Essays on commodity and energy markets: Commodity pricing, financialization, and fundamental drivers

Dissertation zur Erlangung des akademischen Grades
Doctor rerum politicarum
der Technischen Universität Dortmund

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Dortmund, August 2017

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Acknowledgment

First and foremost I want to thank my advisor Peter N. Posch. I appreciate all his contributions of time and ideas to make my time as Ph.D. student productive and stimulating. I am incredibly grateful to Peter for being patient with me and enabling me reaching my professional goals. Peter has given me the freedom to pursue various projects without objection. I would also like to thank Christiane Pott and Nadine Georgiou for refereeing my thesis.

Our fantastic research group contributed immensely to my personal and professional time. I am genuinely grateful to Daniel, Timotheos, Vladislav, Janis, Philipp, and Gerrit for their good advices and source of friendships. Of course, I am also thankful to Nils and Marius for their splendid research assistance and their hours of laborious work.

I especially thank my parents and brothers. I would not have made it this far without them. I thank them for all their advices and support in every respect. And most of all for my loving, supportive, encouraging, and patient partner Birthe whose faithful support during all ups and downs of this Ph.D. is so appreciated.

Thank you.

1 Introduction

While the oil price hit $145 per barrel in 2008, its price varies around $47 in July 2017. Similarly, prices of wheat have fallen from $1,282 per bushel in 2008 to $480 and prices of nickel even have slumped from $51,600 per ton in 2007 to $9,557 in July 2017. In 2007 and 2008, several commodities were soaring partly driven by strong demand from emerging markets but have plummeted due to the global financial crisis and slowing economic growth. Following a second price peak in 2012 a sharp price decline gave momentum to an alternative view where the increasing participation of financial institutions in these markets is seen as main driver for the increased volatility (Gilbert & Pfuderer 2014).

With a growing world population and rising standards of living the demand for energy, agriculture and construction raw materials is increasing. In addition to short-term fluctuations, commodity prices are therefore also characterized by long-term trends and long cycles. As increases in the extraction capacity of raw commodities and its investment projects might take several years (Erten & Ocampo 2013), those long-term commodity price developments are of great interest for economic conditions of commodity-abundant developing countries. Hence, the past years not only raised important questions what most important drivers of commodity prices are, but also underlines the importance of a deeper understanding of how various commodity prices are related.

The present thesis addresses three key questions on commodity price movements: How can short-term commodity price changes be explained? What is the influence of financial speculation on commodity prices and what are the fundamental drivers of long-term commodity price developments? To answer those questions the thesis consists of three self-contained chapters. These chapters examine short and long-term commodity price developments and the relation between energy and non-fuel commodity markets. Chapter 2 identifies latent common factors in a sample of 31 commodity futures returns and examines how these can be applied to the pricing of commodity returns. Based on results of Chapter 2, the following Chapter 3 estimates how increased financial investments in commodity markets affect the futures market of seventeen agriculture commodities. Chapter 4 focuses on long-term non-fuel commodity price movements and how these can be linked to the availability of energy.

For equities a large body of litertature already concludes that size, value and momentum are most important factors in explaining the cross-sectional variation of returns (Daskalaki et al. 2014). Unlike equities, no such asset pricing model based on macro-factors, equity-motivated factors, or standard principal component factors could be identified for individual commodity futures' returns until today. Chapter 2 seeks to fill this gap based on the co-movement of commodity returns determined by the data itself.

As price movements in individual commodities are increasingly volatile since the beginning of the 2000s, market participants often claim that these movements are caused by idiosyncratic or commodity specific shocks. However, if there are fundamental or technical relationships between commodities, the question arises whether an apparent co-movement of various commodities can explain the cross-sectional variation of individual commodity prices. Applying the generalized dynamic factor model originally proposed by Forni et al. (2000) and modified by Forni et al. (2015) Chapter 2 identifies a latent common factor not only for a broad sample of thirty-one commodity futures' returns but also for subgroups of agriculture, metals, precious metals, energy, and livestock commodities. These common factors are assumed to be related to undefined but fundamental macroeconomic values like the US dollar's exchange rate, global inventory levels, and demand and supply. To test whether the estimated common factors can explain the cross-section of individual commodity returns, the standard two-pass approach of Fama & MacBeth (1973) is adopted. Including at least energy's and agriculture's common factors, Chapter 2 shows that two- or three-factor models may explain individual commodity returns between 2011 and 2015. These findings indicate a recent weakening of the heterogeneity assumption of commodity prices.

Additional analyses of sub-periods reveal increasing correlations between the common factor of thirty-one commodity futures' returns and changes in gold and oil prices during the financial crisis. As oil and gold prices are closely related to financial markets during times of financial turmoil (Baur & McDermott 2010), it is further concluded that the increased correlation indicates the rising influence of financial investments on commodity prices. Based on these findings, Chapter 3 aims to investigate how financial investors affect agriculture prices.

Due to their negative correlation to traditional asset classes like stocks or bonds investors discovered commodities as part of their portfolio diversification during the recent decades. However, since 2007-08 that correlation not only disappeared but gave way to a strong co-movement of the beforehand heterogeneous asset class of commodities, cf. Lübbers & Posch (2016). Following the price peak of 2012 a sharp price decline gave momentum to a view where the increasing participation of financial institutions in commodity markets is seen as main driver for the high volatility (Gilbert & Pfuderer 2014). The increasing participation of financial institutions is often referred to as the *financialization of commodity markets*. To address the question whether financialization distorts commodity prices researches often focus on commodity index traders as proxy for institutional investors (Basak & Pavlova 2016). One of the leading proponents of the idea that commodity index investment was a major driver of the sharp increase of commodity prices during the recent financial crisis is Michael W. Masters (2008). However, the literature does not find clear evidence of the relation between commodity index investment and commodity price changes so far. Introducing a financialization index, Chapter 3 closes this gap by showing that financial investors significantly affect the variation in the co-movement of agriculture commodity prices.

As commodities tend to move together over time Chapter 3 constructs a common factor extracted from a panel of seventeen agriculture commodity prices based on the panel analysis of nonstationarity in idiosyncratic and common components of Bai & Ng (2004). Similar to Chapter 2, this common factor reflects key characteristics of agriculture commodity prices and is assumed to be driven by fundamental forces. In order to show that financial investors significantly affect the variation in the co-movement of these commodities a financial speculation index based on weekly commodity index traders' long open interest is constructed. The speculation index represents the investment behaviour of large institutional investors who allocate their portfolios according to compositions of major commodity market indices like the S&P GSCI. To assess the effect of changes in institutional investors' investment positions on the entire agriculture sector a structural vector autoregression model and forecasting error variance decompositions are applied. The analysis indicates that changes in the intensity of financial speculation have a non-negligible influence on agriculture commodity markets. In order to avoid financial investments affecting agriculture markets the relative share of commodity index traders' long open interest should not be significantly higher than 28%.

Compared to short-term periods of booms and busts addressed in Chapter 2 and 3, also long-run trends of commodity prices have important implications not only for economies but also for companies heavily relying on the extraction and production of raw commodities. Long-term commodity price developments therefore are of great interest not only to academic literature but also to policy makers. So far, the literature finds strong empirical evidence that global economic growth, real interest rates, macroeconomic uncertainty, and energy prices are among the key drives of non-fuel commodity price developments in the long-run, cf. Byrne et al. (2013). Chapter 4 extends this branch of literature and takes a fresh approach on the relation of energy and non-fuel commodity prices.

Energy plays a major role throughout social and economic development (Hall et al. 2014). However, it is not just the energy produced what matters most, but the relation between the energy that is produced and the amount of energy that is needed in the production process. This ratio of energy returned to energy invested is called *Energy Return On Investment* (EROI). All economic systems and processes depend on the amount of surplus energy available to the system. Oil fields discovered in the early 1930s provided more than 80[1] (Court & Fizaine 2017) units of oil for every unit of oil invested in the extraction process (EROI of 80:1). However, since the middle of the last century an increasing proportion of the energy output is diverted to producing that energy (Lambert et al. 2012) - in 2014, the global EROI of oil was around 13:1. Tverberg (2012) and Hall et al. (2014) conclude that a declining EROI might have large impacts on world economic growth. The lower the EROI the more economic activity or money must be diverted to extracting and producing the energy leaving less funds available for economic growth (Hall et al. 2014). As most renewables and non-conventional fossil fuels have substantially lower EROI values than conventional fossil fuels (Lambert et al. 2012) the consequences of an energy transition on commodity price developments are unclear.

Chapter 4 estimates how the decreasing global EROI of oil might affect long-term commodity price developments. The estimation of the EROI follows a price-based approach as proposed in

[1] Other researchers found EROIs of US oil of around 100:1.

Court & Fizaine (2017). To assess long-term effects of decreasing surplus energy on commodity prices Chapter 4 relies on both, the widely used Grilli & Yang (1988) commodity price index and on individual agriculture and metal commodities. Based on a structural vector autoregression model and forecasting error variance decomposition (similar to Chapter 3) Chapter 4 finds evidence that commodity prices significantly depend on the amount of surplus energy available to economies. It shows that the lower the EROI, the higher are commodity prices. During times of strong economic growth, the effect of changes in the EROI of oil on commodity prices is lower than in times of weaker economic growth. This might have serious consequences in times of weakening economic growth and in times of decreasing EROI of the energy supply mix. Simultaneously considering GDP growth rates and the EROI of main energy sources might therefore help to estimate fundamental effects of a changing energy supply mix on commodity price developments.

In summary, this thesis contributes to three important topics of the literature on commodity and energy markets: (i) Commodity pricing, (ii) financialization of commodity markets, (iii) and fundamental drivers. Chapter 2 suggests that two- or three-factor models including energy's or agriculture's common factors can explain cross-sectional commodity returns. These findings indicate an increasing homogeneity of the commodity markets in recent years. Based on results of Chapter 2, Chapter 3 shows that financial investors significantly affect the variation in the co-movement of agriculture commodity prices. To avoid financial interests affecting agriculture markets the relative share of commodity index traders' long open interest should not be significantly higher than 28%. Finally, Chapter 4 finds evidence that commodity prices depend on the amount of surplus energy available to economies. During times of strong economic growth, the effect of changes in the EROI of oil on commodity prices is lower than in times of weaker economic growth. This might have serious consequences in times of weakening economic growth and decreasing EROI of the energy supply mix.

2 Commodities' common factor: An empirical assessment of the markets' drivers[2]

On a global scale, commodities will gain even more importance in the future, as demand for agricultural and construction materials will grow with a growing world population, and global demand for fossil fuels will at least remain constant until 2040, even with increasing renewable-energy production (EIA 2016). Thus, the development of commodity markets will play an important role in both economics and politics. Despite these trends, market movements in individual commodities are increasingly volatile, movements that market participants often claim are caused by idiosyncratic shocks. However, if there are fundamental or technical relationships between commodities, the question arises concerning whether this apparent co-movement can explain the cross-sectional variation of individual commodity prices. Since no factors have yet been proposed that can explain the cross-section of individual futures' returns (Daskalaki et al. 2014), we seek to fill this gap based on the co-movement of commodity returns determined by the data itself.

