the true causal relationship between variables, it provides predictive causality and improves the estimation of a dependent variable.[67] Evidence on the existence or direction of causality between speculation and commodity prices is mixed. For example, Huchet and Fam (2016) present evidence in support of Granger causality from changes in non-commercial positions to agricultural commodity prices including wheat, sugar, coffee, and corn. Others, however, find evidence to the contrary and argue that non-commercial trader positions do not Granger-cause prices (Brunetti and Buyuksahin, 2009; Stoll and Whaley, 2010; Buyuksahin and Harris, 2011) and index trader positions generally cannot predict agricultural futures returns (Hamilton and Wu, 2015). Instead, price changes drive speculative positions (Alquist and Gervais, 2013; Andreasson et al., 2016). However, most prior studies either rely on raw non-commercial

[66] While Bessembinder et al. (2014) find little significant evidence for predatory strategies present in the crude oil futures market but rather liquidity-supporting effects, research on momentum trading, i.e. trading on existing trends, indicates a tendency of overreaction in asset markets at long horizons (e.g. Hong and Stein, 1999). Building on Moskowitz et al. (2012), I create a dummy that illustrates a 12-week time-series momentum strategy with a 1-week holding period, i.e. if the average return of the last 12 weeks is positive or zero, the dummy is 1 and if the average return of the last 12 weeks is negative, the dummy is set to 0. While the momentum dummy is negative and highly significant, i.e. at the 1 percent level, which suggests strong impact of momentum on the estimation of commodity futures returns, all variables of interest remain significant and with their respective signs as highlighted in the main analysis.

[67] Hereinafter, I use the terms Granger causality and causality synonymously.

positions that neglect the trading of other market participants or use measures that insufficiently account for non-reportable positions (e.g. Working's T-index) which have been found to gain considerable influence in agricultural commodity markets (Meyer, 2017).

To measure the impact of commodity market financialization on prices, returns, and the volatility thereof, most prior research focuses on the evaluation of non-commercial speculation (cf. Haase et al, 2016), i.e. the financial speculation stemming from traders that are purely interested in financial gains and neither the production nor consumption of the underlying.[68] In addition to the increase in trading volume and open interest, the financialization of commodity markets allows more traders to access and participate in financial commodity markets. As a result, the average number of reportable traders, i.e. traders that meet the minimum reporting threshold in open interest set by the CFTC, increased simultaneously. For example, the number of traders engaged in trading crude oil futures almost quadrupled from an average of 184 in 1995 to almost 700 in 2017.[69] To answer the question of who affects the price of commodities and whether the financialization of commodity markets plays a key role, it is not sufficient to focus on whether the effects come from commercial or non-commercial open interest increases throughout the last two decades. Instead, I argue that trader concentration plays a significant role in explaining recent developments in commodity markets. Trades by both commercial and non-commercial traders affect the (expected) demand and supply for commodities. Their actions, on average, like any other market participant such as producers and consumers, affect the equilibrium

[68] Surprisingly, most research focuses on the negative impact, or the existence of such, on commodity prices, but pays significantly less attention to the general effects of financial trading. As highlighted, the effect of trading by hedgers (commercial speculation) and speculators (non-commercial speculation) on the price is similar. Thus, it should be less of a question of whether non-commercial speculation affects prices, but rather if non-commercial speculation disproportionally affects commodity prices, i.e. if there is a stronger effect stemming from non-commercials compared to commercials. By implying that commercial speculation (hedging) is good and non-commercial hedging is bad, one assumes that the intentions underlying the trading of commercial speculators differ to those of non-commercials. Yet, it should be obvious that every trader's goal is the same: To achieve the highest possible price for their sales and the lowest possible price for their purchases. I address this issue by extending the focus from excess non-commercial speculation to net long speculation by commercials and non-commercials by using disaggregated data in Section 4.3.1 and further consider the effect of the overall open interest in commodity futures markets.

[69] For other commodities, the increase is comparable. For example, the number of traders in corn almost doubled from 572 in 1995 to 1,077 in 2017, and copper experienced a trader increase of 409 percent from 102 in 1995 to 417 in 2017. In average for the 10 commodities evaluated in this study, the trader count increased from 209 in 1995 to 532 in 2017, which illustrates a percental increase of 254 percent. During the same time, the ratio of commercial to non-commercial traders (i.e. count of commercial traders / count of non-commercial traders) decreased from 2.1 to 0.5 for crude oil. Thus, while there has been one non-commercial trader for every to two commercial traders in 1995, the sides have switched until 2017, where the market is occupied by two non-commercial traders for each commercial trader.

and thus price of the underlying commodity. Ultimately, the absolute and relative size of the trades matter, too. Yet, the relative size, and thus trader concentration of futures traders, has experienced comparably little attention in prior research[70]. This is surprising, as prior work highlights the significant link between market concentration and prices (Weiss, 1989), which is expected to also exist in futures markets. Whereas the main goal of suppliers is to receive the highest possible price, the demand side wants to pay the lowest possible price (Mankiw and Taylor, 2011). When the number of suppliers on a market is small, the market power of each supplier increases and thus positively influences the market price. Conversely, a higher market concentration on the demand side equips each market participant with (on average) higher market power and thus puts downward pressure on the price. Particularly when relatively large traders change their position, one should be able to see a stronger influence on the extreme returns of commodity futures, i.e. the outer quantiles.

According to a report by the CFTC (2008a), there is no significant relationship between large short-term futures trader concentration and silver prices. However, their study focuses on the market share of the four largest traders but disregards the overall market structure. Combined with the relatively short research period from 2005 to 2007 that purely focuses on the period leading up to the global financial crisis (GFC) where commodity prices have generally experienced an upward trend and the focus on silver, the study might not fully account for the real impact of trader concentration.[71] Recent regulatory changes such as the MiFID II directive in the EU, however, indicate that policymakers are aware of the potentially negative impact of trader concentration and thus limit the latitude of market participants.[72] While ap Gwilym and Ebrahim (2013) argue that position limits cannot confine market manipulation and are counterproductive, traders on the London Metal Exchange blame JPMorgan's excessive market share in physical aluminium for higher prices despite the long-lasting supply glut on the market (Sanderson et al., 2016). What might have been attributed to non-commercial trading in prior research might really be the result of

[70] Whereas prior studies often focus on the manipulative motives of market concentration, I am interested in the general, mid to longer-term relationship between market/trader structure and commodity returns. For more information on the economics of commodity manipulation, please refer to Pirrong (2017).
[71] Other studies, such as Oellerman and Farris (1986) find comparable results for live cattle futures. However, as their study also concentrates on a few large firms (four-firm concentration) and the research period is dated (1977-1981) I pay less attention to these studies.
[72] According to article 58 paragraph 2 of MiFID II (Directive 2014/65/EU), traders must report precise holding positions at least daily to avoid trading beyond the set limits (cf. European Parliament, 2014).

trader concentration. The question of “who?” affects commodity prices might be less a matter of trader type but rather relative size.

With the inflow of long index investor capital, and thus impact on future demand, into commodity markets, the price equilibrium has been increased beyond the expected changes based on the fundamentals (e.g., Masters, 2008). Yet, the question remains whether this impact has influenced the price or simply increased the open interest on the markets. This present study closes this gap and provides a thorough analysis of the relationship between the effects of the financialization of commodity markets, measured by speculation and trader concentration, and commodity futures price changes, particularly at the extremes. The hypothesis tested in this study is as follows:

H_1: The financialization of commodity markets affects commodity futures returns.

This study extends prior research by thoroughly analysing the commodity futures return distribution, shedding light on the precise impact of non-commercial speculation at the extremes, and identifying the effects of trader concentration on returns. This helps to identify the measures that are affected by financialization, i.e. speculation and trader concentration, and their transmission to commodity futures returns via the financial and the signalling channel. Overall, this study addresses the research question: What is the effect of financialization on commodity futures returns?

4.3 DATA AND METHODOLOGY

4.3.1 DATA

The primary sources of the daily and weekly data are the Thomson Reuters database for financial and economic data (Datastream), the Commitment of Traders (COT) futures only report by the CFTC, the disaggregated Commitment of Traders (DCOT) futures only report by the CFTC, and the Federal Reserve Bank of St. Louis. The research period spans from 3rd January 1995 to 7th March 2017 for a total of 1,156 weeks. The sample includes the rise of commodity financialization from the early 2000s onwards, the surge in commodity prices between 2006 and 2008, the slump of prices following the GFC in 2008, the temporary recovery until the third quarter of 2011, and the continuous decline in prices afterwards. Data obtained from the COT report includes open interest, grouped as commercial, non-commercial, and non-reportable[73]. For the robustness tests I also use disaggregated data (DCOT) comprising open interest separated into producer/merchant/processor/user[74], swap dealer, and managed money for the period from 13th June 2006 to 7th March 2017. The CFTC publishes the weekly snapshots of Tuesday's end-of-day open interest at 3.30pm Eastern Time each Friday, except for public holidays. Futures prices are in continuous time format and represent the price of the nearest contract month. On the expiration date, the position is rolled over to the next available contract. The ten commodities used have been selected based on the relative size and availability of the commodities compared to their peers in the individual commodity classes agricultural, metals, and energy. They are: corn, soybeans, sugar, cotton, gold, silver, copper, platinum, natural gas, and crude oil. All futures price time-series are quoted in USD. I use Tuesday-to-Tuesday[75] and Friday-to-Friday settlement prices to construct the times-series' weekly returns for each commodity and match it with the open interest data. The weekly returns are calculated as $R_t = ln\ (P_t\ /\ P_{t-1})$ with R_t as returns and P_t as futures settlement price.

In addition, I obtain other information to control for general market conditions. Following prior research, I consider variables with good estimation power for exchange-traded commodity returns (e.g., Frankel, 2014; Andreasson et al., 2016). Variables include the trade-weighted USD index, which provides a trade-weighted foreign exchange value average of the USD relative to a basket of major trading currencies, the S&P 500 composite index as proxy for equity market risk, the TED spread as a proxy for credit risk, and the real 3-month USD interbank interest rate, which is calculated by deducting the year-on-year change of the US consumer price index from the USD 3-month interbank rate. Moreover, I follow Henderson et al. (2014) and include the Baltic Dry Index (BDI) which measures the

[73] Beginning in 1998, the COT reporting for corn and soybeans was changed from bushels to contracts (CFTC, 2017). To ensure data consistency throughout the research period, I transform the open interest before 1998 by dividing the reported numbers by 5.
[74] The term used by the CFTC is producer/merchant/processor/user and represents all traders that primarily produce or process the traded commodities.
[75] If the data are captured for another weekday, I calculate the appropriate weekly return, i.e. always from reporting date to reporting date. Thus, the interval between the reports can be shorter or longer than 1 week, depending on the reporting schedule. As most, i.e. >98.5%, of reports capture Tuesday data, I keep the term Tuesday returns. While some studies use the Tuesday to Tuesday returns calculation (e.g. Kim, 2015), others prefer Wednesday to Tuesday (e.g. Bohl and Stephan, 2013) or Wednesday to Wednesday returns (Silvennoinen and Thorp, 2013), I believe that my approach is most accurate as it covers the same period as the open interest.

shipping rates for most dry commodities transported by sea, as a proxy for global demand for commodities.

Table 4.1: Descriptive Statistics

Panel A: Commodity Futures Returns and Controls

	Mean		*StDev*		*Skew*		*Kurt*		*LLC(HT)*	
	Rep.	*Pub.*	*Rep.*	*Pub.*	*Rep.*	*Pub.*	*Rep.*	*Pub.*	*Rep.*	*Pub.*
Commodity Futures Returns										
Total	0.06%	0.06%	4.50%	4.46%	0.36	0.22	20.3	19.3	-81.3***	-81.0***
Agricultural	0.03%	0.02%	4.39%	4.35%	0.96	1.16	38.9	39.0	-52.1***	-51.1***
Metals	0.09%	0.09%	3.32%	3.39%	-0.28	-0.73	7.58	9.89	-49.6***	-50.4***
Energy	0.07%	0.07%	6.36%	6.22%	0.06	-0.15	6.33	5.22	-38.0***	-37.6***
Commodity-Specific Market Liquidity – either log returns (LR), first difference (FD), or level ()										
Total	0.24	0.23	0.15	0.15	1.94	5.91	15.3	175.2	-46.8***	-50.3***
Agricultural	0.20	0.19	0.11	0.14	1.30	14.7	5.98	553.6	-34.4***	-41.9***
Metals	0.25	0.24	0.17	0.16	2.34	1.87	19.1	11.3	-26.7***	-26.7***
Energy	0.30	0.27	0.14	0.13	1.09	0.95	4.93	4.48	-19.7***	-20.5***
Market Controls – either log returns (LR) or first difference (FD)										
S&P 500 – LR	0.14%	0.14%	2.40%	2.40%	-0.71	-0.77	7.70	9.48	-90.1***	-78.3***
RIR – FD	-0.43%	-0.42%	21.1%	21.3%	0.43	0.44	25.5	27.9	-81.7***	-81.3***
TED – LR	-0.09%	-0.05%	14.4%	13.6%	1.24	0.32	18.3	6.17	-86.3***	-82.0***
TW USD – LR	0.01%	0.01%	0.97%	0.97%	-0.13	0.13	4.37	4.19	-79.5***	-80.3***
BDI – LR	-0.06%	-0.05%	7.21%	7.04%	-0.08	-0.13	9.78	7.19	-53.5***	-52.5***

Panel B: Excess Net-Long Non-Commercial Speculation (ESV), Long Trader Concentration (LTC), Short Trader Concentration (STC), and Open Interest

	Mean	*StDev*	*Skew*	*Kurt*	*LLC(HT)*	*LLC(HT) – T*
ESV (in 100,000's contracts)						
Total	0.76	1.76	1.32	6.87	-4.63***	-72.1***
Agricultural	1.00	1.72	1.43	5.79	-2.63***	-44.6***
Metals	0.69	1.19	1.95	7.35	-4.89***	-45.6***
Energy	0.43	2.55	1.06	4.83	-0.50	-33.9***
LTC						
Total	6.81	4.30	1.01	3.65	-3.77***	-100***
Agricultural	6.48	3.42	0.34	2.10	-2.41***	-61.1***
Metals	5.17	2.94	0.99	3.48	-2.37***	-61.1***
Energy	10.7	5.53	0.12	1.93	-1.73**(***)	-54.1***
STC						
Total	10.4	7.46	1.98	20.0	-5.15***	-100***
Agricultural	7.29	5.67	0.34	2.10	-1.64**(***)	-58.6***
Metals	11.0	6.82	3.67	59.4	-8.42***	-67.9***
Energy	15.5	8.66	0.56	3.22	-2.52***	-51.7***
Open Interest (in 100,000's contracts)						
Total	4.03	4.19	1.48	4.48	-0.47	-83.5***
Agricultural	4.57	3.83	1.12	3.32	-1.05	-47.9***
Metals	1.41	1.30	1.58	5.01	-0.56	-52.1***
Energy	8.21	4.83	0.54	2.22	0.99	-49.3***

Notes: This table provides descriptive statistics for the ten commodity futures returns between 3rd January 1995 and 7th March 2017 totalling 1,156 observations for each commodity. With Rep. as reporting date (i.e. day when open interest is captured), Pub. as publishing day (i.e. day when open interest is published), StDev as standard deviation, S&P 500 as S&P 500 composite index, RIR as real interest rate, TED as TED spread, TW USD as trade-weighted USD index, BDI as Baltic Dry Index, LR as log returns, FD as first difference, T for transformed time-series by either log returns or first difference, LLC as Levin-Lin-Chu unit root test, and HT as Harris-Tzavalis unit-root test. Both LLC and HT test the null hypothesis that all the panels contain a unit root. The commodities are grouped as agricultural (corn, soybeans, sugar No. 11, cotton No. 2), metals (gold, silver, copper, platinum), and energy (crude oil, natural gas). For commodity futures returns, the mean and standard deviation are quoted in percent. Although the controls are based on the same data for each commodity, the different number of observations lead to slightly different summary statistics. I report the summary statistics for the commodity with most observations. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

Table 4.1 provides descriptive statistics for the ten commodity futures returns between 3rd January 1995 and 7th March 2017, totalling 1,156 observations for each commodity. The abbreviations are defined as: Rep. as reporting date (i.e. day when open interest is captured), Pub. as publishing day (i.e. day when open interest is published), StDev as standard deviation, S&P 500 as S&P 500 composite index, RIR as real interest rate, TED as TED spread, TW USD as trade-weighted USD index, BDI as Baltic Dry Index, LR as log returns, FD as first difference, T for transformed time-series by either log returns or first difference, LLC as Levin-Lin-Chu unit root test, and HT as Harris-Tzavalis unit-root test. Both LLC and HT test the null hypothesis that all the members of the panel contain a unit root. The commodities are grouped into three categories: agricultural (corn, soybeans, sugar No. 11, cotton No. 2), metals (gold, silver, copper, platinum), and energy (crude oil, natural gas). For commodity futures returns, the mean and standard deviation are quoted in percent. Table 4.1 shows that all returns and trader concentration and most ESV time-series are stationary at levels. Only metals ESV, all total open interest, and the controls time-series needed to be transformed to achieve stationarity. Moreover, the descriptive statistics suggest that the distribution of commodity futures returns, like most controls time-series, is positively skewed and leptokurtic, which indicates that the time-series have fat tails. The commodity-specific pairwise correlations between the variables ESV, LTC, and STC suggest high correlation between the variables.[76]

4.3.2 METHODOLOGY

The real impact of the financialization of commodity markets on commodity futures returns has long been a matter of dispute among researchers (cf. Haase et al., 2016). I argue that the financialization effects are transmitted to commodity futures returns via several mechanisms. First, the impact is not limited to the immediate response of the market to trading, i.e. the financial channel. Instead, I argue that information about trading activates the signalling channel, which represents the response of market participants to information linked to trading futures. The reporting schedule of the CFTC reports allows me to differentiate between the two transmission channels, as the information on the financial data captured each Tuesday is only published on the following Friday. Second, it is not sufficient to focus

[76] I use commodity-specific pairwise correlations to account for the heterogeneity of the ten commodities. While the pairwise correlations of ESV and LTC (average: 0.21) range between -0.35 (natural gas) and 0.74 (platinum) and of ESV and STC (average: 0.57) between -0.24 (natural gas) and 0.83 (sugar), LTC and STC (average: 0.42) indicate a range from -0.17 (copper) to 0.79 (natural gas). To account for the correlation between independent variables in the panel regression models, I first rely on the variance inflation factor after running the models to test for multicollinearity. These tests do not indicate multicollinearity in most estimations. Second, I drop two out of three variables to test if the coefficient and its significance for the remaining variable remains constant. For most of the panel regressions, the coefficients and their significance remain comparable to the models including all three variables. Only in a few cases does the significance of the three main variables slightly reduce, but it remains for all of them well below the 5 percent level.

on the total amount of or any calculations on the open interest held in the futures markets as it has been done in prior research (e.g. Bosch and Pradkhan, 2015; Andreasson et al., 2016; Brunetti et al., 2016). Instead, the financialization of commodity markets also led to the entrance of new traders that may have changed the trader concentration and thus the importance of and dependence on a few large traders in the market. As a result, global commodity futures markets might have become more robust to individual trader position changes. To estimate this effect, it is not sufficient to concentrate on the open interest. Instead, the concentration of traders on the futures market might significantly contribute to the explanation of variations in the price and returns of commodity futures. Thus, this section details the measures for both non-commercial speculation and trader concentration.

Excess Net Long Non-Commercial Open Interest

To evaluate the impact of non-commercial speculation on commodities, one must find a measure that accurately represents the level of excess speculation in the market. While some excess speculation is necessary for a market to function well, too much excess speculation might lead to bubbles. Commercial traders (hedgers) primarily use financial products to actively mitigate their price risk but non-commercial traders (speculators) mostly use those financial products to speculate. The negative connotation of speculation in society and its deteriorating effects on economic health overshadow the positive impact on the financial markets which include the provision of liquidity, price discovery mechanisms, a reduction in hedging costs, and better integration of commodity markets with financial markets (Fattouh et al., 2012; Irwin and Sanders, 2012).

Prior studies often rely on the Working T-index (e.g., Irwin and Sanders, 2010; Buyuksahin and Robe, 2014; Andreasson et al., 2016; Robe and Wallen, 2016), which is a measure of excess speculation. It is derived from the ratio of speculation to hedging of short and long positions of commercial and non-commercial open interest without considering the direction of speculation and without considering the non-reportable interest. A healthy value ranges between 1.00 and 1.15 which ensures sufficient liquidity in the market (Irwin and Sanders, 2010). The Working T-index (WTI) is calculated as:

$$WTI = 1 + \frac{SS}{(HL + HS)} \; if \; (HS \geq HL) \tag{4.1}$$

$$WTI = 1 + \frac{SL}{(HL + HS)}\ if\ (HS < HL) \tag{4.2}$$

with open interest held by commercial (hedgers) and non-commercial (speculators) traders classified as SS for speculation short, SL for speculation long, HS for hedging short, and HL for hedging long. Despite its wide use in prior research, the WTI has some limitations.

First, the WTI strictly separates hedgers and speculators and assumes that both take positions only based on their classification. While this might have been true in the past, Buyuksahin and Harris (2011) argue that the traditional definition of hedgers and speculators loses its relevance as both parties can speculate. Moreover, every purchase of commodities that is not used for current consumption is speculation (Kilian and Murphy, 2014). Although I appreciate that the classification suits the availability of data, one must accept that this restriction limits the validity of the results. Second, the WTI does not distinguish between long and short speculation, thus preventing one from taking the direction of speculation into account when evaluating its impact on commodity prices. Third, the WTI uses hedger's open interest to determine the appropriate numerator. In theory, this approach is reasonable, as all market participants can clearly be identified as either hedgers or speculators. In practice, this distinction is impossible because the data contains a third group, the non-reportable positions. Thus, net hedger (commercial) and net speculator (non-commercial) open interest positions do not usually offset each other. This leads to the fourth limitation, the disregard of non-reportable open interest. This position consolidates all trades that fall below the threshold set by the CFTC. While some commodities are dominated by large traders, small or non-reportable traders have a considerable market share for others. Between 1995 and early-2017, the average share of non-reportable open interest ranged between 6 percent for crude oil and 25 percent for corn.[77] Thus, the non-reportable positions might noticeably impact the study outcome and should therefore be considered, too.

Although some studies attempt to overcome these flaws, few have succeeded. For example, Shanker (2017) extends the WTI calculation and proposes two measures of adequate and excess speculation. Instead of neglecting the non-reportable data, the researcher follows prior studies (Irwin et al., 2009; Sanders et al., 2010; Etienne et al., 2016) and allocates the non-reportable open interest by assuming that the ratio of commercial to

[77] A4.1 in the appendix illustrates the share of non-reportable open interest per commodity.

non-commercial positions remains stable between reportable and non-reportable positions.[78] While this approach considers all open interest, it assumes that the ratio between hedgers and speculators is similar for reportable and non-reportable open interest, which might not be appropriate. Prior analysis by IHS Markit (O'Donnell, 2016) suggests that small producers hedge significantly more than large producers of oil and gas. Moreover, based on a sample of 2,797 non-financial US firms between 1994 and 2009, Chen and King (2014) find that only 25.6 percent of agriculture, forest, and fishing firms and 33.1 percent of miners and oil & gas producers use commodity price hedging. A report by PricewaterhouseCoopers (2016) complements these findings and suggests that mining companies hardly use financial derivatives to hedge their price risk. Although hedging is common among precious metal miners (GFMS, 2016) and has proven to be beneficial for gold miners and other companies (Baur, 2014; Chen and King, 2014; O'Connor et al., 2016), mining companies are reluctant to establish appropriate hedging programmes. Logically, most non-reportable open interest is held by either consumers or speculators, which can only passively influence the production of the goods. Therefore, non-reportable positions do not represent the overall market and one should not use the ratio of reportable open interest to allocate non-reportable positions.

Tadesse et al. (2014) indirectly address this issue and focus on the excess speculative positions held by non-commercial traders and argue that excess net long positions by those traders put upward pressure on prices that might eventually lead to bubbles. The measure of excess speculation, denoted as ESV, can be written as:

$$ESV_t = \sum_{d=1}^{N_t} \frac{[(NCL_d - NCS_d) - (CL_d - CS_d)]}{N_t} \tag{4.3}$$

Or simplified

$$ESV_t = (NCL_t - NCS_t) - (CL_t - CS_t) \tag{4.4}$$

with N_t as number of days d per month t where CFTC position data are available, non-commercial long (NCL_t), non-commercial short (NCS_t), commercial long (CL_t), and commercial short (CS_t) open interest positions. While the ESV's initial purpose is to

[78] Others, such as Behmiri et al. (2016) simply use a 50/50 ratio and equally allocate the non-reportable information to reportable commercial and non-commercial data.

measure excess speculation and it does not actively incorporate non-reportable positions, it considers all open interest information. The initial formula can be rewritten as:

$$NCL_t + CL_t + NRL_t = NCS_t + CS_t + NRS_t \tag{4.5}$$

$$(NCL_t - NCS_t) + (NRL_t - NRS_t) = -(CL_t - CS_t) \tag{4.6}$$

$$ESV_t = 2 * (NCL_t - NCS_t) + (NRL_t - NRS_t) \tag{4.7}$$

$$ESV_t = -2 * (CL_t - CS_t) - (NRL_t - NRS_t) \tag{4.8}$$

with non-commercial long (NCL_t), non-commercial short (NCS_t), commercial long (CL_t), and commercial short (CS_t), non-reportable long (NRL_t), and non-reportable short (NRS_t) open interest positions. With this approach, Tadesse et al. (2014) provide a measure that focuses on the difference between the net long positions of non-commercial and commercial traders and thus incorporates all the information content arising from net open interest.

Trader Concentration

In addition to speculation, I further evaluate the impact of trader concentration. I separate long and short open interest to investigate the impact of long and short trader concentration. The ratios of reportable to non-reportable long and short open interest extends the analysis from whether non-commercial trading affects commodity futures returns to whether trader concentration matters. I introduce two new measures that capture the ratio between reportable and non-reportable open interest, i.e. large market participants that satisfy the minimum threshold set by the CFTC in relation to traders with less exposure.[79] The variables are calculated as:

For long positions:

$$LTC_t = \frac{Reportable\ Open\ Interest\ Long_t}{Non - Reportable\ Open\ Interest\ Long_t} \tag{4.9}$$

For short positions:

$$STC_t = \frac{Reportable\ Open\ Interest\ Short_t}{Non - Reportable\ Open\ Interest\ Short_t} \tag{4.10}$$

[79] The reporting limits are commodity-specific and may change over time. For example, current reporting limits are set to 250 contracts for corn, 150 for soybeans, and 350 for crude oil (CME Group, 2017b).

with LTC as long reportable to non-reportable open interest and STC as short reportable to non-reportable open interest at time t.

Econometric Models

In this study, I first apply a panel regression model with commodity fixed effects[80] to estimate the impact of speculative and trader concentration on returns. The model can be written as:

$$CFR_{it} = \alpha + \beta SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it} \tag{4.11}$$

with α, β, δ as coefficients, CFR_{it} as commodity-specific futures log returns, $SPEC_{it}$ as a speculative measures vector consisting of $SPEC_{it} = [ESV_{it}, LTC_{it}, STC_{it}]$. Control variables are represented by the vector, F_{it}, which includes: OI as total open interest per commodity, TWI as the trade-weighted USD index, SP500 as the S&P 500 composite index, TED as the TED spread, RIR as the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity (as in Manera et al., 2016) and calculated as ML = Trade Volume / Open Interest), BDI as the Baltic Dry Index, DotCom as a dummy variable for the dot-com bubble between the years 2000 and 2002, GFC as a dummy variable for the GFC between the years 2008 and 2009, EDC as a dummy variable for the European debt crisis between the years 2010 and 2012 and ε_{it} as error term for each commodity i at time t. I estimate standard errors using the Driscoll–Kraay procedure to account for cross-sectional dependence, as the Breusch-Pagan LM test of independence and the Pesaran CD test both indicate cross-sectional dependence.[81] Depending on the panel unit root and stationary tests, I either calculate periodical log changes or first differences. To evaluate the individual commodity effects, I mirror the panel analysis and rely on a mix of regression models to analyse the commodity-specific interaction between returns and speculation. I begin with an OLS regression that estimates the mean interaction between the variables of interest. The OLS regression model can be written as:

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[80] I also run a regression with random effects and compare both models using both, the Breusch-Pagan Lagrange multiplier test and the Hausman specification test which confirm the superiority of the fixed effects approach. The results are available upon request.

[81] As a robustness test, I also use Newey-West standard errors to further account for autocorrelations and obtain comparable results.

$$CFR_t = \alpha + \beta SPEC_t + \delta F_t + \varepsilon_t \tag{4.12}$$

with α, β, δ as coefficients, CFR_t as commodity-specific futures log returns, $SPEC_t$ and F_t as commodity-specific variables as defined in (4.11), and ε as the error term at time t.

Second, I adopt a quantile regression estimator with nonadditive commodity fixed effects introduced by Powell (2016) to estimate a quantile regression model for panel data.[82] The model builds on a quantile regression (QR) model originally developed by Koenker and Bassett (1978). Prior attempts that merge quantile regression and longitudinal data rely on additive fixed effects (Koenker, 2004). However, this approach leads to biased estimates (Hausman et al., 2016; Smith, 2016; Boumparis et al., 2017). The nonadditive approach by Powell (2016) maintains the non-separable error term that is traditionally associated with quantile regression (Aldieri and Vinci, 2017) and further ensures the comparability with cross-sectional regression (Boumparis et al., 2017). Moreover, it is particularly useful in a setup where one expects the variable effects to be heterogenous throughout the outcome distribution (Powell, 2016). As an alternative to quantile regression, prior studies truncate the data based on the value of the dependent variable. For example, Kim (2015) pools all commodities with returns of 10 or 20 percent over a period of 5, 10, or 20 weeks. While this method concentrates on the strongest deviations of returns during a specific time, it might be inappropriate for the estimation of the relationship between speculation and commodity returns. First, concentrating on the top 10 or 20 percent of returns assumes that the impact of speculation on commodity returns is constant for all commodities, i.e. all commodities respond similarly to speculation. As commodities are a diverse asset class driven by different intrinsic and extrinsic factors, the magnitude of speculation may differ among them. Moreover, the revaluation of the dataset, i.e. checking if the commodity returns are equal or higher than 10 percent, may lead to changes in the dataset each period. Consequently, I would effectively compare different base data, i.e. a different mix of commodities, each period. Second, pooling the commodities with high returns favours commodities that experience relatively higher volatility, even if this volatility may stem from factors that are unrelated to speculation. While speculation may influence all commodities, limiting the sample to the most volatile commodities neglects potentially valuable information. Third,

[82] I use the Stata package by Baker et al. (2016) to estimate the quantile regression for panel data (QRPD) model.

this method assumes that speculation has a large effect on commodity returns. As I do not know the size of the impact of speculation, limiting the analysis to extreme returns may falsely truncate the data. In support, Koenker and Hallock (2001) argue that such a truncation of data, i.e. dividing the sample into subsets based on the unconditional distribution of the response variable, followed by OLS regression on the subsets is fruitless and leads to highly undesirable results. Quantile regression addresses these issues as it evaluates the conditional distribution for a τ-th quantile of each commodity instead of dictating a percentage threshold on the dependent variable that is equally applicable for all commodities. Moreover, the focus on the median (50th percentile) or other quantiles instead of the conditional mean, deals more robustly with outliers, which is particularly fruitful for turbulent financial markets. Quantile regression enables me to scrutinise extreme price changes and their precise relationship with the independent variables. While the mean regression assumes that the explanatory power of the regressors for the dependent variable is constant, quantile regression evaluates different quantiles of the response variable. With this, it is possible to identify potentially nonlinear relationships between the return structure of returns and its regressors. If one finds a significant skewed impact of the speculation and trader concentration measures on returns, it is possible to conclude whether the regressors are reinforcing, stabilising, or destabilising. Following Powell (2016) and Boumparis et al. (2017), the underlying model can be written as:

$$CFR_{i,t} = \sum_{j=1}^{k} D'_{i,t}\beta_j(U^*_{i,t}) \tag{4.13}$$

where $CFR_{i,t}$ is the commodity futures return for each commodity, β_j is the parameter of interest for each of the k ∈ ℕ* regressors, $D_{i,t}$ = [$SPEC_{i,t}, F_{i,t}$] is the vector of regressors, and $U^*_{i,t}$ is the non-separable error term traditionally associated with quantile estimation. $D'_{i,t}\beta(\tau)$ is strictly increasing in τ and the model is linear-in-parameters. For a τ-th quantile ($0 < \tau < 1$) of $CFR_{i,t}$, the quantile regression relies on the conditional restriction:

$$P\left(CFR_{i,t} \leq D'_{i,t}\beta(\tau)\middle|D_{i,t}\right) = \tau \tag{4.14}$$

The parameters of interest are estimated as:

$$\hat{\beta}(\tau) = arg \min_{b \in \beta} \widehat{g'}(b) \hat{A} \hat{g}(b) \tag{4.15}$$

for some weighting matrix $\hat{A}$. Markov Chain Monte Carlo (MCMC) optimisation is used to estimate the model as it produces satisfactory estimates (Powell, 2016). The individual commodity equivalent is a quantile regression as in Koenker and Bassett (1978) and Buchinsky (1998) that is defined as:

$$CFR_i = \pi + \gamma_\tau SF'_i + u_{\tau_i} \quad Quant_\tau(CFR_i|SF_i) = \gamma_\tau SF'_i \tag{4.16}$$

For a τ-th quantile ($0 < \tau < 1$) of CFR_i, the parameters can be estimated using the quantile regression minimisation of the objective function:

$$\min_\gamma \left\{ \sum_{i:CFR_i \geq SF'_i\gamma} \tau|CFR_i - SF'_i\gamma| + \sum_{i:CFR_i < SF'_i\gamma} (1-\tau)|CFR_i - SF'_i\gamma| \right\} \tag{4.17}$$

with π as coefficient, γ_τ as a vector of coefficients with $\gamma_\tau = [\gamma_{SPEC}, \gamma_F]$, CFR_i as commodity-specific futures returns, $Quant_\tau(CFR_i|SF_i)$ as the conditional quantile of CFR_i, conditional on the vector of regressors $SF_i = [SPEC_i, F_i]$, $SPEC_i$ as a speculative measures vector consisting of $SPEC_i = [ESV_i, LTC_i, STC_i]$, F_i as a vector of fundamental explanatory variables and dummies, and the error term u_{τ_i}.

Third, to test for Granger non-causality for the panel dataset of this study, I adopt a model presented by Dumitrescu and Hurlin (2012) and implemented by Lopez and Weber (2017) for heterogeneous panel data with fixed coefficients that uses cross-sectional averaged Wald statistics of Granger non-causality for a strictly balanced dataset. The underlying linear model is defined as:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \tag{4.18}$$

with time-fixed α_i, the lag-order K ∈ ℕ* which is constant across all individuals i, $y_{i,t}$ and $x_{i,t}$ as observations of two stationary variables for i at time t, which in this case are returns and ESV. Both coefficients $\gamma_i^{(k)}$ and $\beta_i^{(k)}$ are constant over time but can vary across i. If past values of x_i significantly estimate the current value of y_i even when past values of y_i are included in the model, then x_i Granger-causes y_i. Using (4.18), one can test homogenous non-causality as:

$$H_0: \beta_i = 0 \quad \forall i = 1, \ldots, N \tag{4.19}$$

As there can be causality for some units i in the panel but not necessarily for all, the alternative hypothesis is defined as:

$$H_1: \beta_i = 0 \quad \forall i = 1, \ldots, N_1 \tag{4.20}$$

$$H_1: \beta_i \neq 0 \quad \forall i = N_1 + 1, N_1 + 2, \ldots, N \tag{4.21}$$

where $N_1 \in [0, N-1]$ is unknown and $0 \leq N_1/N < 1$. Therefore, if $N_1 = 0$ there is causality for all individuals i and if $N_1 = N$ there is no causality and H_1 reduces to H_0. Following Dumitrescu and Hurlin (2012), I use the average individual Wald statistics for the cross-section of each individual i corresponding to (4.19). It can be written as:

$$\bar{W} = \frac{\sum_{i=1}^{N} W_{i,T}}{N} \tag{4.22}$$

with $\bar{W}$ as the average value of the i-individual Wald statistics $W_{i,T}$ for time T.[83] As this test statistic is designed to detect causality for panel data, some individuals within this panel may not have a causal relationship even though H_0 for the panel is rejected. The corresponding Z-statistic, under the assumption that $W_{i,T}$ is independently and identically distributed (i.i.d.) across all i and $T, N \to \infty$, i.e. $T \to \infty$ first and then $N \to \infty$, follows a standard normal distribution and can be written as:

$$\bar{Z} = \sqrt{\frac{N}{2K}} * (\bar{W} - K) \quad \xrightarrow[T,N\to\infty]{d} N(0,1) \tag{4.23}$$

[83] Please refer to Dumitrescu and Hurlin (2012) for the definition of $W_{i,T}$.