Factor models allow the joint driver of commodities' returns to be extract. In this chapter we apply a one-sided representation of the generalized dynamic factor model (GDFM hereafter) originally proposed by Forni et al. (2000) and modified by Forni et al. (2015) to decompose the commodities' returns into a common market factor that influences all commodities and an idiosyncratic (or commodity-specific) factor that is individual to each commodity. We assume that the common market factor is related to undefined but fundamental macroeconomic values like the US dollar's exchange rate, global inventory levels, and demand and supply. Based on the GDFM, we investigate whether the common market factor can price the cross-section of individual commodity futures' returns for various periods of time. During the 2008 global financial crisis, commodity markets' correlations with other markets changed dramatically, so

[2] This chapter is based on the paper of Lübbers & Posch (2016). One version of the paper was presented at the 10th International Conference on Computational and Financial Economics 2016, Sevilla, and is published in the *Journal of Commodity Markets*.

we emphasize this structural change by investigating sub-periods before, during, and after the crisis.

Our contribution to the literature is twofold. We add a methodological tool to the analysis of commodity markets and find that 12% of the variation in commodity returns can be explained by a common market factor during the period from 1996 to 2015, but 16% was explained by the common market factor during the financial crisis, when it was increasingly correlated with changes in gold and oil prices. Since oil and gold prices are closely linked to the financial markets during times of financial crises, this increased correlation indicates the influence of financialization on commodity prices. We also identify common factors for the subgroups of agriculture, metals, precious metals, energy, and livestock. The explanatory power of their common factors is significantly higher than that of the whole commodity sector, varying between 52% (energy) and 23% (agriculture) for the period from 1996 to 2015. These groups' explained variation shows the idiosyncratic difference between groups of commodities, but we find that the common market factor of our whole sample is highly correlated with the common factor of the agriculture sector only. Assuming that the common factor of the whole commodity sector represents global macroeconomic developments of the commodity markets and thus also of the global economy, we may see the common movement of the agriculture sector as a representation of these developments.

Our second contribution is to show the explanatory power of the common factor in explaining the cross-sectional returns. Based on the approach from Fama & MacBeth (1973), our common factor of the whole commodity sector cannot explain the cross-sectional returns of our set of individual commodities. Even during periods of financial crisis or at the beginning of the financialization of the commodity market in the early 2000s, we find no evidence for a commodity pricing model based on only one factor determined by the data itself. In line with Daskalaki et al. (2014), we consider commodities to be a heterogeneous class of assets until 2011, but from 2011 to 2015 two- or three-factor models that include at least energy's and agriculture's common factors may price individual commodity returns. These results support the importance of these two sectors and indicate a recent weakening of the heterogeneity assumption of commodities. We illustrate that a dynamic factor model may be superior to factor models that are based on static principle components when estimating asset pricing models.

In the remainder of this chapter, we continue with a literature review, followed by an overview of the data used in the model. The penultimate section examines the cross-sectional commonality, while the final section concludes.

2.1 Literature review

Researchers have used factor models to understand commodity markets as early as Pindyck & Rotemberg (1988), who show that prices of unrelated raw commodities have a persistent tendency to move together, even in excess of macroeconomic variables like inflation, industrial production, interest rates, and exchange rates. Some following investigations confirm this finding, while others reject it. Deb et al. (1996) and Karstanje et al. (2013) examine the co-movement of factors that drive commodity futures curves in price levels and in futures curve shapes and conclude, based on the dynamic Nelson-Siegel model, that individual futures' curves are driven by common components, whereas the commonality mostly is sector-specific. Vansteenkiste (2009) and Byrne et al. (2013) extract common unobserved factors from individual non-fuel commodity prices using principal component techniques. Vansteenkiste (2009) finds periods of changing co-movement, suggesting that supply, global demand, exchange rate, and real interest rate are important factors when describing the co-movement. This finding is in line with Frankel (2006), Calvo (2008), and Wolf (2008), who find that real interest rates, excess liquidity, and shifts in global supply and demand drive commodity prices. Based on returns, Christoffersen et al. (2014) and Yin & Han (2015) find evidence of a factor structure in daily and monthly commodity futures' returns and volatilities. Comparing commodity and equity markets, Christoffersen et al. (2014) conclude that commodity market returns have been detached from those of equity markets since 2010, whereas commodity volatility shows a nontrivial degree of integration with the volatility of equity markets.

The asset pricing literature seeks to identify observable factors that can explain the cross-section of commodity futures' returns. The two seminal theories on this subject are motivated by hedging pressure and the theory of storage. According to Dusak (1973), commodity futures risk premiums are related to systemic risk and to net positions of hedgers in futures markets, the latter of which is also known as hedging pressure. De Roon et al. (2000) argue that futures prices deviate from expected future spot prices because of the risk premiums that investors expect to earn or pay when investing in futures markets. Gorton et al. (2013) show that low inventory levels for individual commodities is associated with high risk premiums for their respective futures, seen as rewards for taking the risk of stock outs. Among others, Szymanowska et al. (2014) identify two additional types of risk premiums for commodity futures portfolios: spot premiums that are related to the risk in the underlying commodity and term premiums that are related to changes in the basis. Erb & Harvey (2006), Gorton & Rouwenhorst (2006), and Liu & Tang (2011) relate futures risk premiums to the basis or carry, and Bakshi et al. (2013) extend this framework to include an average commodity factor, a commodity carry factor, and a commodity momentum factor to explain both the cross-sectional and the time-series variation of commodity returns. Roache (2008), Shang (2011), Etula (2013), and Basu & Miffre (2013) find that macro factors like the real interest rate, foreign exchange variables, and hedging pressure affect the pricing of commodities. Daskalaki et al. (2014) deviate from the standard procedure in the asset pricing literature by using individual commodity futures instead of portfolios. They argue that the small cross-section of commodities means that only a small number of portfolios can be created and that their formation may conceal the heterogeneous structure of individual commodities. Based on macro-factor models, equity-motivated models, and standard principal components, their results reveal no asset pricing model that prices the cross-section of individual commodity futures’ returns.

We take a fresh approach by introducing Forni et al.'s (2000) generalized dynamic factor model to the pricing of individual commodity futures’ returns. Researchers traditionally use dynamic factor models to construct economic indicators like the coincident indicator of the Euro area business cycle (EuroCOIN), cf. Hallin & Liška (2007). They also apply the GDFM, among others, to provide a data-driven definition of the unobservable market liquidity for the S&P 500 (Hallin et al. 2011) and a volatility decomposition of the S&P 100 (Barigozzi & Hallin 2015). Stock & Watson (1989) use factor models to study economic issues like the determination of a reference cycle in macroeconomic data and the finance literature uses factor models to identify insurable risk[3]. Using the GDFM, we focus on commodity-specific data-driven factors and extend the universe of Vansteenkiste (2009) and Byrne et al. (2013) to include both non-fuel commodities and the whole energy sector.

2.2 Data

We use a broad cross-section of thirty-one commodity futures. The data are based on Thomson Reuters Datastream continuation series data sets. Our sample period is from 1 January 1996 to 31 July 2015. We divide the data set into five sectors: energy, agriculture, livestock, precious metals, and metals. For each commodity and its futures we create a continuous time series of daily excess log-returns using a rollover strategy. For the nearest-to-maturity series, we take a position in the nearest-to-maturity contract until the first business day of the notional contract month. At this time we take prices from the next trading contract month, which then becomes the nearest-to-maturity contract. We use the first- and second-nearest-to-maturity futures contracts for our estimations, as these are the most liquid contracts. (For a similar approach, see, e.g., DeRoon et al. (2000))

Since our sample consists of a wide range of commodities, there are large differences in the seasonal behavior of prices. Since seasonal effects might conceal both the true underlying movement in each series and non-seasonal effects, we run regressions against monthly dummy variables and take the residuals (as the de-seasonalized time series) as input variables for the GDFM in the following section[4].

Table 2.1 shows descriptive statistics of average yearly returns, standard deviations, and the months that show seasonal effects for the nearest-to-maturity futures of each commodity.

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[3] See, for example, Ng et al. (1992), Harvey et al. (1992), Weide (2002), Connor et al. (2006), Sentana et al. (2008), and Jurado et al. (2013), who consider the decomposition of equity return series.

[4] Our final results did not change significantly without seasonal adjustment.

Table 2.1: Descriptive statistics. This table presents percentage annualized mean returns, standard deviations, and the months showing seasonal effects for each commodity. The data are based on daily observations of the 31 nearest-to-maturity and most liquid commodity futures contracts for the time period from 01.01.1996 to 07.30.2015. The panel is divided into the subgroups agriculture, precious metals, energy, livestock, and metals. Underlined commodities are not listed in one or the other of the two most important commodity indices (i.e., Bloomberg commodity index and S&P GSCI index).

	Av. Return	St. deviation	Seasonal effects
		Agriculture	
Corn	0.05	28.27	Jul., Dec.
Wheat	0.71	30.13	Jul.
<u>Oats</u>	-0.15	36.11	-
<u>Rough Rice</u>	0.9	25.73	Jun.
Soybeans	1.73	24.16	Feb., Jul., Sep.
Canola	0.71	19.58	Sep.
Coffee	1.37	36.66	Jun.
Cocoa	4.7	28.98	Jun., Oct.
Cotton	-1.21	28.35	Dec.
Sugar	-0.14	36.11	Mar., Jun., Jul.
<u>Lumber</u>	-0.38	30.21	Sep., Nov.
<u>Orange Juice</u>	0.24	31.75	-
Average	0.71	29.67	
		Precious Metals	
Gold	5.16	16.68	Sep.
Silver	5.23	28.73	-
Platinum	4.55	21.7	Jan., Feb.
<u>Palladium</u>	7.82	32.53	Jan., Feb.
Average	5.69	24.91	
		Energy	
WTI Crude	4.55	36.04	-
Brent Crude	5.34	33.26	-
NY Harbor	5.01	34.58	-
Gas Oil	5.05	30.67	Oct.
Natural Gas	0.28	54.77	Sep.
Average	4.05	37.86	

		Livestock	
Lean Hogs	2.26	32.39	Apr., Aug., Sep., Oct., Dec.
Feeder Cattle	6.21	14.12	May
Live Cattle	3.91	16.14	Apr., Aug.
Average	4.13	20.88	
		Metals	
Copper	3.41	24.24	-
Al 99.7%	-0.19	19.12	May
Al Alloy	0.61	16.88	May
Nickel	1.6	33.37	-
Zinc 99.995%	3.23	25.06	-
Lead	4.38	27.25	Jul.
Tin 99.85%	4.69	23.31	Jan.
Average	2.53	24.18	

Palladium has the highest yearly average return and coffee the highest standard deviation. By breaking the data into commodity groups, we observe that the agriculture sector has the second-highest standard deviation but the lowest average return. Many agricultural commodities are harvested only once a year and prices might be highest (while inventories are lowest) just prior to the harvest season. The energy sector exhibits the highest average yearly standard deviation and shows significant seasonal effects only for natural gas and gas oil, as demand is highest during the cold months or just before, when gas inventories are filled for the winter season. Finally, the precious metals sector shows the highest average yearly return. Only six commodities in our sample (oats, rough rice, lumber, orange juice, palladium, aluminum alloy) are not listed in one or the other of the two most important commodity indices, the Bloomberg commodity index and the S&P GSCI index. Except for palladium, which shows the highest average return, these commodities do not behave substantially differently from the listed commodities.