If $\bar{Z}$ is larger than the corresponding normal critical values (p-value ≤ 0.05), H_0 can be rejected and one can conclude that x_i Granger-causes y_i. For each variable pair, i.e. returns and one of the three regressors ESV, LTC, and STC, lags are chosen based on the Akaike information criterion (AIC). The individual commodity Granger causality tests use a comparable setup that relies on a simple vector autocorrelation (VAR) model that adopts a variable setup as in equation (4.11). Afterwards, pairwise Granger causality tests are executed. Lags for the VAR model are chosen based on the AIC.

Instead of using panel regression, which basically uses a 1/n weighting, one may suggest building an index based on a commodity-specific weighting to account for the relative importance of each commodity. However, I believe that in the absence of a sound theoretical basis such an approach has the potential to introduce biases. First, as both returns and the open interest data used to calculate ESV, LTC, and STC have the same basis for weighting (e.g. production output) the weighting would effectively cancel out. Second, if I apply different weightings to the individual variables without a sound theoretical basis, I am effectively manipulating the data. Third, by using any weighting other than 1/n, I may disproportionally under- or overvalue commodities that are traded more than others. For example, gold is heavily traded on the market, but its production in metric tonnes is relatively low compared to industrial metals, which are traded significantly less. If I would use production data to weight the returns, I would undervalue the importance of gold in favour of industrial metals.

Still, the question remains as to whether panel regression provides an advantage over individual commodity evaluation. I argue that panel regression provides a first overview on the potential homogeneity among commodities regarding non-commercial speculation. While commodities undoubtedly have heterogenous characteristics, i.e. they are driven by individual commodity factors, there are also influences that affect all commodities, or certain commodity groups. These effects may be equally influential for all commodities but may also impact commodity prices differently, i.e. the coefficients may differ in magnitude and direction. In fact, the Breusch-Pagan LM test of independence and the Pesaran CD test both indicate cross-sectional dependence between the ten commodity future returns. Another important issue to consider is that the panel regression approach may result in a misinterpretation error. If the regressors of interest only affect a few commodities, the results may indicate that all are affected (or not) in the same way. As highlighted above, panel regression basically uses a 1/n weighting. Thus, I estimate the effect of the regressors on the dependent variable and assume that this effect is comparable for all commodities in the sample. However, the indicated heterogeneity of commodities is not limited to the question of whether their prices are affected by a variable or not. Often, it is the direction and the magnitude of the effect on each commodity that matters. Thus, due to the heterogenous characteristics of commodities and possibility of misleading results, the study is not limited to the panel regression but further evaluates each of the ten commodities individually to more completely identify the interactions between non-commercial speculation, trader concentration, and commodity futures returns.

4.4 EMPIRICAL RESULTS

4.4.1 THE FINANCIAL EFFECT OF SPECULATION AND TRADER CONCENTRATION

To capture the direct estimation power of excessive speculation (ESV) and market concentration (LTC and STC), I estimate both a panel regression with commodity fixed effects and a quantile regression with nonadditive commodity fixed effects for the 5th, 10th, 25th, 50th (median), 75th, 90th, and 95th quantiles for Tuesday's returns.

The consolidated findings in Table 4.2 for the fixed effects panel regression confirm the highly statistically significant positive impact of excessive net long speculation on returns found in prior research, which suggests reinforcing rather than weakening effects of speculation. However, the quantile regression reveals that this effect is not constant for the entire return distribution. Instead, I find highly statistically significant evidence for a positive effect of excessive net long speculation on the left tail and a negative effect on the right tail of returns, which confirms a stabilising impact of speculation on the returns. The stabilising effect observed, i.e. support at the lower tail and reduction at the upper tail, of speculation on returns is rather the reaction of non-commercial traders to changes in the futures price. When prices fall, non-commercial traders increase their positions, which leads to an increase in non-commercial open interest. Conversely, traders reduce their open interest by taking profits when prices increase. This might be due to traders who calculate expected prices of the commodities and use short-term market fluctuations, i.e. variations from their expected price, to profit. Shifting to trader concentration, the long and short concentration significantly influence returns. The coefficients suggest a gradually decreasing negative effect of LTC. LTC is significantly negative for the lower quantiles of returns and the magnitude of the coefficient incrementally decreases with increasing quantiles. Although the coefficients for STC are positive and significant at the 1 percent level in the mean model, the quantile regression suggests that the effect on returns is positive and larger at both tails instead of positive and gradually increasing.[84]

Table 4.2: Quantile and Panel Fixed Effects Regression – Financial Effect

			Commodity Futures Returns						
			Quantile						
Financial Effect		PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV	All	0.0016***	0.0051***	0.0038***	0.0027***	0.0011***	0.0002***	0.0001***	-0.0008***
	Agri	0.0019***	0.0023***	0.0029***	0.0016***	0.0014***	0.0010***	0.0020***	0.0011***
	Metals	0.0011***	0.0052***	0.0045***	0.0015***	0.0003*	0.0003	-0.0023***	-0.0027***
	Energy (_f)	0.0760***	0.0738***	0.0787***	0.0749***	0.0810***	0.0638***	0.0680***	0.0709***
LTC	All	-0.0007***	-0.0023***	-0.0019***	-0.0012***	-0.0004***	0.0002***	0.0001***	-0.0001***
	Agri	-0.0012***	-0.0007***	-0.0010***	-0.0013***	-0.0008***	-0.0003***	-0.0016***	-0.0019***
	Metals	-0.0004*	0.0011***	0.0005***	0.0001	-0.0003***	0.0000	-0.0012***	-0.0019***
	Energy	0.0000	0.0040***	0.0005	0.0015***	0.0004***	-0.0009***	-0.0028***	-0.0046***
STC	All	0.0003***	0.0005***	0.0004***	0.0003***	0.0001***	0.0001***	0.0003***	0.0008***
	Agri	0.0010***	0.0001***	0.0002***	0.0006***	0.0005***	0.0010***	0.0016***	0.0024***
	Metals	0.0002**	0.0002***	0.0001***	0.0001***	0.0002***	0.0001***	0.0001***	-0.0000***
	Energy	-0.0002	-0.0029***	-0.0008***	-0.0010***	0.0000	0.0007***	0.0016***	0.0025***

Notes: This table illustrates the results of the panel regression with commodity fixed effects (PD-FE) and quantile regression with nonadditive commodity fixed effects (QRPD) for the financial effect of commodity futures returns between 3rd January 1995 and 7th March 2017 totalling 1,156 observations for each of the 10 commodities. With _f and _r indicating first differences and log returns respectively. With ESV, LTC, and STC as focus variables. For the PD-FE model, I use Driscoll-Kraay standard errors to account for cross-sectional dependence. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. Detailed results are in Appendix A4.2.

The models are defined as:

PD-FE: $CFR_{it} = \alpha + \mu SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$

QRPD: $CFR_{i,t} = \sum_{j=1}^{k} D'_{i,t}\beta_j(U^*_{i,t})$ $\quad P\left(CFR_{i,t} \le D'_{i,t}\beta(\tau)\middle|D_{i,t}\right) = \tau$ $\quad \hat{\beta}(\tau) = arg \min_{b\in\beta} \hat{g}'(b)\,\hat{A}\hat{g}(b)$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, DotCom as a dummy variable for the dot-com bubble between the years 2000 and 2002, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t. With β_j as the parameter of interest for each of the k ∈ N* regressors, D' = [SPEC, F] is the vector of regressors, and U* is the non-separable error term traditionally associated with quantile estimation. For a τ-th quantile (0 < τ < 1) of CFR.

Commodities, much like other asset classes, are driven by various extrinsic and intrinsic factors. A basket of different commodities is somewhat like the S&P500.[85] While some factors such as economic growth may impact all stocks, others only affect sub-sectors of the S&P500. Likewise, this applies to commodities. Some factors may purely affect the price of crude oil and may not – or to a much lesser extent – affect the price of corn. To account for the heterogeneity of commodity classes, I group commodities based on their nature, i.e.

[84] Higher short trader concentration leads to relatively higher market power of few short traders. As short traders, i.e. suppliers, desire higher prices, I would expect stronger coefficients at the upper quantiles of returns. Instead, the 5th and 95th quantile of returns both show stronger, positive coefficients compared to the centre of the distribution.

[85] Whereas the S&P 500 is weighted by the market capitalisation of the individual components, my approach assumes an equally-weighted portfolio.

agriculture (corn, soybeans, sugar, cotton), metals (gold, silver, copper, platinum), and energy (crude oil and natural gas) commodities. First, the mean estimation coefficients suggest that returns of all commodity sub-classes react positively and highly significantly (1 percent) to ESV. However, the quantile regression coefficients differ among the three sub-classes and confirm the heterogeneity claim. While the impact of the ESV for agricultural commodities tends to decrease at higher quantiles, the coefficients remain almost constant for energy commodities. Only for metals, one can observe the stabilising effect found for the overall commodity basket. Thus, the often-drawn conclusion in prior research that speculation is reinforcing or stabilising cannot be confirmed per se as it depends on the commodity group. Overall, the results suggest that speculation has a stabilising effect on returns overall, and on metal returns in particular, and a reinforcing effect on agricultural and energy returns. Moreover, the effect of non-commercial speculation on returns, indicated by the magnitude of the coefficients, is small. The findings for trader concentration are also different for each commodity class. Whereas returns of agricultural commodities respond to changes in both trader concentration measures, STC is the only concentration variable associated with metal returns, while energy returns are not influenced by either concentration variable.

Table 4.3: Instrumental Variable Quantile Regression

	Commodity Futures Returns						
Quantile	5th	10th	25th	50th	75th	90th	95th
ESV	0.0032***	0.0028***	0.0024***	0.0010***	0.0003***	-0.0009***	0.0007***
	(0.0003)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
LTC	-0.0024***	-0.0019***	-0.0015***	0.0001	0.0003**	0.0010***	0.0003**
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0002)
STC	0.0002***	0.0003***	0.0003***	-0.0001***	-0.0003***	-0.0000	0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)

Notes: This table illustrates the quantile regression for panel data with commodity fixed effects and instrumental variables, i.e. the lags of the three regressors at t-1 and t-2, for the research period from 3rd January 1995 to 7th March 2017, totalling 1,156 for each of the 10 commodities. With ESV, LTC, and STC as focus variables. Note that the instrumental variable model concentrates on the dependent variable, the three regressors ESV, LTC, and STC and their respective lags at t-1 and t-2 as instruments. All controls are omitted from the model. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

The model is defined as:

QRPD: $CFR_{i,t} = \sum_{j=1}^{k} D'_{i,t}\beta_j(U^*_{i,t})$ $\quad P\left(CFR_{i,t} \le D'_{i,t}\beta(\tau)\middle|D_{i,t}\right) = \tau$ $\quad \hat{\beta}(\tau) = arg\min_{b\in\beta} \hat{g}'(b)\,\hat{A}\hat{g}(b)$

with CFR as commodity-specific futures log returns, β_j as the parameter of interest for each of the k ∈ N* regressors, D' is the vector of regressors with regressors ESV, LTC, and STC and instrumental variables ESV_{t-1}, ESV_{t-2}, LTC_{t-1}, LTC_{t-2}, STC_{t-1}, STC_{t-2}, and U^* is the non-separable error term traditionally associated with quantile estimation. For a τ-th quantile (0 < τ < 1) of CFR.

To test for endogeneity, I reduce the main quantile regression as in equation (4.13) to purely focus on returns and three main regressors ESV, LTC, and STC. Following Aldieri and Vinci (2017) and Boumparis et al. (2017), I add lagged versions of all three estimators for t-1 and t-2. In line with the main analysis, non-commercial net open interest (ESV) continues to stabilise returns rather than reinforcing them and the coefficients for both LTC and STC remain comparable to the main analysis.

The Financial Effect on Individual Commodities

While fixed effects panel regression provides an equally-weighted analysis that controls for all unobserved time-invariant variables in the model, it may not fully factor in the heterogeneity of each commodity (cf. Brooks and Prokopczuk, 2013). I now individually evaluate the effects of speculation and trader concentration for each of the ten commodities. The results are reported in Table 4.4. While the individual commodity mean regression results support the findings of the panel regression, the STC coefficient for silver is significant and negative compared to the positive coefficient for metals overall. As in the panel regression, the effect of ESV in the quantile regression can be allocated into three groups. However, quantile regression illustrates the heterogeneity in the relationships between speculation and returns across individual commodities. For example, ESV has a stronger stabilising, i.e. positive effect on the left tail of the return distribution, i.e. the 5^{th} to 50^{th} quantiles for soybeans and gold, a constant positive effect on the whole distribution of returns for corn, cotton, platinum, natural gas, and crude oil, and significantly stronger reinforcing effects on the left and right tail of returns for silver and copper. For highly traded non-agricultural commodities such as gold, I find a positive effect of the ESV on returns across the whole distribution. Shifting to the trader concentration measures LTC and STC, I find evidence that most agricultural commodities show a tendency for a stronger significant negative impact of LTC and positive impact of STC on the lower quantiles of returns.

While LTC significantly reduces returns for metals, particularly gold and copper, in the mean model, the quantile regression suggests a constant negative impact for gold but a gradually decreasing (i.e. strengthening) effect for copper. Thus, positive returns are influenced more strongly by LTC than negative returns. For these two commodities, STC is significant at the left tail of returns. A negative coefficient for STC across the whole distribution is exhibited for silver, which suggests that increases in short trader concentration negatively affect returns. For energy commodities, the non-significance of LTC and STC observed in the panel regression remains for natural gas. However, the quantile regression coefficients for crude oil indicate a significantly positive (LTC) and negative (STC) relationship with returns. When returns are in the 50^{th} quantile or higher, returns significantly correlate with LTC and STC. These findings suggest that the impact of trader concentration is stronger if returns are positive and that trader concentration for crude oil is reinforcing for long trader concentration and dampening for short trader concentration.

Table 4.4: Commodity-Individual OLS and QR – Financial Effect

	Commodity Futures Returns											
	Corn						Soybeans					
		Quantile						Quantile				
	OLS	5^{th}	10^{th}	50^{th}	90^{th}	95^{th}	OLS	5^{th}	10^{th}	50^{th}	90^{th}	95^{th}
ESV	0.0016***	**-0.0006**	**0.0006**	0.0023***	0.0029***	0.0023**	0.0029***	0.0036**	0.0031***	0.0031***	0.0028**	0.0018
	(0.0006)	(0.0010)	(0.0010)	(0.0006)	(0.0009)	(0.0011)	(0.0007)	(0.0017)	(0.0010)	(0.0008)	(0.0012)	(0.0012)
LTC_r	-0.123***	-0.192***	-0.164***	-0.146***	-0.089***	-0.0498	-0.119***	-0.162***	-0.143***	-0.106***	-0.065***	-0.0472**
	(0.0243)	(0.0402)	(0.0367)	(0.0210)	(0.0311)	(0.0473)	(0.0180)	(0.0264)	(0.0172)	(0.0152)	(0.0186)	(0.0223)
STC_r	0.1433***	0.1710***	0.1881***	0.1803***	0.0804**	0.0394	0.0965***	0.1405***	0.1445***	0.0865***	0.0247	0.0051
	(0.0334)	(0.0548)	(0.0493)	(0.0281)	(0.0405)	(0.0621)	(0.0195)	(0.0276)	(0.0223)	(0.0181)	(0.0214)	(0.0218)
ML	0.0966**	0.1426**	0.1122*	0.0758*	-0.0574	0.0084	0.1859***	0.2029***	0.1608***	0.1858***	0.1552***	0.1683***
	(0.0420)	(0.0722)	(0.0647)	(0.0387)	(0.0531)	(0.0892)	(0.0263)	(0.0373)	(0.0341)	(0.0268)	(0.0332)	(0.0361)
OI_r	0.0397**	-0.106***	-0.087***	0.0351**	0.1361***	0.1639***	0.0246**	-0.0356*	-0.0191	0.0355***	0.0839***	0.0818***
	(0.0183)	(0.0311)	(0.0267)	(0.0173)	(0.0222)	(0.0344)	(0.0112)	(0.0191)	(0.0131)	(0.0100)	(0.0138)	(0.0123)
SP500_r	0.0969*	0.0581	-0.0230	0.0383	0.1163*	0.1402	0.1250***	0.0270	0.0662	0.0931**	0.1338***	0.1734**
	(0.0571)	(0.0842)	(0.0821)	(0.0498)	(0.0672)	(0.0939)	(0.0419)	(0.0847)	(0.0510)	(0.0431)	(0.0507)	(0.0694)
RIR_f	-0.0150*	-0.026***	-0.0154	-0.0090	-0.0175**	-0.0167	-0.0091	-0.0287**	-0.016***	-0.0037	0.0010	0.0029
	(0.0083)	(0.0093)	(0.0102)	(0.0062)	(0.0081)	(0.0102)	(0.0067)	(0.0128)	(0.0053)	(0.0041)	(0.0065)	(0.0072)
TED_r	-0.0073	0.0162	-0.0024	-0.0038	-0.0089	-0.0122	-0.0067	-0.0076	-0.0118	-0.0068	-0.0080	-0.0134
	(0.0074)	(0.0122)	(0.0105)	(0.0072)	(0.0090)	(0.0150)	(0.0063)	(0.0122)	(0.0083)	(0.0074)	(0.0089)	(0.0104)
TWI_r	-0.776***	-0.627***	-0.651***	-0.446***	-0.827***	-0.957***	-0.663***	-0.695***	-0.596***	-0.636***	-0.631***	-0.621***
	(0.1313)	(0.1703)	(0.2039)	(0.1242)	(0.1892)	(0.2525)	(0.1043)	(0.1957)	(0.1306)	(0.1109)	(0.1465)	(0.1560)
BDI_r	0.0075	-0.0338	-0.0126	-0.0043	0.0078	0.0309	0.0135	-0.0091	0.0010	-0.0077	0.0255	0.0232
	(0.0168)	(0.0253)	(0.0315)	(0.0175)	(0.0279)	(0.0301)	(0.0145)	(0.0337)	(0.0133)	(0.0155)	(0.0209)	(0.0178)
DotCom	0.0031	0.0108**	0.0029	-0.0043*	0.0117***	0.0061	0.0024	0.0035	0.0009	0.0031	-0.0019	-0.0002
	(0.0030)	(0.0053)	(0.0039)	(0.0026)	(0.0044)	(0.0064)	(0.0024)	(0.0035)	(0.0035)	(0.0026)	(0.0027)	(0.0035)
GFC	-0.0042	-0.037***	-0.0235	-0.0023	0.0240**	0.0245***	-0.0048	-0.0244**	-0.028***	-0.0025	0.0140*	0.0168*
	(0.0059)	(0.0077)	(0.0170)	(0.0073)	(0.0111)	(0.0089)	(0.0047)	(0.0102)	(0.0046)	(0.0057)	(0.0074)	(0.0096)
EDC	-0.0039	0.0041	-0.0051	-0.0071	-0.0031	-0.0022	-0.0043	-0.0016	-0.0021	-0.0019	-0.0092**	-0.0077
	(0.0041)	(0.0080)	(0.0063)	(0.0044)	(0.0059)	(0.0079)	(0.0026)	(0.0083)	(0.0031)	(0.0031)	(0.0042)	(0.0062)
Constant	-0.010***	-0.035***	-0.023***	-0.008***	0.0104**	0.0211***	-0.010***	-0.037***	-0.031***	-0.013***	0.0081*	0.0185***
	(0.0035)	(0.0065)	(0.0053)	(0.0030)	(0.0051)	(0.0069)	(0.0035)	(0.0064)	(0.0039)	(0.0033)	(0.0042)	(0.0052)
R^2	0.115	0.168	0.112	0.058	0.103	0.126	0.195	0.183	0.158	0.111	0.142	0.141

	Commodity Futures Returns											
	Sugar						Cotton					
		Quantile						Quantile				
	OLS	5^{th}	10^{th}	50^{th}	90^{th}	95^{th}	OLS	5^{th}	10^{th}	50^{th}	90^{th}	95^{th}
ESV	0.0013	0.0053	0.0071***	**0.0007**	**-0.0027**	**-0.0030**						
	(0.0016)	(0.0040)	(0.0017)	(0.0014)	(0.0020)	(0.0027)						
ESV_f							0.1412***	0.1469***	0.1289***	**0.1352*** **	0.1229***	**0.1365*** **
							(0.0094)	(0.0211)	(0.0118)	(0.0071)	(0.0145)	(0.0240)
LTC_r	-0.160***	-0.107***	-0.123***	-0.187***	-0.130***	-0.147***	-0.0299*	-0.0088	-0.043***	-0.036***	-0.0101	0.0097
	(0.0176)	(0.0353)	(0.0235)	(0.0152)	(0.0186)	(0.0316)	(0.0171)	(0.0281)	(0.0158)	(0.0104)	(0.0209)	(0.0348)
STC	0.0007*	-0.0007	-0.0012**	0.0008*	0.0019***	0.0021**	0.0004**	0.0004	0.0003	0.0003**	0.0005	0.0003
	(0.0004)	(0.0013)	(0.0006)	(0.0005)	(0.0006)	(0.0010)	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0003)	(0.0005)
ML	0.0473*	-0.190***	-0.131***	0.0366	0.1553***	0.1585***	0.0106	-0.0892**	-0.072***	-0.0192	0.1027***	0.1219***
	(0.0243)	(0.0481)	(0.0363)	(0.0242)	(0.0293)	(0.0519)	(0.0165)	(0.0348)	(0.0221)	(0.0126)	(0.0306)	(0.0425)
OI_r	0.1813***	0.4110***	0.3337***	0.1644***	0.0459	0.0270	0.0628**	0.2362***	0.1331***	0.0321	-0.0078	0.0004
	(0.0434)	(0.0748)	(0.0533)	(0.0302)	(0.0374)	(0.0790)	(0.0288)	(0.0538)	(0.0313)	(0.0200)	(0.0433)	(0.0724)
SP500_r	0.0294	-0.0561	0.1212*	0.0926*	-0.0261	-0.0905	0.1816***	0.2109**	0.2261***	0.1328***	0.1485*	0.1532
	(0.0588)	(0.1234)	(0.0706)	(0.0493)	(0.0682)	(0.1219)	(0.0539)	(0.0905)	(0.0456)	(0.0384)	(0.0863)	(0.1296)
RIR_f	-0.0010	0.0056	-0.0001	-0.0021	0.0035	0.0000	0.0032	0.0121	0.0062*	-0.0087**	0.0067	0.0135
	(0.0068)	(0.0136)	(0.0062)	(0.0061)	(0.0086)	(0.0140)	(0.0055)	(0.0101)	(0.0033)	(0.0044)	(0.0088)	(0.0115)
TED_r	-0.0035	-0.0070	-0.0011	-0.0105	-0.0033	-0.0328	0.0008	-0.0152	-0.025***	0.0060	0.0114	0.0032
	(0.0099)	(0.0221)	(0.0133)	(0.0089)	(0.0098)	(0.0221)	(0.0089)	(0.0212)	(0.0065)	(0.0058)	(0.0136)	(0.0192)
TWI_r	-0.3928**	-0.2612	-0.1749	-0.2790**	-0.4580**	-0.5486*	-0.3183**	-0.3388	-0.2069	-0.1215	-0.3671*	-0.3144
	(0.1970)	(0.3464)	(0.1816)	(0.1338)	(0.1882)	(0.3067)	(0.1250)	(0.2541)	(0.1379)	(0.1005)	(0.2120)	(0.2591)
BDI_r	-0.049***	-0.1146**	-0.062***	-0.0213	-0.0755**	-0.0819**	0.0070	-0.0303	-0.0101	0.0007	0.0113	-0.0089
	(0.0187)	(0.0473)	(0.0179)	(0.0195)	(0.0303)	(0.0364)	(0.0154)	(0.0370)	(0.0217)	(0.0137)	(0.0260)	(0.0353)
DotCom	0.0035	-0.0111	-0.0129*	0.0046	0.0046	0.0067	0.0026	-0.0016	-0.0035	0.0022	0.0111**	0.0194**
	(0.0042)	(0.0072)	(0.0078)	(0.0034)	(0.0038)	(0.0120)	(0.0032)	(0.0093)	(0.0025)	(0.0026)	(0.0056)	(0.0098)
GFC	0.0013	-0.0293	-0.0190**	0.0042	0.0179*	0.0239***	0.0006	-0.026***	-0.0203**	0.0042	0.0159	0.0247***
	(0.0057)	(0.0205)	(0.0078)	(0.0064)	(0.0108)	(0.0088)	(0.0044)	(0.0070)	(0.0084)	(0.0047)	(0.0098)	(0.0083)
EDC	-0.0061	-0.0193	-0.023***	-0.0052	0.0130	0.0154***	-0.0000	-0.0261*	-0.026***	0.0022	0.0244**	0.0533***
	(0.0043)	(0.0120)	(0.0043)	(0.0040)	(0.0105)	(0.0058)	(0.0048)	(0.0133)	(0.0040)	(0.0037)	(0.0118)	(0.0103)
Constant	-0.015***	-0.036***	-0.025***	-0.014***	0.0082	0.0217**	-0.0076**	-0.042***	-0.028***	-0.0018	0.0123**	0.0258***
	(0.0046)	(0.0121)	(0.0066)	(0.0040)	(0.0052)	(0.0089)	(0.0036)	(0.0089)	(0.0042)	(0.0026)	(0.0054)	(0.0090)
R^2	0.118	0.111	0.101	0.093	0.131	0.129	0.245	0.192	0.201	0.181	0.140	0.139

Table 4.4 cont.

	Commodity Futures Returns											
	Gold						Silver					
		Quantile						Quantile				
	OLS	5th	10th	50th	90th	95th	OLS	5th	10th	50th	90th	95th
ESV	0.0006	0.0045***	0.0026***	**0.0004**	**0.0012**	0.0004	0.0127***	0.0245***	0.0128**	0.0083**	0.0176***	0.0254***
	(0.0007)	(0.0008)	(0.0008)	(0.0006)	(0.0010)	(0.0013)	(0.0030)	(0.0050)	(0.0051)	(0.0032)	(0.0052)	(0.0043)
LTC_r	-0.057***	-0.041***	-0.048***	-0.051***	-0.053***	-0.058***	-0.0251	-0.0083	-0.0115	-0.0150	-0.0195	-0.0096
	(0.0085)	(0.0083)	(0.0079)	(0.0056)	(0.0055)	(0.0113)	(0.0210)	(0.0266)	(0.0264)	(0.0135)	(0.0205)	(0.0223)
STC	0.0001	-0.0006**	-0.0000	0.0003	0.0001	0.0004	-0.0010***	-0.0016**	-0.0008	-0.0003	-0.001***	-0.001***
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0003)	(0.0007)	(0.0006)	(0.0004)	(0.0003)	(0.0004)
ML	0.0005	-0.039***	-0.036***	-0.0002	0.0328***	0.0360***	0.0005	-0.071***	-0.0359**	-0.0028	0.0522***	0.0627***
	(0.0066)	(0.0093)	(0.0071)	(0.0047)	(0.0073)	(0.0087)	(0.0075)	(0.0191)	(0.0166)	(0.0064)	(0.0105)	(0.0151)
OI_r	0.1277***	0.1497***	0.1466***	0.1059***	0.0859***	0.0999***	0.1856***	0.3506***	0.2137***	0.1133***	0.1292***	0.0766***
	(0.0138)	(0.0163)	(0.0140)	(0.0097)	(0.0154)	(0.0216)	(0.0324)	(0.0415)	(0.0426)	(0.0228)	(0.0352)	(0.0259)
SP500_r	-0.0233	0.0422**	0.0471	0.0112	-0.0258	-0.0935**	0.1542***	0.1988**	0.1820**	0.1053***	0.1722***	0.1428***
	(0.0260)	(0.0201)	(0.0316)	(0.0221)	(0.0368)	(0.0452)	(0.0450)	(0.0772)	(0.0713)	(0.0407)	(0.0588)	(0.0551)
RIR_f	-0.0043	-0.0031	-0.0076*	-0.007***	-0.0041	-0.0078	-0.0071	-0.0126	-0.0190*	-0.016***	0.0034	0.0037
	(0.0038)	(0.0031)	(0.0043)	(0.0023)	(0.0035)	(0.0056)	(0.0059)	(0.0114)	(0.0109)	(0.0047)	(0.0070)	(0.0070)
TED_r	0.0136***	0.0167***	0.0130***	0.0089***	0.0126**	0.0096	0.0075	-0.0255**	-0.0065	0.0111*	0.0087	0.0139**
	(0.0039)	(0.0044)	(0.0048)	(0.0025)	(0.0056)	(0.0076)	(0.0079)	(0.0124)	(0.0141)	(0.0063)	(0.0086)	(0.0068)
TWI_r	-1.008***	-1.030***	-0.935***	-0.944***	-0.898***	-0.931***	-1.7502***	-1.582***	-1.495***	-1.727***	-1.404***	-1.473***
	(0.0769)	(0.0500)	(0.0906)	(0.0559)	(0.0860)	(0.1108)	(0.1420)	(0.1763)	(0.1725)	(0.1063)	(0.1624)	(0.1665)
BDI_r	-0.0069	-0.0016	-0.0083	-0.0142*	0.0053	-0.0116	0.0096	0.0285	0.0241	-0.0008	0.0273	0.0368
	(0.0090)	(0.0113)	(0.0118)	(0.0085)	(0.0133)	(0.0161)	(0.0156)	(0.0314)	(0.0174)	(0.0142)	(0.0214)	(0.0296)
DotCom	0.0011	0.0036*	0.0037**	-0.0003	0.0007	0.0003	0.0036	0.0074	0.0047	0.0020	-0.0018	-0.0037
	(0.0014)	(0.0018)	(0.0016)	(0.0013)	(0.0022)	(0.0025)	(0.0025)	(0.0054)	(0.0048)	(0.0026)	(0.0038)	(0.0034)
GFC	-0.0002	-0.014***	-0.0051	-0.0041	0.0074	0.0083	0.0034	-0.0053	-0.0052	-0.0013	0.0088	0.0162
	(0.0029)	(0.0029)	(0.0041)	(0.0025)	(0.0056)	(0.0102)	(0.0046)	(0.0068)	(0.0072)	(0.0049)	(0.0071)	(0.0161)
EDC	-0.0007	-0.0031	0.0007	-0.0022	-0.0022	-0.0047	0.0035	0.0075	-0.0009	0.0070**	-0.013***	-0.0057
	(0.0020)	(0.0034)	(0.0037)	(0.0023)	(0.0027)	(0.0032)	(0.0035)	(0.0071)	(0.0049)	(0.0032)	(0.0045)	(0.0081)
Constant	-0.0019	-0.015***	-0.015***	-0.0025	0.0090***	0.0119***	-0.0001	-0.040***	-0.030***	-0.0016	0.0273***	0.0313***
	(0.0020)	(0.0024)	(0.0025)	(0.0017)	(0.0025)	(0.0037)	(0.0033)	(0.0075)	(0.0064)	(0.0035)	(0.0041)	(0.0045)
R^2	0.351	0.259	0.230	0.211	0.224	0.252	0.272	0.247	0.195	0.134	0.197	0.218

	Commodity Futures Returns											
	Copper						Platinum					
		Quantile						Quantile				
	OLS	5th	10th	50th	90th	95th	OLS	5th	10th	50th	90th	95th
ESV	0.0078***	**0.0135****	**0.0053**	**0.0050**	0.0116***	0.0118**						
	(0.0029)	(0.0058)	(0.0045)	(0.0034)	(0.0033)	(0.0048)						
ESV_f							0.3024***	0.2550***	0.2717***	0.2849***	0.3063***	0.3144***
							(0.0197)	(0.0355)	(0.0302)	(0.0156)	(0.0358)	(0.0234)
LTC_r	-0.039***	-0.0286*	-0.0167	-0.036***	-0.055***	-0.074***	-0.0053	-0.0115	-0.0035	-0.0027	-0.0048	0.0022
	(0.0110)	(0.0152)	(0.0115)	(0.0085)	(0.0090)	(0.0186)	(0.0080)	(0.0141)	(0.0092)	(0.0055)	(0.0111)	(0.0162)
STC	0.0005**	0.0012***	0.0009***	0.0006**	0.0002	0.0001	0.0001	0.0001	0.0002	0.0000	-0.0001	-0.0002
	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0004)	(0.0004)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0002)	(0.0002)
ML	0.0026	-0.031***	-0.036***	0.0040	0.0192***	0.0110	-0.0095	-0.063***	-0.052***	-0.0055	0.0379**	0.0667***
	(0.0080)	(0.0118)	(0.0138)	(0.0089)	(0.0067)	(0.0116)	(0.0081)	(0.0183)	(0.0139)	(0.0067)	(0.0157)	(0.0245)
OI_r	0.0656***	0.1272***	0.0787***	0.0899***	0.0455**	-0.0023	0.0858***	0.1317***	0.0999***	0.0711***	0.0379*	0.0369*
	(0.0226)	(0.0323)	(0.0184)	(0.0177)	(0.0213)	(0.0319)	(0.0146)	(0.0233)	(0.0162)	(0.0107)	(0.0210)	(0.0204)
SP500_r	0.3157***	0.3007***	0.2916***	0.2352***	0.2858***	0.3399***	0.1135***	0.1979***	0.1128***	0.1000***	0.1782***	0.1374**
	(0.0515)	(0.0800)	(0.0432)	(0.0345)	(0.0482)	(0.0985)	(0.0349)	(0.0765)	(0.0413)	(0.0310)	(0.0521)	(0.0633)
RIR_f	0.0047	-0.0108	-0.0097**	0.0014	0.0194***	0.0121	-0.0033	0.0051	-0.0033	-0.0048	0.0040	0.0009
	(0.0054)	(0.0123)	(0.0044)	(0.0039)	(0.0070)	(0.0123)	(0.0053)	(0.0074)	(0.0057)	(0.0033)	(0.0056)	(0.0079)
TED_r	0.0025	0.0256*	0.0080	-0.0015	0.0012	0.0068	0.0002	-0.0128	-0.0099	0.0022	-0.0090	-0.0066
	(0.0068)	(0.0133)	(0.0070)	(0.0061)	(0.0081)	(0.0133)	(0.0084)	(0.0115)	(0.0061)	(0.0049)	(0.0081)	(0.0129)
TWI_r	-0.898***	-0.586***	-0.734***	-0.926***	-0.797***	-0.904***	-0.930***	-1.130***	-0.929***	-0.698***	-0.932***	-0.912***
	(0.1129)	(0.2187)	(0.1011)	(0.1024)	(0.1307)	(0.1899)	(0.1002)	(0.1599)	(0.1048)	(0.0691)	(0.1214)	(0.1787)
BDI_r	0.0364**	0.0531*	0.0479***	0.0236*	0.0192	-0.0143	0.0268	0.0278	0.0243	-0.0010	0.0242	0.0075
	(0.0144)	(0.0296)	(0.0176)	(0.0135)	(0.0190)	(0.0264)	(0.0164)	(0.0224)	(0.0155)	(0.0073)	(0.0151)	(0.0206)
DotCom	-0.0015	0.0058	0.0033	-0.0056**	-0.009***	-0.0162*	0.0026	-0.0107	-0.0074	0.0031	0.0141***	0.0194**
	(0.0025)	(0.0044)	(0.0030)	(0.0025)	(0.0031)	(0.0084)	(0.0027)	(0.0114)	(0.0049)	(0.0028)	(0.0050)	(0.0087)
GFC	0.0037	-0.0118	-0.0057	-0.0013	0.0153	0.0239	-0.0015	-0.046***	-0.0273**	0.0008	0.0246***	0.0361***
	(0.0045)	(0.0268)	(0.0101)	(0.0043)	(0.0094)	(0.0147)	(0.0049)	(0.0095)	(0.0138)	(0.0035)	(0.0062)	(0.0075)
EDC	-0.0013	0.0064	0.0077***	-0.0002	-0.008***	-0.0079	-0.0013	-0.0016	-0.0032	-0.0015	0.0027	0.0042
	(0.0027)	(0.0044)	(0.0028)	(0.0025)	(0.0029)	(0.0072)	(0.0020)	(0.0041)	(0.0029)	(0.0018)	(0.0037)	(0.0054)
Constant	-0.0047**	-0.054***	-0.036***	-0.0040	0.0307***	0.0461***	0.0010	-0.023***	-0.017***	0.0010	0.0195***	0.0227***
	(0.0024)	(0.0055)	(0.0036)	(0.0027)	(0.0035)	(0.0051)	(0.0016)	(0.0037)	(0.0027)	(0.0014)	(0.0032)	(0.0038)
R^2	0.196	0.173	0.146	0.104	0.119	0.116	0.347	0.329	0.287	0.215	0.207	0.220

Table 4.4 cont.