2.3 Construction of common factors

The purpose of this chapter is to identify latent common market factors and to determine whether these factors can price the thirty-one individual commodity futures' returns. In order to achieve this goal, we apply the one-sided representation of the GDFM Forni et al. (2015) introduce, which decomposes asset returns Y_{it} into a common market factor X_{it} and a commodity-specific factor Z_{it} based on the concept of dynamic principal components (PC) introduced by Brillinger (1981). In dynamic PC analysis, the time series are weighted according to their signal-to-noise ratios, and factors are estimated in the frequency domain as linear combinations of contemporaneous time series *and their lags*. Hence, dynamic PC can be seen as a weighted version of the static PC, which considers only contemporaneous co-movements of variables (Eickmeier & Ziegler 2008). According to Forni et al. (2015) and Barigozzi & Hallin (2015), the GDFM can be summarized as

$$\begin{aligned} Y_{it} &= "common"_{it} + "idiosyncratic"_{it} \\ &=: X_{it} + Z_{it} =: \sum_{k=1}^{q} b_{ik}(L) u_{kt} + Z_{it}, \qquad i \in N, t \in \mathbb{Z}, \end{aligned} \tag{2.1}$$

where

- Y_{it} is a centered and weakly stationary process and has a spectral density, with $\boldsymbol{Y}_n := \{Y_{n,t} = (Y_{1t}, Y_{2t}, \dots, Y_{nt})' | t \in \mathbb{Z}\}$;
- $\boldsymbol{u} := \left\{\boldsymbol{u_t} = \left(u_{1t} u_{2t} \dots u_{qt}\right)' | \ t \in \mathbb{Z}\right\}$ is a q-dimensional orthonormal unobservable white noise vector, also called common shocks;
- the common factors X_{it} are driven by a vector of common shocks u_{kt}, k = 1, 2, ..., q;
- the idiosyncratic *n*-dimensional processes $\boldsymbol{Z_n} := \left\{\boldsymbol{Z_{n,t}} = (Z_{1t} Z_{2t} \dots Z_{nt})' | \ t \in \mathbb{Z}\right\}$ have zero mean and finite variances for any *n*, with θ-a.e. bounded (as $n \to \infty$) dynamic eigenvalues, for $\theta \in [-\pi, \pi]$;
- the processes Z_{kt1} and u_{ht2} are mutually orthogonal for any *k, h,* t_1, and t_2;
- the filters $b_{ik}(L)$ are one-sided and square-summable, which means that $\sum_{m=1}^{\infty} b_{ikm}^2 < \infty$ for all $i \in \mathbb{N}$ and $k = 1, \dots, q$; L stands for the lag operator; and
- q is minimal with respect to these properties.

Forni et al. (2015) show that, given certain assumptions, the process $\boldsymbol{Y}_n$ admits a VAR representation of the form:

$$\left(\boldsymbol{I_n} - \boldsymbol{A_n}(\boldsymbol{L})\right)\boldsymbol{Y_{n,t}} = \boldsymbol{H_n}\boldsymbol{u_t} + \left(\boldsymbol{I_n} - \boldsymbol{A_n}(\boldsymbol{L})\right)\boldsymbol{Z_{n,t}} =: \boldsymbol{H_n}\boldsymbol{u_t} + \widetilde{\boldsymbol{Z_{n,t}}}, \qquad \boldsymbol{t} \in \mathbb{Z}, \qquad (2.2)$$

where $\boldsymbol{H}_n$ is a full-rank $n \times q$ matrix of constants, $\boldsymbol{A}_n(L)$ is an $m(q+1) \times m(q+1)$ block diagonal matrix of one-sided filters, and $\widetilde{\boldsymbol{Z}_{n,t}} = \left(\boldsymbol{I}_n - \boldsymbol{A}_n(L)\right)\boldsymbol{Z}_{n,t}$ is idiosyncratic. Assume that n is an integer multiple of (q + 1), that is $n = m(q+1)$ for some $m \in \mathbb{N}$. As the right side of Equation 2.2 shows, the unlagged common shocks $\boldsymbol{u}_t$ are loaded via matrix loadings $\boldsymbol{H}_n$ (Barigozzi & Hallin 2015).

For the estimation of the common and idiosyncratic factors, we follow Barigozzi & Hallin (2015) and Forni et al. (2015):

a. To determine the common market factor and the idiosyncratic factor of the sample, the common shocks $\boldsymbol{u_t}$ have to be estimated based on the spectral density matrices $\boldsymbol{\Sigma}_n^Y(\theta)$ and $\boldsymbol{\Sigma}_n^X(\theta)$ of the return series Y_{it} and the common factor X_{it}, respectively. The latter is based on the eigenvectors corresponding to $\boldsymbol{\Sigma}_n^Y(\theta)$'s q largest dynamic eigenvalues and $\boldsymbol{\Sigma}_n^Z(\theta) := \boldsymbol{\Sigma}_n^Y(\theta) - \boldsymbol{\Sigma}_n^X(\theta)$.
b. By means of the classical inverse Fourier transform of $\boldsymbol{\Sigma}_n^X(\theta)$, we estimate the autocovariances $\boldsymbol{\Gamma}_{n,k}^X(\theta),\ k \in \mathbb{Z}$ of the level common factors.
c. From each of the $m\ (q+1) \times (q+1)$ diagonal blocks of $\boldsymbol{\Gamma}_{n,k}^X(\theta)$ we estimate the order and the coefficients of a $(q+1)$-dimensional VAR model, which yields an estimator of the block diagonal operator $\boldsymbol{A}_n(L)$ in Equation 2.2.
d. Projecting $\widetilde{Y_{\iota t}}$ (where $\widetilde{\boldsymbol{Y}_n} = \left(\boldsymbol{I}_n - \boldsymbol{A}_n(L)\right)\boldsymbol{Y}_n$) on their q largest static principal components provides an estimate $\boldsymbol{e}_n = \boldsymbol{H}_n\boldsymbol{u}$ of the common innovation process $\boldsymbol{e}_n$.
e. The estimator of the idiosyncratic factor is obtained as $\widetilde{\boldsymbol{Z}_n} = \left(\boldsymbol{I}_n - \boldsymbol{A}_n(L)\right)\boldsymbol{Y}_n - \boldsymbol{e}_n$.

A heuristic approach proposed in Forni et al. (2000) and an information criterion introduced in Hallin & Liška (2007) can be applied to estimate the number of common shocks q. Both are based on the number of diverging eigenvalues of the returns' spectral density matrix. In the heuristic approach the average of frequencies θ of the first q eigenvalues diverges where the average of the $(q+1)_{th}$ one is relatively stable. We proceed as follows:

1. We consider our sample of thirty-one commodities for different periods of time.
2. We estimate the number q of common shocks u in each sample based on the heuristic

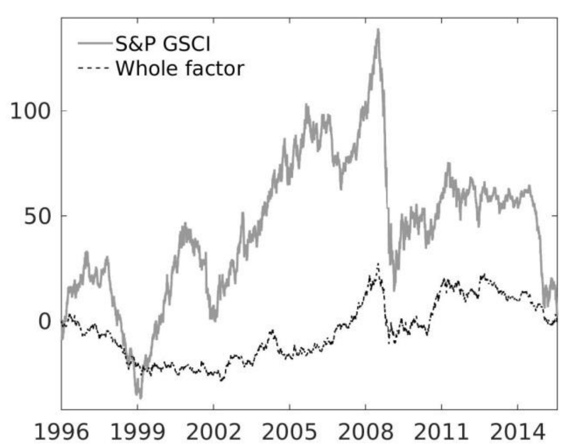
approach of Forni et al. (2000) (Table 2.2). To determine the number of diverging eigenvalues, we use a preassigned minimum of 5% for the explained variance. The common shocks *u* yield the common factors X_{it}.

3. We take the *equal-weighted average of the common factors* X_{it} and interpret this equally weighted market factor of all commodities as the common response of these commodities to undefined underlying macroeconomic variables.
4. We then use the aggregated common factor to explain the cross section of individual commodity futures' returns (in Section 2.4).
5. We repeat steps 1 - 4 using subgroups of commodities- that is, agriculture, energy, precious metals, metals, and livestock.

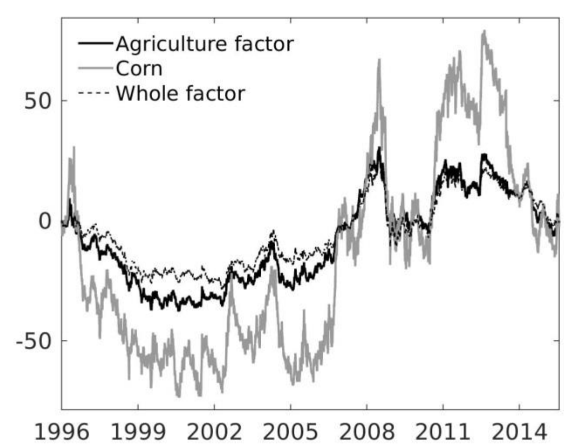
The application of these steps opens a new empirical facet to the debate on the number of factors that drive the commodity markets and to an application thereof to the asset pricing literature.

Figure 2.1 (i) compares the cumulated index of the *equal-weighted average of the common factors* (step 3) of all thirty-one commodities with the S&P GSCI. Figures 2.1 (ii) – (vi) show the cumulative index of the thirty-one commodities and the cumulative index of the equal-weighted average of the common factors of the five subgroups of energy, agriculture, livestock, metals, and precious metals individually. We compare these with the cumulative log-return series of the most frequently traded commodity in each subgroup.

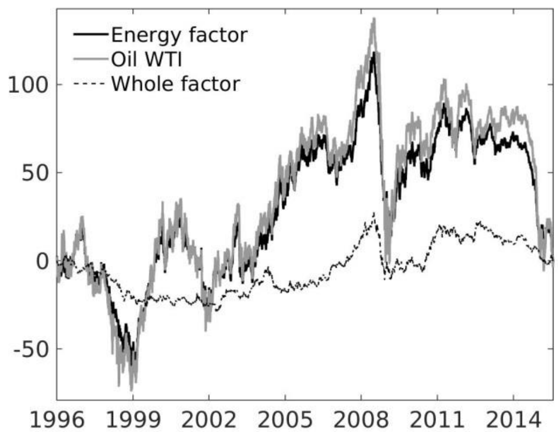
(i) Commodities' common factor vs. S&P GSCI



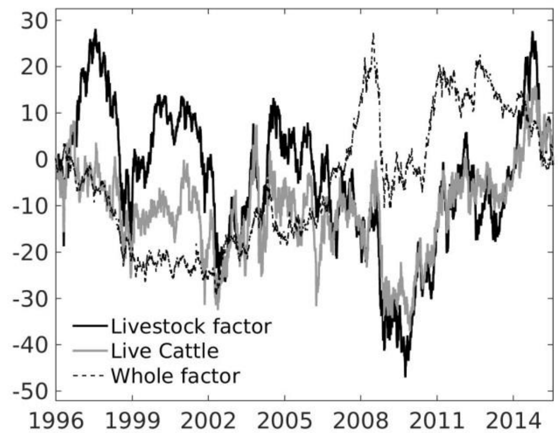
(ii) Agriculture's common factor vs. Corn vs. whole sector's common factor



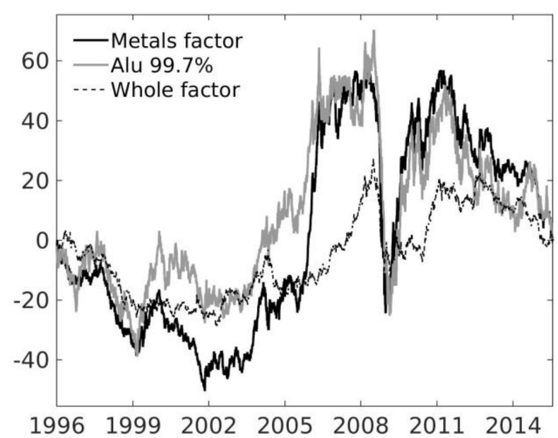
(iii) Energy's common factor vs. Oil WTI vs. whole sector's common factor