	Commodity Futures Returns											
	Natural Gas						Crude Oil					
		Quantile						Quantile				
	OLS	5th	10th	50th	90th	95th	OLS	5th	10th	50th	90th	95th
ESV_f	0.1222***	0.0905***	0.0996***	0.1348***	0.1222***	0.1387***	0.0607***	**0.0644*****	0.0721***	0.0590***	0.0586***	**0.0563*****
	(0.0116)	(0.0170)	(0.0128)	(0.0090)	(0.0151)	(0.0280)	(0.0045)	(0.0081)	(0.0075)	(0.0039)	(0.0045)	(0.0074)
LTC_r	0.0089	0.0477	0.0299	0.0032	0.0406	0.1070	0.0171	-0.0440	-0.0022	0.0366***	<u>0.0748***</u>	0.0474*
	(0.0246)	(0.0523)	(0.0437)	(0.0263)	(0.0284)	(0.0718)	(0.0197)	(0.0317)	(0.0291)	(0.0139)	(0.0203)	(0.0283)
STC	-0.0001	-0.0001	-0.0006*	0.0001	0.0005	-0.0001						
	(0.0002)	(0.0005)	(0.0003)	(0.0002)	(0.0004)	(0.0006)						
STC_r							-0.0349*	-0.0178	-0.0415	-0.046***	-0.062***	-0.068***
							(0.0181)	(0.0291)	(0.0272)	(0.0138)	(0.0174)	(0.0252)
ML	0.0570**	-0.0573	-0.0230	0.0163	0.1814***	0.1783***	-0.0108	-0.110***	-0.079***	-0.0116	0.0475***	0.0664***
	(0.0264)	(0.0501)	(0.0313)	(0.0212)	(0.0349)	(0.0592)	(0.0125)	(0.0225)	(0.0213)	(0.0078)	(0.0098)	(0.0208)
OI_r	0.1247**	0.0660	0.1085	0.1404***	-0.1278*	-0.0771	0.1417***	0.2797***	0.2032***	0.1510***	0.0525	-0.0280
	(0.0610)	(0.1311)	(0.0862)	(0.0494)	(0.0750)	(0.1601)	(0.0455)	(0.0585)	(0.0718)	(0.0343)	(0.0490)	(0.0745)
SP500_r	0.2178***	-0.2294	-0.0456	0.1846**	0.5254***	0.2554*	0.2691***	0.3672***	0.2911***	0.2079***	0.1524**	0.2197**
	(0.0824)	(0.1846)	(0.0962)	(0.0840)	(0.1518)	(0.1495)	(0.0732)	(0.1218)	(0.1016)	(0.0552)	(0.0622)	(0.1062)
RIR_f	-0.0027	0.0003	-0.0103	-0.0062	-0.0102	-0.0102	0.0029	0.0049	-0.0066	-0.0085	0.0243***	0.0296**
	(0.0111)	(0.0214)	(0.0161)	(0.0088)	(0.0154)	(0.0249)	(0.0063)	(0.0100)	(0.0129)	(0.0056)	(0.0062)	(0.0142)
TED_r	0.0165	0.0256	0.0080	0.0134	0.0065	0.0237	0.0145	-0.0084	0.0189	0.0105	0.0051	0.0123
	(0.0162)	(0.0303)	(0.0199)	(0.0132)	(0.0207)	(0.0393)	(0.0109)	(0.0206)	(0.0178)	(0.0076)	(0.0115)	(0.0138)
TWI_r	-0.571***	-0.7178*	-0.942***	-0.3491*	-0.7685**	-0.9596**	-0.859***	-0.8009**	-0.807***	-0.755***	-0.786***	-0.843***
	(0.2098)	(0.3901)	(0.2572)	(0.1844)	(0.3279)	(0.4217)	(0.1551)	(0.3183)	(0.2494)	(0.1266)	(0.1198)	(0.2565)
BDI_r	0.0538**	0.0158	-0.0061	0.0260	0.0304	0.0766	0.0432**	0.0891***	0.0518**	0.0183	0.0131	0.0646*
	(0.0262)	(0.0516)	(0.0273)	(0.0261)	(0.0398)	(0.0597)	(0.0207)	(0.0306)	(0.0258)	(0.0177)	(0.0173)	(0.0345)
DotCom	0.0077	-0.0383**	-0.0315**	0.0051	0.0304**	0.0263	0.0027	-0.0290	-0.0005	0.0011	0.0156***	0.0202***
	(0.0068)	(0.0189)	(0.0139)	(0.0092)	(0.0133)	(0.0173)	(0.0045)	(0.0204)	(0.0142)	(0.0048)	(0.0059)	(0.0062)
GFC	0.0017	-0.0148	-0.027***	-0.0011	0.0150*	0.0042	0.0015	-0.0048	-0.0147*	0.0001	0.0078	0.0062
	(0.0081)	(0.0094)	(0.0097)	(0.0092)	(0.0085)	(0.0105)	(0.0062)	(0.0132)	(0.0082)	(0.0057)	(0.0055)	(0.0139)
EDC	-0.0070	0.0323***	0.0159***	-0.0048	-0.030***	-0.0291	0.0017	0.0369***	0.0271***	0.0045*	-0.023***	-0.023***
	(0.0054)	(0.0083)	(0.0052)	(0.0045)	(0.0079)	(0.0178)	(0.0034)	(0.0054)	(0.0057)	(0.0023)	(0.0028)	(0.0050)
Constant	-0.0113*	-0.089***	-0.059***	-0.0040	0.0215*	0.0680***	0.0031	-0.036***	-0.026***	0.0032	0.0358***	0.0412***
	(0.0067)	(0.0162)	(0.0105)	(0.0056)	(0.0115)	(0.0183)	(0.0039)	(0.0065)	(0.0065)	(0.0025)	(0.0039)	(0.0068)
R^2	0.135	0.076	0.074	0.089	0.113	0.101	0.262	0.178	0.166	0.176	0.162	0.165

<u>Notes</u>: This table illustrates the detailed results of the OLS and quantile regression with robust standard errors (Huber/White/sandwich estimator) for commodity futures returns between 3rd January 1995 and 7th March 2017 with 1,157 to 1,159 observations, depending on the commodity. With OLS regression models and quantile regression for lower quantiles (5th and 10th), median (50th), and upper quantiles (90th and 95th). For the OLS regression, the R^2 represents the adjusted R^2. For quantile regression, I calculate the pseudo R^2 as $R^2 = 1 -$ (sum of weighted deviations about estimated quantile / sum of weighted deviations about raw quantile) as suggested by Koenker and Machado (1999). With _f and _r indicating first difference and log returns respectively. With ESV, LTC, and STC as focus variables, OI as total open interest, ML as market liquidity, SP500 as Standard & Poor's 500 composite index, RIR as real interest rate, TED as TED spread, TWI as trade-weighted USD index, BDI as Baltic Dry Index, and DotCom, GFC, and EDC as dummies for crisis periods throughout the research period. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Following Clogg et al. (1995), I use a Z-test to check if the regression coefficients of the OLS model (1) and the quantile regressions for each ESV, LTC, and STC are significantly different. With a Z-value of ≥1.64 corresponding with the significance level of 5 percent or lower. The formula can be written as: $Z = (\beta_1 - \beta_2) / [(SE\beta_1)^2+(SE\beta_2)^2]^{1/2}$, with β as coefficients and SEβ as standard error of β. <u>Underlined</u> QR coefficients represent significantly (5%) different coefficients compared to the OLS model. **Bold** QR coefficients indicate significant coefficients based on a simple lagged QR model, which indicate Granger causality.

<u>The models are defined as:</u>

OLS: $CFR_t = \alpha + \mu SPEC_t + \delta F_t + \varepsilon_{it}$

QR: $CFR_i = \pi + \gamma_\tau SF'_i + u_{\tau_i} \quad Quant_\tau(CFR_i|SF_i) = \gamma_\tau SF'_i$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, DotCom as a dummy variable for the dot-com bubble between the years 2000 and 2002, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012, SF' = [SPEC, F] is the vector of regressors, and u is the error term traditionally associated with quantile estimation. and ε as error term of the OLS at time t. For a τ-th quantile (0 < τ < 1) of CFR.

4.4.2 The Causality between Returns, Speculation, and Trader Concentration

Mean Granger Causality

So far, I show that speculation, proxied by ESV, and returns have a stabilising relationship for the panel of ten commodities and mostly reinforcing relationships when examined for each commodity individually. Independent variables in a linear regression model estimate the relationship with the dependent variable and show how a dependent variable reacts to changes in the predictors. Much like correlation, linear regression (usually) only reveals the interaction between variables but provides little explanation on their causation, i.e. whether a variable is useful to forecast another variable. In some cases, the causal relationship is clear. For example, prior studies (e.g. Roll, 1984) show the significant impact of weather events on the price of frozen orange juice concentrate. Here, the causality is obvious, i.e. weather events drive the price of frozen orange juice concentrate. It is, of course, highly unlikely that changes in frozen orange juice concentrate prices have any influence on the weather. Other relationships, however, are less obvious. This includes the variables of interest in this study. While Huchet and Fam (2016) argue that speculation is driving agricultural commodity prices, Tang and Xiong (2012) warn that non-commercial traders simply hold information about future changes in demand and supply and thus predict the price changes, leading to reverse causality. Likewise, most prior literature argues that non-commercial trader positions do not Granger-cause prices (Brunetti and Buyuksahin, 2009; Stoll and Whaley, 2010; Buyuksahin and Harris, 2011), index trader positions generally cannot predict agricultural futures returns (Hamilton and Wu, 2015), and long-short speculators do not Granger-cause commodity futures returns volatility (Miffre and Brooks, 2013). Instead, price changes drive speculation (Alquist and Gervais, 2013; Andreasson et al., 2016). However, less attention has been devoted to metals and their causal relationship with speculation and other measures than to the Working T-index and the causal relationship between speculation and returns at the extremes.

The obtained coefficients reported in Table 4.5 suggest that speculation does not Granger-cause returns. While the first column indicates the value for y, i.e. the dependent variable, the first row indicates the value for x, i.e. the independent variable that potentially Granger-causes y for each pairwise test. For example, with a Z-value of -0.2018 (all commodities, 1995 to 2017), the null hypothesis that ESV does not Granger-cause commodity futures returns cannot be rejected. Thus, one must accept H_0, i.e. ESV does not Granger-cause commodity futures returns.

Table 4.5: Panel Granger Causality

All Commodities – 1995 to 2017				
y / x	CFR	ESV	LTC	STC
CFR	-	-0.2018	-0.8590	0.7431
ESV	18.4989***	-	11.0547***	6.2852***
LTC	11.9983***	17.2145***	-	12.9397***
STC	16.4028***	29.4499***	15.8522***	-

All Commodities – 2003 to 2017				
y / x	CFR	ESV	LTC	STC
CFR	-	-0.4110	0.3393	1.4920
ESV	13.7810***	-	4.5446***	2.6429***
LTC	10.4968***	11.4402***	-	9.2934***
STC	11.7103***	21.5351***	10.1976***	-

All Commodities – 2003 to June 2008				
y / x	CFR	ESV	LTC	STC
CFR	-	-1.1777	-0.5052	0.6401
ESV	2.6192***	-	4.1990***	3.3588***
LTC	1.2066	5.0979***	-	5.8536***
STC	2.0684**	11.7076***	7.1991***	-

All Commodities – July 2008 to 2011				
y / x	CFR	ESV_f	LTC	STC
CFR	-	1.4416	1.0020	3.3990***
ESV_f	0.3146	-	-1.4209	0.5003
LTC	4.6954***	5.1751***	-	7.1350***
STC	4.8475***	10.0148***	3.5717***	-

Agriculture – 1995 to 2017				
y / x	CFR	ESV	LTC	STC
CFR	-	-1.1327	1.6849*	-1.0368
ESV	13.8964***	-	10.1175***	6.5143***
LTC	8.1725***	12.3731***	-	12.6037***
STC	10.0411***	11.2170***	20.1777***	-

Metals – 1995 to 2017				
y / x	CFR	ESV	LTC	STC
CFR	-	0.5864	1.1721	1.6991*
ESV	8.2912***	-	5.8146***	-0.5741
LTC	5.0338***	10.2448***	-	5.2752***
STC	10.2495***	28.7414***	1.4866	-

Energy – 1995 to 2017				
y / x	CFR	ESV_f	LTC	STC
CFR	-	-0.2758	-0.2890	0.7249
ESV_f	13.0018***	-	-0.2526	4.5421***
LTC	6.6294***	4.7294***	-	5.2774***
STC	9.8134***	10.1323***	11.5208***	-

Notes: This table illustrates the Z-statistics of the pairwise Granger non-causality test for panel data. With the first column indicating y, i.e. the dependent variable, and the first row indicating x, i.e. the independent variable that potentially Granger-causes y for each pairwise test. AIC and BIC are used to determine the appropriate lag length for each pair. Reported figures represent the coefficients based on AIC. The research period runs between 3rd January 1995 and early March 2017 totalling 1,156 observations for each commodity (10 commodities, 11,560 observations in total). With _f and _r indicating first difference and log returns respectively. With ESV, LTC, and STC as variables of interest. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.
For example, with a Z-value of -0.2018 (all commodities, entire research period), the null hypothesis that ESV does not Granger-cause commodity futures returns cannot be rejected. Thus, one must accept H_0, i.e. ESV does not Granger-cause Commodity futures returns.

In fact, I cannot find any evidence of Granger causality from speculation to returns for either the full research period from 1995 to 7th March 2017, or for the sub-periods that include the financialization period from 2002 onwards including the GFC and EDC. Moreover, all commodity-class sub-samples indicate comparable non-significant coefficients, i.e. cannot confirm any Granger causality from speculation to returns. Instead, the coefficients indicate highly significant, i.e. at the 1 percent level, Granger casualty from returns to speculation. These findings confirm prior research for Granger causality from speculation to prices and returns for agricultural and energy commodities (Brunetti and Buyuksahin, 2009; Buyuksahin and Harris, 2011; Alquist and Gervais, 2013; Andreasson et al., 2016).

Furthermore, I extend prior research and provide evidence in favour of Granger causality from metal returns to speculation and show that both trader concentration measures LTC and STC are significantly Granger-caused by returns. Thus, returns not only cause changes in speculative open interest but also lead to changes in trader concentration. Moreover, the findings suggest little significant evidence for bidirectional Granger causality.

In fact, almost none of the variables of interest seem to Granger-cause returns. Only during the aftermath of the GFC to the end of 2011, one can observe bidirectional Granger causality between returns and STC.

Table 4.6: Commodity-Individual Granger Causality

	Lags	ESV	LTC	STC
Corn	1	No / Yes***	No / Yes**	No / No
Soybeans	1	No / Yes***	Yes* / No	No / No
Sugar	1	No / Yes***	Yes* / Yes***	No / No
Cotton	1	No / Yes***	Yes* / Yes**	No / No
Gold	2	No / Yes***	No / Yes*	No / No
Silver	2	No / Yes***	No / No	Yes* / No
Copper	2	No / Yes***	Yes*** / Yes**	Yes* / No
Platinum	2	No / Yes***	Yes* / No	Yes** / No
Natural Gas	4	No / Yes***	No / No	No / Yes***
Crude Oil	4	No / Yes***	No / No	No / Yes**

Notes: This table illustrates the results of the Granger causality test for the individual commodities between 3rd January 1995 and 7th March 2017. With the **first** "Yes" and "No" as the answer to "Do ESV, LTC, or STC, Granger-cause commodity futures returns?" and the **second** "Yes" and "No" as the answer to "Do commodity futures returns Granger-cause ESV, LTC, or STC?" * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

Following the approach in the panel analysis, I use Granger causality tests to identify the lead/lag relationship between individual commodity futures returns and the main explanatory variables. Table 4.6 presents the findings of the Granger causality test for the individual commodities between 3rd January 1995 and 7th March 2017. While the first "Yes" or "No" in column 3 of the table answers the question "Do ESV, LTC, or STC, Granger-cause commodity futures returns?", the second "Yes" or "No" that follows the slash in the same column answers the question "Do commodity futures returns Granger-cause ESV, LTC, or STC?" For example, one can see that the Granger causality tests at lag 1 for corn suggest that ESV is not Granger-causing corn futures returns. Instead, corn futures returns Granger-cause ESV with a statistical significance that holds at the 1 percent level. In line with the panel Granger causality reported in Table 4.5, the results summarised in Table 4.6 indicate that ESV does not Granger-cause the returns of any of the ten commodities analysed. Instead, the Granger causality tests uniformly suggest that returns Granger-cause ESV at a significance level of 1 percent. The relationship between trader concentration and returns is less clear. While the results for bidirectional Granger causality of returns and LTC for soybeans, gold, silver, platinum, natural gas, and crude oil are non-significant, the test results for other commodities suggest reverse Granger causality, i.e. from LTC to returns (corn, sugar, cotton). Only for copper, I find significant, i.e. at the 5 percent significance level, bi-directional Granger causality between returns and LTC. STC results, on the other side, mostly suggest no Granger causality, with platinum being the only commodity that indicates Granger causality from STC to returns. For natural gas and crude oil, I find the opposite, i.e. significant Granger causality from returns to STC, which suggests that returns significantly Granger-cause short trader concentration.

Overall, I find little evidence that changes in open interest, whether it is commercial or non-commercial, significantly Granger-cause returns. In fact, the results suggest the opposite: returns lead to changes in open interest. Put simply, traders use information about price changes to adjust their positions[86]. In other words, changes in future economic outlook trigger changes in the supply-demand equilibrium. This leads to an adjustment of the fair value of the underlying price. Following the change in the underlying price, market participants adjust their exposure accordingly, which leads to a change in open interest. In the end, the answer to the question of whether non-commercial open interest improves the estimation of commodity futures returns is yes. However, the findings also reveal that non-commercial open interest does not Granger-cause returns.[87]

Quantile Regression Granger Causality

To reveal the lead/lag relationship between two variables, Granger causality uses lagged values of the dependent and independent variables to determine the forecasting power of the latter on the former, which is usually accomplished with some sort of mean regression. However, as indicated by the quantile regression outcomes, the relationship between returns and ESV may not be as linear as the mean model assumes. In the spirit of Granger causality, I adopt a model that switches the ESV_i with a lagged version of such, i.e. at time $t-1$, and further add a lagged version of the dependent variable CFR_i at time $t-1$.[88] The model for the τ-th quantile ($0 < \tau < 1$) can be written as:

[86] This reinforces Soros' (2008) claim that trend chasers and uninformed traders enter markets following positive returns. I further test this claim in the following sections that are concerned with the signalling effect.
[87] It must be highlighted that, while the presented results provide evidence in favour of Granger causality from returns to speculation, bidirectional Granger causality cannot be fully ruled out. Bidirectional Granger causality may not happen at the same frequency, i.e. while the effects from speculation to returns might happen quite fast, the reverse effects take longer time and are thus the only causality measurable at weekly frequency. To truly analyse their bidirectional relationship, data at higher frequency is necessary.
[88] Reboredo and Ugolini (2017) use a comparable approach to determine the causal link between gold stock prices and gold prices. While the researchers find that gold prices significantly Granger-cause Australian gold mining stocks, the causal relationship of gold prices with European, Middle Eastern, and African mining stocks is non-significant. However, the researchers attribute little attention to the potential bias stemming from gold price hedging, which is common among gold miners. Thus, the inability to establish a Granger-causal link between gold and gold miner prices might thus be simply based on an efficient price hedging approach of the companies evaluated. Splitting the observed mining stocks into hedgers and non-hedgers might help to mitigate this bias.

$$CFR_i = \pi + \alpha_\tau CFR_{i,t-1} + \beta_\tau ESV_{i,t-1} + \gamma_\tau SFE'_i + u_{\tau_i} \tag{4.24}$$

$$ESV_i = \pi + \alpha_\tau ESV_{i,t-1} + \beta_\tau CFR_{i,t-1} + \gamma_\tau SFE'_i + u_{\tau_i} \tag{4.25}$$

with CFR_i as commodity futures returns, SFE'_i as the vector of regressors consisting of LTC_i, STC_i, and all fundamental explanatory variables and dummies as in equation (4.11). The equation is then complemented by Wald tests for all lagged ESV_i, which is in this case ESV_i at time $t-1$. Bold figures in Table 4.4 indicate the quantiles with a significant lagged impact from ESV to returns. Like the individual commodity mean Granger causality tests, I find little evidence of Granger causality from ESV to returns. However, for a few commodities I find significant Granger causality from ESV to returns for some quantiles. Specifically, for corn and copper, the results suggest a significant (5 percent) lagged impact on the left tail of the return distribution. While for sugar, cotton, and gold, I find similarly significant effects on the right tail of the return distribution and for crude oil, a positive lagged impact can be found for both extremes, i.e. the 5th and 95th quantile of the returns. For all other commodities, the coefficients remain non-significant. Evaluating the opposite direction, i.e. the lagged impact from returns to ESV, I find consistent significance for most commodities, which suggest that the lagged impact from returns to ESV is stronger than the lagged impact from ESV to returns. Nevertheless, these findings also reveal that Granger causality, i.e. the lead/lag relationship between variables, may not be as constant as other approaches assume. Instead, it seems that the relationship between the returns and speculation is quantile-dependent and may change based on the conditional distribution of returns. This observation may have significant implications for the estimation of the returns. While speculation does not impact the returns on average, the returns of some commodities significantly respond to changes in speculation, depending upon the direction of the returns. For example, while crude oil returns are on average not driven by speculation, extreme returns, i.e. at the 5th and 95th quantile, are driven by speculation.

4.4.3 ROBUSTNESS EXERCISE FOR THE FINANCIAL EFFECT

The Financial Effect of Disaggregated Open Interest

With the beginning of June 2006, the CFTC started to publish a disaggregated COT report that distinguishes between several types of traders, i.e. merchants, swap dealers, and managed money[89]. While the separation used for the analysis so far only differentiates between commercial and non-commercial open interest, i.e. hedgers or speculators, the disaggregated COT report allows further differentiation between commercial open interest comprised mostly of merchant and swap dealer open interest. Whereas merchants are hedgers that use the futures market to mitigate their price risk for a product they are producing, selling, or using, swap dealers use the futures market to hedge their price risk stemming from swap contracts. Often, swap dealers are commercial or investment banks or insurance companies, as these institutions typically have sufficient funds to ensure their creditworthiness and mitigate the potential credit risk for the counterparty (CFTC, 2008b). For example, the counterpart of the swap dealer might be a pension fund or other long-term oriented investor but can also include speculative traders (CFTC, 2018) that prefer to mitigate their price risk exposure by using swap contracts instead of getting directly involved in futures investing, which might be due to costs, experience, risk exposure, or the effort to roll over the standardised futures contracts. Moreover, the counterparty can be an issuer of ETF's, which does not use physical commodities or futures contracts to back its exposure but synthetically tracks the performance of an underlying commodity index by engaging in swaps[90]. These ETF's are then used to invest in commodities without any interest in consuming or producing the goods, i.e. speculation. While the swap dealers themselves hedge their price risk, their counterparties might, in fact, be speculative traders. As swap dealers usually mitigate their price risk by entering futures contracts, their involvement in the futures market is a direct proxy for both hedging and speculative demand. For example, while airlines may use swaps to mitigate price risk related to their jet fuel demand, which marks this trade as hedging, financial speculators may enter swaps to speculate. As both swap contracts may be handled by the same swap dealer, the disaggregated COT report enables separation of the commercial open interest into two categories: (a) traditional hedgers' open interest, stemming from producers, consumers, users, or merchants of the underlying commodity and (b) swap dealers, that might engage in commodity futures due to their commercial and non-commercial swap contract counterparts.

[89] I neglect the fourth and fifth group reported in the disaggregated COT report, the other reportables and the non-reportables, for this exercise.

[90] For example, the iShares Diversified Commodity Swap UCITS ETF, which holds net assets of more than 1.3 bn USD, uses unfunded total return swaps (iShares, 2018).

The focus of prior research has been on managed money, which typically includes institutional investors. Irwin and Sanders (2012) claim that passive index investment does not lead to commodity price bubbles but may even be beneficial for the market, while Bosch and Pradkhan (2015) find little evidence for a short-term impact of managed money on precious metal returns. Likewise, Miffre and Brooks (2013) find no support for a destabilising effect of speculation, measured by managed money open interest, on commodity prices. The results reported here partially contradict these studies. The findings in the first results column of Table 4.7 indicate a significant relationship between the two variables long managed money open interest (MM_long), short managed money open interest (MM_short) and returns. Long managed money open interest reinforces returns. The coefficient of 0.004 suggests that for each 100,000 long contracts of open interest by traders allocated to the managed money group, returns increase by 0.004 percent. In contrast, short managed money open interest reduces returns. The coefficient of -0.0034 suggests that for each 100,000 short contracts by traders allocated to the managed money group, returns decrease by 0.0034 percent. This indicates that managed money open interest has a slightly stronger increasing effect for the same number of contracts in open interest compared to the decreasing effect that is associated with decreasing open interest. The impact of the consolidated managed money net positions (MM_net), i.e. long minus short open interest, on returns is non-significant. Moreover, while I do not find a significant impact of long swap dealer open interest (Swap_long) on returns, changes in short positions (Swap_short) significantly increase returns. More precisely, if short swap dealer open interest increases by 1 percent, one can see an increase of 0.0134 percent in returns. The significance remains when I evaluate the impact of net swap dealer open interest (Swap_net), where one can observe a negative impact of net swap open interest on returns. Likewise, the impact on returns of long merchants' open interest (Merch_long), which usually represents the consumer-side, is non-significant. However, much like swap dealer open interest, changes in short positions (Merch_short), i.e. producers, significantly increase returns. For each 1 percent increase in merchants' short open interest, returns increase by 0.2 percent. Shifting to net positions (Merch_net), the impact remains significant but switches to a negative impact in the mean model. These results suggest that changes in merchants' open interest, i.e. open interest by traders that are primarily interested in either selling their produced commodities or consuming those commodities, have a stronger effect on returns that the open interest stemming from managed money.

Table 4.7: Disaggregated Data

		Commodity Futures Returns						
		Quantile						
LONG	PD-FE	5th	10th	25th	50th	75th	90th	95th
Merch_long	-0.0013	-0.0077***	-0.0065***	-0.0027***	-0.0027***	-0.0019***	-0.0002***	0.0014***
	(0.0016)	(0.0001)	(0.0003)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
Swap_long	0.0033	-0.0105***	-0.0092***	-0.0072***	0.0026***	0.0080***	0.0146***	0.0198***
	(0.0022)	(0.0001)	(0.0005)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
MM_long	0.0040***	0.0130***	0.0119***	0.0085***	0.0021***	-0.0015***	-0.0076***	-0.0115***
	(0.0013)	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
LTC	-0.0006**	-0.0012***	-0.0007***	-0.0006***	-0.0002***	-0.0002***	-0.0006***	-0.0007***
	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
STC	0.0003**	-0.0007***	-0.0003***	-0.0002***	0.0001***	0.0003***	0.0008***	0.0013***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ML	0.0087	-0.0238***	-0.0218***	-0.0134***	0.0075***	0.0236***	0.0422***	0.0502***
	(0.0069)	(0.0002)	(0.0010)	(0.0001)	(0.0004)	(0.0000)	(0.0002)	(0.0000)
OI _r	0.1255***	0.2208***	0.2293***	0.1672***	0.1434***	0.1026***	0.0797***	0.0525***
	(0.0220)	(0.0003)	(0.0034)	(0.0005)	(0.0012)	(0.0002)	(0.0011)	(0.0000)
SP500_r	0.2278***	0.3348***	0.3086***	0.2631***	0.2106***	0.1782***	0.1633***	0.0946***
	(0.0502)	(0.0011)	(0.0105)	(0.0002)	(0.0032)	(0.0001)	(0.0005)	(0.0000)
RIR_f	-0.0032	-0.0053***	-0.0091***	-0.0101***	-0.0065***	-0.0022***	0.0061***	0.0058***
	(0.0041)	(0.0001)	(0.0005)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)
TED_r	-0.0039	-0.0152***	0.0016	0.0005***	-0.0009***	0.0030***	-0.0037***	-0.0019***
	(0.0070)	(0.0003)	(0.0022)	(0.0000)	(0.0003)	(0.0000)	(0.0001)	(0.0000)
TWI_r	-1.1273***	-1.0758***	-0.9613***	-1.0501***	-1.0672***	-1.1133***	-1.0722***	-1.1630***
	(0.1152)	(0.0031)	(0.0242)	(0.0010)	(0.0062)	(0.0002)	(0.0015)	(0.0001)
BDI_r	0.0144	0.0387***	0.0125***	-0.0008***	0.0062***	0.0218***	0.0111***	0.0184***
	(0.0092)	(0.0003)	(0.0008)	(0.0001)	(0.0007)	(0.0000)	(0.0001)	(0.0000)
GFC	0.0017	-0.0280***	-0.0163***	-0.0077***	0.0001	0.0113***	0.0182***	0.0231***
	(0.0028)	(0.0000)	(0.0003)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
EDC	-0.0008	-0.0040***	0.0002	-0.0001***	-0.0006***	-0.0004***	0.0023***	0.0061***
	(0.0017)	(0.0000)	(0.0003)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
		Quantile						
SHORT	PD-FE	5th	10th	25th	50th	75th	90th	95th
Merch_short_r	0.1968***	0.2329***	0.2220***	0.2000***	0.1921***	0.2048***	0.2296***	0.2190***
	(0.0143)	(0.0002)	(0.0024)	(0.0002)	(0.0008)	(0.0004)	(0.0001)	(0.0001)
Swap_short_r	0.0134***	0.0091***	0.0105***	0.0142***	0.0143***	0.0136***	0.0096***	0.0108***
	(0.0029)	(0.0001)	(0.0003)	(0.0000)	(0.0002)	(0.0001)	(0.0001)	(0.0000)
MM_short	-0.0034**	-0.0126***	-0.0112***	-0.0057***	-0.0012***	0.0027***	0.0057***	0.0083***
	(0.0014)	(0.0000)	(0.0001)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
LTC	-0.0001	-0.0009***	-0.0009***	-0.0003***	0.0001***	0.0002***	0.0003***	0.0002***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
STC	0.0003**	-0.0001***	0.0001***	-0.0000***	0.0001***	0.0001***	0.0002***	0.0005***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ML	0.0078	-0.0225***	-0.0168***	-0.0074***	0.0082***	0.0190***	0.0182***	0.0259***
	(0.0065)	(0.0000)	(0.0009)	(0.0000)	(0.0009)	(0.0001)	(0.0000)	(0.0000)
OI _r	-0.0533**	0.0751***	0.0238***	-0.0269***	-0.0725***	-0.0929***	-0.1244***	-0.1035***
	(0.0219)	(0.0003)	(0.0025)	(0.0006)	(0.0025)	(0.0004)	(0.0003)	(0.0002)
SP500_r	0.2186***	0.3289***	0.3367***	0.2667***	0.2111***	0.1721***	0.1398***	0.1378***
	(0.0492)	(0.0009)	(0.0043)	(0.0003)	(0.0029)	(0.0005)	(0.0001)	(0.0002)
RIR_f	-0.0028	-0.0019***	-0.0099***	-0.0089***	-0.0057***	-0.0023***	0.0041***	0.0062***
	(0.0042)	(0.0000)	(0.0002)	(0.0000)	(0.0003)	(0.0001)	(0.0000)	(0.0000)
TED_r	-0.0017	-0.0208***	-0.0026***	-0.0011***	-0.0008	0.0019***	0.0005***	0.0002***
	(0.0069)	(0.0002)	(0.0009)	(0.0001)	(0.0010)	(0.0001)	(0.0001)	(0.0000)
TWI_r	-1.0104***	-1.0223***	-0.8377***	-0.8906***	-0.9353***	-0.9465***	-1.0684***	-1.0730***
	(0.1195)	(0.0013)	(0.0041)	(0.0009)	(0.0079)	(0.0012)	(0.0003)	(0.0000)
BDI_r	0.0148	0.0084***	0.0128***	0.0013***	0.0070***	0.0082***	0.0179***	0.0297***
	(0.0095)	(0.0002)	(0.0015)	(0.0002)	(0.0008)	(0.0001)	(0.0001)	(0.0000)
GFC	0.0012	-0.0380***	-0.0246***	-0.0105***	0.0028***	0.0172***	0.0254***	0.0344***
	(0.0026)	(0.0000)	(0.0004)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)
EDC	0.0000	-0.0100***	-0.0033***	-0.0006***	0.0004*	0.0029***	0.0067***	0.0115***
	(0.0016)	(0.0000)	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)

Table 4.7 cont.

		Commodity Futures Returns						
		Quantile						
NET	PD-FE	5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}
Merch_net	-0.0025**	0.0073***	0.0049***	0.0026***	-0.0012***	-0.0051***	-0.0086***	-0.0115***
	(0.0011)	(0.0000)	(0.0006)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Swap_net_f	-0.0605***	-0.0653***	-0.0519***	-0.0700***	-0.0693***	-0.0578***	-0.0613***	-0.0601***
	(0.0073)	(0.0005)	(0.0070)	(0.0001)	(0.0020)	(0.0004)	(0.0000)	(0.0005)
MM_net	0.0016	0.0118***	0.0099***	0.0071***	0.0007***	-0.0040***	-0.0088***	-0.0115***
	(0.0011)	(0.0001)	(0.0010)	(0.0000)	(0.0002)	(0.0001)	(0.0000)	(0.0000)
LTC	-0.0004	-0.0017***	-0.0019***	-0.0012***	-0.0001***	0.0002***	0.0002***	-0.0000
	(0.0003)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
STC	0.0002*	-0.0001***	0.0001	0.0001***	0.0002***	0.0003***	0.0006***	0.0008***
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ML	0.0105	-0.0284***	-0.0215***	-0.0080***	0.0171***	0.0255***	0.0438***	0.0584***
	(0.0068)	(0.0002)	(0.0009)	(0.0001)	(0.0018)	(0.0003)	(0.0000)	(0.0005)
OI _r	0.1183***	0.2404***	0.1939***	0.1730***	0.1149***	0.0765***	0.0562***	0.0501***
	(0.0219)	(0.0007)	(0.0142)	(0.0003)	(0.0024)	(0.0008)	(0.0003)	(0.0016)
SP500_r	0.2316***	0.3667***	0.2528***	0.2750***	0.2331***	0.1730***	0.1947***	0.1031***
	(0.0506)	(0.0015)	(0.0284)	(0.0004)	(0.0097)	(0.0013)	(0.0001)	(0.0015)
RIR_f	-0.0031	-0.0046***	-0.0133***	-0.0117***	-0.0105***	-0.0035***	0.0049***	0.0038***
	(0.0041)	(0.0000)	(0.0014)	(0.0000)	(0.0006)	(0.0001)	(0.0000)	(0.0001)
TED_r	-0.0033	-0.0080***	-0.0106***	0.0038***	-0.0018***	0.0038***	-0.0078***	0.0203***
	(0.0072)	(0.0004)	(0.0018)	(0.0001)	(0.0005)	(0.0002)	(0.0000)	(0.0008)
TWI_r	-1.0953***	-1.0735***	-1.0888***	-0.9369***	-1.0140***	-1.1322***	-1.0846***	-1.3741***
	(0.1176)	(0.0030)	(0.0896)	(0.0003)	(0.0051)	(0.0041)	(0.0006)	(0.0041)
BDI_r	0.0154*	0.0197***	0.0139***	0.0021***	0.0122***	0.0199***	0.0092***	0.0222***
	(0.0093)	(0.0001)	(0.0012)	(0.0001)	(0.0007)	(0.0005)	(0.0000)	(0.0006)
GFC	0.0010	-0.0288***	-0.0195***	-0.0105***	0.0005**	0.0118***	0.0221***	0.0290***
	(0.0027)	(0.0001)	(0.0006)	(0.0000)	(0.0002)	(0.0001)	(0.0000)	(0.0001)
EDC	-0.0011	-0.0074***	-0.0017***	-0.0019***	-0.0009	0.0005***	0.0028***	0.0053***
	(0.0016)	(0.0001)	(0.0004)	(0.0000)	(0.0007)	(0.0001)	(0.0000)	(0.0001)

Notes: This table illustrates the period results of the panel regression with commodity fixed effects (PD-FE) and quantile regression with nonadditive commodity fixed effects (QRPD) for the financial effect of commodity futures returns for the restricted research period where disaggregated data are available from June 2006 to 7th March 2017 with 561 observations for each commodity. With 10 commodities, 4 commodities each for agriculture (corn, soybeans, sugar, cotton), metals (gold, silver, copper, platinum), and 2 energy commodities (crude oil and natural gas). With _f and _r indicating first difference and log returns. With merch (producer/user), swap (swap dealers), and MM (managed money) as focus variables for commercial and non-commercial open interest, OI as total open interest, ML as market liquidity, SP500 as Standard & Poor's 500 composite index, RIR as real interest rate, TED as TED spread, TWI as trade-weighted USD index, BDI as Baltic Dry Index, and GFC and EDC as dummies for crisis periods throughout the research period. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

The models are defined as:

PD-FE: $CFR_{it} = \alpha + \mu SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$

QRPD: $CFR_{i,t} = \sum_{j=1}^{k} D'_{i,t}\beta_j(U^*_{i,t})$ $\quad P\left(CFR_{i,t} \le D'_{i,t}\beta(\tau)\middle|D_{i,t}\right) = \tau$ $\quad \hat{\beta}(\tau) = arg \min_{b\in\beta} \hat{g}'(b)\,\hat{A}\hat{g}(b)$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [MERCH, SWAP, MM, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t. With β_j as the parameter of interest for each of the k ∈ N* regressors, D' = [SPEC, F] is the vector of regressors, and U* is the non-separable error term traditionally associated with quantile estimation. For a τ-th quantile (0 < τ < 1) of CFR.