(iv) Livestock's common factor vs. Live Cattle vs. whole sector's common factor



(v) Industrial metals' common factor vs. Aluminum 99.7% vs. whole sector's common factor



(vi) Precious metals' common factor vs. Gold vs. whole sector's common factor

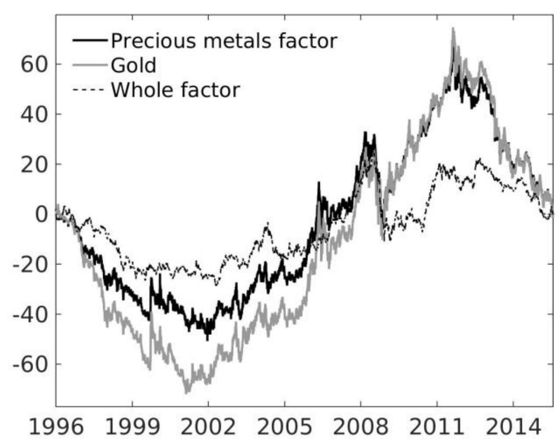
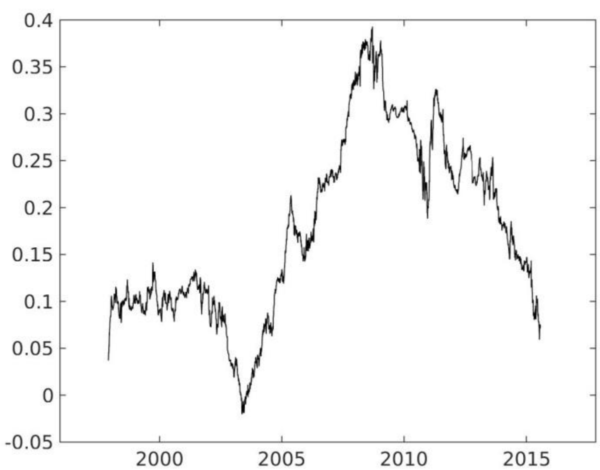
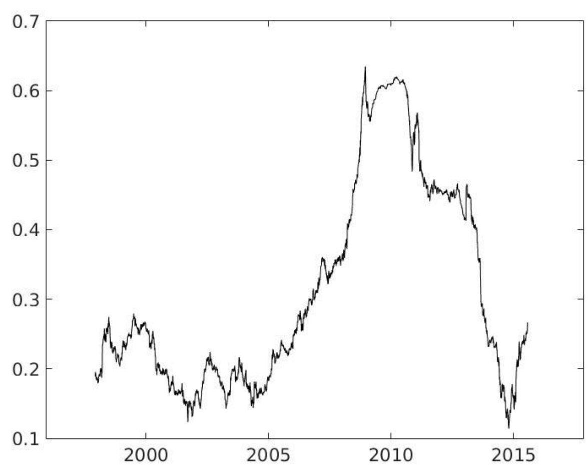


Figure 2.1: Cumulated indices of common return factors. This figure presents cumulative indices of the equal-weighted average of the common factors and the most traded commodities for each subgroup for the period from 01.01.1996 to 07.30.2015.
(i) shows the common factor of the whole commodity sample (black) with the S&P GSCI (gray).
(ii) – (vi) compare the average common factor of the five commodity subgroups (black) with the most traded commodity of each group (gray) and the common factor of the whole commodity sample (dotted).

Figure 2.1 (i) shows that the S&P GSCI and the common factor have moved in similar patterns since the beginning of the financial crisis in 2007. However, over the entire period from 1996 to 2015, the S&P GSCI seems to be more volatile and exhibits stronger decreases and increases in index levels. In contrast, the common factor is characterized by approximately four regimes: From 1996 to 2000 the common factor exhibits a downward trend, whereas from 2001 to 2005, a time period referred to as the beginning of financialization, a small upward trend occurs. The following period, from 2006 to 2010, includes the financial crisis and a strong increase in prices, peaking in mid-2008 and falling to a level slightly higher than before the crisis in 2010. The last period, from 2011 to 2015, covers the rise and recent fall in commodity prices. All of the following estimations are divided into these four time periods. Figures 2.1 (ii) – (vi) show that the common movement of all commodities is similar to the common movement of the agricultural sector (correlation of 0.93 over the entire period). The oil price and the common factor of the energy sector are similar over the entire period, indicating the importance of the oil price for the energy sector.



(i) This figure presents the correlation between changes in the *gold* price and the average market factor of the whole commodity sample based on a rolling window of two years.



(ii) This figure presents the correlation between changes in the *oil* price and the average market factor of the whole commodity sample based on a rolling window of two years.

Figure 2.2: Correlation between gold and oil price changes and the common factor of the whole commodity sample

Figure 2.2 further analyses the relation between the common factor of the whole commodity sample and the precious metals and energy sector. It shows the correlation between changes in gold and oil prices and the market factor of the whole commodity sample based on a rolling window of two years. It seems that the correlation between oil price changes and the common market factor peaked during the financial crisis. Similarly, Tang & Xiong (2012) find that the prices of non-energy futures have become increasingly correlated with oil prices since the early 2000s and argue that these results reflect the financialization of the commodity markets.

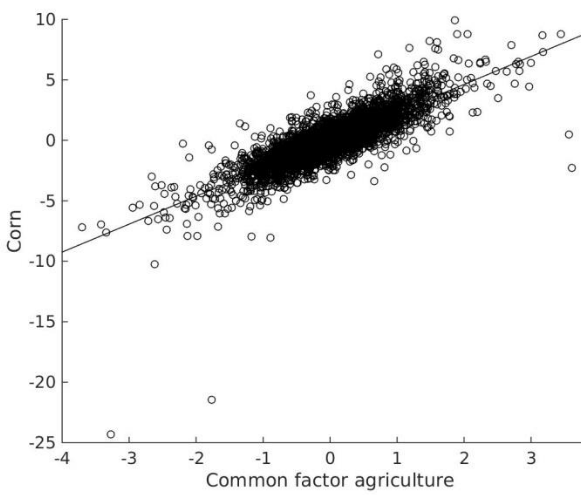
In addition, the gold price and the common factor of the precious metals sector have been almost perfectly correlated since 2008, and the correlation between gold price changes and the common movement of the whole commodity sector also increased sharply during the financial crisis, from below zero to almost 40%. Since gold is directly linked to the financial markets (i.e., the stock markets often see gold as a hedge and a safe haven during a financial crisis (Baur & McDermott 2010)), we see this as evidence of the financial markets' increased influence on commodity prices during financial crises.

Table 2.2: Determination of the number *q* of common shocks *u*. This table presents the number q of common shocks u and the fraction of the total variation in commodity futures' returns that these q shocks explain, based on Forni et al. (2000). Results are shown for the period from 01.01.1996 to 07.30.2015, and for four subsets of this period of time.

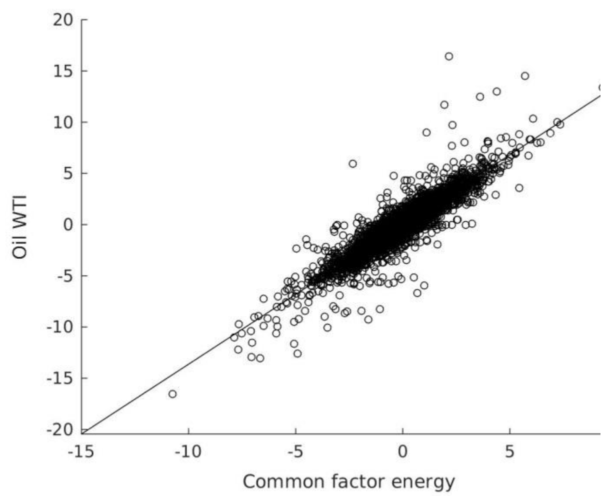
	1996 - 2015		1996 - 2000		2001 - 2005		2006 - 2010		2011 - 2015	
	# common shocks q	Expl. variation	# common shocks q	Expl. variation	# common shocks q	Expl. variation	# common shocks q	Expl. variation	# common shocks q	Expl. variation
All Commodities	5	52%	6	59%	6	57%	4	56%	6	61%
Agriculture	7	77%	6	77%	8	83%	6	77%	7	80%
Energy	3	92%	3	90%	3	93%	3	95%	3	95%
Metals	4	88%	5	90%	4	89%	4	90%	4	91%
Precious Metals	2	80%	2	78%	2	80%	2	78%	2	94%
Livestock	1	53%	1	57%	1	52%	1	53%	1	48%

Table 2.2 shows the number q of common shocks used in the GDFM during each observation period, based on Forni et al. (2000). For the whole sample, the first four to six common shocks explain only 52–61% of the variation in the commodity futures' returns, indicating the heterogeneity of the commodity market[5]. The results for the sub-sample estimations are entirely different: For the energy, metals, and precious metals sectors, we need fewer factors and can explain 78–95% of the variation in the data. The share of explained variation of the first q dynamic eigenvalues increases from the first period (1996–2000) to the last period (2011–2015) for almost all samples. Similarly, Figure 2.3 provides scatter plots of the common factors of each subsector and the most frequently traded commodity of each of these sectors. The R^2 shows that the explanatory power of the common factors varies between 61% for the livestock sector and 82% for the energy sector.

Agriculture's common factor vs .Corn,
$R^2 = 0.64$



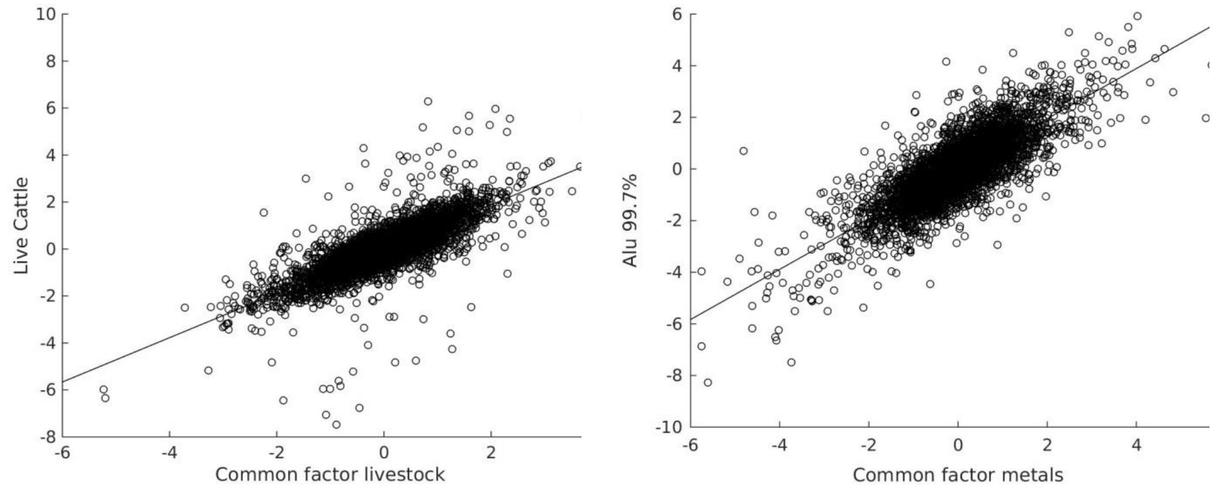
Energy's common factor vs. Oil WTI,
$R^2 = 0.82$



Livestock's common factor vs. Live Cattle,
$R^2 = 0.61$

Industrial metals' common factor vs. Al 99.7%,
$R^2 = 0.62$

[5] Barigozzi and Hallin (2015) show, that the number q of common shocks for the S&P100 is equal to one.



Precious metals' common factor vs. Gold,

$R^2 = 0.67$

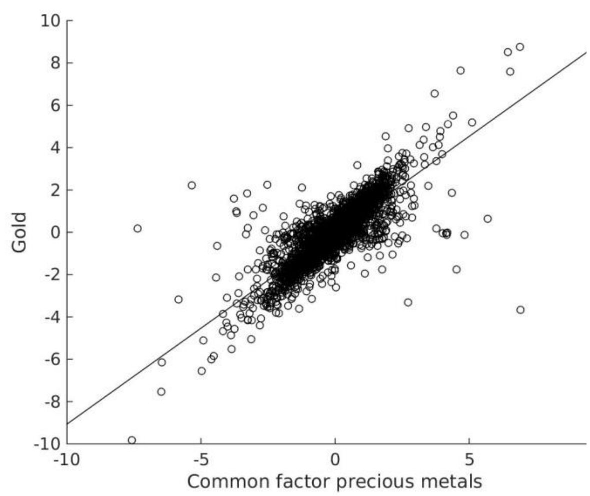


Figure 2.3: Commodity returns and their common factors. This figure presents bivariate scatter plots of average common factors X_t and the most frequently traded commodities for each subgroup for the period between 01.01.1996 and 07.30.2015.

In the next step, we measure the contribution of the common factors X_{it} to the total variation in returns by the ratio of the sum of the empirical variances of the common factors X_{it} and the returns Y_{it} (Barigozzi & Hallin 2015):

$$R^2 := \frac{\sum_{i=1}^{n}\sum_{t=1}^{T}(X_{it})^2}{\sum_{i=1}^{n}\sum_{t=1}^{T}(Y_{it})^2}, \tag{2.3}$$

The return variation explained by the common factors is summarized in Table 2.3. The common market factor explains 12% of the variation in commodity returns for the 1996–2015 period but increases to as much as 16% during the financial crisis. For purposes of comparison, Yin & Han (2015) identify a global factor that accounts for 16.86% of monthly commodity price fluctuations from 1991 to 2014. These numbers are small compared to equity markets: based on the GDFM, Barigozzi & Hallin (2015) obtain a common factor that accounts for 36% of the total variation in S&P100 returns.

Table 2.3 shows that the variation in individual commodity prices that is explained by the market factor increases until 2010, after which it decreases for most commodities. These findings partly contradict the results of Yin & Han (2015), who find an increasing commonality among commodities from 2004 to 2014. One explanation for the increased importance of the global factor could be investors' growing interest in commodities, which changes commodities' sensitivity to international influences, cf. Yin & Han (2015). As above, our results support these findings for 2001 to 2010 but indicate that international and investor influences on commodity prices might have weakened again after 2010.

Table 2.3: Return variance explained by the common factor of the whole commodity sample. This table presents the share of variance explained by the common factor of the full sample for the period from 01.01.1996 to 07.30.2015, and for four sub-periods. If all variation is driven by the common factor X_{it}, these ratios approach 1 (i.e., $R^2 = \frac{\sum_{i=1}^{n}\sum_{t=1}^{T}(X_{it})^2}{\sum_{i=1}^{n}\sum_{t=1}^{T}(Y_{it})^2}$). We highlight units where the ratio of the common variation to the sample variation is greater than 0.5, which shows that a substantial degree of variation in the commodity time series' is explained by the common factor. Underlined commodities are not listed in one of the two most important commodity indices (i.e., Bloomberg commodity index and S&P GSCI index).

	1996 - 2015	1996 - 2000	2001 - 2005	2006 - 2010	2011 - 2015
			Agriculture		
Corn	**0.64**	**0.62**	**0.58**	**0.64**	**0.63**
Wheat	**0.54**	0.48	0.49	**0.56**	**0.60**
<u>Oats</u>	0.39	0.49	0.22	0.47	0.38
<u>Rough Rice</u>	0.14	0.12	0.10	0.20	0.16
Soybeans	**0.60**	**0.61**	**0.60**	**0.60**	0.47
Canola	0.46	0.42	0.47	0.46	0.35
Coffee	0.05	0.01	0.08	0.20	0.07
Cocoa	0.03	0.02	0.05	0.11	0.01
Cotton	0.13	0.04	0.08	0.22	0.07
Sugar	0.06	0.02	0.01	0.16	0.11
<u>Lumber</u>	0.02	0.00	0.04	0.03	0.01
<u>Orange Juice</u>	0.01	0.03	0.06	0.01	0.01
			Precious Metals		
Gold	0.04	0.05	0.04	0.13	0.07
Silver	0.07	0.04	0.05	0.16	0.08
Platinum	0.04	0.02	0.07	0.09	0.09
<u>Palladium</u>	0.02	0.01	0.08	0.06	0.08
			Energy		
WTI Crude	0.09	0.09	0.11	0.17	0.03
Brent Crude	0.09	0.09	0.12	0.16	0.04
NY Harbor	0.08	0.08	0.11	0.15	0.04
Gas Oil	0.05	0.06	0.08	0.07	0.02
Natural Gas	0.02	0.02	0.05	0.04	0.02
			Livestock		
Lean Hogs	0.02	0.03	0.01	0.01	0.01
Feeder Cattle	0.12	0.16	0.05	0.04	0.08
Live Cattle	0.10	0.09	0.04	0.07	0.07
			Metals		
Copper	0.05	0.07	0.16	0.11	0.07
Al 99.7%	0.04	0.09	0.17	0.09	0.06
<u>Al Alloy</u>	0.03	0.09	0.12	0.05	0.03
Nickel	0.03	0.06	0.09	0.06	0.06

Zinc 99.995%	0.03	0.05	0.14	0.07	0.06
Lead	0.03	0.04	0.11	0.07	0.05
Tin 99.85%	0.03	0.03	0.07	0.05	0.03
Aggregated Sample	0.12	0.10	0.12	0.16	0.13

These findings are also supported by Christoffersen et al. (2014), who conclude that commodity market returns have diverged from equity market returns since 2010.

Table 2.3 reveals that the common factor explains a substantial degree of the variation (at least 50%) in the prices of corn, wheat, and soybeans but plays only a minor role in explaining price variations in all other commodities. During the financial crisis, the commonality of the prices increased slightly for all commodities except the metals sector. These findings again indicate the heterogeneity of commodity prices even during a financial crisis and the beginning of financialization.

The explanatory power of the subsectors' common factors is significantly higher (Table 2.4), as the explained variation in each sample varies between 23% (agriculture) and 52% (energy) for the whole time period. However, we do not see a trend of rising co-movement across all sectors. The explanatory power of the energy sector's common factor and the agriculture sector's common factor has been almost constant since 2006 and 2001, respectively. Only the precious metals sector stands out, with the common factor explaining 92% of the variation in the individual returns from 2011 to 2015.

Table 2.4: Return variance explained by the sub-samples' common factors. This table presents the share of variance explained by the common factor of the five sub-samples for the whole period from 01.01.1996 – 07.30.2015 and for four sub-periods. If all variation is driven by the common factor X_{it} of each subgroup, these ratios approach 1 (i.e., $R^2 = \frac{\sum_{i=1}^{n}\sum_{t=1}^{T}(X_{it})^2}{\sum_{i=1}^{n}\sum_{t=1}^{T}(Y_{it})^2}$). We highlight units where the ratio of the common variation to the sample variation is greater than 0.5, which shows that a substantial degree of variation in the commodity time series is explained by the respective common factor.

	1996 - 2015	1996 - 2000	2001 - 2005	2006 - 2010	2011 - 2015
Agriculture	0.23	0.18	0.28	0.28	0.27
Precious Metals	0.46	0.34	**0.67**	**0.63**	**0.92**
Energy	**0.52**	**0.53**	**0.52**	**0.57**	**0.57**
Livestock	0.34	0.35	**0.64**	0.47	0.37
Metals	0.46	0.35	0.47	**0.56**	**0.61**

Our findings are partly in line with the literature; for example, Kat & Oomen (2006) and Karstanje et al. (2013) confirm that correlations between commodity groups are low and mostly insignificant, but correlations within these groups are much stronger.

2.4 Cross-sectional commodity returns

To test whether our estimated common factors in Section 2.3 can price the cross-section of individual commodity return series, we adopt the standard two-pass approach from Fama & MacBeth (1973). Their procedure is a relative of cross–sectional regression and is typically applied to asset-pricing models. In the first step, we run a time series regression on excess returns R_t and the common factor X_t to estimate betas:

$$R_t^i = a_i + \beta_i' X_t + \epsilon_t^i \; t = 1,2, \dots, T \; for \; each \; i. \tag{2.4}$$

In the second step, the β's are used to run cross-sectional regression to estimate the risk premium λ at each time period:

$$R_t^i = intercept_t \; + \; \beta_i' \lambda_t + \alpha_{it} \;\; i = 1,2, \dots, N \; for \; each \; t. \tag{2.5}$$

Then estimates of λ (the slope or the risk premium) and α are the averages across time. Because we do not compute the variance of the average estimates for each period but do so across the time series of these estimates, this approach allows us to calculate standard errors that are corrected for cross-sectional correlation (Cochrane 2001).

To estimate the betas in the first-pass regression, we use a rolling window of 500 trading days. While Fama & MacBeth (1973) apply a rolling window of five years, Fama & French (1997), Ang & Chen (2007), and Lewellen & Nagel (2006) show that exposure to market risk is time-varying and argue that long time intervals may cause the estimates of conditional betas to be noisy (Ang et al. 2006). For robustness analysis, we also apply window sizes of one and five years, as well as the whole sample in estimating the betas. We find the most promising results using a window size of two years.

The second-pass regression tests whether the common factors explain our commodity returns and the premiums awarded for exposure to the various commodity sectors. To correct for the errors-in-variables problem, we adjust the standard errors of the risk premium estimation by the adjustment Shanken (1992) proposes.

Risk premium - Table 2.5 reports the average risk premiums and their t-statistics for four panels of common factors and four periods of time as result of the cross-sectional regression of Fama & MacBeth (1973),

$$R_t^i = intercept_t + \sum_j \beta_i^j * Risk\ premia_{j,t} + \alpha_{it} \quad i = 1,2,\ldots,N\ for\ each\ t, \tag{2.6}$$

where *j* describes the number of factors for each panel.

Table 2.5: Risk premiums for common factors. Summary results for the cross sectional regression of the two-pass approach from Fama & MacBeth (1973) $R_t^i = intercept_t + \sum_j \beta_i^j * Risk\ premia_{j,t} + \alpha_{it},\ for\ i = 1,2,\ldots,N$. The table reports results for five average *common* factors and five periods of time. We show estimated constant coefficients, the risk premiums, their t-statistics, and the average adjusted R^2. Our test asset sample consists of the 31 individual nearest-to-maturity commodity futures' returns. The corresponding t-statistics are corrected by the Shanken (1992) adjustment. Significant coefficients at the 10%, 5%, and 1% significance levels are denoted with *, **, and ***, respectively.