More precisely, when I switch short managed money open interest with log returns of short managed money open interest (to make it comparable to log changes in merchants' open interest in the initial model), one can see that, while both coefficients are statistically significant at the 1 percent level (p = 0.000) the coefficient for log changes in merchants' open interest is four times larger than that for log returns of short managed money open interest. The quantile regression further reveals that net merchants' open interest increases returns at the left tail but reduces them at the right tail, which supports the stabilising hypothesis. Likewise, net managed money open interest presents a similar picture when looking at the whole distribution of returns. In contrast, swap dealer open interest indicates the opposite, i.e. it appears to destabilise returns. As the main findings for ESV and returns suggest that the Granger-causal relationship between the two variables runs from returns to ESV, the conclusion as to whether open interest is stabilising or destabilising only holds if one identifies the Granger-causal relationship between the disaggregated open interest and returns, which is discussed in the next section.

Disaggregated Granger Causality

Table 4.8 presents the findings of the Granger causality test for the individual commodities disaggregated dataset from June 2006 to 7th March 2017. While the first column indicates the value for y, i.e. the dependent variable, the first row indicates the value for x, i.e. the independent variable that potentially Granger-causes y for each pairwise test. For example, with a Z-value of 0.6366, I cannot reject the null hypothesis that net merchants' open interest (Merch_net, i.e. long merchants' open interest minus short merchants' open interest) does not Granger-cause returns of all ten commodities, i.e. net merch open interest does not Granger-cause returns for all ten commodities.

Table 4.8: Granger Causality – Disaggregated Data

All Commodities					**All Commodities – June 2006 to June 2008**				
y / x	**CFR**	**Merch_net**	**Swap_net_f**	**MM_net**	**y / x**	**CFR**	**Merch_net_f**	**Swap_net_f**	**MM_net_f**
CFR	-	0.6366	-0.5481	-1.2956	CFR	-	-0.3854	0.3948	0.2435
Merch_net	13.2308***	-	8.1968***	26.8708***	Merch_net_f	2.1800**	-	5.4424***	7.7050***
Swap_net_f	17.8967***	10.9720***	-	25.8607***	Swap_net_f	3.5558***	3.4607***	-	3.0616***
MM_net	10.4625***	4.7586***	0.8320	-	MM_net_f	0.7695	0.3380	0.7445	-
All Commodities – July 2008 to end-2011					**Agriculture**				
y / x	**CFR**	**Merch_net_f**	**Swap_net_f**	**MM_net**	**y / x**	**CFR**	**Merch_net**	**Swap_net_f**	**MM_net**
CFR	-	1.7581*	-0.3915	-0.7722	CFR	-	-0.7635	-0.1541	-1.2541
Merch_net_f	1.7157*	-	1.2756	6.0142***	Merch_net	3.2781***	-	0.7129	2.2640**
Swap_net_f	1.4062	3.5053***	-	6.6441***	Swap_net_f	4.7856***	9.3535***	-	2.2664**
MM_net	1.1203	26.7815***	-0.5771	-	MM_net	11.5493***	4.9011***	-0.3201	-
Metals					**Energy**				
y / x	**CFR**	**Merch_net**	**Swap_net**	**MM_net**	**y / x**	**CFR**	**Merch_net_f**	**Swap_net_f**	**MM_net**
CFR	-	-0.7167	0.2220	-0.1228	CFR	-	-0.7542	-0.4213	-0.9498
Merch_net	12.7318***	-	13.1275***	31.0162***	Merch_net_f	8.2378***	-	0.5033	13.1214***
Swap_net	3.4137***	6.4685***	-	10.1423***	Swap_net_f	16.2731***	4.7113***	-	28.0164***
MM_net	4.6433***	2.6474***	3.5650***	-	MM_net	0.4949	0.6170	0.9192	-

Notes: This table illustrates the Z-statistics of the Granger causality test for panel data. With the first column indicating y, i.e. the dependent variable, and the first row indicating x, i.e. the independent variable that potentially Granger causes y. I use AIC and BIC to determine the appropriate lag length for each pair. Reported figures represent the coefficients based on AIC. The research period runs between June 2006 and 7th March 2017 totalling 561 observations for each commodity. With _f and _r indicating first difference and log returns respectively. With producer/user/merchant (merch), swap dealers (swap), and managed money (MM), both for long and short positions. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. For example, with a Z-value of 0.6366, I cannot reject the null hypothesis that net merch open interest does not Granger-cause returns of all ten commodities, i.e. net merch open interest does not Granger-cause returns for all ten commodities.

In support of the findings for ESV, I find supportive evidence for Granger causality from returns to speculation rather than the opposite. In fact, none of the three measures of net open interest, i.e. merchants, swap dealers, and managed money, significantly Granger-cause returns. Both periods June 2006 to June 2008 and July 2008 to December 2011, indicate little statistically significant evidence for Granger causality from open interest to returns. Switching directions, i.e. testing whether open interest positions are Granger-caused by returns, the statistical significance strengthens. Overall returns significantly Granger-cause net open interest for all commodities, and the subgroups agriculture and metals. Only the net open interest of energies has a no causal relationship with returns during the tested period.

Pre- and Post-2003 Era and the Global Financial Crisis

With the rise of commodity financialization beginning in the early 2000s, commodity markets have attracted an increasing number of non-commercial traders. To test for potential structural changes throughout the research period, the sample is split into two sub-samples from 1995 to 2002 and 2003 to 2017. This approach allows me to investigate the relationship between the regressors and the dependent variable before commodities received more attention by institutional investors. Table 4.9 reports the results. During both periods, the pre-financialization period from 1995 to 2002 and the financialization period starting in 2003, speculation and trader concentration significantly impact the returns. However, the magnitude of the coefficients reduces in the second sub-period, i.e. the positive coefficient of speculation halves. This indicates that the financialization of commodity markets, and thus number of market participants, may have led to a market that is less dependent on just a few traders and therefore more robust to changes in trader concentration. The reducing significance and magnitude of the coefficients from 2003 to 2017 includes periods that led to two peaks in commodity prices. To crystallise the interaction between returns, speculation, and trader concentration throughout the period leading to the GFC in late-2008 and the period shortly after until the end of 2011, where commodities experienced their second peak, I further segment the data. While speculation has been beneficial for the explanation of returns during both surges in commodity prices, STC was particularly significant during the second rush between July 2008 and end-2011. However, the coefficients for LTC suggest that long trader concentration did not play a significant role during both surges in commodity prices during the last two decades.

Table 4.9: Pre- and Post-2003 and the Global Financial Crisis

Panel A: Pre-/Post-2003		***Commodity Futures Returns***							
			Quantile						
		PD-FE	5th	10th	25th	50th	75th	90th	95th
1995-2002	ESV	0.0079***	0.0069***	0.0061***	0.0043***	0.0062***	0.0095***	0.0118***	0.0089***
		(0.0009)	(0.0001)	(0.0003)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)
	LTC	-0.0011*	-0.0091***	-0.0053***	-0.0027***	-0.0002	0.0026***	0.0053***	0.0053***
		(0.0006)	(0.0000)	(0.0006)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
	STC	0.0004**	0.0004***	0.0005***	0.0003***	0.0004***	0.0004***	0.0004***	0.0009***
		(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
2003-2017	ESV	0.0013***	0.0041***	0.0032***	0.0024***	0.0007***	-0.0000	-0.0008***	-0.0008***
		(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	LTC	-0.0006***	-0.0014***	-0.0014***	-0.0012***	-0.0003***	0.0002***	0.0002***	0.0002***
		(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	STC	0.0003**	0.0001***	0.0005***	0.0002***	0.0001***	0.0001***	0.0001***	0.0007***
		(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Panel B: GFC						Quantile			
		PD-FE	5th	10th	25th	50th	75th	90th	95th
2003-200806	ESV	0.0031***	0.0062***	0.0039***	0.0035***	0.0019***	0.0004	0.0008	-0.0012***
		(0.0008)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0010)	(0.0000)
	LTC	-0.0007	-0.0021***	-0.0026***	-0.0012***	-0.0001***	0.0011	0.0010***	0.0018***
		(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0000)
	STC	0.0002	-0.0008***	0.0002***	0.0002***	-0.0001***	-0.0000	0.0001**	0.0009***
		(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
200807-2011	ESV_f	0.0624***	0.0559***	0.0581***	0.0596***	0.0580***	0.0596***	0.0595***	0.0562***
		(0.0056)	(0.0010)	(0.0030)	(0.0003)	(0.0005)	(0.0000)	(0.0008)	(0.0005)
	LTC	-0.0011	-0.0018***	-0.0006	-0.0010***	-0.0001***	-0.0004***	0.0000	0.0004***
		(0.0008)	(0.0001)	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
	STC	0.0007***	0.0007***	0.0005***	0.0003***	-0.0000***	-0.0002***	-0.0002***	0.0005***
		(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)

Notes: This table illustrates the sub-period results of the panel regression with commodity fixed effects (PD-FE) and quantile regression with nonadditive commodity fixed effects (QRPD) for the financial (PD-FE and QR) effect of commodity futures returns for the research sub-periods from 3rd January 1995 to end-December 2002, January 2003 to 7th March 2017, January 2003 to June 2008 (first surge of commodity prices), and July 2008 to December 2011 (GFC). With 10 commodities, 4 commodities each for agriculture (corn, soybeans, sugar, cotton), metals (gold, silver, copper, platinum), and 2 energy commodities (crude oil and natural gas). With _f and _r indicating first difference and log returns respectively. With ESV, LTC, and STC as focus variables. Note that quantile regression for panel data with nonadditive fixed effects relies on a non-separable error term U^* and does not report a separate constant term. While the PD-FE model includes a constant, I refrain from reporting it for reasons of clarity and comprehensibility. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

The models are defined as:

PD-FE: $CFR_{it} = \alpha + \mu SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$

QRPD: $CFR_{i,t} = \sum_{j=1}^{k} D'_{i,t}\beta_j(U^*_{i,t})$ $\quad P\left(CFR_{i,t} \leq D'_{i,t}\beta(\tau) \middle| D_{i,t}\right) = \tau$ $\quad \hat{\beta}(\tau) = arg \min_{b \in \beta} \hat{g}'(b)\, \hat{A}\hat{g}(b)$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, DotCom as a dummy variable for the dot-com bubble between the years 2000 and 2002, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t. With β_j as the parameter of interest for each of the $k \in N^*$ regressors, D' = [SPEC, F] is the vector of regressors, and U^* is the non-separable error term traditionally associated with quantile estimation. For a τ-th quantile ($0 < \tau < 1$) of CFR.

Unknown Structural Breaks

In addition to the separation of the research period based on major events in the commodity markets, the question arises as to whether the cross-sectional time-series' experience unknown structural breaks. To search for potential breaks, an array of tests is applied. While it is expected that structural breaks occur around the same time for each of the commodities (i.e. shortly before the GFC and around the end of 2011), I use an individual commodity

OLS analysis as in equation (4.12) to ensure that all potential structural breaks are identified. First, I begin with the cumulative sum (CUSUM) test to determine whether the model is adequately defined. Only for sugar, can I reject the null hypothesis of no structural break at the 5 percent level, i.e. the models for the other commodities are adequately defined.

Second, I adopt Wald and likelihood ratio (LR) tests for parameter instability and structural change presented by Andrews (1993). Contrary to the CUSUM test, the supremum Wald and LR tests suggest structural breaks for all ten commodities. The identified breaks are spread throughout the research period. They vary for each commodity, with breaks for precious metals (gold and silver) during the early days of the financialization period in 2002/2003 and breaks for all other commodities during the surge of commodity prices leading to the GFC. However, one drawback of the Wald and LR tests is the limitation to single breaks. As it is likely that most commodity prices have experienced more than one break during the last two decades, it is suspected that the data includes multiple structural breaks.

Therefore, the third evaluation uses Bai and Perron's (2003a, 2003b) test for multiple structural breaks, which tests for structural breaks in the regression model. The results in Table 4.10 show that the Bai-Perron test identifies several structural breaks for all commodities. Much like the supremum Wald and LR tests, the breaks for each commodity are at different points in time. Yet, the periods can be segmented into three main groups, namely the pre-financialization period before 2002/2003, the surges in commodity prices during the research period starting in 2002/2003 until 2012/2013, and the stagnation of prices since then. Complementary to the panel regression pre- and post-2003 and GFC sub-samples, the individual commodity least squares evaluation with sub-samples based upon Bai-Perron's test for structural breaks not only confirms the time-varying effects of all three measures of non-commercial speculation and trader concentration but further shows that the effect over time is different for the individual commodities. The effect of ESV is generally stronger before the GFC for most commodities. However, the impact of trader concentration, both long and short, strongly varies for the individual commodities. The effect of LTC and STC on returns weakens over time for some commodities (cotton, gold, silver, platinum), strengthens (sugar, soybeans), or changes its direction for others (corn, copper, crude oil).

Table 4.10: Least Squares with Bai-Perron Structural Breaks – Financial Effect

Commodity Futures Returns						
	Pre-Financialization		Commodity Price Peaks			Post-Peak
Corn	3/1/1995 – 28/4/1998	5/5/1998 – 16/10/2001	23/10/2001 – 22/2/2005	1/3/2005 – 17/6/2008	24/6/2008 – 9/7/2013	16/7/2013 – 7/3/2017
ESV	0.0094***	0.0030	0.0017	0.0019*	0.0007	0.0003
LTC_r	-0.2325***	-0.2061***	-0.1376***	-0.1033*	-0.0987	0.1261**
STC_r	0.1803***	0.2479***	0.1135	0.0014	0.2848***	0.0297
Soybeans	3/1/1995 – 8/9/1998	15/9/1998 – 8/1/2002	15/1/2002 – 10/5/2005	17/5/2005 – 2/9/2008	9/9/2008 – 31/7/2012	7/8/2012 – 7/3/2017
ESV	0.0077***	0.0080*	0.0072*	0.0045**	0.0020*	0.0019**
LTC_r	-0.1278***	-0.0564**	-0.0762	-0.1875***	-0.1488***	-0.1866***
STC_r	0.0302	0.0388	0.0025	0.2000***	0.3096***	0.1696***
Sugar	3/1/1995 – 6/10/1998	13/10/1998 – 23/4/2002	30/4/2002 – 23/8/2005	30/8/2005 – 16/12/2008	22/12/2008 – 24/4/2012	1/5/2012 – 7/3/2017
ESV	0.0004	0.0065	-0.0077	0.0033	0.0099	-0.0009
LTC_r	-0.1583***	-0.1560***	-0.1539***	-0.1311**	-0.2201***	-0.1888***
STC	0.0041	0.0049***	0.00353**	0.0007	-0.0010	0.0017
Cotton	3/1/1995 – 28/4/1998	5/5/1998 – 2/12/2003	9/12/2003 – 27/3/2007	3/4/2007 – 20/7/2010	27/7/2010 – 12/11/2013	19/11/2013 – 7/3/2017
ESV_f	0.1612***	0.2135***	0.1498***	0.1736***	0.0507	0.0910***
LTC_r	-0.0821	0.0035	-0.0583	0.0086	-0.1025**	-0.036
STC	-0.0057	0.0018***	-0.0002	0.0004	0.0021***	0.0001
Gold	3/1/1995 – 27/7/1999	3/8/1999 – 10/12/2002	17/12/2002 – 13/6/2006	20/6/2006 – 22/12/2009	29/12/2009 – 16/4/2013	23/4/2013 – 7/3/2017
ESV	0.0022*	-0.0019	0.0050***	-0.0012	0.0049***	0.0008
LTC_r	-0.0615***	-0.0784***	0.0135	-0.0463*	-0.1022***	-0.034*
STC	0.0008	0.0002	-0.0023**	0.0007***	-0.0002	-0.0001
Silver	3/1/1995 – 2/3/1999	9/3/1999 – 1/4/2003	8/4/2003 – 25/7/2006	1/8/2006 – 20/4/2010	27/4/2010 – 13/8/2013	20/8/2013 – 7/3/2017
ESV	0.0166**	-0.0003	0.0184**	0.0015	0.0331***	0.0134**
LTC_r	-0.0636*	0.0081	0.0439	0.1012	-0.2084***	0.0099
STC	0.0003	0.0000	-0.0043***	-0.0005	-0.0014	-0.0022
Copper	3/1/1995 – 23/2/1999	2/3/1999 – 22/10/2002	29/10/2002 – 28/2/2006	7/3/2006 – 23/6/2009	30/6/2009 – 23/4/2013	30/4/2013 – 7/3/2017
ESV	0.0256**	0.0103**	0.0041	0.0356	0.0066	0.0116**
LTC_r	-0.1085***	-0.0962***	-0.0531	-0.0718*	0.0470**	0.0782***
STC	0.0033	0.0004	0.0003	0.0041	-0.0006	-0.0010
Platinum	3/1/1995 – 5/10/1999	12/10/1999 – 15/7/2003	22/7/2003 – 23/1/2007	30/1/2007 – 1/6/2010	8/6/2010 – 22/10/2013	29/10/2013 – 7/3/2017
ESV_f	0.3528***	0.8156***	0.7860***	0.2948	0.2631***	0.2433***
LTC_r	0.0131	-0.0090	0.0081	-0.0117	-0.0453*	0.0016
STC	0.0005**	0.0002**	0.0007	0.0006	0.0000	0.0002
Natural Gas	3/1/1995 – 28/4/1998	5/5/1998 – 2/10/2001	9/10/2001 – 20/12/2005	27/12/2005 – 15/9/2009	26/5/2009 – 16/10/2012	23/10/2012 – 7/3/2017
ESV_f	0.2398***	0.2088***	0.2242***	0.1437***	0.0972***	0.0222**
LTC_r	-0.1058	-0.0043	-0.0175	-0.0395	0.1586**	-0.0870
STC	0.0100	-0.0012	0.0025**	0.0035***	0.0000	0.0002
Crude Oil	3/1/1995 – 18/4/2000	25/4/2000 – 26/8/2003	2/9/2003 – 19/12/2006	26/12/2006 – 1/6/2010	8/6/2010 – 29/10/2013	5/11/2013 – 7/3/2017
ESV_f	0.1035***	0.0418**	0.0861***	0.0164	0.0526***	0.0372***
LTC_r	0.0676	-0.1428***	0.0125	0.1060***	0.1123***	0.3129***
STC_r	-0.0432	0.1035***	-0.0625	-0.1530***	-0.0486	-0.1646***

Notes: This table illustrates the results of the least squares regression with Bai-Perron structural breaks and Newey-West standard errors for the ten commodities between 3rd January 1995 and 7th March 2017 totalling 1,156 observations for each commodity. With ESV, LTC, and STC as focus variables, _r as log returns, and _f as first difference. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

The model is defined as:

$$CFR_t = \alpha + \mu SPEC_t + \delta F_t + \varepsilon_{it}$$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, and ε as error term at time t.

Commercial and Non-Commercial Trader Concentration

While the time-varying effects are probably the result of changes in individual commodity supply and demand, I take a closer look at the commodities with direction changing coefficients. For example, the LTC coefficient for copper turns significantly positive beginning in mid-2009. A positive coefficient for LTC indicates a positive relationship between LTC, i.e. long trader concentration (e.g. consumers), and returns, which contradicts the expectation that consumers want to pay the lowest price possible. However, long trader concentration includes both open interest of consumers and other traders who also hold long positions, in particular institutional commodity index investors. Moreover, one must remember that LTC measures the ratio of large to small traders. Thus, an increase in LTC can either be the result of an increase in long traders' open interest or a decrease in small traders' open interest. To evaluate the diverging effects of commercial and non-commercial trader concentration, I separate LTC and STC into their commercial and non-commercial parts. Extending (4.9) and (4.10), the separated long and short trader concentration measures can be written as:

$$LTCC_t = \frac{Commercial\ OI\ Long_t}{Non-Reportable\ OI\ Long_t} \tag{4.26}$$

$$LTCNC_t = \frac{Non-Commercial\ OI\ Long_t}{Non-Reportable\ OI\ Long_t} \tag{4.27}$$

$$STCC_t = \frac{Commercial\ OI\ Short_t}{Non-Reportable\ OI\ Short_t} \tag{4.28}$$

$$STCNC_t = \frac{Non-Commercial\ OI\ Short_t}{Non-Reportable\ OI\ Short_t} \tag{4.29}$$

For all three commodities with switching coefficients (corn, copper, crude oil), I create the commercial ($LTCC_t$) and non-commercial ($LTCNC_t$) long trader concentration variables. As crude oil experiences a similar switching behaviour of STC, I also create commercial ($STCC_t$) and non-commercial ($STCNC_t$) short trader concentration variables in the same manner. The findings confirm and oppose the underlying hypothesis for long and short trader concentration, i.e. that long traders want to achieve the lowest price and short traders the highest price possible. If the trader concentration increases, each market participant is equipped with a relatively higher market power, which puts upward (short) or downward (long) pressure on the price. While the obtained coefficients for all for LTCC and STCC mostly confirm this hypothesis, the variables for non-commercial trader concentration indicate the opposite, i.e. negative coefficients for short and positive coefficients for long trader concentration.[91] These findings suggest that, while the relationship for returns and commercial trader concentration works as expected and represents rational trader behaviour, non-commercial trader concentration may not. Moreover, commercial trader concentration has a stronger influence on returns before the rise in financialization for copper and crude oil whereas non-commercial trader concentration has a stronger impact for both commodities afterwards. For corn and soybeans, the significance of commercial and non-commercial trader concentration is constant throughout the research period. All results are reported in Appendix A4.3 and A4.4.

The question arises why the relationship between returns and non-commercial trader concentration is contrasting the rational trader hypothesis. First, correlation is not causation. Although both variables correlate, either no causal relationship may exist or both are driven by a third unobserved variable. However, as I identify a significant and Granger causal relationship for trader concentration overall, it is likely that the variables are connected. Second, large non-commercial traders are less interested in the best price but use commodities for other reasons, e.g. portfolio diversification. Thus, short-term changes of the commodity price might be of less interest, which leads to the observed coefficient behaviour. Third, trader concentration is calculated by dividing large trader open interest by small trader open interest, defined by the reporting threshold set by the CFTC. For non-commercial trader concentration, large traders are institutional investors such as ETF's (numerator). It is assumed that positions are not being adjusted based on small price changes. The denominator of the equation is made up of small non-commercial traders such as day and momentum traders who react to small price changes. For example, if returns increase, the numerator of long trader concentration remains relatively stable, but the denominator decreases as small traders exit their positions. As a result, LTC increases together with returns, which indicates a positive correlation and thus positive coefficient in

[91] In addition to the individual commodity analysis, I evaluate the effects of the separated trader concentration variables on returns in the commodity fixed effects panel regression framework. The results for all 10 commodities confirm the negative and highly significant (1 percent level) impact of LTCC and positive and highly significant (1 percent level) of STCC on returns. However, the coefficients for non-commercial trader concentration, both long and short, remain non-significant, which suggests that overall, commercial trader concentration has a higher explanation power for returns than non-commercial trader concentration.

the least squares regression.[92] To thoroughly understand the interaction between trader concentration and returns, further research is necessary. For example, one might be interested in a potential time-varying Granger causal relationship between trader concentration, speculation, and returns. As this is beyond the scope of this study, I leave this endeavour for future research.

Overall, one should be aware that these findings, while interesting and worth pursuing further, illustrate the effect of returns on trader concentration and not the other way around. The Granger causality evaluation suggests that LTC and STC of most commodities, either individually or jointly, are not Granger-caused by returns. Instead, returns unidirectionally Granger-cause LTC and STC for most commodities.

4.4.4 THE SIGNALLING EFFECT OF SPECULATION AND TRADER CONCENTRATION

This section aims to address the holistic impact of trading on the price of the underlying. I argue that the impact of futures trading on returns is not solely financial. Prior research concerned with speculation and commodity futures assumes that, if speculation drives commodities, changes in weekly non-commercial open interest should impact price, volatility, and other related measures during the same period. Moreover, it implies that these effects happen immediately. To illustrate this effect, it is best to use an example. Imagine a trader who buys corn futures. All other things being equal, the demand for corn futures increases, which increases the price. This effect is defined as the financial effect, which is evaluated in Sections 4.4.1 to 4.4.3. Additionally, one may expect other market participants to react to those changes once the information is available. I argue that, when herd behaviour[93] is present, it is not only the trader who buys or sells futures that influences the price, but also other traders who follow the first trader. This herd behaviour is denoted as the signalling effect as it follows the signals set by other traders. Studies on monetary policy (e.g., Glick and Leduc, 2012; Scrimgeour 2014), economic events (Roache and Rissi, 2010), or weather conditions (Fleming et al., 2006) show that public information influences

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[92] The valuation of lower frequency data (monthly and yearly) produces comparable coefficients, i.e. opposing coefficients, which contradicts with the short-term trader theory. Moreover, I observe the same coefficient behaviour for short trader concentration, i.e. without (or with fewer) ETF involvement. As detailed information on individual trades is scarce, it may not be possible to link the effects to the individual buyer or seller of futures contracts.

[93] Another term that is often used to describe herd behaviour is the 'bandwagon effect'. I use both terms to describe the same psychological behaviour.

commodity prices. Moreover, Roache and Rissi (2010) argue that the sensitivity of commodities to news has increased since the financialization of the commodity market. Demirer et al. (2015) add that herd behaviour is prominent in grain futures markets during high volatility states, but less so in energy and metal markets. Once the signalling effect of open interest changes, measured by trader concentration, on CFR is identified, market participants such as commodity producers, consumers, and financial investors can better understand commodity market dynamics and incorporate this information into their decision-making processes.

The examination of the signalling effect contains a crucial side benefit. Unlike the financial effect, which measures commodity prices and open interest changes on the same day, the signalling effect uses data gathered each Tuesday and evaluates its impact on returns once the report is published on the subsequent Friday. As a result, the causal relationship between speculation and returns is clear, and is a result of the time difference. The evaluation of the signalling effect not only provides novel insight on herd behaviour and reaction to news related to trading in commodity markets but sheds further light on the causal relationship between speculation and commodity returns and addresses the endogeneity bias highlighted by Buyuksahin and Harris (2011). The ongoing disagreement about the real impact of speculation on returns, paired with the increasing interest in exchange-traded commodities as an alternative investment to stocks and bonds, motivates the investigation to fully understand their relationship. Estimating the signalling effect helps to shed further light on this topic. By evaluating the estimation power of the three regressors of interest to explain returns on the day of the report publication, it is possible to uncover the markets' reaction to the latest information about speculation and trader concentration. In other words, if traders react to these announcements and adjust their positions, returns should change accordingly. Combined with the unambiguous causal relationship between speculation and returns underlying the signalling effect[94], one may conclude that speculation drives returns. More precisely, while I show that non-commercial speculation transmitted by the financial channel does not directly Granger-cause weekly returns, the publication of non-commercial trading information through the signalling channel may be a driver of returns.

[94] The analysis of the signalling effect uses information that is captured each Tuesday to estimate its impact on following Friday's financial data.

Table 4.11: Quantile and Panel Fixed Effects Regression – Signalling Effect

			Commodity Futures Returns						
			Quantile						
Signalling Effect		PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV	All	0.0005	0.0029***	0.0028***	0.0017***	0.0005***	-0.0010***	-0.0015***	-0.0021***
	Agri	0.0004	0.0002**	0.0004***	-0.0000	0.0006***	0.0008***	0.0012***	0.0008***
	Metals	0.0003	0.0037***	0.0033***	-0.0006*	0.0002**	0.0007***	-0.0028***	-0.0044***
	Energy (_f)	0.0204***	0.0120***	0.0414***	0.0206***	0.0213***	0.0200***	0.0170***	0.0241***
LTC	All	0.0000	-0.0009***	-0.0008***	-0.0005***	-0.0001***	0.0004***	0.0006***	0.0006***
	Agri	-0.0003	0.0011***	0.0004***	-0.0005***	0.0002***	0.0008***	-0.0008***	-0.0015***
	Metals	0.0001	0.0015***	0.0010***	0.0004***	0.0006***	0.0003***	-0.0010***	-0.0010***
	Energy	0.0005	0.0056***	-0.0011	0.0016***	0.0007***	-0.0017***	-0.0030***	-0.0055***
STC	All	0.0000	-0.0002***	-0.0000***	-0.0000***	-0.0000**	0.0000***	-0.0000**	0.0003***
	Agri	0.0004**	-0.0011***	-0.0007***	0.0005***	0.0001**	0.0005***	0.0013***	0.0015***
	Metals	-0.0001	0.0001***	-0.0000***	-0.0000***	-0.0002***	-0.0002***	-0.0000***	-0.0002***
	Energy	-0.0005*	-0.0029***	0.0005	-0.0010***	0.0001	0.0009***	0.0016***	0.0029***

Notes: This table illustrates the detailed results of the panel regression with commodity fixed effects (PD-FE) and quantile regression with nonadditive commodity fixed effects (QRPD) for the signalling effect of commodity futures returns between 3rd January 1995 and 7th March 2017 totalling 1,156 observations for each of the 10 commodities. With _f and _r indicating first difference and log returns respectively. With ESV, LTC, and STC as focus variables. Note that quantile regression for panel data with nonadditive fixed effects relies on a non-separable error term U^* and does not report a separate constant term. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Detailed results are in Appendix A4.5.

The models are defined as:

PD-FE: $CFR_{it} = \alpha + \mu SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$

QRPD: $CFR_{i,t} = \sum_{j=1}^{k} D'_{i,t}\beta_j(U^*_{i,t}) \qquad P\big(CFR_{i,t} \leq D'_{i,t}\beta(\tau) \big| D_{i,t}\big) = \tau \qquad \hat{\beta}(\tau) = arg \min_{b \in \beta} \hat{g}'(b)\, \hat{A}\hat{g}(b)$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, DotCom as a dummy variable for the dot-com bubble between the years 2000 and 2002, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t. With β_j as the parameter of interest for each of the $k \in N^*$ regressors, D' = [SPEC, F] is the vector of regressors, and U^* is the non-separable error term traditionally associated with quantile estimation. For a τ-th quantile ($0 < \tau < 1$) of CFR.

Contrary to the financial channel, Table 4.11 shows that the ESV coefficient non-significant for the mean model. Significant evidence of a reinforcing signalling effect that remains reinforcing in the quantile evaluation can only be found for energy commodities, i.e. a market that experiences considerably more attention from institutional investors and traders. Thus, market participants in highly traded markets such as energy commodities appear to follow the direction of non-commercial commodity futures traders once the information becomes public and adjust their positions accordingly. However, the magnitude of this herd behaviour is weaker compared to the financial effect. Shifting to trader concentration, I observe little significance of the variables for both the full basket of commodities and the subsets. Only for agricultural commodities, the mean model estimates a significant (5 percent level), positive impact of short trader concentration.

Expectation vs. Reality

So far, the results for the signalling effect of excess speculation on returns are only significant and reinforcing for energy commodities. However, metals, agricultural, and commodities overall are less affected by the signalling effect of any of the three variables of interest. However, what seems to be non-significance might simply be the result of limited deviation between expectation and reality. In fact, if the base data of the three regressors of interest in the COT report is not too different compared to the expectations of market participants, a non-significant relationship is likely. In the spirit of Bessembinder and Seguin (1993), I use the augmented Dickey-Fuller test[95] to determine whether the time-series are stationary and adopt AR (10) models for stationary and ARIMA (10,1,0) models for non-stationary data to obtain one-step-ahead forecast errors as expected values, defined as:

$$FE_{i,j,t} = X_{i,j,t} - E\left[X_{i,j,t} | X_{i,j,t-\omega}, \omega = 1, \dots, 10\right] \tag{4.30}$$

with $FE_{i,j,t}$ as forecast error, $X_{i,j,t}$ as actual value, and $E[\dots]$ as expected value of $X_{i,j,t}$ estimated using an AR (10) for stationary and ARIMA (10,1,0) for non-stationary data for each commodity i and entity j with $j = [ESV, net(merch, swap, MM)]$, which represent merchants, i.e. commercials (merch), swap dealers (swap), and managed money (MM). This variable is added to equation (4.11). To truly compare ESV and the measures of net open interest by trader type, I limit this analysis to the shortened research period starting mid-June 2006. The results are reported in Tables 4.12 and 4.13.

In line with the prior analysis of the signalling effect, I only observe a positive signalling effect of ESV on returns for energy commodities. However, once the ESV is switched with the forecast error as explanatory variable, the significance of the coefficients increases. For commodities overall and the three subgroups agricultural, metals, and energy, the forecast error of ESV significantly (1 percent level) increases returns. Thus, traders react to unexpected changes in non-commercial open interest once the reported figures deviate from the expected, i.e. previous values. While the absolute size of ESV plays a subordinate role for the signalling effect, deviations from the expected value of ESV significantly explain variations in returns.

The individual commodity results, which are reported in Appendix A4.7, further suggest that agricultural commodities and metals are influenced by expectation deviations, i.e. forecast errors, of ESV. Only for energy commodities, i.e. natural gas and crude oil, the

[95] In addition, I run Phillips-Perron tests to confirm the findings. If the recommendations following both tests are ambiguous, the Dickey-Fuller test with generalised least squares (DFGLS) is used.

forecast error variable is non-significant. Moreover, I test if the signalling effect experiences breaks between June 2006 and the end of the research period in 2017. This break analysis helps me to reveal if the signalling effect has become more relevant during the recent years and whether the reliance of traders on CFTC reports has changed. To identify unknown breaks, I use least squares regressions with Bai-Perron structural breaks. The obtained coefficients, which can be found in Appendix A4.10, suggest that the effect stemming from expectation deviations of non-commercial speculation increases since the last commodity price peak end-2011 for some commodities such as silver, platinum, and crude oil. This indicates that investors' awareness of and interest in the CFTC COT report has increased. As a result, markets react stronger to deviations in the expected excess non-commercial speculative open interest. Traders and other market participants benefit from these findings as they allow them to adequately consider the effect in their trading decision process.