		Risk premiums					*t-Statistics*						
Period	Intercept	Whole	Agriculture	Energy	Metals	Precious Metals	Intercept	Whole	Agriculture	Energy	Metals	Precious Metals	Adj. $\overline{R}^2$
Panel A													
1996 - 2015	0.015	-0.004	-	-	-	-	1.29	-0.41	-	-	-	-	0.19
1996 - 2000	-0.017	0.01	-	-	-	-	-0.85	0.75	-	-	-	-	0.14
2001 - 2005	0.055	-0.004	-	-	-	-	2.22	-0.2	-	-	-	-	0.17
2006 - 2010	0.023	0.007	-	-	-	-	0.64	0.23	-	-	-	-	0.25
2011 - 2015	-0.022	-0.016	-	-	-	-	-0.93	-0.99	-	-	-	-	0.14
Panel B													
1996 - 2015	0.015	-	-0.008	0.004	-	-	1.48	-	-0.66	0.15	-	-	0.27
1996 - 2000	-0.008	-	0.059	-0.013	-	-	-0.45	-	-0.63	0.89	-	-	0.25
2001 - 2005	0.053	-	-0.027	0.057	-	-	2.27	-	-1.05	0.81	-	-	0.28
2006 - 2010	0.033	-	0.008	-0.015	-	-	0.98	-	0.22	-0.2	-	-	0.32
2011 - 2015	0.001	-	-0.039*	-0.093*	-	-	0.06	-	-1.66	-1.66	-	-	0.23
Panel C													
1996 - 2015	0.011	-	-0.006	0.008	-	0.004	1.11	-	-0.49	0.3	-	0.19	0.31
1996 - 2000	-0.017	-	-0.009	0.067	-	0.048	-0.9	-	-0.44	1.01	-	1.08	0.28
2001 - 2005	0.048	-	-0.024	0.06	-	0.007	2.14	-	-0.94	0.85	-	0.09	0.31
2006 - 2010	0.023	-	0.011	-0.015	-	0.059	0.71	-	0.31	-0.19	-	0.81	0.35
2011 - 2015	0.005	-	-0.04*	-0.089	-	-0.09	0.24	-	-1.73	-1.58	-	-1.32	0.28
Panel D													
1996 - 2015	0.011	-	-0.005	0.008	0.007	-	1.11	-	-0.4	0.33	0.39	-	0.32
1996 - 2000	-0.002	-	-0.017	0.051	-0.007	-	-0.09	-	-0.79	0.77	-0.26	-	0.28
2001 - 2005	0.03	-	-0.014	0.075	0.048	-	1.28	-	-0.55	1.07	1.25	-	0.32
2006 - 2010	0.041	-	0.004	-0.027	-0.015	-	1.35	-	0.11	-0.35	-0.22	-	0.39
2011 - 2015	0.004	-	-0.041*	-0.091	-0.039	-	0.17	-	-1.74	-1.64	-0.91	-	0.29

Panel A displays the results of the cross-sectional regression of the commodity futures' returns against the common factor of the whole commodity sample. We find risk premiums between *-160bps* to *100bps* for the four periods of time, which are statistically not significant. Unreported results show that no single factor explains the cross-sectional returns in a stand-alone setting. Based on at least two factors, we see significant risk premiums for agriculture and energy sector's common factors (Table 2.5's Panels B, C, and D, respectively). The energy sector's and (mainly) the agriculture sector's common factors seem to be most important and influential, even though these factors are significant only at the 10% level and explain 23–29% of commodity returns during the time period from 2011 to 2015. In each of these cases, the risk premiums on the agriculture sector's common factor are around -4%, and those of the energy sector are around -9%. The explanatory power of these models increases when the metals sector or the precious metals sector is included (Table 2.5's Panels C and D, respectively). During the financial crisis, when co-movement of commodities increased slightly (Table 2.3), no commodity-specific factor explains commodity prices' cross-sectional movement.

In line with Gorton et al. (2013), Table 2.5 reveals changing risk premiums over time[6]. Commodity futures' risk premiums vary across commodities and over time, depending on the levels of physical inventory (Gorton et al. 2013). Assuming our common factors are driven by fundamental commodity variables like inventory levels, hedging pressure, and demand and supply, our results (from 1996 to 2010) are supported by Gorton et al. (2013), who find no evidence that the positions of participants in futures markets predict risk premiums. Furthermore, Table 2.5 partly confirms the results of DeRoon et al. (2000) in showing that both the futures own hedging pressure and cross-hedging pressure from the group of a certain sector of commodities (not across different classes of commodities) significantly affected futures' returns from 1996 to 2010.

As Tang & Xiong (2012) and Yin & Han (2015) argue, there was increased co-movement during a period including the financial crisis that might have been driven by financial markets rather than fundamental commodity factors. Therefore, we do not find significant risk

[6] We did not test whether these changes are statistically significant or are caused by randomness in the coefficients.

premiums based on commodity-specific factors for this period (Table 2.5). However, we see decreased co-movement of the commodity sector during the 2011–2015 period (Table 2.3). Assuming segmented commodity and financial markets (Christoffersen et al. 2014), the statistically significant risk premiums shown in Table 2.5 indicate that the cross-section of individual commodity futures' returns has been driven by commodity-specific factors rather than by financial ones since 2011. When controlling for common changes in the agriculture and energy sectors, we find first evidence of a fundamental-driven commodity market since 2011. These results support the importance of the energy and the agriculture sector for all other commodities and hence economic developments in general. This interpretation sheds new light on the findings of De Roon et al. (2000) and Daskalaki et al. (2014), who show that commodity-specific factors cannot explain commodity returns in a cross-sectional setting.

Robustness checks - As Table 2.3 shows, the common factor explains only 12% of the total variations in the returns of all commodities from 1996 to 2015. We thus test whether commodity-specific (idiosyncratic) factors contain information that we can use for pricing these commodities. In a first robustness check, we repeat our estimation based on the commodity-specific factors instead of the common factor to see whether the average of all commodity-specific factors explains the cross-section of individual commodity futures' returns (cf. Step 3, Section 2.3). In addition, as Tang & Xiong (2012) show that prices of non-energy futures have been increasingly correlated with oil prices since the early 2000s, we test whether idiosyncratic oil price changes can separately price the cross-section of our commodity sample. Table 2.6 reports the results of the cross-sectional regression of the two-pass approach from Fama & MacBeth (1973).

Table 2.6: Risk premiums for idiosyncratic factors. Summary results for the cross-sectional regression of the two-pass approach from Fama & MacBeth (1973) $R_t^i = intercept_t + \sum_j \beta_i^j * Risk\ premia_{j,t} + \alpha_{it},\ for\ i = 1,2,\dots,N$. The table reports results for five average *idiosyncratic* factors and five periods of time. For each model, we show the estimated constant coefficients, the risk premiums, their t-statistics, and the average adjusted R^2. Our test asset sample consists of the 31 individual nearest-to-maturity commodity futures' returns. The corresponding t-statistics are corrected by the Shanken (1992) adjustment. Significant coefficients at the 10%, 5%, and 1% significance level are denoted with *, **, and ***, respectively.

			Risk premiums					*t-Statistics*						
Period	Intercept	Whole	Agriculture	Energy	Oil price changes	Precious Metals		Intercept	Whole	Agriculture	Energy	Oil price changes	Precious Metals	Adj. $\overline{R}^2$
Panel A														
1996 - 2015	0.008	0.005	-	-	-	-		0.74	0.57	-	-	-	-	0.22
1996 - 2000	-0.043	0.032	-	-	-	-		-1.94	1.76	-	-	-	-	0.18
2001 - 2005	0.015	0.028	-	-	-	-		0.61	1.54	-	-	-	-	0.20
2006 - 2010	0.035	-0.011	-	-	-	-		0.93	-0.35	-	-	-	-	0.29
2011 - 2015	-0.036	-0.009	-	-	-	-		-1.6	-0.45	-	-	-	-	0.18
Panel B														
1996 - 2015	0.017	-	-0.005	-0.002	-	-	-	1.55	-	-0.62	-0.15	-	-	0.25
1996 - 2000	0.005	-	-0.023	0.057	-	-	-	0.23	-	-1.17	1.55	-	-	0.23
2001 - 2005	0.044	-	0.001	0.029	-	-	-	1.96	-	0.06	0.83	-	-	0.21
2006 - 2010	0.021	-	0.01	-0.057	-	-	-	0.55	-	0.39	-1.08	-	-	0.29
2011 - 2015	-0.061***	-	0.016	0.004	-	-	-	-2.62	-	0.91	0.1	-	-	0.23
Panel C														
1996 - 2015	0.015	-	-0.004	-0.002	-	-0.003		1.4	-	-0.56	-0.17	-	-0.21	0.29
1996 - 2000	-0.014	-	-0.021	0.061*	-	0.103***		-0.69	-	-1.04	1.66	-	2.64	0.27
2001 - 2005	0.042*	-	0	0.028	-	-0.012		1.87	-	-0.01	0.83	-	-0.18	0.25
2006 - 2010	0.004	-	0.012	-0.061	-	0.028		0.1	-	0.48	-1.16	-	0.28	0.32
2011 - 2015	-0.06***	-	0.014	0	-	0		-2.61	-	0.81	-0.01	-	-0.01	0.27
Panel D														
1996 - 2015	0.007	-	-	-	0.028	-		0.64	-	-	-	1.38	-	0.18
1996 - 2000	-0.011	-	-	-	0.066	-		-0.51	-	-	-	1.54	-	0.12
2001 - 2005	0.037	-	-	-	0.05	-		1.77	-	-	-	0.98	-	0.15
2006 - 2010	0.023	-	-	-	0.03	-		0.56	-	-	-	0.56	-	0.25
2011 - 2015	-0.033	-	-	-	-0.038	-		-1.77	-	-	-	-0.94	-	0.17

Only Table 2.6's Panel B shows significant risk premiums for the idiosyncratic energy and precious metals factors when controlling for the agriculture sector's idiosyncratic factor during the period from 1996 to 2000. No other idiosyncratic factors are priced. Fernandez-Perez et al. (2016) find similar results for the idiosyncratic volatility of commodity futures' returns when controlling for phases of backwardation and contango in their pricing model.

Another issue could relate to the agriculture sub-set's being larger than any other, which might introduce data-selection biases in the estimations of the common factors. To address this concern, we construct a balanced sample using the three commodities with the highest average daily trading volume of each sector. The resulting common factor remains similar (0.82 correlation) to the average common factor of all thirty-one commodity returns. The pricing model that is based on the balanced sample fails to explain the cross-sectional commodity futures' returns.

2.5 Concluding remarks

We adopt the *generalized dynamic factor model* and its one-sided representation, as introduced by Forni et al. (2015), for a sample of thirty-one commodity futures' returns in order to extract the common movement of all these return series. We interpret the resulting common (market) factor as the common response of these commodities to underlying macroeconomic factors like the US dollar's exchange rate, global inventory levels, and demand and supply.

Our analysis reveals an increased co-movement of commodity futures' returns during the 2008 financial crisis, when the common factor of the whole commodity sector is increasingly correlated with changes in gold and oil prices. Using our full sample (1996 to 2015), we also find a high correlation between the common factor of all commodities and the common factor of the agriculture sector. By applying the approach from Fama & MacBeth (1973), we find first indications of asset pricing models that can explain individual commodity futures' returns based on two- or three-factor models that include at least the energy sector's and the agriculture sector's common factors as of 2011. Our results indicate a recent weakening of the heterogeneity assumption of commodities and shed new light on the findings of De Roon et al. (2000) and Daskalaki et al. (2014), who argue that, when controlling for non-marketable risk, equilibrium commodity futures' expected returns are driven only by the individual features of the corresponding commodity contracts.

However, further research could focus on refining the proposed methodology toward a more robust pricing of individual commodities in order to clarify the underlying drivers of the commodity markets in recent years. This clarification could have important geopolitical implications and implications for the risk management of companies that depend heavily on raw materials.

3 Are agriculture markets driven by investors' allocation? Evidence from the co-movement of commodity prices[7]

Since the beginning of the 2000s, agriculture commodity prices have been trending upwards with volatile periods and two main price peaks in 2008 and 2012. A justification for the varying prices of agricultural products can be seen in global economic growth as key driver of commodity demand (Bruno et al. 2016) and in the dynamic interrelationships between energy and agriculture markets (Nazlioglu et al. 2013). Following the price peak of 2012 a sharp price decline gave momentum to an alternative view where the increasing participation of financial institutions in these markets is seen as main driver for the high volatility (Gilbert & Pfuderer 2014). While the recent decades investors discovered commodities as part of their portfolio diversification due to their negative correlation to other 'classical' asset classes like stocks or bonds. However, during the financial crisis 2007 that correlation not only disappeared but gave way to a strong co-movement of the beforehand heterogeneous asset class of commodities, cf. Lübbers & Posch (2016).

This chapter focuses on these two changes to the agricultural commodity market: the financialization of commodity markets and the co-movement of commodity prices. We shed light on the short-run dynamics of the co-movement of agriculture commodity prices and quantify the effect of commodity index traders on agriculture prices' co-movement.

Since commodities tend to move together over time we construct a common factor extracted from a panel of seventeen agriculture commodity prices. The common factor obtains from the data itself based on the panel analysis of nonstationarity in idiosyncratic and common components of Bai & Ng (2004). This common factor reflects key characteristics of agriculture commodity prices and is assumed to be driven by fundamental forces, similar in all agriculture commodities being less disrupted by idiosyncratic drivers.

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[7] This chapter is based on the paper of Lübbers & Posch (2017). One version of the paper was presented at the Energy and Commodity Markets Annual Meeting 2017, Oxford.

To measure the effect of investors' interest in commodity markets we construct a financial speculation index based on CFTC's Commitments of Traders supplementary reports and the weekly commodity index traders' long open interest. The speculation index represents the investment behaviour of large institutional investors who allocate their portfolios according to compositions of major commodity market indices like the S&P GSCI, and not based on individual commodities. To assess the effect of changes in institutional investors' investment positions on the entire agriculture sector we make use of a structural vector autoregression model and forecasting error variance decomposition.

We find evidence that a higher relative share of index investors' long open interest increases the correlation or co-movement of individual agriculture commodity prices. We show that a significant fraction of the common factor's variation is explained by changes in commodity index traders' long open interest. Our results have strong political implications and affect the risk management of companies heavily relying on raw materials. While we find the effect of financialization on commodity markets to be time-dependent in order to avoid financial speculation directly affecting commodity price changes, our results indicate that the relative share of CITs' long to total open interest should not be significantly higher than 28%.

In the remainder of this chapter, we continue with a literature review, followed by an overview of the data used in the model and a description of the financialization index. The penultimate sections determine the co-movement of agriculture commodity prices and its driving forces in a structural VAR approach, while the final section concludes.

3.1 Literature review

A vast body of literature has been developed to examine the co-movement of commodity prices and to identify its most important macroeconomic drivers. A prominent foundation on the co-movement of commodity prices was published by Pindyck & Rotemberg (1988) showing that prices of unrelated commodities tend to move together, even in excess of inflation, industrial production, interest rates, and exchange rates and argue that this is due to commodity speculation. Recently, Yin & Han (2015) decompose commodity prices into global, sectoral, and idiosyncratic components and indicate that the importance of the global factor increases significantly since 2004. Based on dynamic factor models or structural VAR approaches Vansteenkiste (2009), Akram (2009), Byrne et al. (2013), and Chen et al. (2014) conclude that the co-movement of commodity prices is negatively correlated with real interest rates, U.S. dollar, and uncertainty. In addition, Byrne et al. (2013) and Vansteenkiste (2009) identify oil as a driving factor for non-fuel commodities.

In order to address the question whether institutional investors affect commodity prices researches often focus on commodity index traders as a proxy for institutional investors (Basak & Pavlova 2016). One of the leading proponents of the idea that commodity index investment was a major driver of the sharp increase of commodity prices during the recent financial crisis is Michael W. Masters. Masters (2008) distinguishes between traditional speculators and index speculators, so called commodity index traders (CITs) who hold commodities in fixed proportions according to most prominent commodity indices. Traditional speculators provide liquidity by both buying and selling futures whereas index speculators mostly buy futures and roll their positions. Hence, they would only consume liquidity and not provide any benefit to the futures market. Basically, Masters (2008) argues that the long-only position from index funds let to the build-up of a commodity price bubble in 2007/2008. In a theoretical framework Brunetti & Reiffen (2014) and Basak & Pavlova (2016) explore how the presence of institutional investors affects commodity prices. The latter argue that in the presence of institutional investors, futures prices of all commodities rise, with futures prices of index commodities increasing to greater extend. Additionally, volatilities and equity-commodity correlations increase when institutional investors are present. Empirically, only a few studies could partially prove this statement. McPhail et al. (2012) use a structural VAR model for global demand, speculation and energy prices in explaining monthly corn price volatility. They find speculation only to be important in the short run. In the long-run energy and global demand are most important drivers. Tang & Xiong (2012) show that prices of non-energy commodity futures have become increasingly correlated with oil prices since the early 2000s. The effect is even stronger for commodities listed in two popular commodity indices. Their finding helps to explain the large increase in the price volatility of non-energy commodities around 2008 and reflects the financialization of the commodity markets (Tang & Xiong 2012). Similarly, Henderson et al. (2015) conclude that flows of financial investors cause increases and decreases in commodity futures prices when they are passed through to and withdrawn from the futures markets. Using instrumental variables Gilbert & Pfuderer (2014) find weak evidence that changes in index positions can help predict futures changes in CBOT corn and wheat contracts. If applied to the whole range of grains and oilseed markets they did not find Granger-causal impacts between index fund positions and U.S. grains and oil seed futures. This is in line with Gilbert (2010), Stoll & Whaley (2010), Sanders & Irwin (2011), Capelle-Blancard & Coulibaly (2011), and Irwin & Sanders (2012) who do not find any causal link between commodity index activity and commodity futures prices. When focusing on the commodity-equity co-movement to examine the impact of financialization of the grain and livestock sector Bruno et al. (2016) show that world business cycle shocks have a substantial long-lasting impact on the co-movement between agriculture and equity markets, but financial speculation's impact is not statistically significant in all their model specifications.

So far, the literature does not find clear evidence of the relation between commodity index investment and commodity price changes. We close this gap by combining both branches of the literature reviewed above and identify a common factor for the agriculture sector as well as construct a financialization index based on long open interest of commodity index traders.

3.2 Measure of financialization and data description

In order to estimate how commodity index traders affect variations in commodity prices we use a cross-section of seventeen agriculture commodity futures. The weekly data obtains from the most liquidly traded first- and second-nearest-to-maturity futures contracts from 03 January 2006 to 29 March 2016 assessed via Thomson Reuters Datastream continuation series. This results in a panel of time series data with time dimension $T=534$ and cross-sectional dimension $N=34$. Descriptive statistics for each agriculture price time series are shown in Table 3.1.

Table 3.1: Descriptive statistics. Underlined commodities are neither listed in the S&P GSCI nor in the Bloomberg Commodity Index. The augmented Dickey-Fuller t-statistics with an intercept and the null of nonstationarity are shown. The null hypothesis is rejected at least at the 5% significance level if the values for test statistics are less than -2.86. In addition, weekly averages of the total open interest (OI) in each commodity and of the commodity index traders (CITs' OI) in each commodity are described. Futures contract months for each commodity are shown in the last column.

		Average			
	ADF	Total OI	CITs' OI long	CITs' OI short	Contracts traded
Cocoa	-2.24	188,064	27,664	3,218	Mar/May/Jly/Sep/Dec
Coffee 'C'	-1.68	191,792	46,472	3,547	Mar/May/Jly/Sep/Dec
Corn	-2.16	1,742,637	424,819	50,464	Mar/May/Jly/Sep/Dec
Cotton	-2.14	267,317	75,995	5,387	Mar/May/Jly/Oct/Dec
Soybean Meal	-2.18	394,685	78,623	15,220	Jan/Mar/May/Jly/Aug/Sep/Oct/Dec
Soybean Oil	-2.29	354,769	88,711	8,384	Jan/Mar/May/Jly/Aug/Sep/Oct/Dec
Soybeans	-2.35	743,286	164,471	21,800	Jan/Mar/May/Jly/Aug/Sep/Nov
Sugar	-2.32	949,624	276,496	45,225	Mar/May/Jly/Oct
Chicago Wheat	-2.60	512,927	196,254	25,525	Mar/May/Jly/Sep/Dec
Kansas Wheat	-2.51	157,173	40,387	2,468	Mar/May/Jly/Sep/Dec
<u>Oats</u>	-2.23	12,584	-	-	Mar/May/Jly/Sep/Dec
<u>Lumber</u>	-2.62	7,855	-	-	Jan/Mar/May/Jly/Sep/Nov
<u>Rough Rice</u>	-2.52	13,608	-	-	Jan/Mar/May/Jly/Sep/Nov
<u>Canola</u>	-2.84	145,583	-	-	Jan/Mar/May/Jly/Nov
Lean Hogs	-2.52	251,215	84,840	3,687	Feb/Apr/May/Jun/Jly/Aug/Oct/Dec
Live Cattle	-0.97	353,613	110,491	3,153	Feb/Apr/Jun/Aug/Oct/Dec
Feeder Cattle	-1.18	40,821	7,622	629	Jan/Mar/Apr/May/Aug/Sep/Oct/Nov
Average		372,209	124,834	14,516	

Most traded agriculture commodities in general and by commodity index traders in particular are corn, sugar, soybeans, and Chicago wheat. To adjust for the difference of the volume and open interests in these commodities we focus on an equally weighting of the traders' positions relative to each market. Oats, lumber, rough rice, and canola, are less frequently traded than the aforementioned and not listed in either the Standard and Poor's Goldman Sachs Commodity Index (GSCI hereafter) or in the Bloomberg Commodity index.

Our approach focuses on variables which affect short-term price variations of agriculture futures prices. As the agriculture sector is highly energy intensive we proxy short-term supply shocks on agriculture prices by WTI oil price changes, cf. Byrne et al. (2013). We do not consider the effects of weather changes on the supply of agriculture commodities in our estimations, since weather is idiosyncratic as it affects individual commodities at a certain time. Second, to control for the negative relation between the co-movement of commodity prices and the U.S. dollar we use the U.S. dollar effective exchange rate published by the Federal Reserve Bank of St. Louis. Third, to analyze the effect of large investors on agriculture prices we construct a measure of financialization based on weekly commodity index traders' long open interest published in the CFTC's Commitments of Traders supplementary reports. It provides information on the open interest of commodity index traders for thirteen U.S. agricultural futures contracts. Index trader data are drawn from the noncommercial (e.g. managed funds, pension funds, and other institutional investors) and commercial (e.g. swap dealers) categories of the COT report. These traders are generally replicating a commodity index by establishing long futures positions and rolling those positions forward from futures to futures in the corresponding commodity (CFTC 2006).