Table 4.12: Expectation vs. Reality

	Commodity Futures Returns									
	ESV-All	ESV-All	ESV-AG	ESV-AG	ESV-PM	ESV-PM	ESV-IM	ESV-IM	ESV-EN	ESV-EN
ESV	0.0001		0.0002		-0.0004		-0.0005			
	(0.0004)		(0.0005)		(0.0008)		(0.0036)			
ESV_r									0.0127**	
									(0.0055)	
FE[ESV]		0.0176***		0.0186***		0.0144***		0.0388***		0.0120**
		(0.0028)		(0.0035)		(0.0039)		(0.0137)		(0.0060)
Obs.	5,610	5,610	2,244	2,244	1,683	1,683	561	561	1,122	1,122

Notes: This table illustrates the results of the panel regression with commodity fixed effects for the signalling effect of returns between June 2006 and 7th March 2017 totalling 561 observations for each commodity (10 commodities, agriculture (AG: corn, soybeans, sugar, cotton), precious metals (PM: gold, silver, platinum), industrial metals (IM: copper), and energy commodities (EN: crude oil and natural gas)). With _f and _r indicating first difference and log returns respectively. With ESV as focus variable and obs. as observations. I use Driscoll-Kraay standard errors to account for cross-sectional dependence. With FE[…] indicating the forecast error for each of the series, estimating by either AR (10) for stationary or ARIMA (10,1,0) for non-stationary time-series. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. Detailed results are stored in Appendix A4.6. Commodity-individual results are stored in Appendix A4.7.

The model is defined as:

$$CFR_{it} = \alpha + \mu SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC] or SPEC = [FE[ESV], LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t.

The Signalling Effect of Disaggregated Open Interest

The disaggregated net open interest data extends these findings and indicates a significant signalling effect of the forecast errors for both agricultural and energy returns. While agricultural commodities are primarily driven by forecast errors on the open interest of merchants and swap dealers, i.e. traders that have either a direct commercial or longer-term investment interest in the underlying and are thus often in the centre of public debate, energy commodities, which are amongst the most frequently traded commodities, are influenced by forecast errors in the open interest of swap dealers and managed money, i.e. non-commercial traders that are mostly interested in short-term financial gains and not the commodity itself.

Table 4.13: Expectation vs. Reality Disaggregated Data

	Commodity Futures Returns									
	DISS-All	DISS-All	DISS-AG	DISS-AG	DISS-PM	DISS-PM	DISS-IM	DISS-IM	DISS-EN	DISS-EN
Merch_net	-0.0024**		-0.0043**		0.0056		0.0002			
	(0.0011)		(0.0019)		(0.0054)		(0.0173)			
Merch_net_f									-0.0462**	
									(0.0198)	
FE[Merch]		-0.0121		-0.0498***		0.0057		0.0008		0.0157
		(0.0089)		(0.0106)		(0.0180)		(0.0487)		(0.0225)
Swap					0.0026		0.0068			
					(0.0079)		(0.0217)			
Swap_net_f	-0.0187**		-0.0048						-0.0083	
	(0.0091)		(0.0175)						(0.0141)	
FE[Swap]		0.0011		-0.0424**		-0.0174		-0.0200		0.0478**
		(0.0128)		(0.0184)		(0.0199)		(0.0619)		(0.0202)
MM	-0.0012		-0.0044**		0.0042		0.0008		0.0033	
	(0.0012)		(0.0019)		(0.0074)		(0.0144)		(0.0025)	
FE[MM]		0.0325***		-0.0137		0.0283		0.0629*		0.0719***
		(0.0077)		(0.0096)		(0.0188)		(0.0360)		(0.0123)
Obs.	5,610	5,610	2,244	2,244	1,683	1,683	561	561	1,122	1,122

Notes: This table illustrates the results of the panel regression with commodity fixed effects for the signalling effect of returns between June 2006 and 7th March 2017 totalling 561 observations for each commodity (10 commodities, agriculture (AG: corn, soybeans, sugar, cotton), precious metals (PM: gold, silver, platinum), industrial metals (IM: copper), and energy commodities (EN: crude oil and natural gas)). With _f and _r indicating first difference and log returns respectively. With producer/user (merch), swap dealers (swap), and managed money (MM), and obs. as observations. I use Driscoll-Kraay standard errors to account for cross-sectional dependence. With FE[…] indicating the forecast error for each of the series, estimating by either AR (10) for stationary or ARIMA (10,1,0) for non-stationary time-series. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. Detailed results are stored in Appendix A4.6.

The model is defined as:

$$CFR_{it} = \alpha + \mu SPEC'_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC' as disaggregated speculative measures vector consisting of SPEC' = [MERCH, SWAP, MM, LTC, STC] or SPEC' = [FE[MERCH], FE[SWAP], FE[MM], LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t.

The findings manifest the previously obtained findings that traders are less concerned with the absolute size of open interest but react stronger to unexpected changes in such. Moreover, the disaggregated open interest results show that the effect on agricultural and energy commodities is stronger compared to metals.[96] The individual commodity results, which are reported in Appendix A4.8, further suggest that agricultural commodities are primarily affected by expectation deviations, i.e. forecast errors, of merchants' open interest. Both natural gas and crude oil returns experience a positive, highly significant signalling

[96] As metal producers tend to hedge little or none of their production (PricewaterhouseCoopers, 2016), but agricultural producers often sell their future harvest on the market, changes in merchant open interest may signal changes in the expected future harvest. Thus, increases in both the merchant open interest and the forecast error in merchant open interest signal higher expected future yield, which should reduce the market price and thus reduce the price and returns today.

effect that stems from expectation deviations for the measure of non-commercial speculation, i.e. managed money.

The Signalling Effect of Speculation on the Realised Volatility

Finally, I evaluate the volatility of returns and their interaction with ESV, forecast error of ESV, LTC, and STC by using a constant only mean model of returns and the former four main regressors as explanatory variables in the variance equation. Detailed results are reported in Appendix A4.11. As I cannot reject the null hypothesis that the errors are not autoregressive conditional heteroskedastic based on the ARCH-LM test for silver and sugar, I limit this evaluation to the eight remaining commodities. The asymmetry terms suggest that the volatility of corn and soybeans returns is significantly more affected by positive shocks, whereas negative shocks have a greater impact on the volatility of copper and crude oil returns. Except for copper, the magnitude of symmetric shocks is relatively stronger and often statistically more significant than the asymmetric shocks. The results also suggest that the volatility of corn, soybeans, and natural gas returns are significantly affected by ESV and the forecast error of ESV. In contrast, the volatility of gold and copper returns is only affected by expectation errors and not by ESV. This confirms that traders are less concerned with the absolute size of open interest but react more strongly to unexpected changes. Although the financial effect of speculation on returns might be ambiguous, the signalling effect of speculation clearly shows that markets react to news on speculative and non-speculative open interest, which is particularly present when the actual values deviate from the expected open interest.

4.5 CONCLUSION

This study evaluates non-commercial speculation, trader concentration, and their explanatory power of these variables to explain the return distribution of a basket of ten commodity futures. Not only does it evaluate the mean impact of speculation and trader concentration, but it further extends prior research by analysing the varying impact of the regressors on different quantiles of returns. With this approach, I scrutinise the quantiles of returns, focussing on the extremes, to identify the nonlinear explanatory power of speculation and trader concentration. Granger causality tests for heterogenous panel data complement the evaluation by identifying the direction of the impact. Moreover, the evaluation of the signalling effect provides a novel extension of prior research which primarily focuses on the financial effect.

The results imply that speculation stabilises the futures returns of a panel of ten commodities and the subgroup of four metals: gold, silver, copper, and platinum. Moreover, the results suggest that speculation reinforces the returns of the energy and agricultural subgroups. The commodity-specific findings indicate that ESV has a stronger stabilising, i.e. positive effect on the left tail of the return distribution, i.e. the 5^{th} to 50^{th} quantiles for soybeans and gold, a constant positive effect on the whole distribution of returns for corn, cotton, platinum, natural gas, and crude oil, and significantly stronger reinforcing effects on the left and right tail of returns for silver and copper. Thus, for most individual commodities, the results indicate a reinforcing relationship between ESV and returns, for both the mean and quantile regressions. This confirms the misinterpretation error that can arise from the use of panel regression, described earlier, as the results for some commodities do not coincide with the findings for their respective commodity group. Moreover, for all commodities, the effect of non-commercial speculation on returns, indicated by the magnitude of the coefficients, is small. The obtained coefficients suggest that the impact of changes in open interest on futures returns is miniscule. Yet, the impact of merchants' open interest, i.e. traders primarily concerned with producing or consuming the commodities, is approximately four times[97] stronger than the effects stemming from non-commercial hedging (i.e. managed money open interest). Thus, the effect of non-commercial, i.e. speculative, trading on futures returns is smaller than the effects stemming from commercial trading. Granger causality tests, on a weekly basis, reveal that the leading driver is, in fact, returns and not speculation. This is consistent with the idea that relatively low prices induce non-commercial speculators to buy futures and when prices rise beyond a certain point, non-commercial speculators sell their positions. These findings apply for all ten tested commodities and are important for regulators, investors, and other parties that are interested in the factors that influence commodity prices. Investors and traders gain from these findings by realising that their actions, on a weekly basis, do not drive returns. In addition, the results for the signalling effect show that market participants use information on changes in non-commercial open interest and adjust their exposure accordingly. This effect is

[97] Please refer to Chapter 4.4.3 for more details.

particularly present when non-commercial speculation deviates from its expected value. Investors can benefit from these findings by developing a better understanding of the interactions between trader concentration and speculation in commodity futures markets and thus improve their financial models accordingly. Moreover, instead of imposing new regulations on trading and position limits, regulators may be well-advised to review their position in favour of a more transparent, market-oriented approach. This may include publishing daily reports of trading volumes and open interest and may further include the reporting of the names of the trading parties. That is, if more information is available, the impact of each publication is likely to be less. Future research may further analyse the impact of trader participation and concentration, extend the investigation to other commodities or asset classes, estimate a model that combines quantile regression and Granger causality for panel data, or use trading data at higher frequencies to evaluate the potential intraweek or intraday Granger causality between speculation and returns.

Overall, the findings suggest that financialization does not destabilise commodity markets. The growing interest and investment during the last two decades have attracted more traders which has led to more robust markets that are less prone to changes in trader concentration. Moreover, the information content of CFTC's Commitment of Traders report significantly affects returns once the information is available to the public. In the end, the answer to the question of whether non-commercial speculation improves the estimation of commodity futures returns, would appear to be yes. However, the findings also reveal that non-commercial speculation does not Granger-cause commodity futures returns at weekly frequencies.

CHAPTER 5 CONCLUSION AND FUTURE RESEARCH

To understand and forecast changes in commodity prices, one must identify the influential factors that impact and potentially drive them. Only then, is it possible to reveal their relationships with commodity prices and understand how they interact. This thesis provides an extension of prior research by identifying and quantifying the relationships between environmental, macroeconomic, and intra-market forces and commodity prices, returns, and the volatility thereof. The findings are beneficial for several stakeholders. First, and foremost, the results allow commodity producers and consumers to better understand commodity market behaviour and the effects of commodity-specific, market-specific, macroeconomic, and environmental factors on the financial feasibility and stability of their operations and thus enable them to actively adjust their risk management. Second, the results equip investors with key information to optimise their models and thus portfolios. Likewise, insurers can adjust their policies or provide new products to customers that require specific weather insurance. Third, policy makers may be particularly interested in the findings on monetary policy and non-commercial speculation and their relationship with commodity markets and may use them to develop regulations and guidelines that are better aligned with actual market interactions. Instead of introducing strict position limits as required by MiFID II (ESMA, 2018), which may reduce the positive effects that speculators bring to commodity markets, such as providing liquidity to hedgers (Brunetti and Buyuksahin, 2009), it can be more rewarding for policy makers to publish all trading information in real time, so that all market participants can understand who is currently trading, what commodities and derivatives they are trading, and the directions of their trades. This can reduce potential asymmetric information and thus strengthen commodity markets.

Chapter 2 provides new insights into the effects of weather anomalies on exchange-traded aluminium. It begins with temperature and precipitation anomalies, measured by self-created global weather anomaly indices that consider mine-specific weather station data, and their effect on aluminium futures returns and changes in aluminium inventory. Precipitation anomalies are found to significantly reduce global inventory changes. Particularly when weather data are unavailable and precipitation anomalies occur on multiple days, the reducing effect on inventory changes is significant. Despite this, the effect on aluminium futures returns is limited. The limited significance that is observed might be the result of an increase in the oversupply of aluminium since 2009, which has also dampened the statistical significance of the impact of precipitation anomalies on changes in aluminium inventory. In addition to inventory and futures returns, abnormal stock returns on an index of equally-weighted index of bauxite mining and aluminium producing firms are found to be driven by temperature anomalies. Anomalies observed on the same day as the abnormal returns, anomalies that have been captured during non-trading days, and multi-day anomalies are significant at least at the 10 percent significance level. These findings imply that despite the high costs that weather events can impose on mining operations (cf. BHP Billiton, 2015), there is a limited effect on exchange-traded aluminium futures returns. Moreover, if the coefficients are significant, the obtained results suggest that the magnitude of weather anomalies on aluminium returns and inventory changes is miniscule. Thus, practitioners should not be too concerned about the short-term effects of weather events on the global aluminium price, as inventories seem to sufficiently buffer for those effects. The second contribution to the literature is rooted in the novel method of combining global weather station-specific data, which equips other academics and practitioners with a fast and computationally simple approach to evaluate weather effects for different economic applications. For example, one could calculate precipitation and temperature anomaly indices for large cities with a high demand for industrial metals to estimate the effect of weather anomalies on demand. As bauxite and other metal mines are often located in remote areas with limited weather information, future research may re-evaluate the findings once the availability of weather information improves. This includes weather information nearest to the evaluated mines and weather information from mines in countries such as China, where reliable weather information is scarce. Lastly, future research may focus on the relationships between earlier steps in the process chain and retest the findings for other metals such as gold and copper. Especially for commodities with lower inventory stocks or perishable commodities, the results may differ.

Chapter 3 evaluates the impact of changes in global liquidity due to monetary policy changes and their impact on the price of non-ferrous metals and gold. The chapter provides a novel measure of global unconventional monetary policy in relation to global liquidity, defined as a global multiplier ratio, and a global measure of real interest rates. Compared to its individual measures, the global multiplier ratio provides a better measurement of market and central bank induced liquidity. It is found that the global multiplier ratio significantly increases the price of an index of non-ferrous metals overall and copper in particular. These results suggest that an increase in the ability of an economy to utilise fresh central bank liquidity has a positive effect on the development of industrial metal prices. However, the significance of the positive effect of the global multiplier ratio on the price of industrial metals appears to be only significant during the period surrounding the GFC and only significantly influences the price of copper. The global real interest rate, which has been found to significantly reduce the aluminium price in prior research for lower frequency data, has little significant impact on industrial metal prices. The study indicates that the effect of real interest rates is subsumed by the addition of the multiplier ratio, which suggests that this is a more important determinant of industrial metal prices than real interest rates. Conversely, changes in the global real interest rate significantly reduce the price of gold, but the global multiplier ratio seems to have a negligible effect. Overall, the findings suggest that a market's ability to absorb central bank liquidity and translate it into economic growth might be more important than the level of global real interest rates for the estimation of industrial metal prices. Despite the limited statistical significance of the results, the global multiplier ratio allows investors and academics to quickly and efficiently quantify the impact of global central bank market interventions and consider the associated effects on commodity prices in their models. With this measure, it is possible to illustrate whether the intended effects of quantitative easing, i.e. an increase in lending and thus market liquidity, are sufficiently transmitted to the markets, which is particularly interesting for policy makers. The results imply that, on a monthly and quarterly basis, policy makers should not worry too much about the effects of their actions on industrial metal and gold prices. Moreover, the findings indicate that the global approach provides better estimates than the focus on US measures in prior research. For example, I show that the correlation of China's real interest rate with industrial metal prices is stronger than the correlation with the US real interest rate. These findings are fruitful for other academics who are interested in the analysis of monetary policy and indicate that future research should shift from a focus on US markets towards a more global approach. Although the US is still the largest single economy as of 2016, the arrival of Asian consumers led by China as the largest importer of coal and non-ferrous metals, with a share well above 40 percent (World Bank, 2015; IMF, 2016) may alter the leading impact of the US on commodity market dynamics. Furthermore, researchers may gain from using the trade data employed in this study, which explains a considerable share of variations of the price of industrial metals and gold. These data are freely available and offered by the

International Trade Centre, a joint agency of the World Trade Organization and the United Nations. Given that monetary policy, and particularly unconventional monetary policy since the GFC, deserves considerable attention, these results serve as a fresh reminder of the consequences of market interventions by central banks and their impact on areas that experience less attention in an inflation-targeting environment. Moreover, it remains unclear if the found interactions between the global multiplier ratio, the global real interest rate, and metal prices will change once the central banks reduce their holdings in fixed income assets.

Chapter 4 investigates the interaction of non-commercial speculation, trader concentration, and their explanatory power on the return distribution of a basket of ten different commodity futures. It extends prior research by evaluating the quantiles of the commodity futures return distributions. The findings indicate a stabilising effect of non-commercial speculation for commodity futures returns for a panel of ten commodities, the subgroup metals, and some individual commodities. For most individual commodities, i.e. 8 out of 10, the results indicate a reinforcing relationship between ESV and returns, for both the mean and quantile regression. Granger causality tests reveal that non-commercial speculation, which is associated with increasing effects on commodity prices, is not Granger-causing commodity futures returns. Instead, commodity futures returns Granger-cause non-commercial speculation. This is consistent with the idea that relatively low prices induce non-commercial speculators to buy futures and that when prices rise beyond a certain point, non-commercial speculators sell their positions. In addition, the results for the signalling effect show that traders use information on changes in non-commercial open interest to adjust their positions. This effect is particularly evident when non-commercial speculation deviates from its expected value. Non-commercial traders, particularly large ones, are perceived to have deeper market knowledge. Thus, their actions are used as guidance for other, potentially less informed traders. Once data at higher frequency become available, future research might be able to answer the question of whether the Granger causal effect from non-commercial speculation to commodity futures is, indeed, unidirectional. Due to the unavailability of data at higher frequency, this question must be left unanswered for now. The implications and contributions to the literature that can be drawn from the fourth chapter are threefold. First, the obtained coefficients suggest that the impact of changes in open interest on futures returns is miniscule. Nevertheless, the impact of merchants' open interest is approximately four times[98] stronger than the effects stemming from non-commercial hedging. Thus, the effect of non-commercial, i.e. speculative, trading on futures returns is smaller than the effects stemming from commercial trading. Second, on a weekly basis, there is no significant lagged impact of speculative trading on any of the ten tested commodity futures returns. These findings are important for regulators, investors, and other parties that are interested in the factors that drive commodity prices. Investors and traders benefit from these findings by realising that their actions, on a weekly basis, do not drive returns. The results contrast with the poor image of speculation in society and the media and its perceived negative economic impact, which overshadows its potentially positive impact on financial markets. These include the provision of liquidity, aiding the price discovery mechanisms, reducing hedging costs, and better integration of commodity markets with financial markets (Fattouh et al., 2012; Irwin and Sanders, 2012). Third, the findings suggest that markets react to information on commodity futures open interest once it becomes public. In particular, when excess non-commercial speculation deviates from its expected value, one can observe a highly significant impact on futures returns. Instead of imposing new regulations on trading and position limits, regulators may be well-advised to review their approach in favour of a more transparent and market-oriented approach. This could include publishing daily reports of trading volumes and open interest and the names of the trading parties. If more information is made available, its publication is likely to have a minimal impact.

Higher frequency data are crucial for future research. Whether one wants to test for a bidirectional causal relationship between non-commercial speculation and commodity futures returns or link intraday financial data with intraday weather data to see how the markets interact, analysis that draws on higher frequency data will be most important to cope with the ever-increasing speed of trading. Moreover, the question of potential endogeneity biases present in a model is another fruitful field for future research. It is necessary to identify instrumental variables that can cope with high frequency data and the fast-changing environment present in financial markets. Lastly, more reliable proxies for global commodity inventory and production output or more accurate and better reporting standards for global imports and exports would enable researchers to significantly improve the accuracy of

[98] Please refer to Chapter 4.4.3 for more details.

commodity pricing models. Financial market behaviour is time-variant and depends upon multiple observed and yet to be observed factors that do not necessarily have to be obvious or easily detectable. The results of prior research are time specific and we do not yet have a model that is able to generalise well to multiple time periods. Only if one keeps up with innovations and new regulations, is it possible to adequately price exchange-traded commodities. This task is therefore left for future research endeavours.

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APPENDICES

A2.1: Correlation of Daily Weather and Non-Weather Variables with Threshold

	P_D_MAUabs			T_D_MaUabs		
Observations	3653	3653	3653	3653	3653	3653
Threshold, Percentile	-	90th	95th	-	90th	95th
Deflated Price_r	0.003	-0.008	-0.006	0.003	-0.015	-0.025
Global Inventory_r	-0.031*	-0.017	-0.009	0.012	0.031*	0.035**
Global Demand_r	0.026	0.015	0.022	-0.071***	-0.053***	-0.047***
Monetary Policy_r	-0.001	-0.013	-0.003	0.019	0.013	0.008
TWI_r	0.009	0.009	0.014	0.001	-0.03	-0.003
CBOE VIX	-0.073***	-0.057***	-0.046***	0.006	0.011	0.031*
SP500_r	0.008	0.008	0.008	-0.020	-0.005	-0.008
Global Supply	0.048***	0.023	0.012	-0.077***	-0.093***	-0.081***

Notes: This table shows the results of a pairwise correlation matrix of two weather indices and all other non-weather variables with varying observations and increasing percentile thresholds, whereby 3653 observations illustrate the overall research period of 3653 trading days between 1st January 2001 and 31st December 2014. The data source is a NOAA daily dataset. The parameters are defined as: P for precipitation, T for temperature, D for daily data, and MaU for mine-specific and USGS information. Variables ending with abs indicate the absolute weather indices. Furthermore, all variables ending with _r are the logarithmic periodical changes. The parameters are defined as Deflated Price as the deflated 3-month futures aluminium price, Global Inventory as LME inventory stocks, Global Demand as Baltic Dry Index, Monetary Policy as real interest rate, TWI as the trade-weighted USD index, CBOE VIX as the VIX index, SP500 as the S&P 500 index, and Global Supply as the USGS output. All variables that are not available on a daily or monthly scale are distributed by cubic spline interpolation. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

A2.2: Sample Calculation of Weather Index Values

	Mine A					Mine B					
Time	W	M	N	UAV	WAV	W	M	N	UAV	WAV	TIV
t_0	0.2	24.90	24.40	0.50	0.10	0.8	21.10	21.10	0.00	0.00	0.10
t_1	0.2	24.70	22.10	2.60	0.52	0.8	24.20	21.30	2.90	2.32	2.84
t_2	0.25	24.10	21.10	3.00	0.75	0.75	24.60	21.20	3.40	2.55	3.30
t_3	0.3	23.70	24.00	0.30	0.09	0.7	22.20	21.40	0.80	0.56	0.65
t_4	0.32	24.70	22.70	2.00	0.64	0.68	24.70	21.60	3.10	2.11	2.75

Notes: This table provides a simplified example application of equation 1. This example consists of only two mines A and B and for the research period t_0 to t_4. The parameters are defined as: W as Weight, M as Measurement, N as Normal, UAV as Unweighted Anomaly Value, WAV as Weighted Anomaly Value, and TIV as Total Index Value for period $_t$.
With UAV = M – N, WAV = (M – N) * W, and TIV = $WAV_{mine\ 1} + WAV_{mine\ 2}$.

A3.1: Pairwise Correlation

Panel A: Level	**Overall**	**Pre-Crisis (01/06 – 11/08)**	**FED (12/08 – 12/15)**	**FED QE1 (12/08 – 03/10)**	**FED QE2 (11/10 – 06/11)**	**FED QE3 (09/12 – 12/13)**	**BoJ (08/11 – 12/15)**	**ECB (03/15 – 12/15)**
Industrial Metals / Global MR	67.24%	64.45%	19.50%	-35.08%	-36.02%	40.88%	72.74%	-74.86%
Gold / Global MR	-75.77%	-58.15%	-22.29%	-31.46%	-66.29%	45.36%	78.85%	-81.54%
Industrial Metals / Global RIR	2.40%	35.07%	-79.39%	-70.87%	20.71%	-85.56%	-83.28%	70.52%
Gold / Global RIR	-78.56%	-73.93%	-76.72%	-84.54%	-96.55%	-80.65%	-84.52%	73.98%
SP 500 / Global MR	-12.67%	75.72%	-88.09%	-48.21%	-73.39%	-56.26%	-85.64%	-40.37%
JPM Gbl Bonds TR / Global MR	-89.02%	-68.23%	-30.20%	-49.90%	9.81%	7.14%	70.43%	-42.59%
SP 500 / Global RIR	19.61%	57.42%	14.87%	-71.58%	-23.96%	75.58%	87.57%	-1.68%
JPM Gbl Bonds TR / Global RIR	-72.14%	-67.94%	-66.05%	-52.95%	-40.14%	-74.05%	-81.06%	43.34%
Panel B: First Difference								
Industrial Metals / Global MR	71.53%	89.04%	76.58%	-7.62%	34.22%	-16.45%	94.84%	98.92%
Gold / Global MR	81.42%	37.34%	85.29%	-13.54%	14.97%	-19.80%	93.35%	99.76%
Industrial Metals / Global RIR	-22.39%	-29.25%	-16.66%	-27.01%	-61.64%	-66.88%	36.18%	66.53%
Gold / Global RIR	-11.34%	-48.64%	-8.16%	-59.47%	-18.06%	-56.10%	35.35%	63.69%
SP 500 / Global MR	95.89%	73.10%	97.57%	-29.74%	11.24%	-26.27%	98.88%	99.84%
JPM Gbl Bonds TR / Global MR	92.93%	3.34%	98.14%	10.36%	13.11%	-62.91%	99.29%	99.97%
SP 500 / Global RIR	7.53%	-11.25%	14.31%	-40.93%	-32.34%	44.30%	49.48%	58.54%
JPM Gbl Bonds TR / Global RIR	8.09%	-17.19%	12.03%	6.97%	28.19%	-50.67%	43.47%	62.61%

Notes: This table reports the pairwise correlation between industrial metals and gold prices, the S&P 500 composite index, the JPM Global Bonds total return index, and the global multiplier ratio (MR) and global real interest rate (RIR). It differentiates between different period during the last decade to emphasize periods that have experienced increasing quantitative easing measures by the Federal Reserve (FED), the European Central Bank (ECB), and the Bank of Japan (BoJ) and the research period from January 2006 to December 2015 overall. With data at level in panel A and data at first difference in panel B. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Robust standard errors (Huber/White/sandwich estimator) in parentheses.

A3.2: GARCH (1,1)

	Monthly		**Quarterly**	
	Mean Model	Variance Model	Mean Model	Variance Model
Global Multiplier Ratio	-	-13.02***	-	-6.805***
		(4.217)		(1.813)
ARCH Term	-	0.0617	-	-0.0200
		(0.0439)		(0.0921)
GARCH Term	-	0.896***	-	0.828***
		(0.0528)		(0.151)
Constant	-0.0273*	-8.099***	-0.0668	-5.347***
	(0.0149)	(1.796)	(0.0483)	(1.417)
Observations	119	119	39	39

Notes: This table illustrates the monthly and quarterly GARCH (1,1) results for the SPGSI. The research period runs from January (February due to first differences) 2006 to December 2015. This leads to 119 observations for the monthly and 39 for the quarterly time-series. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$. Standard errors in parentheses.

A3.3: OLS Regression Results – Crude Oil, Natural Gas, and Wheat

Panel A – Monthly	***Crude Oil***	***Crude Oil***	***Natural Gas***	***Natural Gas***	***Wheat No. 2***	***Wheat No. 2***
	(1)	(2)	(3)	(4)	(5)	(6)
Global Multiplier Ratio	0.1579***	0.0988	-0.0029	-0.0029	0.0050	-0.0002
	(0.0569)	(0.0769)	(0.0079)	(0.0087)	(0.0070)	(0.0077)
Real Interest Rate Index	-0.0523***	-0.0485***	-0.0046*	-0.0045	-0.0005	-0.0011
	(0.0191)	(0.0173)	(0.0028)	(0.0029)	(0.0020)	(0.0021)
Trade-Weighted USD Index – Unwrought	-0.0299***	-0.0199***	-0.0007	-0.0006	-0.0008*	-0.0005
	(0.0048)	(0.0057)	(0.0007)	(0.0009)	(0.0004)	(0.0005)
Cash-Forward Spread	0.6600**	0.5551*	0.1722	0.1592	0.1191	0.1384
	(0.2904)	(0.2880)	(0.1786)	(0.1885)	(0.0932)	(0.1085)
Imports in USD		0.0000***		0.0000		-0.0000
		(0.0000)		(0.0000)		(0.0000)
S&P 500		0.0154		0.0011		-0.0008
		(0.0190)		(0.0023)		(0.0018)
CBOE VIX		-0.0013		0.0001		-0.0002
		(0.0023)		(0.0003)		(0.0002)
Inventory Stocks qty		0.0000		-0.0000		
		(0.0000)		(0.0000)		
Constant	0.0094*	0.0058	-0.0000	-0.0001	0.0007	0.0008
	(0.0052)	(0.0052)	(0.0007)	(0.0007)	(0.0005)	(0.0006)
Observations	119	119	119	119	119	119
R^2	0.4984	0.5629	0.0826	0.0897	0.0734	0.0911
Panel B – Quarterly	(7)	(8)	(9)	(10)	(11)	(12)
Global Multiplier Ratio	0.2165**	0.0188	0.0037	0.0051	-0.0002	-0.0008
	(0.0817)	(0.0843)	(0.0124)	(0.0196)	(0.0109)	(0.0115)
Real Interest Rate Index	-0.0361	-0.0170	-0.0060**	-0.0056**	-0.0018	-0.0010
	(0.0234)	(0.0131)	(0.0029)	(0.0023)	(0.0031)	(0.0033)
Trade-Weighted USD Index – Unwrought	-0.0375***	-0.0096	-0.0013	-0.0007	-0.0011	-0.0007
	(0.0049)	(0.0067)	(0.0008)	(0.0007)	(0.0007)	(0.0010)
Cash-Forward Spread	1.9113**	1.1167*	0.4338	0.2003	0.4908	0.6061
	(0.7801)	(0.5477)	(0.3379)	(0.2822)	(0.3466)	(0.3590)
Imports in USD		0.0000***		0.0000**		0.0000
		(0.0000)		(0.0000)		(0.0000)
S&P 500		0.0090		0.0042		-0.0033
		(0.0124)		(0.0025)		(0.0029)
CBOE VIX		-0.0050**		0.0002		-0.0004
		(0.0021)		(0.0005)		(0.0004)
Inventory Stocks qty		0.0000		-0.0000		
		(0.0000)		(0.0000)		
Constant	0.0332**	0.0066	0.0004	-0.0012	0.0027	0.0033*
	(0.0163)	(0.0127)	(0.0019)	(0.0017)	(0.0016)	(0.0019)
Observations	39	39	39	39	39	39
R^2	0.7613	0.8946	0.3233	0.4601	0.1918	0.2701

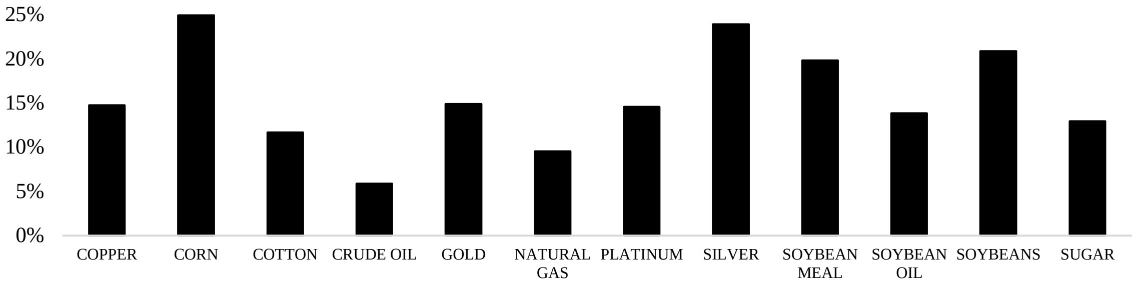
Notes: This table illustrates the monthly and quarterly OLS regression results for crude oil natural gas, and wheat spot prices. The research period runs from January (February due to first differences) 2006 to December 2015. This leads to 119 observations for the monthly and 39 for the quarterly data. Normality of the residuals can be rejected at the 5% level for models 3, 4, 5, 6, and 10 using the skewness-kurtosis and Shapiro-Wilk tests. The augmented Dickey-Fuller test suggests stationarity for all residuals at the 1% level. For all models, I use robust standard errors (Huber/White/sandwich estimator) to control for heteroscedasticity. The correlogram with 95% confidence bands suggests autocorrelation for higher lags and for models 1, 5, and 6 from lag 1 onwards in the monthly time-series. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. Robust standard errors (Huber/White/sandwich estimator) in parentheses.

The models are defined as:

For crude oil and natural gas: $CI_t = \alpha + \beta_1 MR_t + \beta_2 RIR_t + \beta_3 FX_t + \beta_4 CFS_t + \beta_5 IBM_t + \beta_6 SP500_t + \beta_7 VIX_t + \beta_8 INV_t + \varepsilon_t$
For wheat: $CI_t = \alpha + \beta_1 MR_t + \beta_2 RIR_t + \beta_3 FX_t + \beta_4 CFS_t + \beta_5 IBM_t + \beta_6 SP500_t + \beta_7 VIX_t + \varepsilon_t$

With α as intercept, CI as commodity index changes, MR as multiplier ratio, RIR as real interest rate, FX as global base metal trade-weighted USD index, CFS as cash-forward spread, IBM as imports of ores of and unwrought base metals, SP500 as S&P 500 composite index, VIX as S&P 500 volatility index, INV as inventory stocks, and ε as error term. All variables are at time t or time t-1 respectively. All variables at first difference. All data are gathered from Thomson Reuters Datastream, the International Trade Centre, and the US Energy Information Administration (EIA). Due to limited data availability, I use US inventory data for crude oil and natural gas. For wheat, I omit the inventory variable due to insufficient availability of data.

A4.1: Average Share of Non-Reportable Open Interest



Notes: This figure illustrates the share of the average non-reportable open interest for a range of commodities between 3rd January 1995 and 7th March 2017. The value is calculated as: average of non-reportable open interest per commodity / (average of non-reportable open interest per commodity + average of reportable open interest per commodity) * 100.

A4.2: Quantile and Panel Fixed Effects Regression – Financial Effect – Details

Panel A: All Commodities	*Commodity Futures Returns*							
		Quantile						
	PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV	0.0016***	0.0051***	0.0038***	0.0027***	0.0011***	0.0002***	0.0001***	-0.0008***
	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
LTC	-0.0007***	-0.0023***	-0.0019***	-0.0012***	-0.0004***	0.0002***	0.0001***	-0.0001***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
STC	0.0003***	0.0005***	0.0004***	0.0003***	0.0001***	0.0001***	0.0003***	0.0008***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ML	0.0118**	-0.0415***	-0.0270***	-0.0129***	0.0103***	0.0331***	0.0526***	0.0686***
	(0.0046)	(0.0001)	(0.0001)	(0.0001)	(0.0011)	(0.0001)	(0.0001)	(0.0001)
OI_r	0.1482***	0.2217***	0.2096***	0.1623***	0.1283***	0.1295***	0.1137***	0.0667***
	(0.0130)	(0.0002)	(0.0009)	(0.0002)	(0.0014)	(0.0001)	(0.0001)	(0.0005)
SP500_r	0.1763***	0.2020***	0.1795***	0.1672***	0.1131***	0.1434***	0.1660***	0.1709***
	(0.0324)	(0.0010)	(0.0007)	(0.0002)	(0.0074)	(0.0008)	(0.0006)	(0.0012)
RIR_f	-0.0037	-0.0084***	-0.0081***	-0.0064***	-0.0089***	-0.0058***	0.0038***	0.0003***
	(0.0036)	(0.0001)	(0.0001)	(0.0000)	(0.0009)	(0.0001)	(0.0001)	(0.0001)
TED_r	0.0044	0.0015***	0.0062***	0.0011***	0.0023***	0.0055***	0.0040***	0.0044***
	(0.0037)	(0.0001)	(0.0001)	(0.0000)	(0.0004)	(0.0001)	(0.0001)	(0.0001)
TWI_r	-0.8830***	-0.7051***	-0.6326***	-0.7967***	-0.8458***	-0.7700***	-0.7920***	-0.8640***
	(0.0893)	(0.0003)	(0.0023)	(0.0002)	(0.0029)	(0.0013)	(0.0005)	(0.0017)
BDI_r	0.0129	0.0138***	0.0134***	0.0016***	0.0012*	0.0204***	0.0098***	0.0099***
	(0.0088)	(0.0002)	(0.0001)	(0.0001)	(0.0007)	(0.0002)	(0.0001)	(0.0004)
DotCom	0.0024	-0.0031***	-0.0015***	-0.0003***	0.0001	0.0033***	0.0095***	0.0090***
	(0.0015)	(0.0000)	(0.0001)	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0001)
GFC	0.0010	-0.0275***	-0.0162***	-0.0075***	-0.0005	0.0096***	0.0174***	0.0225***
	(0.0026)	(0.0001)	(0.0000)	(0.0000)	(0.0007)	(0.0001)	(0.0001)	(0.0001)
EDC	-0.0010	-0.0029***	0.0008***	0.0000***	-0.0000	-0.0015***	-0.0020***	-0.0014***
	(0.0015)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)

Notes: This table illustrates the detailed results of the panel regression with commodity fixed effects (PD-FE) and quantile regression with nonadditive commodity fixed effects (QRPD) for the financial effect of commodity futures returns between 3rd January 1995 and 7th March 2017 totalling 1,156 observations for each commodity (10 commodities, 11,560 observations in total, 4 commodities each for agriculture in panel B (corn, soybeans, sugar, cotton), metals in panel C (gold, silver, copper, platinum), and 2 energy commodities in panel D (crude oil and natural gas)). With _f and _r indicating first difference and log returns respectively. With ESV, LTC, and STC as focus variables, OI as total open interest, ML as market liquidity, SP500 as Standard & Poor's 500 composite index, RIR as real interest rate, TED as TED spread, TWI as trade-weighted USD index, BDI as Baltic Dry Index, and DotCom, GFC, and EDC as dummies for crisis periods throughout the research period. Note that quantile regression for panel data with nonadditive fixed effects relies on a non-separable error term U^* and does not report a separate constant term. While the PD-FE model includes a constant, I refrain from reporting it for reasons of clarity and comprehensibility. The constant terms for the PD-FE models are (with standards errors in parentheses): panel B: -0.0023* (0.0013); panel C: -0.0069*** (0.0024); panel D: -0.0008 (0.0015); panel E: -0.0022 (0.0034). For the PD-FE model, I use Driscoll-Kraay standard errors to account for cross-sectional dependence. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

The models are defined as:

PD-FE: $CFR_{it} = \alpha + \mu SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$

QRPD: $CFR_{i,t} = \sum_{j=1}^{k} D'_{i,t}\beta_j(U^*_{i,t})$ $\quad P\left(CFR_{i,t} \leq D'_{i,t}\beta(\tau)\middle|D_{i,t}\right) = \tau$ $\quad \hat{\beta}(\tau) = arg \min_{b\in\beta} \hat{g}'(b)\, \hat{A}\hat{g}(b)$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, DotCom as a dummy variable for the dot-com bubble between the years 2000 and 2002, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t. With β_j as the parameter of interest for each of the $k \in N^*$ regressors, D' = [SPEC, F] is the vector of regressors, and U^* is the non-separable error term traditionally associated with quantile estimation. For a τ-th quantile (0 < τ < 1) of CFR.

A4.2 cont.

Panel B: Agriculture					*Commodity Futures Returns*			
					Quantile			
	PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV	0.0019***	0.0023***	0.0029***	0.0016***	0.0014***	0.0010***	0.0020***	0.0011***
	(0.0004)	(0.0001)	(0.0000)	(0.0004)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
LTC	-0.0012***	-0.0007***	-0.0010***	-0.0013***	-0.0008***	-0.0003***	-0.0016***	-0.0019***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
STC	0.0010***	0.0001***	0.0002***	0.0006***	0.0005***	0.0010***	0.0016***	0.0024***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
ML	0.0299***	-0.0206***	-0.0185***	0.0010	0.0308***	0.0497***	0.0623***	0.0759***
	(0.0099)	(0.0007)	(0.0001)	(0.0012)	(0.0011)	(0.0008)	(0.0001)	(0.0002)
OI_r	0.1763***	0.3129***	0.2665***	0.2332***	0.1771***	0.1166***	0.0580***	0.0643***
	(0.0202)	(0.0048)	(0.0006)	(0.0022)	(0.0029)	(0.0009)	(0.0004)	(0.0012)
SP500_r	0.1361***	0.2017***	0.1446***	0.1632***	0.1523***	0.0800***	0.1250***	0.0894***
	(0.0445)	(0.0032)	(0.0010)	(0.0242)	(0.0103)	(0.0065)	(0.0006)	(0.0021)
RIR_f	-0.0045	-0.0094***	-0.0009***	-0.0080***	-0.0043***	-0.0063***	0.0003***	-0.0054***
	(0.0045)	(0.0003)	(0.0001)	(0.0009)	(0.0002)	(0.0003)	(0.0001)	(0.0002)
TED_r	-0.0022	-0.0086***	0.0027***	0.0025	0.0029	-0.0015***	-0.0002**	-0.0132***
	(0.0052)	(0.0010)	(0.0002)	(0.0041)	(0.0044)	(0.0006)	(0.0001)	(0.0003)
TWI_r	-0.5761***	-0.2874***	-0.4976***	-0.2971**	-0.5682***	-0.5466***	-0.5909***	-0.7484***
	(0.0952)	(0.0092)	(0.0023)	(0.1243)	(0.0043)	(0.0071)	(0.0022)	(0.0053)
BDI_r	-0.0047	-0.0038***	-0.0160***	-0.0039	-0.0174***	0.0076***	-0.0015**	-0.0151***
	(0.0105)	(0.0014)	(0.0002)	(0.0129)	(0.0017)	(0.0014)	(0.0006)	(0.0004)
DotCom	0.0012	0.0012***	-0.0013***	-0.0006	0.0031*	0.0039***	0.0056***	0.0066***
	(0.0019)	(0.0002)	(0.0001)	(0.0013)	(0.0018)	(0.0004)	(0.0000)	(0.0002)
GFC	-0.0002	-0.0353***	-0.0208***	-0.0058**	0.0043**	0.0017**	0.0209***	0.0217***
	(0.0030)	(0.0002)	(0.0001)	(0.0028)	(0.0019)	(0.0007)	(0.0000)	(0.0001)
EDC	-0.0010	-0.0137***	-0.0166***	0.0035	0.0018***	0.0025***	0.0092***	0.0124***
	(0.0024)	(0.0005)	(0.0001)	(0.0032)	(0.0005)	(0.0002)	(0.0001)	(0.0001)

Panel C: Metals					*Commodity Futures Returns*			
					Quantile			
	PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV	0.0011***	0.0052***	0.0045***	0.0015***	0.0003*	0.0003	-0.0023***	-0.0027***
	(0.0004)	(0.0000)	(0.0000)	(0.0005)	(0.0002)	(0.0003)	(0.0000)	(0.0000)
LTC	-0.0004*	0.0011***	0.0005***	0.0001	-0.0003***	-0.0000	-0.0012***	-0.0019***
	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0000)	(0.0000)
STC	0.0002**	0.0002***	0.0001***	0.0001***	0.0002***	0.0001***	0.0001***	-0.0000***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
ML	0.0029	-0.0680***	-0.0411***	-0.0201***	0.0014*	0.0257***	0.0444***	0.0572***
	(0.0057)	(0.0001)	(0.0001)	(0.0012)	(0.0008)	(0.0008)	(0.0001)	(0.0002)
OI_r	0.1169***	0.1633***	0.1265***	0.1101***	0.1064***	0.1062***	0.1104***	0.0883***
	(0.0127)	(0.0005)	(0.0003)	(0.0016)	(0.0045)	(0.0023)	(0.0002)	(0.0001)
SP500_r	0.1536***	0.2267***	0.1887***	0.1583***	0.1047***	0.0524***	0.1150***	0.1488***
	(0.0278)	(0.0010)	(0.0005)	(0.0110)	(0.0026)	(0.0126)	(0.0003)	(0.0004)
RIR_f	-0.0023	-0.0051***	-0.0067***	-0.0132***	-0.0035***	-0.0033***	0.0006***	0.0040***
	(0.0037)	(0.0001)	(0.0000)	(0.0020)	(0.0010)	(0.0008)	(0.0001)	(0.0000)
TED_r	0.0060	0.0073***	0.0029***	0.0116***	0.0033**	0.0124***	0.0120***	0.0168***
	(0.0048)	(0.0002)	(0.0001)	(0.0027)	(0.0014)	(0.0020)	(0.0001)	(0.0001)
TWI_r	-1.2125***	-1.1441***	-1.1208***	-1.1531***	-1.0993***	-0.8600***	-1.0428***	-1.2118***
	(0.1046)	(0.0025)	(0.0010)	(0.0147)	(0.0120)	(0.0186)	(0.0010)	(0.0007)
BDI_r	0.0146	0.0269***	0.0107***	-0.0013	-0.0023**	0.0101***	0.0212***	0.0155***
	(0.0124)	(0.0001)	(0.0002)	(0.0046)	(0.0009)	(0.0025)	(0.0001)	(0.0002)
DotCom	0.0012	0.0041***	0.0020***	0.0014	-0.0005**	0.0038***	-0.0029***	-0.0030***
	(0.0015)	(0.0001)	(0.0001)	(0.0009)	(0.0002)	(0.0010)	(0.0000)	(0.0000)
GFC	0.0004	-0.0186***	-0.0125***	-0.0060***	-0.0007*	0.0072***	0.0156***	0.0227***
	(0.0032)	(0.0001)	(0.0001)	(0.0015)	(0.0004)	(0.0008)	(0.0000)	(0.0000)
EDC	-0.0001	0.0051***	-0.0002***	0.0052***	0.0003	0.0005***	0.0005***	0.0005***
	(0.0019)	(0.0000)	(0.0000)	(0.0016)	(0.0005)	(0.0002)	(0.0000)	(0.0000)

A4.2 cont.

Panel D: Energy		*Commodity Futures Returns*						
		Quantile						
	PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV_f	0.0760***	0.0738***	0.0787***	0.0749***	0.0810***	0.0638***	0.0680***	0.0709***
	(0.0054)	(0.0004)	(0.0024)	(0.0001)	(0.0029)	(0.0002)	(0.0002)	(0.0002)
LTC	-0.0000	0.0040***	0.0005	0.0015***	0.0004***	-0.0009***	-0.0028***	-0.0046***
	(0.0003)	(0.0000)	(0.0004)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
STC	-0.0002	-0.0029***	-0.0008***	-0.0010***	0.0000	0.0007***	0.0016***	0.0025***
	(0.0002)	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
ML	0.0151	-0.0295***	-0.0282***	-0.0164***	0.0029***	0.0186***	0.0680***	0.0988***
	(0.0123)	(0.0012)	(0.0016)	(0.0005)	(0.0007)	(0.0006)	(0.0004)	(0.0014)
OI_r	0.1360***	0.2068***	0.0381*	0.1720***	0.1549***	0.1347***	-0.0003	0.0770***
	(0.0473)	(0.0031)	(0.0220)	(0.0003)	(0.0022)	(0.0019)	(0.0012)	(0.0098)
SP500_r	0.2432***	0.2367***	0.2442***	0.2295***	0.2271***	0.2341***	0.3289***	0.4415***
	(0.0660)	(0.0037)	(0.0265)	(0.0009)	(0.0114)	(0.0027)	(0.0017)	(0.0182)
RIR_f	0.0008	-0.0211***	0.0144***	-0.0070***	-0.0065***	0.0022***	0.0135***	0.0023**
	(0.0076)	(0.0006)	(0.0044)	(0.0001)	(0.0010)	(0.0004)	(0.0002)	(0.0010)
TED_r	0.0146	0.0456***	0.0134***	0.0138***	0.0155***	0.0150***	0.0080***	0.0381***
	(0.0097)	(0.0008)	(0.0008)	(0.0002)	(0.0016)	(0.0005)	(0.0003)	(0.0006)
TWI_r	-0.6866***	-0.5897***	-0.5675***	-0.6186***	-0.2910***	-0.6007***	-0.6524***	-1.0327***
	(0.1652)	(0.0119)	(0.0413)	(0.0019)	(0.0763)	(0.0023)	(0.0071)	(0.0078)
BDI_r	0.0472**	0.0818***	-0.0026	0.0340***	0.0238***	0.0357***	0.0172***	0.0531***
	(0.0199)	(0.0009)	(0.0022)	(0.0002)	(0.0058)	(0.0008)	(0.0004)	(0.0019)
DotCom	0.0041	-0.0330***	0.0019	-0.0032***	0.0090***	0.0182***	0.0211***	0.0179***
	(0.0040)	(0.0003)	(0.0043)	(0.0001)	(0.0015)	(0.0002)	(0.0001)	(0.0003)
GFC	0.0000	-0.0287***	-0.0260***	-0.0061***	-0.0052***	0.0100***	0.0129***	0.0127***
	(0.0056)	(0.0004)	(0.0004)	(0.0001)	(0.0009)	(0.0002)	(0.0002)	(0.0004)
EDC	-0.0018	0.0317***	0.0225***	0.0052***	-0.0047***	-0.0105***	-0.0222***	-0.0145***
	(0.0033)	(0.0003)	(0.0010)	(0.0001)	(0.0016)	(0.0002)	(0.0001)	(0.0008)

A4.3: Commercial and Non-Commercial Trader Concentration

	Commodity Futures Returns									
	Corn	Corn	Soybeans	Soybeans	Sugar	Sugar	Cotton	Cotton	Gold	Gold
ESV	0.0012**	0.0007	0.0023***	0.0001	0.0005	-0.0005			0.0004	0.0008
	(0.0005)	(0.0004)	(0.0007)	(0.0013)	(0.0015)	(0.0018)			(0.0006)	(0.0008)
ESV_f							0.1413***	0.1448***		
							(0.0094)	(0.0096)		
LTC_r	-0.1241***		-0.1196***		-0.1614***		-0.0296*		-0.0566***	
	(0.0244)		(0.0181)		(0.0176)		(0.0171)		(0.0085)	
LTCC						-0.0057***		-0.0005		-0.0016**
						(0.0014)		(0.0010)		(0.0006)
LTCC_r		-0.2124***		-0.1822***						
		(0.0172)		(0.0144)						
LTCNC_r		0.0813***		0.0849***		0.0290**		0.0027		0.0221***
		(0.0161)		(0.0116)		(0.0115)		(0.0092)		(0.0055)
STC					0.0009*		0.0004**		0.0001	
					(0.0004)		(0.0002)		(0.0002)	
STC_r	0.1468***		0.0983***							
	(0.0336)		(0.0208)							
STCC				0.0027*		0.0013*		0.0006**		-0.0002
				(0.0015)		(0.0008)		(0.0002)		(0.0002)
STCC_r		0.2319***								
		(0.0203)								
STCNC		-0.0013		-0.0042**		0.0055**		-0.0003		0.0002
		(0.0011)		(0.0019)		(0.0022)		(0.0011)		(0.0004)
STCNC_r										
R^2	0.113	0.336	0.192	0.312	0.117	0.066	0.244	0.242	0.351	0.318
	Silver	Silver	Copper	Copper	Platinum	Platinum	NatGas	NatGas	Crude	Crude
ESV	0.0114***	0.0114***	0.0072***	0.0074**						
	(0.0028)	(0.0032)	(0.0028)	(0.0036)						
ESV_f					0.3030***	0.2938***	0.1206***	0.1003***	0.0607***	0.0496***
					(0.0197)	(0.0213)	(0.0120)	(0.0119)	(0.0045)	(0.0048)
LTC_r	-0.0264		-0.0389***		-0.0053		0.0005		0.0174	
	(0.0209)		(0.0110)		(0.0079)		(0.0263)		(0.0196)	
LTCC				0.0006		-0.0021**		-0.0025*		-0.0001
				(0.0007)		(0.0010)		(0.0015)		(0.0006)
LTCC_r		-0.0859***								
		(0.0084)								
LTCNC_r		0.0629***		0.0438***		0.0049		0.0896***		0.0403***
		(0.0132)		(0.0094)		(0.0068)		(0.0172)		(0.0142)
STC	-0.0008***		0.0005**		0.0000		-0.0001			
	(0.0003)		(0.0002)		(0.0001)		(0.0002)			
STC_r									-0.0342*	
									(0.0181)	
STCC		-0.0012***		0.0004		0.0000		0.0016*		-0.0002
		(0.0004)		(0.0003)		(0.0001)		(0.0009)		(0.0004)
STCC_r										
STCNC		0.0002				-0.0001				
		(0.0008)				(0.0004)				
STCNC_r				-0.0319***				-0.0221		-0.0565***
				(0.0057)				(0.0136)		(0.0133)
Adj. R^2	0.270	0.374	0.194	0.218	0.346	0.351	0.132	0.154	0.262	0.273

<u>*Notes:*</u> This table illustrates the results of the OLS regression with robust standard errors (Huber/White/sandwich estimator) for commodity futures returns between 3rd January 1995 and 7th March 2017. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

<u>*The model is defined as:*</u>

$$CFR_t = \alpha + \mu SPEC_t + \delta F_t + \varepsilon_{it}$$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC] or SPEC = [ESV, LTCC, LTCNC, STCC, STCNC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, and ε as error term at time t. Depending on ADF and PP tests for unit roots, log returns or first differences are used to transform the individual time-series.

A4.4: Granger Causality – Commercial and Non-Commercial

	Lags	*LTCC*	*LTCNC*	*STCC*	*STCNC*
Corn	2	Yes** / No	No / Yes**	No / Yes***	No / Yes***
Soybeans	2	Yes* / No	No / No	No / No	No / Yes*
Sugar	2	No / Yes***	Yes*** / Yes*	No / Yes***	No / No
Cotton	2	No / Yes**	No / No	No / No	No / No
Gold	2	No / Yes***	No / No	No / No	No / No
Silver	2	No / Yes***	No / No	No / No	No / Yes**
Copper	2	No / Yes***	No / No	No / No	No / Yes***
Platinum	2	No / No	No / Yes*	Yes** / No	No / Yes***
Natural Gas	4	No / No	No / No	No / Yes***	No / No
Crude Oil	4	No / Yes*	No / No	No / Yes***	No / No

Notes: This table illustrates the results of the Granger causality test for the individual commodities between 3rd January 1995 and 7th March 2017. With the **first** "Yes" and "No" as the answer to "Does the regressor, i.e. LTCC, LTCNC, STCC, or STCNC Granger-cause commodity futures returns?" and the **second** "Yes" and "No" as the answer to "Do commodity futures returns Granger-cause the regressors i.e. LTCC, LTCNC, STCC, or STCNC?" * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

A4.5: Quantile and Panel Fixed Effects Regression – Signalling Effect – Details

Panel A: All Commodities	***Commodity Futures Returns***							
		Quantile						
	PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV	0.0005	0.0029***	0.0028***	0.0017***	0.0005***	-0.0010***	-0.0015***	-0.0021***
	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LTC	-0.0000	-0.0009***	-0.0008***	-0.0005***	-0.0001***	0.0004***	0.0006***	0.0006***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
STC	-0.0000	-0.0002***	-0.0000***	-0.0000***	-0.0000**	0.0000***	-0.0000**	0.0003***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ML	0.0002	-0.0602***	-0.0411***	-0.0196***	0.0041***	0.0270***	0.0390***	0.0471***
	(0.0043)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
OI_r	0.0348***	0.1089***	0.0721***	0.0326***	0.0157***	0.0121***	0.0146***	-0.0111***
	(0.0107)	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0004)	(0.0003)
SP500_r	0.1876***	0.2423***	0.2727***	0.2156***	0.1482***	0.1260***	0.0913***	0.1212***
	(0.0311)	(0.0004)	(0.0006)	(0.0001)	(0.0009)	(0.0003)	(0.0011)	(0.0005)
RIR_f	-0.0073**	-0.0069***	-0.0057***	-0.0072***	-0.0043***	-0.0052***	-0.0087***	-0.0098***
	(0.0033)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0002)	(0.0000)
TED_r	0.0069*	0.0033***	-0.0011***	0.0001*	0.0027***	0.0047***	0.0088***	0.0161***
	(0.0041)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)
TWI_r	-0.9281***	-0.7656***	-0.8469***	-0.8881***	-0.9147***	-0.8427***	-0.9033***	-0.8058***
	(0.0773)	(0.0037)	(0.0011)	(0.0005)	(0.0015)	(0.0008)	(0.0015)	(0.0005)
BDI_r	0.0140	0.0306***	0.0199***	0.0044***	0.0048***	0.0075***	0.0145***	0.0100***
	(0.0086)	(0.0002)	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0003)	(0.0001)
DotCom	0.0022	-0.0010***	-0.0005***	0.0010***	0.0003***	0.0020***	0.0047***	0.0077***
	(0.0016)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
GFC	0.0012	-0.0266***	-0.0167***	-0.0076***	0.0018***	0.0091***	0.0179***	0.0216***
	(0.0028)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
EDC	0.0005	0.0035***	-0.0010***	-0.0007***	-0.0001***	0.0009***	0.0029***	0.0016***
	(0.0016)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)

Notes: This table illustrates the detailed results of the panel regression with commodity fixed effects (PD-FE) and quantile regression with nonadditive commodity fixed effects (QRPD) for the signalling effect of commodity futures returns between 3rd January 1995 and 7th March 2017 totalling 1,156 observations for each commodity (10 commodities, 11,560 observations in total, 4 commodities each for agriculture in panel B (corn, soybeans, sugar, cotton), metals in panel C (gold, silver, copper, platinum), and 2 energy commodities in panel D (crude oil and natural gas)). With _f and _r indicating first difference and log returns respectively. With ESV, LTC, and STC as focus variables, OI as total open interest, ML as market liquidity, SP500 as Standard & Poor's 500 composite index, RIR as real interest rate, TED as TED spread, TWI as trade-weighted USD index, BDI as Baltic Dry Index, and DotCom, GFC, and EDC as dummies for crisis periods throughout the research period. Note that quantile regression for panel data with nonadditive fixed effects relies on a non-separable error term U^* and does not report a separate constant term. While the PD-FE model includes a constant, I refrain from reporting it for reasons of clarity and comprehensibility. The constant terms for the PD-FE models are (with standards errors in parentheses): panel B: -0.0001 (0.0013); panel C: -0.0031* (0.0017); panel D: 0.0016 (0.0016); panel E: -0.0014 (0.0035). For the PD-FE model, I use Driscoll-Kraay standard errors to account for cross-sectional dependence. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

The models are defined as:

PD-FE: $CFR_{it} = \alpha + \mu SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$

QRPD: $CFR_{i,t} = \sum_{j=1}^{k} D'_{i,t}\beta_j(U^*_{i,t})$ $\quad P\left(CFR_{i,t} \leq D'_{i,t}\beta(\tau)\middle|D_{i,t}\right) = \tau$ $\quad \hat{\beta}(\tau) = arg\min_{b\in\beta} \hat{g}'(b)\,\hat{A}\hat{g}(b)$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, DotCom as a dummy variable for the dot-com bubble between the years 2000 and 2002, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t. With β_j as the parameter of interest for each of the $k \in \mathbb{N}^*$ regressors, $D' = [SPEC, F]$ is the vector of regressors, and U^* is the non-separable error term traditionally associated with quantile estimation. For a τ-th quantile (0 < τ < 1) of CFR.

A4.5 cont.

Panel B: Agriculture				***Commodity Futures Returns***				
				Quantile				
	PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV	0.0004	0.0002**	0.0004***	-0.0000	0.0006***	0.0008***	0.0012***	0.0008***
	(0.0004)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
LTC	-0.0003	0.0011***	0.0004***	-0.0005***	0.0002***	0.0008***	-0.0008***	-0.0015***
	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
STC	0.0004**	-0.0011***	-0.0007***	0.0005***	0.0001**	0.0005***	0.0013***	0.0015***
	(0.0002)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ML	0.0054	-0.0990***	-0.0457***	-0.0061***	0.0035***	0.0427***	0.0484***	0.0754***
	(0.0046)	(0.0004)	(0.0002)	(0.0014)	(0.0009)	(0.0005)	(0.0002)	(0.0001)
OI_r	0.0607***	0.1251***	0.1032***	-0.0636***	0.0368***	0.0163***	-0.0617***	-0.0877***
	(0.0185)	(0.0024)	(0.0004)	(0.0182)	(0.0035)	(0.0021)	(0.0011)	(0.0006)
SP500_r	0.1776***	0.3073***	0.2478***	0.0941***	0.1388***	0.0568***	0.0804***	0.1085***
	(0.0407)	(0.0082)	(0.0008)	(0.0297)	(0.0029)	(0.0071)	(0.0022)	(0.0010)
RIR_f	-0.0044	-0.0091***	-0.0056***	0.0159***	-0.0048***	-0.0016***	-0.0014***	-0.0092***
	(0.0042)	(0.0002)	(0.0001)	(0.0042)	(0.0007)	(0.0004)	(0.0002)	(0.0002)
TED_r	0.0004	0.0073***	-0.0068***	-0.0584***	0.0096***	0.0024***	-0.0040***	-0.0013***
	(0.0063)	(0.0006)	(0.0001)	(0.0169)	(0.0014)	(0.0008)	(0.0001)	(0.0001)
TWI_r	-0.7107***	-0.6636***	-0.7281***	-0.5931***	-0.5955***	-0.6081***	-0.7991***	-0.6634***
	(0.0938)	(0.0082)	(0.0028)	(0.0317)	(0.0107)	(0.0168)	(0.0028)	(0.0017)
BDI_r	-0.0017	-0.0032***	-0.0245***	-0.0026	-0.0097***	-0.0058***	0.0223***	-0.0077***
	(0.0102)	(0.0004)	(0.0004)	(0.0026)	(0.0016)	(0.0020)	(0.0007)	(0.0003)
DotCom	0.0021	0.0076***	-0.0019***	-0.0042***	-0.0011**	0.0045***	0.0072***	0.0056***
	(0.0021)	(0.0003)	(0.0001)	(0.0009)	(0.0005)	(0.0002)	(0.0001)	(0.0001)
GFC	0.0014	-0.0182***	-0.0117***	-0.0063***	-0.0049***	-0.0011	0.0175***	0.0298***
	(0.0032)	(0.0001)	(0.0001)	(0.0013)	(0.0010)	(0.0008)	(0.0002)	(0.0001)
EDC	0.0001	-0.0034***	-0.0051***	-0.0053***	-0.0043***	0.0007*	0.0092***	0.0164***
	(0.0027)	(0.0001)	(0.0001)	(0.0016)	(0.0004)	(0.0004)	(0.0001)	(0.0001)

Panel C: Metals				***Commodity Futures Returns***				
				Quantile				
	PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV	0.0003	0.0037***	0.0033***	-0.0006*	0.0002**	0.0007***	-0.0028***	-0.0044***
	(0.0004)	(0.0000)	(0.0000)	(0.0003)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
LTC	0.0001	0.0015***	0.0010***	0.0004***	0.0006***	0.0003***	-0.0010***	-0.0010***
	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0001)	(0.0000)	(0.0000)
STC	-0.0001	0.0001***	-0.0000***	-0.0000***	-0.0002***	-0.0002***	-0.0000***	-0.0002***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ML	-0.0070	-0.0595***	-0.0470***	-0.0231***	-0.0126***	0.0050***	0.0401***	0.0534***
	(0.0067)	(0.0000)	(0.0001)	(0.0004)	(0.0016)	(0.0017)	(0.0002)	(0.0001)
OI_r	0.0189**	0.0416***	0.0120***	0.0072***	0.0060***	-0.0188***	0.0353***	0.0475***
	(0.0093)	(0.0001)	(0.0001)	(0.0026)	(0.0010)	(0.0039)	(0.0004)	(0.0001)
SP500_r	0.1607***	0.2832***	0.2423***	0.1777***	0.1253***	0.1148***	0.1227***	0.1260***
	(0.0363)	(0.0003)	(0.0002)	(0.0049)	(0.0041)	(0.0061)	(0.0005)	(0.0014)
RIR_f	-0.0064*	-0.0034***	-0.0103***	-0.0024***	0.0003	0.0123***	-0.0051***	-0.0053***
	(0.0036)	(0.0000)	(0.0001)	(0.0005)	(0.0011)	(0.0016)	(0.0000)	(0.0001)
TED_r	0.0048	-0.0068***	-0.0076***	0.0040***	0.0035***	0.0079***	0.0127***	0.0372***
	(0.0050)	(0.0000)	(0.0001)	(0.0008)	(0.0002)	(0.0004)	(0.0002)	(0.0001)
TWI_r	-1.2125***	-1.2216***	-1.1781***	-1.1971***	-1.1385***	-1.0661***	-1.0102***	-0.9464***
	(0.0906)	(0.0015)	(0.0007)	(0.0082)	(0.0068)	(0.0111)	(0.0010)	(0.0023)
BDI_r	0.0207	0.0317***	0.0196***	0.0110***	0.0002	0.0103***	0.0179***	0.0338***
	(0.0137)	(0.0002)	(0.0001)	(0.0005)	(0.0024)	(0.0012)	(0.0002)	(0.0003)
DotCom	0.0006	0.0057***	0.0048***	0.0066***	-0.0057***	-0.0006*	-0.0037***	-0.0048***
	(0.0016)	(0.0000)	(0.0000)	(0.0009)	(0.0011)	(0.0003)	(0.0001)	(0.0000)
GFC	0.0012	-0.0282***	-0.0164***	0.0014	-0.0052**	0.0191***	0.0227***	0.0283***
	(0.0034)	(0.0000)	(0.0000)	(0.0015)	(0.0021)	(0.0007)	(0.0000)	(0.0001)
EDC	0.0022	0.0022***	-0.0003***	0.0031***	0.0002	0.0009*	0.0060***	0.0044***
	(0.0020)	(0.0000)	(0.0000)	(0.0004)	(0.0004)	(0.0005)	(0.0001)	(0.0001)

A4.5 cont.

Panel D: Energy	*Commodity Futures Returns*							
		Quantile						
	PD-FE	5th	10th	25th	50th	75th	90th	95th
ESV_f	0.0204***	0.0120***	0.0414***	0.0206***	0.0213***	0.0200***	0.0170***	0.0241***
	(0.0047)	(0.0003)	(0.0010)	(0.0001)	(0.0045)	(0.0004)	(0.0001)	(0.0004)
LTC	0.0005	0.0056***	-0.0011	0.0016***	0.0007***	-0.0017***	-0.0030***	-0.0055***
	(0.0004)	(0.0000)	(0.0007)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
STC	-0.0005*	-0.0029***	0.0005	-0.0010***	0.0001	0.0009***	0.0016***	0.0029***
	(0.0003)	(0.0000)	(0.0004)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
ML	0.0126	-0.0886***	0.0622***	-0.0149***	-0.0057	0.0399***	0.0787***	0.0525***
	(0.0132)	(0.0004)	(0.0179)	(0.0002)	(0.0042)	(0.0005)	(0.0004)	(0.0009)
OI_r	0.0059	0.1512***	-0.5222***	0.0010	-0.0015	-0.0925***	-0.1397***	-0.1300***
	(0.0492)	(0.0025)	(0.0832)	(0.0014)	(0.0165)	(0.0021)	(0.0021)	(0.0037)
SP500_r	0.2545***	0.4805***	0.6512***	0.2570***	0.1672***	0.1440***	0.1123***	0.2851***
	(0.0749)	(0.0035)	(0.0500)	(0.0018)	(0.0146)	(0.0035)	(0.0048)	(0.0024)
RIR_f	-0.0136	-0.0274***	0.0794***	-0.0132***	-0.0114***	-0.0267***	-0.0181***	-0.0122***
	(0.0083)	(0.0006)	(0.0128)	(0.0002)	(0.0018)	(0.0005)	(0.0003)	(0.0001)
TED_r	0.0226*	0.0544***	-0.0703***	0.0222***	0.0009	0.0313***	0.0106***	0.0195***
	(0.0115)	(0.0006)	(0.0130)	(0.0004)	(0.0070)	(0.0007)	(0.0005)	(0.0006)
TWI_r	-0.7474***	-0.1556***	0.5431***	-0.7805***	-0.7193***	-0.7507***	-0.8600***	-0.8707***
	(0.1668)	(0.0175)	(0.1857)	(0.0033)	(0.0207)	(0.0053)	(0.0057)	(0.0028)
BDI_r	0.0318*	0.0394***	-0.1004***	0.0250***	0.0476***	0.0273***	0.0264***	-0.0286***
	(0.0189)	(0.0002)	(0.0206)	(0.0003)	(0.0112)	(0.0008)	(0.0011)	(0.0006)
DotCom	0.0041	-0.0088***	0.0028*	-0.0053***	0.0048***	0.0084***	0.0075***	0.0159***
	(0.0043)	(0.0004)	(0.0017)	(0.0001)	(0.0011)	(0.0001)	(0.0003)	(0.0002)
GFC	-0.0017	-0.0395***	-0.0325***	-0.0053***	-0.0048**	0.0101***	-0.0052***	0.0008*
	(0.0056)	(0.0004)	(0.0026)	(0.0001)	(0.0020)	(0.0005)	(0.0002)	(0.0004)
EDC	-0.0016	0.0202***	0.0122***	0.0075***	-0.0051***	-0.0075***	-0.0175***	-0.0222***
	(0.0031)	(0.0003)	(0.0011)	(0.0001)	(0.0010)	(0.0003)	(0.0002)	(0.0004)

A4.6: Expectation vs. Reality – Signalling Effect

					Commodity Futures Returns					
Panel A	ESV-All	ESV-All	ESV-AG	ESV-AG	ESV-PM	ESV-PM	ESV-IM	ESV-IM	ESV-EN	ESV-EN
ESV	0.0001		0.0002		-0.0004		-0.0005			
	(0.0004)		(0.0005)		(0.0008)		(0.0036)			
ESV_r									0.0127**	
									(0.0055)	
FE[ESV]		0.0176***		0.0186***		0.0144***		0.0388***		0.0120**
		(0.0028)		(0.0035)		(0.0039)		(0.0137)		(0.0060)
LTC	0.0002	0.0003	-0.0006	-0.0005	0.0003	0.0003	0.0003	0.0002		
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0008)	(0.0008)		
LTC_r									0.0447*	0.0440*
									(0.0233)	(0.0233)
STC	0.0000	-0.0000	0.0003	0.0002	-0.0002	-0.0002*			-0.0004	-0.0004
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)			(0.0003)	(0.0003)
STC_r							-0.0054	-0.0103		
							(0.0155)	(0.0159)		
ML	-0.0018	-0.0023	0.0193	0.0174	-0.0201*	-0.0201*	0.0154	0.0141	0.0257*	0.0256*
	(0.0077)	(0.0075)	(0.0131)	(0.0122)	(0.0107)	(0.0106)	(0.0167)	(0.0145)	(0.0150)	(0.0150)
OI_r	0.0108	-0.0080	0.0493	0.0219	0.0420**	0.0214	0.0059	0.0070	-0.2506***	-0.2509***
	(0.0175)	(0.0168)	(0.0305)	(0.0286)	(0.0210)	(0.0221)	(0.0375)	(0.0362)	(0.0597)	(0.0597)
SP500_r	0.2155***	0.2136***	0.2083***	0.2016***	-0.0010	0.0041	0.6223***	0.6234***	0.3492***	0.3484***
	(0.0469)	(0.0463)	(0.0560)	(0.0560)	(0.0764)	(0.0764)	(0.0966)	(0.0979)	(0.0993)	(0.0994)
RIR_f	-0.0084*	-0.0081*	-0.0069	-0.0067	-0.0086**	-0.0087**	-0.0002	0.0003	-0.0120	-0.0122
	(0.0044)	(0.0045)	(0.0054)	(0.0055)	(0.0044)	(0.0044)	(0.0076)	(0.0076)	(0.0111)	(0.0111)
TED_r	0.0009	0.0016	-0.0101	-0.0085	0.0099	0.0102	-0.0114	-0.0105	0.0173	0.0178
	(0.0078)	(0.0078)	(0.0105)	(0.0104)	(0.0093)	(0.0095)	(0.0156)	(0.0156)	(0.0207)	(0.0207)
TWI_r	-1.1274***	-1.1081***	-0.8299***	-0.8125***	-1.6664***	-1.6525***	-1.1148***	-1.0585***	-0.8460***	-0.8503***
	(0.1097)	(0.1076)	(0.1390)	(0.1375)	(0.1364)	(0.1343)	(0.1797)	(0.1832)	(0.2065)	(0.2062)
BDI_r	0.0173*	0.0166*	-0.0020	-0.0039	0.0243	0.0242	0.0183	0.0173	0.0480**	0.0474**
	(0.0091)	(0.0090)	(0.0113)	(0.0110)	(0.0158)	(0.0155)	(0.0191)	(0.0190)	(0.0189)	(0.0189)
GFC	0.0017	0.0017	0.0004	0.0006	0.0012	0.0008	0.0066	0.0062	-0.0028	-0.0028
	(0.0029)	(0.0028)	(0.0033)	(0.0031)	(0.0036)	(0.0035)	(0.0055)	(0.0054)	(0.0061)	(0.0061)
EDC	0.0011	0.0010	-0.0006	-0.0007	0.0044*	0.0041	0.0016	0.0009	-0.0022	-0.0022
	(0.0017)	(0.0016)	(0.0029)	(0.0027)	(0.0026)	(0.0025)	(0.0034)	(0.0027)	(0.0033)	(0.0033)
Constant	-0.0023	-0.0018	-0.0006	-0.0007	0.0067	0.0074*	-0.0097	-0.0087	0.0010	0.0010
	(0.0038)	(0.0037)	(0.0072)	(0.0068)	(0.0043)	(0.0043)	(0.0074)	(0.0072)	(0.0092)	(0.0093)
Obs.	5,610	5,610	2,244	2,244	1,683	1,683	561	561	1,122	1,122

Notes: This table illustrates the results of the panel regression with commodity fixed effects for the signalling effect of commodity futures returns between June 2006 and 7th March 2017 totalling 561 observations for each commodity (10 commodities, agriculture (AG: corn, soybeans, sugar, cotton), precious metals (PM: gold, silver, platinum), industrial metals (IM: copper), and energy commodities (EN: crude oil and natural gas)). With _f and _r indicating first difference and log returns respectively. With ESV, producer/user (merch), swap dealers (swap), and managed money (MM), LTC, and STC as focus variables, OI as total open interest, ML as market liquidity, SP500 as Standard & Poor's 500 composite index, RIR as real interest rate, TED as TED spread, TWI as trade-weighted USD index, BDI as Baltic Dry Index, GFC and EDC as dummies for crisis periods throughout the research period, and obs. as observations. I use Driscoll-Kraay standard errors to account for cross-sectional dependence. With FE[…] indicating the forecast error for each of the series, estimating by either AR (10) for stationary or ARIMA (10,1,0) for non-stationary time-series. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

The models are defined as:

Panel A: $CFR_{it} = \alpha + \mu SPEC_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$

Panel B: $CFR_{it} = \alpha + \mu SPEC'_{it} + \delta F_{it} + (commodity\ fixed\ effects)_i + \varepsilon_{it}$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC] or SPEC = [FE[ESV], LTC, STC], SPEC' as disaggregated speculative measures vector consisting of SPEC' = [MERCH, SWAP, MM, LTC, STC] or SPEC' = [FE[MERCH], FE[SWAP], FE[MM], LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t.

A4.6 cont.

	Commodity Futures Returns									
Panel B	DISS-All	DISS-All	DISS-AG	DISS-AG	DISS-PM	DISS-PM	DISS-IM	DISS-IM	DISS-EN	DISS-EN
Merch_net	-0.0024**		-0.0043**		0.0056		0.0002			
	(0.0011)		(0.0019)		(0.0054)		(0.0173)			
Merch_net_f									-0.0462**	
									(0.0198)	
FE[Merch]		-0.0121		-0.0498***		0.0057		0.0008		0.0157
		(0.0089)		(0.0106)		(0.0180)		(0.0487)		(0.0225)
Swap					0.0026		0.0068			
					(0.0079)		(0.0217)			
Swap_net_f	-0.0187**		-0.0048						-0.0083	
	(0.0091)		(0.0175)						(0.0141)	
FE[Swap]		0.0011		-0.0424**		-0.0174		-0.0200		0.0478**
		(0.0128)		(0.0184)		(0.0199)		(0.0619)		(0.0202)
MM	-0.0012		-0.0044**		0.0042		0.0008		0.0033	
	(0.0012)		(0.0019)		(0.0074)		(0.0144)		(0.0025)	
FE[MM]		0.0325***		-0.0137		0.0283		0.0629*		0.0719***
		(0.0077)		(0.0096)		(0.0188)		(0.0360)		(0.0123)
LTC	0.0003	0.0002	-0.0005	-0.0004	0.0003	0.0003	0.0001	0.0001		
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0008)	(0.0008)		
LTC_r									0.0489**	0.0346
									(0.0231)	(0.0218)
STC	-0.0000	-0.0000	0.0002	0.0002	-0.0001	-0.0003*			-0.0007*	-0.0004
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)			(0.0004)	(0.0003)
STC_r							-0.0052	-0.0059		
							(0.0154)	(0.0168)		
ML	-0.0029	-0.0030	0.0213	0.0181	-0.0204*	-0.0205*	0.0147	0.0155	0.0269*	0.0200
	(0.0077)	(0.0075)	(0.0132)	(0.0122)	(0.0107)	(0.0105)	(0.0178)	(0.0145)	(0.0149)	(0.0149)
OI_r	0.0073	-0.0085	0.0499	0.0180	0.0420**	0.0218	0.0048	0.0096	-0.2525***	-0.2523***
	(0.0176)	(0.0167)	(0.0306)	(0.0289)	(0.0210)	(0.0222)	(0.0380)	(0.0366)	(0.0595)	(0.0591)
SP500_r	0.2173***	0.2102***	0.2137***	0.1993***	-0.0009	0.0048	0.6211***	0.6227***	0.3454***	0.3233***
	(0.0468)	(0.0462)	(0.0563)	(0.0562)	(0.0765)	(0.0766)	(0.0968)	(0.0974)	(0.0981)	(0.0989)
RIR_f	-0.0081*	-0.0080*	-0.0067	-0.0069	-0.0086*	-0.0087**	-0.0001	-0.0001	-0.0113	-0.0138
	(0.0044)	(0.0045)	(0.0053)	(0.0055)	(0.0044)	(0.0044)	(0.0076)	(0.0076)	(0.0112)	(0.0113)
TED_r	0.0009	0.0015	-0.0110	-0.0084	0.0098	0.0104	-0.0112	-0.0107	0.0175	0.0160
	(0.0078)	(0.0078)	(0.0106)	(0.0104)	(0.0092)	(0.0095)	(0.0157)	(0.0156)	(0.0206)	(0.0204)
TWI_r	-1.1217***	-1.0975***	-0.8236***	-0.8094***	-1.6656***	-1.6481***	-1.1148***	-1.0466***	-0.8527***	-0.8132***
	(0.1100)	(0.1080)	(0.1408)	(0.1388)	(0.1367)	(0.1337)	(0.1795)	(0.1853)	(0.2021)	(0.2066)
BDI_r	0.0178*	0.0162*	-0.0015	-0.0049	0.0243	0.0244	0.0177	0.0188	0.0452**	0.0445**
	(0.0091)	(0.0090)	(0.0111)	(0.0109)	(0.0159)	(0.0156)	(0.0190)	(0.0191)	(0.0189)	(0.0188)
GFC	0.0013	0.0015	0.0009	0.0009	0.0014	0.0008	0.0065	0.0065	-0.0012	-0.0029
	(0.0029)	(0.0028)	(0.0034)	(0.0032)	(0.0036)	(0.0035)	(0.0056)	(0.0054)	(0.0060)	(0.0061)
EDC	0.0009	0.0009	0.0011	0.0000	0.0048*	0.0041	0.0012	0.0010	-0.0011	-0.0014
	(0.0017)	(0.0016)	(0.0029)	(0.0027)	(0.0026)	(0.0026)	(0.0036)	(0.0026)	(0.0033)	(0.0033)
Constant	-0.0041	-0.0012	-0.0078	-0.0016	0.0077*	0.0080*	-0.0101	-0.0078	0.0054	0.0021
	(0.0038)	(0.0036)	(0.0075)	(0.0068)	(0.0045)	(0.0043)	(0.0081)	(0.0072)	(0.0104)	(0.0090)
Obs.	5,610	5,610	2,244	2,244	1,683	1,683	561	561	1,122	1,122

A4.7: Commodity-Individual Signalling Effect with Expectations

	Commodity Futures Returns									
	Corn	Corn	Soybeans	Soybeans	Sugar	Sugar	Cotton	Cotton	Gold	Gold
ESV	-0.0000				0.0003				-0.0006	
	(0.0008)				(0.0021)				(0.0010)	
ESV_f			0.0214***				0.0140			
			(0.0042)				(0.0108)			
FE[ESV]		0.0201***		0.0201***		0.0136**		0.0192*		0.0074**
		(0.0046)		(0.0043)		(0.0060)		(0.0115)		(0.0030)
LTC	-0.0014	-0.0013	-0.0010	-0.0010*	-0.0014	-0.0012	-0.0001	-0.0001	0.0008	0.0007
	(0.0018)	(0.0017)	(0.0006)	(0.0006)	(0.0016)	(0.0014)	(0.0008)	(0.0008)	(0.0007)	(0.0007)
LTC_r										
STC					-0.0002	-0.0003	0.0004	0.0004	-0.0001	-0.0002
					(0.0010)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
STC_r	0.0801	0.0865	0.0301	0.0304						
	(0.0574)	(0.0546)	(0.0359)	(0.0363)						
ML	-0.0269	-0.0578	-0.0187	-0.0062	-0.0987	-0.1153	0.0861*	0.0834	0.0649***	0.0376
	(0.0867)	(0.0830)	(0.0500)	(0.0497)	(0.0754)	(0.0756)	(0.0509)	(0.0507)	(0.0222)	(0.0243)
OI_r	-0.0072	-0.0123	0.0123	0.0137	0.0734**	0.0709**	0.0362	0.0358	-0.0107	-0.0117
	(0.0283)	(0.0266)	(0.0135)	(0.0135)	(0.0328)	(0.0327)	(0.0321)	(0.0322)	(0.0077)	(0.0073)
SP500_r	0.1853**	0.1669**	0.2437***	0.2433***	0.1581*	0.1551*	0.2456***	0.2477***	-0.1955***	-0.1907***
	(0.0788)	(0.0793)	(0.0625)	(0.0627)	(0.0915)	(0.0910)	(0.0909)	(0.0912)	(0.0513)	(0.0517)
RIR_f	-0.0141	-0.0132	-0.0029	-0.0030	-0.0082	-0.0079	-0.0031	-0.0032	-0.0060	-0.0060
	(0.0098)	(0.0097)	(0.0076)	(0.0076)	(0.0085)	(0.0085)	(0.0082)	(0.0082)	(0.0041)	(0.0040)
TED_r	0.0120	0.0138	-0.0027	-0.0036	-0.0487***	-0.0469***	-0.0004	0.0000	0.0238**	0.0237**
	(0.0167)	(0.0163)	(0.0134)	(0.0134)	(0.0173)	(0.0171)	(0.0150)	(0.0151)	(0.0101)	(0.0101)
TWI_r	-1.0581***	-1.0209***	-0.8829***	-0.8870***	-0.5929***	-0.5823***	-0.7323***	-0.7261***	-1.3707***	-1.3548***
	(0.2197)	(0.2115)	(0.1620)	(0.1623)	(0.2198)	(0.2200)	(0.1826)	(0.1832)	(0.1067)	(0.1051)
BDI_r	0.0115	0.0080	0.0116	0.0139	-0.0563**	-0.0572**	0.0169	0.0167	0.0131	0.0130
	(0.0191)	(0.0190)	(0.0155)	(0.0155)	(0.0223)	(0.0222)	(0.0187)	(0.0187)	(0.0126)	(0.0124)
GFC	-0.0015	-0.0018	-0.0056	-0.0060	0.0074	0.0078	0.0015	0.0016	0.0037	0.0027
	(0.0060)	(0.0058)	(0.0057)	(0.0057)	(0.0063)	(0.0062)	(0.0049)	(0.0049)	(0.0037)	(0.0035)
EDC	0.0026	0.0007	-0.0010	-0.0011	-0.0061	-0.0057	0.0005	0.0005	0.0053*	0.0044
	(0.0050)	(0.0044)	(0.0029)	(0.0029)	(0.0054)	(0.0050)	(0.0048)	(0.0048)	(0.0029)	(0.0029)
Constant	0.0140	0.0140	0.0077	0.0082	0.0056	0.0055	-0.0093	-0.0093	0.0010	0.0029
	(0.0159)	(0.0150)	(0.0073)	(0.0074)	(0.0170)	(0.0168)	(0.0116)	(0.0115)	(0.0082)	(0.0081)
Observations	561	561	561	561	561	561	561	561	561	561
R^2	0.105	0.154	0.170	0.165	0.079	0.087	0.095	0.097	0.296	0.301

Notes: This table illustrates the results of the OLS regression with robust standard errors (Huber/White/sandwich estimator) for the signalling effect of commodity futures returns between June 2006 and 7th March 2017 totalling 561 observations for each commodity (10 commodities, agriculture (AG: corn, soybeans, sugar, cotton), precious metals (PM: gold, silver, platinum), industrial metals (IM: copper), and energy commodities (EN: crude oil and natural gas)). With _f and _r indicating first difference and log returns respectively. With ESV, LTC, and STC as focus variables, OI as total open interest, ML as market liquidity, SP500 as Standard & Poor's 500 composite index, RIR as real interest rate, TED as TED spread, TWI as trade-weighted USD index, BDI as Baltic Dry Index, GFC and EDC as dummies for crisis periods throughout the research period, and obs. as observations. With FE[…] indicating the forecast error for each of the series, estimating by either AR (10) for stationary or ARIMA (10,1,0) for non-stationary time-series. * indicates the statistical significance, with *** for $p<0.01$, ** for $p<0.05$, and * for $p<0.1$.

The model is defined as:

$$CFR_t = \alpha + \mu SPEC_t + \delta F_t + \varepsilon_{it}$$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC] or SPEC = [FE[ESV], LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term at time t.

A4.7 cont.

	Commodity Futures Returns									
	Silver	Silver	Copper	Copper	Platinum	Platinum	NatGas	NatGas	Crude	Crude
ESV			-0.0005							
			(0.0041)							
ESV_f	0.0841***				0.1320***		0.0045		0.0103	
	(0.0183)				(0.0277)		(0.0119)		(0.0064)	
FE[ESV]		0.0840***		0.0388***		0.1576***		0.0039		0.0100
		(0.0211)		(0.0134)		(0.0300)		(0.0120)		(0.0065)
LTC			0.0003	0.0002					0.0007	0.0007
			(0.0007)	(0.0007)					(0.0007)	(0.0007)
LTC_r	-0.0123	-0.0127			-0.0021	-0.0018	0.0379	0.0375		
	(0.0236)	(0.0237)			(0.0147)	(0.0146)	(0.0582)	(0.0581)		
STC	-0.0011	-0.0011			-0.0001	-0.0001	-0.0005	-0.0005	-0.0013**	-0.0013**
	(0.0007)	(0.0007)			(0.0002)	(0.0002)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
STC_r			-0.0054	-0.0103						
			(0.0169)	(0.0169)						
ML	-0.0315	-0.0274	0.0059	0.0070	-0.0040	-0.0043	-0.3645***	-0.3648***	-0.1986***	-0.1991***
	(0.0530)	(0.0544)	(0.0351)	(0.0341)	(0.0313)	(0.0311)	(0.1184)	(0.1183)	(0.0631)	(0.0633)
OI_r	-0.0316	-0.0318	0.0154	0.0141	-0.0302*	-0.0299*	0.1088***	0.1091***	-0.0103	-0.0106
	(0.0215)	(0.0215)	(0.0144)	(0.0128)	(0.0162)	(0.0162)	(0.0330)	(0.0329)	(0.0161)	(0.0161)
SP500_r	0.0878	0.0835	0.6223***	0.6234***	0.1179	0.1154	0.1394	0.1395	0.5387***	0.5374***
	(0.0866)	(0.0867)	(0.0857)	(0.0857)	(0.0855)	(0.0856)	(0.1187)	(0.1186)	(0.0905)	(0.0909)
RIR_f	-0.0092	-0.0102	-0.0002	0.0003	-0.0121*	-0.0127**	-0.0066	-0.0066	-0.0192**	-0.0195**
	(0.0079)	(0.0079)	(0.0091)	(0.0090)	(0.0062)	(0.0062)	(0.0166)	(0.0166)	(0.0097)	(0.0098)
TED_r	0.0129	0.0123	-0.0114	-0.0105	-0.0006	-0.0012	0.0213	0.0214	0.0135	0.0142
	(0.0170)	(0.0171)	(0.0143)	(0.0143)	(0.0122)	(0.0121)	(0.0290)	(0.0290)	(0.0190)	(0.0188)
TWI_r	-2.2075***	-2.2046***	-1.1148***	-1.0585***	-1.3560***	-1.3418***	-0.5908*	-0.5902*	-1.0772***	-1.0840***
	(0.1994)	(0.2011)	(0.1938)	(0.1965)	(0.1241)	(0.1235)	(0.3064)	(0.3063)	(0.2549)	(0.2567)
BDI_r	0.0411*	0.0390*	0.0183	0.0173	0.0306	0.0296	0.0588*	0.0588*	0.0387*	0.0379*
	(0.0214)	(0.0215)	(0.0184)	(0.0184)	(0.0202)	(0.0200)	(0.0307)	(0.0307)	(0.0230)	(0.0230)
GFC	0.0008	0.0006	0.0066	0.0062	-0.0013	-0.0014	-0.0018	-0.0018	-0.0023	-0.0024
	(0.0055)	(0.0055)	(0.0053)	(0.0053)	(0.0046)	(0.0046)	(0.0094)	(0.0094)	(0.0075)	(0.0075)
EDC	0.0070*	0.0069*	0.0016	0.0009	0.0010	0.0010	-0.0110	-0.0110	0.0066*	0.0067*
	(0.0042)	(0.0042)	(0.0035)	(0.0030)	(0.0026)	(0.0026)	(0.0071)	(0.0071)	(0.0039)	(0.0039)
Constant	0.0221**	0.0224**	-0.0097	-0.0087	0.0072*	0.0073*	-0.0120	-0.0121	0.0150	0.0153
	(0.0112)	(0.0111)	(0.0073)	(0.0073)	(0.0040)	(0.0040)	(0.0182)	(0.0182)	(0.0177)	(0.0177)
Observations	561	561	561	561	561	561	561	561	561	561
R^2	0.309	0.305	0.303	0.310	0.270	0.276	0.062	0.062	0.214	0.213

A4.8: Commodity-Individual Signalling Effect with Expectations – Disaggregated

	Commodity Futures Returns									
	Corn	Corn	Soybeans	Soybeans	Sugar	Sugar	Cotton	Cotton	Gold	Gold
Merch_net	-0.0043*				-0.0028					
	(0.0024)				(0.0039)					
Merch_net_f			-0.0455***				-0.0353*		-0.0168*	
			(0.0082)				(0.0195)		(0.0093)	
FE[Merch]		-0.0477***		-0.0560***		-0.0400**		-0.1124***		-0.0036
		(0.0169)		(0.0155)		(0.0201)		(0.0413)		(0.0179)
Swap_net									-0.0008	
									(0.0061)	
Swap_net_f	-0.0075		-0.0184		-0.0123		-0.1056			
	(0.0242)		(0.0295)		(0.0250)		(0.0775)			
FE[Swap]		-0.0483*		-0.0192		-0.0408		-0.1553*		-0.0148
		(0.0261)		(0.0306)		(0.0339)		(0.0811)		(0.0210)
MM_net	-0.0049*		-0.0003		-0.0035		-0.0140		-0.0017	
	(0.0025)		(0.0019)		(0.0053)		(0.0086)		(0.0047)	
MM_net_f										
FE[MM]		-0.0074		-0.0142		-0.0177		-0.0955*		0.0081
		(0.0146)		(0.0152)		(0.0260)		(0.0501)		(0.0190)
LTC	-0.0012	-0.0010	-0.0009	-0.0009	-0.0017	-0.0012	-0.0001	0.0000	0.0009	0.0007
	(0.0018)	(0.0017)	(0.0006)	(0.0006)	(0.0016)	(0.0014)	(0.0008)	(0.0008)	(0.0007)	(0.0007)
LTC_r										
STC					-0.0001	-0.0003	0.0008**	0.0005*	-0.0001	-0.0003
					(0.0009)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0002)
STC_r	0.0692	0.0557	0.0206	0.0179						
	(0.0574)	(0.0565)	(0.0351)	(0.0363)						
ML	-0.0171	-0.0450	-0.0160	-0.0013	-0.1062	-0.1284	0.0808	0.0867*	0.0439*	0.0359
	(0.0864)	(0.0833)	(0.0489)	(0.0485)	(0.0758)	(0.0790)	(0.0504)	(0.0505)	(0.0244)	(0.0243)
OI_r	-0.0042	-0.0108	0.0120	0.0141	0.0723**	0.0704**	0.0397	0.0353	-0.0109	-0.0121*
	(0.0286)	(0.0264)	(0.0134)	(0.0134)	(0.0330)	(0.0328)	(0.0322)	(0.0319)	(0.0076)	(0.0073)
SP500_r	0.1945**	0.1637**	0.2392***	0.2384***	0.1647*	0.1563*	0.2429***	0.2395***	-0.1927***	-0.1899***
	(0.0788)	(0.0793)	(0.0624)	(0.0623)	(0.0917)	(0.0907)	(0.0926)	(0.0921)	(0.0509)	(0.0519)
RIR_f	-0.0135	-0.0135	-0.0031	-0.0039	-0.0081	-0.0077	-0.0037	-0.0034	-0.0063	-0.0060
	(0.0097)	(0.0097)	(0.0077)	(0.0077)	(0.0085)	(0.0084)	(0.0082)	(0.0082)	(0.0041)	(0.0040)
TED_r	0.0103	0.0140	-0.0029	-0.0038	-0.0491***	-0.0476***	-0.0003	0.0022	0.0237**	0.0237**
	(0.0168)	(0.0164)	(0.0134)	(0.0135)	(0.0171)	(0.0170)	(0.0153)	(0.0149)	(0.0101)	(0.0101)
TWI_r	-1.0362***	-1.0086***	-0.8691***	-0.8684***	-0.6043***	-0.5928***	-0.7294***	-0.7381***	-1.3624***	-1.3507***
	(0.2217)	(0.2130)	(0.1617)	(0.1629)	(0.2222)	(0.2233)	(0.1844)	(0.1837)	(0.1069)	(0.1046)
BDI_r	0.0116	0.0076	0.0106	0.0119	-0.0555**	-0.0586***	0.0166	0.0172	0.0134	0.0131
	(0.0192)	(0.0190)	(0.0155)	(0.0154)	(0.0223)	(0.0222)	(0.0187)	(0.0186)	(0.0127)	(0.0125)
GFC	0.0004	-0.0012	-0.0050	-0.0055	0.0082	0.0079	-0.0005	0.0016	0.0040	0.0028
	(0.0063)	(0.0058)	(0.0057)	(0.0057)	(0.0066)	(0.0062)	(0.0051)	(0.0049)	(0.0046)	(0.0035)
EDC	0.0044	0.0015	-0.0006	-0.0006	-0.0022	-0.0045	0.0007	0.0008	0.0058	0.0046
	(0.0052)	(0.0044)	(0.0030)	(0.0030)	(0.0067)	(0.0050)	(0.0048)	(0.0048)	(0.0039)	(0.0030)
Constant	0.0006	0.0113	0.0069	0.0070	0.0015	0.0052	-0.0136	-0.0121	0.0006	0.0037
	(0.0187)	(0.0153)	(0.0073)	(0.0074)	(0.0168)	(0.0168)	(0.0124)	(0.0117)	(0.0085)	(0.0082)
Observations	561	561	561	561	561	561	561	561	561	561
R^2	0.1108	0.1588	0.1768	0.1749	0.0802	0.0916	0.1015	0.1050	0.2992	0.3039

Notes: This table illustrates the results of the OLS regression with robust standard errors (Huber/White/sandwich estimator) for the signalling effect of commodity futures returns between June 2006 and 7th March 2017 totalling 561 observations for each commodity (10 commodities, agriculture (AG: corn, soybeans, sugar, cotton), precious metals (PM: gold, silver, platinum), industrial metals (IM: copper), and energy commodities (EN: crude oil and natural gas)). With _f and _r indicating first difference and log returns respectively. With ESV, producer/user (merch), swap dealers (swap), and managed money (MM), LTC, and STC as focus variables, OI as total open interest, ML as market liquidity, SP500 as Standard & Poor's 500 composite index, RIR as real interest rate, TED as TED spread, TWI as trade-weighted USD index, BDI as Baltic Dry Index, GFC and EDC as dummies for crisis periods throughout the research period, and obs. as observations. With FE[…] indicating the forecast error for each of the series, estimating by either AR (10) for stationary or ARIMA (10,1,0) for non-stationary time-series. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

A4.8 cont.

	Commodity Futures Returns									
	Silver	Silver	Copper	Copper	Platinum	Platinum	NatGas	NatGas	Crude	Crude
Merch_net			0.0002							
			(0.0174)							
Merch_net_f	-0.1014				-0.2928***		0.0584		0.0123	
	(0.0758)				(0.0870)		(0.0519)		(0.0289)	
FE[Merch]		-0.0326		0.0008		-0.1369		0.0424		0.0029
		(0.0942)		(0.0527)		(0.1388)		(0.0524)		(0.0295)
Swap_net			0.0068		-0.0576					
			(0.0227)		(0.0460)					
Swap_net_f	-0.2050***						0.1260***		0.0386*	
	(0.0647)						(0.0460)		(0.0224)	
FE[Swap]		-0.1076		-0.0200		-0.2648*		0.1141***		0.0328
		(0.0896)		(0.0654)		(0.1413)		(0.0435)		(0.0236)
MM_net	0.0101		0.0008		-0.0595**					
	(0.0093)		(0.0148)		(0.0277)					
MM_net_f							0.0954***		0.0617***	
							(0.0196)		(0.0173)	
FE[MM]		0.1040*		0.0629*		0.1117		0.0904***		0.0551***
		(0.0618)		(0.0359)		(0.1131)		(0.0192)		(0.0176)
LTC			0.0001	0.0001					0.0002	0.0004
			(0.0008)	(0.0008)					(0.0007)	(0.0007)
LTC_r	0.0020	-0.0146			0.0009	-0.0008	0.0230	0.0222		
	(0.0241)	(0.0262)			(0.0149)	(0.0149)	(0.0588)	(0.0588)		
STC	-0.0016*	-0.0012*			0.0002	-0.0002	-0.0004	-0.0005	-0.0010*	-0.0011**
	(0.0009)	(0.0007)			(0.0002)	(0.0002)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
STC_r			-0.0052	-0.0059						
			(0.0168)	(0.0185)						
ML	-0.0344	-0.0248	0.0048	0.0096	0.0126	-0.0013	-0.3541***	-0.3459***	-0.2106***	-0.2119***
	(0.0546)	(0.0564)	(0.0357)	(0.0341)	(0.0306)	(0.0322)	(0.1158)	(0.1167)	(0.0642)	(0.0640)
OI_r	-0.0332	-0.0320	0.0147	0.0155	-0.0289*	-0.0320**	0.0991***	0.0986***	-0.0127	-0.0125
	(0.0221)	(0.0216)	(0.0151)	(0.0129)	(0.0164)	(0.0161)	(0.0322)	(0.0320)	(0.0164)	(0.0163)
SP500_r	0.0800	0.0787	0.6211***	0.6227***	0.1223	0.1155	0.1292	0.1228	0.5080***	0.5132***
	(0.0849)	(0.0861)	(0.0858)	(0.0855)	(0.0887)	(0.0848)	(0.1186)	(0.1191)	(0.0912)	(0.0914)
RIR_f	-0.0093	-0.0106	-0.0001	-0.0001	-0.0112*	-0.0127**	-0.0087	-0.0089	-0.0205**	-0.0202**
	(0.0079)	(0.0080)	(0.0091)	(0.0090)	(0.0062)	(0.0063)	(0.0166)	(0.0166)	(0.0096)	(0.0098)
TED_r	0.0124	0.0133	-0.0112	-0.0107	-0.0026	-0.0007	0.0211	0.0200	0.0134	0.0129
	(0.0169)	(0.0168)	(0.0144)	(0.0142)	(0.0121)	(0.0122)	(0.0280)	(0.0281)	(0.0180)	(0.0179)
TWI_r	-2.2078***	-2.1969***	-1.1148***	-1.0466***	-1.3620***	-1.3362***	-0.5608*	-0.5494*	-1.0340***	-1.0373***
	(0.1989)	(0.2012)	(0.1936)	(0.1971)	(0.1242)	(0.1239)	(0.3031)	(0.3038)	(0.2534)	(0.2566)
BDI_r	0.0416*	0.0394*	0.0177	0.0188	0.0247	0.0302	0.0575*	0.0584*	0.0366	0.0341
	(0.0214)	(0.0215)	(0.0184)	(0.0184)	(0.0202)	(0.0200)	(0.0309)	(0.0309)	(0.0230)	(0.0228)
GFC	0.0012	0.0007	0.0065	0.0065	-0.0033	-0.0012	-0.0017	-0.0021	-0.0029	-0.0026
	(0.0055)	(0.0055)	(0.0054)	(0.0053)	(0.0048)	(0.0046)	(0.0094)	(0.0094)	(0.0074)	(0.0074)
EDC	0.0061	0.0066	0.0012	0.0010	0.0003	0.0010	-0.0098	-0.0107	0.0062	0.0067*
	(0.0042)	(0.0042)	(0.0036)	(0.0030)	(0.0026)	(0.0026)	(0.0070)	(0.0070)	(0.0040)	(0.0040)
Constant	0.0260**	0.0235**	-0.0101	-0.0078	0.0064	0.0095**	-0.0119	-0.0089	0.0194	0.0174
	(0.0123)	(0.0112)	(0.0079)	(0.0074)	(0.0041)	(0.0040)	(0.0179)	(0.0179)	(0.0176)	(0.0177)
Observations	561	561	561	561	561	561	561	561	561	561
R^2	0.3098	0.3089	0.3029	0.3123	0.2625	0.2762	0.0950	0.0930	0.2363	0.2329

Notes cont.:

The model is defined as:

$$CFR_t = \alpha + \mu SPEC'_t + \delta F_t + \varepsilon_{it}$$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC' as disaggregated speculative measures vector consisting of SPEC' = [MERCH, SWAP, MM, LTC, STC] or SPEC' = [FE[MERCH], FE[SWAP], FE[MM], LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012 and ε as error term for each commodity i at time t.

A4.9: Commodity-Individual OLS and QR – Signalling Effect

	Commodity Futures Returns											
	Corn						Soybeans					
		Quantile						Quantile				
	OLS	5th	10th	50th	90th	95th	OLS	5th	10th	50th	90th	95th
ESV	0.0002	-0.004***	-0.0020*	0.0014***	0.0020**	0.0019	0.0013*	-0.0016	-0.0008	0.0019**	0.0016*	0.0014
	(0.0006)	(0.0011)	(0.0011)	(0.0005)	(0.0009)	(0.0014)	(0.0008)	(0.0018)	(0.0012)	(0.0008)	(0.0009)	(0.0012)
LTC_r	-0.072***	-0.0861**	-0.108***	-0.0410**	-0.0304	0.0533	-0.079***	-0.143***	-0.124***	-0.068***	-0.0278	-0.0530*
	(0.0247)	(0.0373)	(0.0296)	(0.0182)	(0.0356)	(0.0355)	(0.0163)	(0.0309)	(0.0213)	(0.0145)	(0.0185)	(0.0300)
STC_r	0.0874***	0.0756	0.1409***	0.0664***	0.0785	-0.0187	0.0512***	0.0837**	0.0625***	0.0587***	0.0438*	0.0348
	(0.0334)	(0.0544)	(0.0355)	(0.0248)	(0.0483)	(0.0517)	(0.0191)	(0.0360)	(0.0240)	(0.0162)	(0.0225)	(0.0290)
ML	-0.0073	0.0586	0.0870	0.0260	-0.213***	-0.1979***	0.0690**	0.1531***	0.1167***	0.0655**	-0.0004	0.0192
	(0.0495)	(0.0702)	(0.0586)	(0.0337)	(0.0565)	(0.0750)	(0.0293)	(0.0547)	(0.0379)	(0.0262)	(0.0321)	(0.0488)
OI_r	0.0028	-0.174***	-0.115***	-0.0025	0.1339***	0.1867***	0.0048	-0.0228	-0.0447**	0.0030	0.0423**	0.0379
	(0.0127)	(0.0292)	(0.0331)	(0.0183)	(0.0374)	(0.0399)	(0.0037)	(0.0312)	(0.0210)	(0.0124)	(0.0175)	(0.0261)
SP500_r	0.1897***	0.3172***	0.2756***	0.1519***	0.0739	0.0321	0.2044***	0.2280***	0.1859***	0.2250***	0.2056***	0.1929**
	(0.0518)	(0.0686)	(0.0671)	(0.0411)	(0.0619)	(0.0960)	(0.0403)	(0.0835)	(0.0643)	(0.0455)	(0.0550)	(0.0868)
RIR_f	-0.0077	-0.0182	-0.0171**	-0.0047	0.0086	0.0096	0.0001	-0.0173	-0.023***	0.0049	0.0148***	0.0028
	(0.0077)	(0.0119)	(0.0071)	(0.0031)	(0.0087)	(0.0116)	(0.0059)	(0.0106)	(0.0068)	(0.0054)	(0.0055)	(0.0083)
TED_r	0.0063	0.0166	-0.0044	0.0123**	0.0028	-0.0029	-0.0022	0.0169	0.0059	-0.0028	-0.0078	-0.0017
	(0.0087)	(0.0149)	(0.0113)	(0.0062)	(0.0135)	(0.0125)	(0.0075)	(0.0155)	(0.0101)	(0.0071)	(0.0083)	(0.0119)
TWI_r	-0.848***	-0.4295**	-0.634***	-0.720***	-0.922***	-1.1999***	-0.766***	-0.2946	-0.770***	-0.702***	-0.674***	-0.894***
	(0.1412)	(0.1907)	(0.1981)	(0.1001)	(0.1790)	(0.2376)	(0.1102)	(0.2106)	(0.1621)	(0.1068)	(0.1379)	(0.2188)
BDI_r	0.0050	0.0302	-0.0120	-0.0112	0.0038	-0.0180	0.0165	0.0560**	0.0013	0.0012	0.0314***	0.0284
	(0.0166)	(0.0240)	(0.0260)	(0.0143)	(0.0254)	(0.0280)	(0.0145)	(0.0260)	(0.0213)	(0.0155)	(0.0120)	(0.0313)
DotCom	0.0020	0.0058	0.0014	-0.0016	0.0107	0.0122**	0.0023	0.0156***	0.0079**	-0.0002	0.0010	-0.0057
	(0.0031)	(0.0072)	(0.0037)	(0.0024)	(0.0067)	(0.0050)	(0.0025)	(0.0048)	(0.0034)	(0.0031)	(0.0044)	(0.0051)
GFC	-0.0002	-0.0056	-0.0085	-0.0018	0.0228***	0.0203**	-0.0019	-0.025***	-0.0212**	-0.0040	0.0202**	0.0245*
	(0.0053)	(0.0046)	(0.0068)	(0.0040)	(0.0038)	(0.0096)	(0.0051)	(0.0057)	(0.0102)	(0.0061)	(0.0091)	(0.0148)
EDC	0.0024	0.0025	-0.0043	-0.0017	0.0037	-0.0013	-0.0010	0.0136*	0.0070*	-0.0005	-0.0032	-0.0062
	(0.0045)	(0.0109)	(0.0084)	(0.0037)	(0.0077)	(0.0148)	(0.0028)	(0.0080)	(0.0037)	(0.0030)	(0.0030)	(0.0058)
Constant	-0.0013	-0.023***	-0.019***	-0.0012	0.0152**	0.0243***	-0.0024	-0.049***	-0.026***	-0.0004	0.0211***	0.0352***
	(0.0025)	(0.0061)	(0.0058)	(0.0031)	(0.0064)	(0.0070)	(0.0015)	(0.0101)	(0.0077)	(0.0036)	(0.0058)	(0.0073)
Obs.	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159	1,159
R^2	0.077	0.148	0.101	0.038	0.097	0.117	0.114	0.136	0.092	0.069	0.083	0.090

Notes: This table illustrates the detailed results of the OLS and quantile regression with robust standard errors (Huber/White/sandwich estimator) for commodity futures returns between 3rd January 1995 and 7th March 2017. With OLS regression models and quantile regression for lower quantiles (5th and 10th), median (50th), and upper quantiles (90th and 95th). For OLS regression, the R^2 represents the adjusted R^2. For quantile regression, I calculate the pseudo R^2 as R^2 = 1 – (sum of weighted deviations about estimated quantile / sum of weighted deviations about raw quantile) as suggested by Koenker and Machado (1999). With _f and _r indicating first difference and log returns respectively. With ESV, LTC, and STC as focus variables, OI as total open interest, ML as market liquidity, SP500 as Standard & Poor's 500 composite index, RIR as real interest rate, TED as TED spread, TWI as trade-weighted USD index, BDI as Baltic Dry Index, DotCom, GFC, and EDC as dummies for crisis periods throughout the research period, and obs. as observations. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1. Following Clogg et al. (1995), I use a Z-test to check if the regression coefficients of the OLS model (1) and the quantile regressions for each ESV, LTC, and STC are significantly different. With a Z-value of ≥1.64 corresponding with the significance level of 5 percent or lower. The formula can be written as: $Z = (\beta_1 - \beta_2) / [(SE\beta_1)^2+(SE\beta_2)^2]^{1/2}$, with β as coefficients and SEβ as standard error of β. Underlined QR coefficients represent significantly (5%) different coefficients compared to the OLS model. **Bold** QR coefficients indicate significant coefficients based on a simple lagged QR model, which indicate Granger causality. Results highlighted in red indicate multicollinearity the variables, which is tested using the variance inflation factor (vif > 10).

The models are defined as:

OLS: $CFR_t = \alpha + \mu SPEC_t + \delta F_t + \varepsilon_{it}$

QR: $CFR_i = \pi + \gamma_\tau SF'_i + u_{\tau_i} \quad Quant_\tau(CFR_i|SF_i) = \gamma_\tau SF'_i$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [ESV, LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, DotCom as a dummy variable for the dot-com bubble between the years 2000 and 2002, GFC as a dummy variable for the Global Financial Crisis between the years 2008 and 2009, EDC as a dummy variable for the European Debt Crisis between the years 2010 and 2012, SF' = [SPEC, F] is the vector of regressors, and u is the error term traditionally associated with quantile estimation. and ε as error term of the OLS at time t. For a τ-th quantile (0 < τ < 1) of CFR.

A4.9 cont.

	Commodity Futures Returns											
	Sugar						Cotton					
		Quantile						Quantile				
	OLS	5^{th}	10^{th}	50^{th}	90^{th}	95^{th}	OLS	5^{th}	10^{th}	50^{th}	90^{th}	95^{th}
ESV	-0.0001	0.0020	0.0009	0.0016	-0.0022	-0.0016						
	(0.0016)	(0.0036)	(0.0021)	(0.0012)	(0.0023)	(0.0030)						
ESV_f							0.0253***	0.0222	0.0162	0.0280***	0.0318***	0.0318*
							(0.0087)	(0.0151)	(0.0118)	(0.0089)	(0.0100)	(0.0191)
LTC_r	-0.060***	-0.0240	-0.0316	-0.062***	-0.0403**	-0.0134	-0.0062	-0.0588**	-0.0234	-0.0055	0.0248*	-0.0044
	(0.0173)	(0.0362)	(0.0248)	(0.0145)	(0.0184)	(0.0224)	(0.0149)	(0.0279)	(0.0175)	(0.0129)	(0.0134)	(0.0245)
STC	0.0003	-0.0001	-0.0001	-0.0003	0.0017**	0.0015*	0.0003*	0.0001	-0.0001	0.0003*	0.0006***	0.0003
	(0.0005)	(0.0012)	(0.0007)	(0.0004)	(0.0007)	(0.0009)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
ML	0.0035	-0.244***	-0.194***	0.0370	0.1570***	0.1603***	0.0008	-0.161***	-0.132***	0.0103	0.1407***	0.1303***
	(0.0265)	(0.0597)	(0.0274)	(0.0256)	(0.0268)	(0.0281)	(0.0215)	(0.0379)	(0.0275)	(0.0193)	(0.0264)	(0.0361)
OI_r	0.0450	0.1889**	0.0721	-0.0337	-0.0315	-0.0429	0.0525*	0.1035***	0.0911***	0.0525**	-0.0042	-0.0258
	(0.0486)	(0.0751)	(0.0463)	(0.0307)	(0.0345)	(0.0323)	(0.0293)	(0.0303)	(0.0317)	(0.0250)	(0.0263)	(0.0526)
SP500_r	0.1499**	0.2118	0.2172**	0.1126**	0.0030	-0.1439*	0.1579***	0.2485***	0.2497***	0.0815*	0.2995***	0.3008***
	(0.0644)	(0.1389)	(0.0876)	(0.0475)	(0.0769)	(0.0805)	(0.0607)	(0.0876)	(0.0636)	(0.0472)	(0.0559)	(0.0989)
RIR_f	-0.0059	-0.0241	-0.0087	-0.0024	-0.0134**	-0.027***	-0.0033	0.0069	0.0016	-0.0065*	-0.0017	-0.0043
	(0.0071)	(0.0147)	(0.0067)	(0.0019)	(0.0056)	(0.0099)	(0.0066)	(0.0097)	(0.0058)	(0.0038)	(0.0066)	(0.0140)
TED_r	-0.0058	-0.0163	-0.0145	-0.0183**	-0.0135	0.0013	0.0026	-0.0191*	-0.0046	-0.0033	0.0014	-0.0047
	(0.0125)	(0.0198)	(0.0138)	(0.0087)	(0.0094)	(0.0164)	(0.0105)	(0.0112)	(0.0118)	(0.0079)	(0.0108)	(0.0165)
TWI_r	-0.565***	-0.4500	-0.563***	-0.500***	-0.622***	-0.621***	-0.610***	-0.860***	-0.761***	-0.471***	-0.571***	-0.831***
	(0.1907)	(0.3303)	(0.1972)	(0.1205)	(0.1939)	(0.2261)	(0.1358)	(0.2255)	(0.1574)	(0.1156)	(0.1580)	(0.2407)
BDI_r	-0.0507**	-0.0979**	-0.0705**	-0.049***	-0.0324	-0.0174	0.0231	0.0077	0.0295	0.0154	0.0067	-0.0017
	(0.0220)	(0.0422)	(0.0332)	(0.0176)	(0.0327)	(0.0389)	(0.0170)	(0.0404)	(0.0183)	(0.0163)	(0.0228)	(0.0316)
DotCom	0.0027	-0.0050	-0.0037	0.0031	0.0061	0.0105**	0.0022	-0.0034	0.0026	-0.0015	0.0095*	0.0040
	(0.0045)	(0.0089)	(0.0045)	(0.0040)	(0.0038)	(0.0051)	(0.0034)	(0.0041)	(0.0058)	(0.0029)	(0.0052)	(0.0064)
GFC	0.0067	-0.038***	-0.0123	0.0013	0.0243*	0.0448***	0.0005	-0.0157	-0.019***	0.0018	0.0108**	0.0130*
	(0.0062)	(0.0143)	(0.0128)	(0.0040)	(0.0141)	(0.0161)	(0.0048)	(0.0129)	(0.0070)	(0.0043)	(0.0045)	(0.0070)
EDC	-0.0027	-0.023***	-0.0046	-0.0074	0.0057	0.0154**	-0.0001	-0.0205**	-0.0068*	-0.0012	0.0217**	0.0376***
	(0.0044)	(0.0067)	(0.0094)	(0.0052)	(0.0091)	(0.0065)	(0.0046)	(0.0100)	(0.0035)	(0.0050)	(0.0099)	(0.0079)
Constant	-0.0042	-0.035***	-0.024***	-0.0039	0.0163***	0.0267***	-0.0044	-0.033***	-0.026***	-0.0038	0.0138***	0.0354***
	(0.0044)	(0.0096)	(0.0060)	(0.0039)	(0.0049)	(0.0055)	(0.0034)	(0.0070)	(0.0044)	(0.0032)	(0.0049)	(0.0079)
Obs.	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157
R^2	0.037	0.099	0.079	0.028	0.076	0.095	0.054	0.105	0.084	0.026	0.077	0.098

	Commodity Futures Returns											
	Gold						Silver					
		Quantile						Quantile				
	OLS	5^{th}	10^{th}	50^{th}	90^{th}	95^{th}	OLS	5^{th}	10^{th}	50^{th}	90^{th}	95^{th}
ESV	-0.0000	0.0013	0.0023*	-0.0001	-0.0005	-0.0001	0.0023	-0.0182*	-0.0019	0.0027	0.0060	0.0033
	(0.0007)	(0.0014)	(0.0013)	(0.0007)	(0.0010)	(0.0012)	(0.0035)	(0.0105)	(0.0044)	(0.0034)	(0.0040)	(0.0036)
LTC_r	-0.0139*	-0.0091	-0.0128	-0.0147**	-0.0149*	-0.0164*	0.0132	-0.0234	-0.0069	0.0171	0.0328*	0.0226
	(0.0081)	(0.0075)	(0.0098)	(0.0058)	(0.0087)	(0.0084)	(0.0155)	(0.0395)	(0.0197)	(0.0122)	(0.0193)	(0.0195)
STC	-0.0000	-0.0005	-0.0005*	0.0002	0.0003	0.0003	-0.0007	0.0008	-0.0003	-0.0004	-0.0001	-0.0003
	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0008)	(0.0002)	(0.0003)	(0.0004)	(0.0004)
ML	0.0006	-0.046***	-0.042***	0.0040	0.0325***	0.0447***	-0.0183	-0.0818**	-0.046***	-0.0059	0.0330***	0.0278*
	(0.0060)	(0.0059)	(0.0086)	(0.0052)	(0.0070)	(0.0104)	(0.0147)	(0.0375)	(0.0114)	(0.0089)	(0.0066)	(0.0151)
OI_r	0.0261**	-0.0025	0.0041	0.0212*	-0.0043	0.0346**	0.0356	0.0467	-0.0165	-0.0070	0.0416	0.0469
	(0.0129)	(0.0145)	(0.0185)	(0.0115)	(0.0127)	(0.0139)	(0.0279)	(0.0582)	(0.0351)	(0.0193)	(0.0323)	(0.0339)
SP500_r	-0.0618*	0.0893*	0.0184	-0.0409	-0.0645*	-0.0758**	0.1383**	0.2705**	0.2244***	0.1019***	0.0737	0.1001*
	(0.0347)	(0.0460)	(0.0386)	(0.0257)	(0.0336)	(0.0339)	(0.0568)	(0.1148)	(0.0582)	(0.0374)	(0.0647)	(0.0580)
RIR_f	-0.0057	-0.016***	-0.014***	-0.0049	-0.0093**	-0.0067*	-0.0066	0.0048	-0.0022	-0.0070**	-0.0100	-0.0045
	(0.0035)	(0.0061)	(0.0045)	(0.0032)	(0.0047)	(0.0037)	(0.0062)	(0.0175)	(0.0088)	(0.0035)	(0.0073)	(0.0065)
TED_r	0.0138***	-0.0093	0.0035	0.0022	0.0189***	0.0242***	0.0036	-0.0082	-0.0005	0.0039	0.0186*	0.0352***
	(0.0052)	(0.0078)	(0.0057)	(0.0039)	(0.0040)	(0.0062)	(0.0081)	(0.0170)	(0.0089)	(0.0052)	(0.0096)	(0.0064)
TWI_r	-1.136***	-0.883***	-1.121***	-1.140***	-0.854***	-0.911***	-1.7202***	-1.560***	-1.709***	-1.473***	-1.311***	-1.231***
	(0.0759)	(0.1058)	(0.1038)	(0.0669)	(0.0891)	(0.0923)	(0.1476)	(0.3267)	(0.1473)	(0.0989)	(0.1463)	(0.1395)
BDI_r	0.0055	-0.0051	-0.0083	-0.0075	0.0138	0.0313*	0.0271	0.0798*	0.0045	0.0088	0.0361*	0.0530**
	(0.0112)	(0.0153)	(0.0163)	(0.0095)	(0.0115)	(0.0176)	(0.0191)	(0.0454)	(0.0190)	(0.0151)	(0.0202)	(0.0230)
DotCom	0.0006	0.0017	0.0001	-0.0010	0.0008	0.0006	-0.0014	0.0038	0.0040	-0.0026	-0.0077*	-0.011***
	(0.0018)	(0.0029)	(0.0023)	(0.0015)	(0.0020)	(0.0032)	(0.0028)	(0.0068)	(0.0029)	(0.0022)	(0.0042)	(0.0042)
GFC	0.0020	-0.0082	-0.0121**	-0.0006	0.0177***	0.0151***	0.0029	-0.0125	-0.020***	0.0049	0.0224**	0.0258***
	(0.0033)	(0.0084)	(0.0051)	(0.0033)	(0.0062)	(0.0051)	(0.0054)	(0.0215)	(0.0055)	(0.0055)	(0.0095)	(0.0067)
EDC	0.0025	0.0020	-0.0020	-0.0010	0.0027	-0.0015	0.0073**	0.0075	0.0021	0.0059*	0.0081**	0.0052
	(0.0023)	(0.0035)	(0.0037)	(0.0024)	(0.0030)	(0.0051)	(0.0037)	(0.0095)	(0.0058)	(0.0033)	(0.0040)	(0.0049)
Constant	0.0007	-0.015***	-0.0070*	-0.0008	0.0119***	0.0157***	0.0094**	-0.032***	-0.023***	0.0051	0.0303***	0.0469***
	(0.0023)	(0.0033)	(0.0037)	(0.0019)	(0.0029)	(0.0031)	(0.0045)	(0.0107)	(0.0043)	(0.0034)	(0.0044)	(0.0052)
Obs.	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158
R^2	0.237	0.212	0.192	0.137	0.151	0.185	0.199	0.182	0.152	0.099	0.148	0.173

A4.9 cont.

	Commodity Futures Returns											
	Copper						Platinum					
		Quantile						Quantile				
	OLS	5th	10th	50th	90th	95th	OLS	5th	10th	50th	90th	95th
ESV	-0.0010	-0.0160**	-0.0079*	-0.0022	0.0081*	0.0105						
	(0.0035)	(0.0064)	(0.0048)	(0.0032)	(0.0049)	(0.0067)						
ESV_f							0.1180***	0.0850**	0.1432***	0.1004***	0.1255***	0.0347
							(0.0225)	(0.0384)	(0.0323)	(0.0222)	(0.0339)	(0.0531)
LTC_r	-0.0085	-0.0102	-0.0145*	-0.0043	-0.0009	0.0002	-0.0065	-0.0134	-0.0078	-0.0033	0.0038	-0.0021
	(0.0093)	(0.0167)	(0.0079)	(0.0078)	(0.0145)	(0.0161)	(0.0082)	(0.0136)	(0.0100)	(0.0072)	(0.0115)	(0.0090)
STC	0.0006**	0.0018***	0.0008**	0.0008***	-0.0001	-0.0008**	-0.0001	0.0003*	0.0001	-0.0002	-0.0003*	-0.0004
	(0.0002)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0003)
ML	-0.0007	-0.065***	-0.041***	-0.0108	0.0408***	0.0299*	-0.0187**	-0.113***	-0.086***	-0.0215**	0.0463***	0.0920***
	(0.0116)	(0.0169)	(0.0153)	(0.0090)	(0.0116)	(0.0172)	(0.0093)	(0.0210)	(0.0173)	(0.0109)	(0.0168)	(0.0231)
OI_r	-0.0094	-0.0187	0.0074	0.0173	-0.0475	-0.0251	0.0124	0.0429*	0.0358	-0.0103	-0.0026	0.0245
	(0.0192)	(0.0285)	(0.0241)	(0.0161)	(0.0297)	(0.0264)	(0.0148)	(0.0226)	(0.0218)	(0.0138)	(0.0181)	(0.0222)
SP500_r	0.4474***	0.4739***	0.4692***	0.4399***	0.2454***	0.2441***	0.1104*	0.1486*	0.1313**	0.1058***	0.1005	0.0096
	(0.0582)	(0.0828)	(0.0447)	(0.0356)	(0.0729)	(0.0659)	(0.0574)	(0.0804)	(0.0579)	(0.0310)	(0.0651)	(0.0466)
RIR_f	0.0010	0.0087	-0.0087	0.0020	0.0064	0.0085	-0.0139**	-0.0174**	-0.019***	-0.0016	-0.0122*	-0.0076
	(0.0071)	(0.0093)	(0.0078)	(0.0039)	(0.0086)	(0.0070)	(0.0055)	(0.0076)	(0.0062)	(0.0030)	(0.0070)	(0.0050)
TED_r	-0.0018	-0.0033	-0.0049	-0.0043	0.0092	0.0091	-0.0037	0.0095	0.0001	-0.0037	-0.0035	-0.0078
	(0.0071)	(0.0109)	(0.0094)	(0.0060)	(0.0107)	(0.0127)	(0.0065)	(0.0104)	(0.0093)	(0.0062)	(0.0101)	(0.0083)
TWI_r	-1.001***	-0.903***	-0.891***	-0.964***	-0.791***	-0.592***	-0.949***	-0.712***	-0.767***	-0.962***	-0.852***	-0.870***
	(0.1267)	(0.2080)	(0.0940)	(0.0991)	(0.1582)	(0.1950)	(0.0914)	(0.1794)	(0.1311)	(0.0827)	(0.1383)	(0.1455)
BDI_r	0.0226	0.0432	0.0353	-0.0063	0.0207	0.0428	0.0288*	0.0450**	0.0315*	0.0167	0.0217	-0.0272
	(0.0169)	(0.0308)	(0.0238)	(0.0151)	(0.0213)	(0.0307)	(0.0171)	(0.0220)	(0.0173)	(0.0116)	(0.0169)	(0.0223)
DotCom	-0.0011	-0.0005	0.0009	-0.0039*	-0.0052	-0.0083**	0.0009	-0.023***	-0.0079	0.0021	0.0050	0.0078***
	(0.0029)	(0.0060)	(0.0032)	(0.0023)	(0.0036)	(0.0035)	(0.0030)	(0.0079)	(0.0055)	(0.0033)	(0.0046)	(0.0029)
GFC	0.0022	-0.0364**	-0.0177*	0.0012	0.0291***	0.0264***	-0.0009	-0.050***	-0.035***	0.0057*	0.0201**	0.0323***
	(0.0049)	(0.0146)	(0.0097)	(0.0051)	(0.0075)	(0.0075)	(0.0046)	(0.0090)	(0.0105)	(0.0031)	(0.0081)	(0.0048)
EDC	0.0001	0.0121*	0.0091*	0.0029	-0.0096*	-0.0007	0.0012	0.0002	0.0017	0.0051	0.0082*	0.0038
	(0.0032)	(0.0070)	(0.0052)	(0.0029)	(0.0053)	(0.0134)	(0.0024)	(0.0032)	(0.0043)	(0.0032)	(0.0044)	(0.0043)
Constant	-0.0043	-0.049***	-0.034***	-0.0037	0.0313***	0.0512***	0.0046**	-0.023***	-0.017***	0.0057***	0.0241***	0.0298***
	(0.0029)	(0.0056)	(0.0043)	(0.0027)	(0.0044)	(0.0052)	(0.0018)	(0.0035)	(0.0031)	(0.0021)	(0.0031)	(0.0042)
Obs.	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158	1,158
R^2	0.191	0.161	0.144	0.098	0.089	0.106	0.160	0.212	0.159	0.094	0.116	0.125

A4.9 cont.

	Commodity Futures Returns											
	Natural Gas						Crude Oil					
		Quantile						Quantile				
	OLS	5th	10th	50th	90th	95th	OLS	5th	10th	50th	90th	95th
ESV_f	0.0370***	0.0056	0.0242**	0.0251**	0.0750***	0.0974***	0.0140***	0.0047	0.0184***	0.0135***	0.0168***	0.0192***
	(0.0105)	(0.0194)	(0.0121)	(0.0108)	(0.0140)	(0.0211)	(0.0053)	(0.0084)	(0.0037)	(0.0044)	(0.0041)	(0.0044)
LTC_r	-0.0144	-0.0432	-0.0221	-0.0508*	0.0559	0.0501	0.0241	-0.075***	-0.0251	0.0248	0.0309***	0.0380
	(0.0273)	(0.0565)	(0.0312)	(0.0273)	(0.0406)	(0.0392)	(0.0175)	(0.0264)	(0.0167)	(0.0173)	(0.0106)	(0.0253)
STC	-0.0003	0.0003	0.0001	-0.0002	-0.0005	-0.0009*						
	(0.0002)	(0.0006)	(0.0002)	(0.0002)	(0.0003)	(0.0005)						
STC_r							-0.0117	0.0688***	0.0162	-0.0329**	-0.0069	-0.0109
							(0.0170)	(0.0250)	(0.0150)	(0.0157)	(0.0158)	(0.0189)
ML	0.0892***	0.0210	-0.0367	0.0857***	0.1724***	0.1367***	-0.0296**	-0.1039***	-0.0868***	-0.0146	0.0474***	0.0242**
	(0.0245)	(0.0428)	(0.0253)	(0.0250)	(0.0298)	(0.0318)	(0.0135)	(0.0264)	(0.0091)	(0.0123)	(0.0112)	(0.0119)
OI_r	-0.0011	0.1706	0.0371	0.0383	-0.1810**	-0.1194	0.0259	0.0048	0.0541	-0.0218	0.0301	-0.1103*
	(0.0617)	(0.1231)	(0.0710)	(0.0620)	(0.0784)	(0.0751)	(0.0539)	(0.0696)	(0.0418)	(0.0400)	(0.0449)	(0.0602)
SP500_r	0.1868**	0.1901	0.2014*	0.1518	0.0919	0.2322	0.2901***	0.2294**	0.3850***	0.3049***	0.3010***	0.3417***
	(0.0889)	(0.1618)	(0.1073)	(0.0967)	(0.1137)	(0.1424)	(0.0753)	(0.1045)	(0.0754)	(0.0620)	(0.0490)	(0.0913)
RIR_f	-0.0079	-0.0078	0.0087	0.0042	-0.0122	-0.0009	-0.0194**	-0.0046	-0.0123	-0.0178**	-0.0083	0.0051
	(0.0132)	(0.0167)	(0.0159)	(0.0059)	(0.0109)	(0.0218)	(0.0078)	(0.0137)	(0.0102)	(0.0075)	(0.0070)	(0.0091)
TED_r	0.0333*	0.0825**	0.0372**	0.0236	0.0316	0.0461**	0.0113	-0.0138	0.0024	0.0105	-0.0149	-0.0040
	(0.0175)	(0.0357)	(0.0180)	(0.0156)	(0.0202)	(0.0204)	(0.0118)	(0.0183)	(0.0107)	(0.0107)	(0.0094)	(0.0137)
TWI_r	-0.709***	0.1299	-0.1422	-0.5482**	-1.116***	-1.468***	-0.809***	-0.2191	-0.559***	-0.807***	-0.891***	-0.595***
	(0.2287)	(0.3922)	(0.2595)	(0.2139)	(0.2572)	(0.2745)	(0.1885)	(0.2291)	(0.1476)	(0.1523)	(0.1459)	(0.1742)
BDI_r	0.0345	0.1048***	0.1329***	0.0121	0.0118	0.1167**	0.0334	0.0170	0.0615***	0.0247	-0.0148	-0.0388
	(0.0277)	(0.0360)	(0.0357)	(0.0310)	(0.0212)	(0.0564)	(0.0210)	(0.0488)	(0.0171)	(0.0212)	(0.0200)	(0.0278)
DotCom	0.0096	0.0022	-0.0017	0.0107	0.0325***	0.0189***	0.0016	-0.0185**	-0.015***	0.0031	0.0055	0.0157**
	(0.0066)	(0.0179)	(0.0106)	(0.0087)	(0.0118)	(0.0071)	(0.0046)	(0.0076)	(0.0039)	(0.0048)	(0.0055)	(0.0079)
GFC	0.0002	-0.0196*	-0.0361**	0.0011	-0.0012	0.0018	0.0019	-0.0242*	-0.0093	-0.0011	0.0061	0.0177
	(0.0080)	(0.0113)	(0.0155)	(0.0091)	(0.0069)	(0.0112)	(0.0077)	(0.0132)	(0.0133)	(0.0063)	(0.0090)	(0.0174)
EDC	-0.0093	0.0101	0.0081	-0.015***	-0.019***	-0.0180*	0.0042	0.0176**	0.0222***	0.0026	-0.018***	-0.024***
	(0.0057)	(0.0115)	(0.0067)	(0.0056)	(0.0065)	(0.0102)	(0.0037)	(0.0081)	(0.0030)	(0.0036)	(0.0026)	(0.0038)
Constant	-0.0142**	-0.121***	-0.075***	-0.0153**	0.0564***	0.0948***	0.0092**	-0.036***	-0.027***	0.0065	0.0398***	0.0622***
	(0.0062)	(0.0169)	(0.0091)	(0.0060)	(0.0094)	(0.0129)	(0.0040)	(0.0066)	(0.0038)	(0.0040)	(0.0041)	(0.0051)
Obs.	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157	1,157
R^2	0.051	0.031	0.028	0.025	0.078	0.090	0.085	0.140	0.119	0.042	0.081	0.082

A4.10: Least Squares with Bai-Perron Structural Breaks – Signalling Effect

	Commodity Futures Returns					
	Commodity Price Peaks			Post-Peak		
Corn	16/6/2006 – 7/11/2008	18/11/2006 – 23/7/2010	30/7/2010 – 6/4/2012	13/4/2012 – 15/11/2013	22/11/2013 – 10/7/2015	17/7/2015 – 10/3/2017
FE[ESV]	0.0408***	0.0011	0.0252*	0.0362*	0.0203***	0.0067
LTC	0.0060	-0.0042	0.0116**	-0.0261***	-0.0048**	-0.0092*
STC_r	0.1298	0.0944	-0.1414	-0.1983	0.2039	0.2398***
Soybeans	16/6/2006 – 18/1/2008	25/1/2008 – 28/8/2009	4/9/2009 – 22/4/2011	29/4/2011 – 15/2/2013	22/2/2013 – 26/9/2014	3/10/2014 – 10/3/2017
FE[ESV]	0.0363**	0.0518	0.0175	0.0213	0.0172	0.0117*
LTC	0.0054**	-0.0005	0.0015	0.0015	-0.0055	-0.0013
STC_r	0.0288	-0.1143	0.1016	0.0568	0.1036*	-0.0156
Sugar	16/6/2006 – 10/3/2017					
FE[ESV]	0.0135**					
LTC	-0.0006					
STC	0.0000					
Cotton	16/6/2006 – 10/3/2017					
FE[ESV]	0.0189*					
LTC	-0.0002					
STC	0.0004					
Gold	16/6/2006 – 10/3/2017					
FE[ESV]	0.0076***					
LTC	0.0002					
STC	-0.0002					
Silver	16/6/2006 – 1/2/2008	8/2/2008 – 11/9/2009	18/9/2009 – 29/4/2011	6/5/2011 – 7/12/2012	14/12/2012 – 19/12/2014	26/12/2014 – 10/3/2017
FE[ESV]	0.04316	0.0373	-0.0296	0.1695	0.1338*	0.0930***
LTC_r	-0.0618	0.0048	0.0629	-0.0223	-0.0402	0.0330
STC	-0.0012	-0.0034*	-0.0003	0.0016	-0.0001	-0.0012
Copper	16/6/2006 – 7/1/2011			14/1/2011 – 10/3/2017		
FE[ESV]	0.0859**			0.0282*		
LTC	0.0008			0.0006		
STC_r	-0.0493*			0.0322*		
Platinum	16/6/2006 – 17/10/2008	24/10/2008 – 16/7/2010	23/7/2010 – 13/4/2012	20/4/2012 – 22/11/2013	29/11/2013 – 3/7/2015	10/7/2015 – 10/3/2017
FE[ESV]	0.4200**	-0.3475**	0.0280	0.2043***	0.1503***	0.2585***
LTC_r	0.0118	-0.0011	-0.0681***	-0.0167	-0.0050	0.00051
STC	0.0000	0.0000	-0.0003	-0.0004	-0.0004	0.0000
Natural Gas	16/6/2006 – 25/1/2008	1/2/2008 – 4/9/2009	11/9/2009 – 15/4/2011	22/4/2011 – 23/11/2012	30/11/2012 – 7/11/2014	14/11/2014 – 10/3/2017
FE[ESV]	0.0626	0.0142	-0.0189	0.0012	0.0217	-0.0004
LTC_r	0.1214	0.0542	0.1510	0.1351	0.0613	0.1048
STC	-0.0086*	0.0029**	-0.0090***	0.0023	0.0000	-0.0006
Crude Oil	16/6/2006 – 12/12/2008	19/12/2008 – 20/8/2010	27/8/2010 – 13/4/2012	20/4/2012 – 22/11/2013	29/11/2013 – 3/7/2015	10/7/2015 – 10/3/2017
FE[ESV]	-0.0042	-0.0389	0.019	0.0095	0.0001	0.0245***
LTC	0.0034	0.0062	0.0006	0.0018	0.0020**	0.0029
STC	-0.0016	-0.0051*	-0.0011	-0.0049***	-0.0011	-0.0051*

Notes: This table illustrates the results of the least squares regression with Bai-Perron structural breaks and Newey-West standard errors for the individual commodities between June 2006 and March 2017. With FE[ESV], LTC, and STC as focus variables.

The model is defined as:

$$CFR_t = \alpha + \mu SPEC_t + \delta F_t + \varepsilon_{it}$$

with α, μ, δ as coefficients, CFR as commodity-specific futures log returns, SPEC as speculative measures vector consisting of SPEC = [FE[ESV], LTC, STC], F as vector of fundamental explanatory variables and dummies with OI as changes in total open interest per commodity, TWI as changes in the trade-weighted USD index, SP500 as changes in the S&P 500 composite index, TED as changes in the TED spread, RIR as first difference of the real 3-month USD interbank interest rate, ML as commodity-specific market liquidity, BDI as changes in the Baltic Dry Index, and ε as error term at time t.

A4.11: EGARCH (1,1) – Signalling Effect

		Volatility of Commodity Futures Returns															
		Corn	Corn	Soybeans	Soybeans	Cotton	Cotton	Gold	Gold	Copper	Copper	Platinum	Platinum	NatGas	NatGas	Crude	Crude
Mean	Constant	-0.0002	-0.0003	0.0032**	0.0034**	0.0019	0.0019	0.0012	0.0020*	-0.0017	-0.0020	-0.0001	0.0001	-0.0026	-0.0026	-0.0012	-0.0011
		(0.0018)	(0.0018)	(0.0013)	(0.0013)	(0.0018)	(0.0018)	(0.0011)	(0.0011)	(0.0015)	(0.0015)	(0.0014)	(0.0013)	(0.0025)	(0.0025)	(0.0019)	(0.0019)
Variance Equation	ESV	0.0130**						-0.0991		0.0276*							
		(0.0064)						(0.0680)		(0.0158)							
	ESV_f			-0.3918***		-0.2191						0.2658		0.4587**		-0.0600	
				(0.1268)		(0.1801)						(1.1479)		(0.1897)		(0.0639)	
	FE[ESV]		-0.1809***		-0.5164***		-0.1435		-0.5712**		0.8779***		-0.0005		0.5333**		-0.0708
			(0.0615)		(0.1597)		(0.1993)		(0.2456)		(0.2427)		(0.9053)		(0.2162)		(0.0644)
	LTC	-0.0162	-0.0107	-0.0112	-0.0098	-0.0134**	-0.0138**	-0.0967**	-0.0779*	-0.0012	-0.0025					-0.0050*	-0.0051*
		(0.0111)	(0.0110)	(0.0087)	(0.0081)	(0.0066)	(0.0066)	(0.0436)	(0.0437)	(0.0029)	(0.0029)					(0.0028)	(0.0028)
	LTC_r											-0.0184	-0.0161	1.2448	1.2265		
												(0.2578)	(0.2577)	(0.9382)	(0.9323)		
	STC					0.0004	0.0005	-0.0037	-0.0118			-0.0633***	-0.0632***	-0.0030	-0.0028	-0.0004	-0.0004
						(0.0018)	(0.0018)	(0.0136)	(0.0104)			(0.0075)	(0.0074)	(0.0025)	(0.0025)	(0.0018)	(0.0018)
	STC_r	-3.6823***	-3.2681***	-0.1132	-0.1145					-0.8349**	-0.9667***						
		(0.9159)	(0.9286)	(0.7288)	(0.7120)					(0.3348)	(0.2936)						
	Constant	-0.6543***	-0.5554***	-0.6205***	-0.5511***	-0.2918**	-0.2868**	-5.6445***	-5.4779***	-0.0975	-0.0834	-11.1787***	-11.1783***	-0.6139**	-0.6098**	-0.1600*	-0.1604*
		(0.1959)	(0.1655)	(0.2193)	(0.2064)	(0.1210)	(0.1219)	(0.8968)	(0.9338)	(0.0669)	(0.0534)	(0.3851)	(0.3863)	(0.2719)	(0.2707)	(0.0882)	(0.0881)
EARCH Terms	L.earch	0.0240	0.1190***	0.1070**	0.1085**	-0.0030	-0.0129	-0.0209	0.0456	-0.0955***	-0.1320***	-0.0074	-0.0035	-0.0280	-0.0311	-0.0867***	-0.0856***
		(0.0333)	(0.0412)	(0.0471)	(0.0466)	(0.0335)	(0.0327)	(0.0611)	(0.0670)	(0.0177)	(0.0211)	(0.0301)	(0.0307)	(0.0420)	(0.0421)	(0.0238)	(0.0240)
	L.earch_a	0.1853***	0.2639***	0.3708***	0.3565***	0.1728***	0.1755***	0.4446***	0.4733***	0.1202***	0.0985***	0.1420***	0.1395***	0.2962***	0.2930***	0.1488***	0.1485***
		(0.0434)	(0.0531)	(0.0674)	(0.0656)	(0.0439)	(0.0453)	(0.1034)	(0.1029)	(0.0308)	(0.0309)	(0.0478)	(0.0481)	(0.0745)	(0.0736)	(0.0312)	(0.0312)
	L.egarch	0.8777***	0.8952***	0.8906***	0.9033***	0.9321***	0.9327***	0.0735	0.1397	0.9825***	0.9833***	-0.8126***	-0.8125***	0.8745***	0.8762***	0.9581***	0.9583***
		(0.0364)	(0.0293)	(0.0396)	(0.0370)	(0.0275)	(0.0276)	(0.1456)	(0.1496)	(0.0123)	(0.0105)	(0.0453)	(0.0458)	(0.0536)	(0.0532)	(0.0187)	(0.0187)

Notes: This table illustrates the results of the EGARCH (1,1) model (Nelson, 1991) with a constant only mean equation for the signalling effect of commodity futures returns between June 2006 and 7th March 2017 totalling 561 observations for each commodity. With _f and _r indicating first difference and log returns respectively. With ESV, LTC, STC, and FE[…] indicating the forecast error for each of the series, estimating by either AR (10) for stationary or ARIMA (10,1,0) for non-stationary time-series as focus variables in the variance equation. Note that the EGARCH analysis is limited to eight commodities, as I cannot reject the null hypothesis that the errors are not autoregressive conditional heteroskedastic based on the ARCH-LM test for silver and sugar. With L.earch as the asymmetric term that tests the asymmetry in the model (i.e. how positive innovations affect CFR compared to negative innovations), L.earch_a as the symmetric term, and L.egarch as the EGARCH term, all at lag t-1. * indicates the statistical significance, with *** for p<0.01, ** for p<0.05, and * for p<0.1.

The model is defined as:

$CFR_t = \alpha + \delta' F_t + \varepsilon_t$ where $\varepsilon_t = \sigma_t \eta_t$ $\quad \ln(\sigma_t^2) = \gamma_0 + \gamma_1 \ln(\sigma_{t-1}^2) + \gamma_2 g(\eta_{t-1}) + \tau_1 ESV_t + \tau_2 F[ESV]_t + \tau_3 LTC_t + \tau_4 STC_t \quad g(\eta_{t-1}) = \theta\eta_{t-1} + \lambda[|\eta_{t-1}| - \mathrm{E}(|\eta_{t-1}|)]$

with α, δ, γ, τ, θ, and λ as coefficients, CFR as the weekly CFR at time t, F as vector of weekly returns of control variables and dummies at time t, ε as error term at time t, σ^2 as the conditional variance, η as a generalised error distribution, and ESV, FE[ESV], LTC, and STC as explanatory variables in the variance equation, where FE[ESV] represents the forecast error of ESV.