The aim of our financialization index for the agriculture sector is to identify whether changes in long positions of CITs may be used as an indicator for financially driven demand pressure on agriculture prices and to identify periods of high or low investment activity of institutional investors. It serves as a direct measure of financial investments in agricultural commodities. Many researchers when investigating the effect of CITs on commodity prices focus on individual commodities only. However, the index allows us to estimate investors' interest in the entire agriculture sector. This is also in line with CITs' behaviour as they rather invest in a basket of commodities listed in an index than in individual commodity futures.

We construct the index in the following way: First, we compute week to week growth rates for each position series and take the equally weighted average of these positions changes. Second, we cumulate the average changes and normalize the index to one starting on 03 January 2006. Note that we do not determine simple averages of open interest as this would weight more on commodities, which are traded more. Figure 3.1 compares our main index of

CITs' long open interest with developments in the total open interest in the entire agriculture sector. The two indices are estimated equivalently.

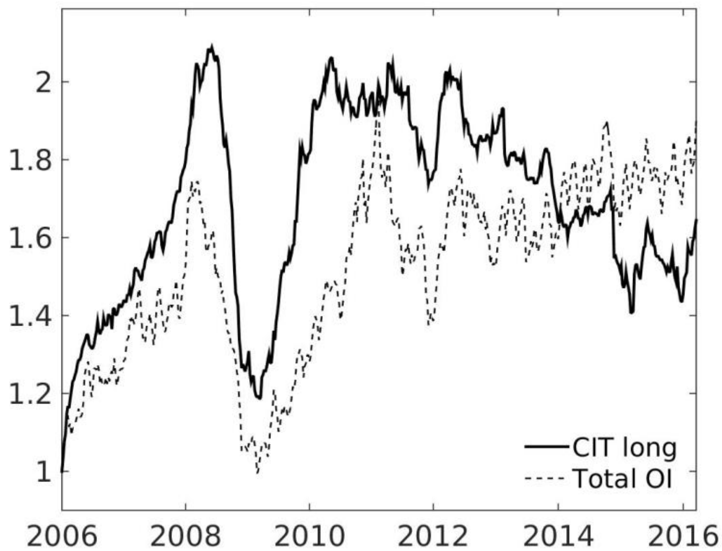


Figure 3.1: Cumulated indices based on equal-weighted growth rates of CITs' open interest and total open interest in agriculture commodities (2006:1 - 2016:3). *Note:* The figure compares cumulated average growth rates of the long open interest of commodity index traders (CITs) and of the total open interest in agriculture commodities over time. For better comparison, both indices are scaled to one. The weekly raw data are received from the U.S. commodity futures trading commission's commitments of traders (COT) reports.

Total open interest (OI) and CITs' long open interest trended upwards until 2008. Then, in 2009 both series fell rapidly to almost the same levels as before the financial crisis in 2006, replicating the development of commodity prices during this period. Subsequently, interest in both indices grew strongly until 2010. However, before the financial crisis and around 2010, the increase in CITs' long open interest was much stronger than in the total open interest. Since 2012, CITs' long open interest is decreasing whereas the total open interest exhibits an upward trend until the beginning of 2016.

Researchers and analysts argue that the sharp increase of CITs' open interest in agriculture commodity markets in 2007 and 2008 is responsible for the price surge during that time (Masters 2008). However, also the total open interest including hedge positions rapidly rose during this period. We thus focus on the development of the relative share of CITs' long and short positions to total open interest rather than the absolute increase and decrease of CITs' positions.

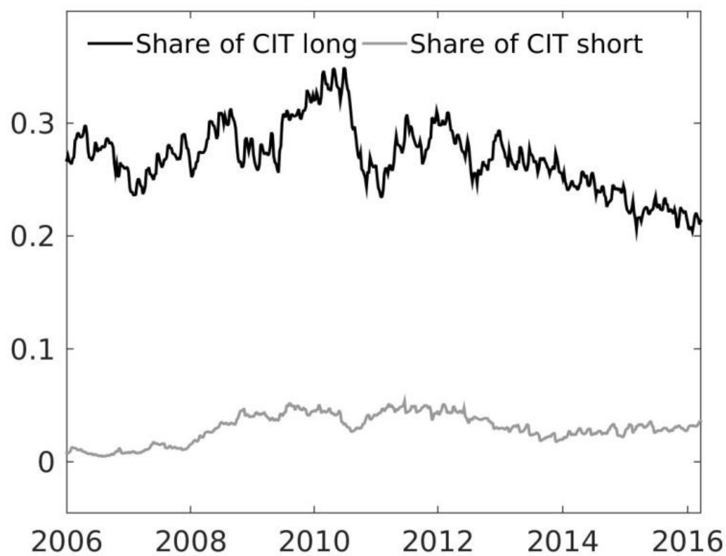


Figure 3.2: Percentage share of CITs' long and short positions to total open interest in agriculture commodities (2006:1 - 2016:3). The figure shows the percentage share of CITs' long and short open interest to total open interest in agriculture commodities over time. The weekly raw data are received from the U.S. commodity futures trading commission's commitments of traders (COT) reports.

Figure 3.2 shows that the average share of CITs' long open interest to the total open interest was greatest in 2010/2011. Until 2008, the percentage share was relatively stable, fluctuating around 27%. The short open interest of commodity index traders plays a minor role over the entire period.

3.3 Agriculture prices' co-movement

In the first step of our analysis we estimate the co-movement of the agriculture sector. We assume that the commodity price series X_{it} can be decomposed into a common F_t and a commodity specific or idiosyncratic factor e_{it}. We consider the intercept only case of the panel analysis of nonstationarity in idiosyncratic and common components (PANIC) introduced by Bai & Ng (2004) in first-differenced form

$$\Delta X_{it} = \lambda_i' \Delta F_t + \Delta e_{it}. \tag{3.1}$$

Applying principal component analysis to ΔX_{it} yields r estimated common factors $\Delta\hat{F}_t$, the factor loadings $\hat{\lambda}_i'$ and the estimated residuals $\Delta\hat{e}_{it} = \Delta X_{it} - \hat{\lambda}_i' \Delta\hat{F}_t$. Re-integrating $\Delta\hat{F}_t$ and the residuals yield the estimated latent common factor of our cross-section of agriculture commodity prices and its individual (idiosyncratic) development.

In order to determine the number r of common factors which is not known a priori we use the IC_{p3} introduced by Bai & Ng (2002). One advantage of the PANIC approach is the determination of the source of nonstationarity. For the idiosyncratic factors we apply the ADF test with no deterministic terms and with an intercept for the common factor. We identify nonstationarity for the common (ADF test statistic of -2.423) and all idiosyncratic factors. The nonstationarity in the agriculture sector is thus both pervasive and variable-specific. Hence, the variations in the common and idiosyncratic factors both contribute to the integratedness of agriculture commodity prices.

We evaluate the importance of the common factor for the variations in commodity prices relative to the idiosyncratic factors in Table 3.2. Except for cocoa, lumber, and livestock, the common factor plays an important role for all agriculture commodities, which is when the explained variation in agriculture prices by the common factor is at least 50% of that explained by their idiosyncratic movements[8]. This is also true for oats, rough rice, and canola, commodities which are not listed in one of the two most famous commodity indices. In contrast, the livestock sector appears to be different from the rest of the agriculture sector as the variation in lean hogs, live cattle, and feeder cattle is almost entirely driven by the idiosyncratic or commodity specific factors. Even though we see some degree of heterogeneity between different classes of the agriculture sector, the variability of most commodities seems to be driven by one nonstationary common factor.

[8] For a similar approach, see for example Byrne et al. (2013)

Table 3.2: Contribution of idiosyncratic and common factors to commodity price variations. This table quantifies the contribution of the variation in the idiosyncratic factors to the total commodity return variation (if all variation is idiosyncratic, $\boldsymbol{R^2}$ tends to 1) [a] and the importance of the common factor relative to the idiosyncratic factors (if all variation is idiosyncratic, then b tends to zero) [b] for the commodity price dynamics. Bold numbers indicate commodities where most of the variation (greater than 0.5) can be explained with the common factor.

	$R^2 = \sigma^2_{\Delta e_{it}} / \sigma^2_{\Delta X_{it}}$ [a]	$\sigma_{\lambda_i F_t} / \sigma_{e_{it}}$ [b]
Cocoa	0.91	0.46
Coffee 'C'	0.77	**0.90**
Corn	0.37	**2.55**
Cotton	0.83	**0.73**
Soybean Meal	0.62	**1.42**
Soybean Oil	0.44	**2.01**
Soybeans	0.41	**2.38**
Sugar	0.81	**0.65**
Chicago Wheat	0.43	**1.95**
Kansas Wheat	0.44	**2.04**
<u>Oats</u>	0.55	**2.06**
<u>Lumber</u>	0.98	0.28
<u>Rough Rice</u>	0.83	**0.86**
<u>Canola</u>	0.58	**1.47**
Lean Hogs	1.00	0.02
Live Cattle	0.99	0.10
Feeder Cattle	1.00	0.00
Average	0.70	**1.17**

Figure 3.3 compares our common factor with the development of the GSCI agriculture. The common factor and the GSCI agriculture index both similarly trended upwards until 2008. Since then, the common factor index level exceeds index values of the GSCI, though both series describe a very similar pattern. The GSCI thus seems to underestimate price increases in commodity futures since 2008/09. As the co-movement of individual commodities is driven by fundamental forces, those observations confirm our approach of looking at the common factor of individual commodities rather than to an index like the GSCI. Looking at Figure 3.1 and 3.2, the strong increase of the common factor in 2010/11 coincides with the period when both the percentage share of CITs' long to total open interest and the financialization index of CITs'

long open interest peaked. Subsequently, since 2014 the total open interest shows a small upward trend (Figure 3.1) while the common factor decreases (Figure 3.3) along with CITs' long open interest (Figure 3.1). We explore the importance of changing interest of commodity index traders on the variability of the co-movement of agriculture commodities more formally in the following section.

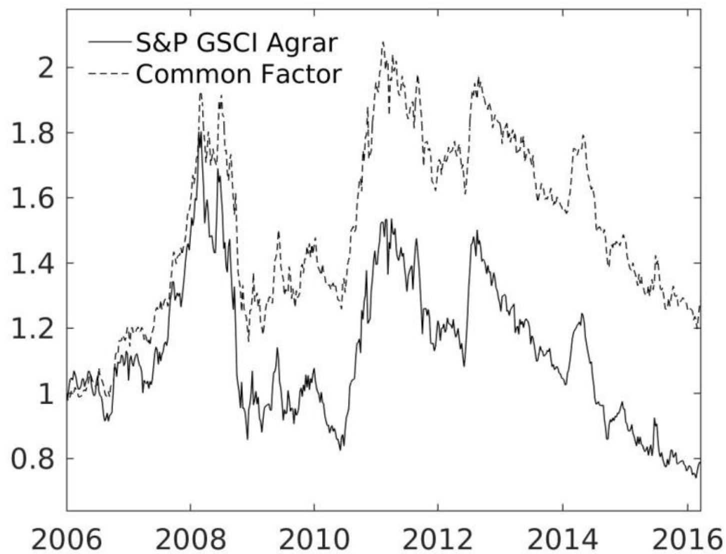


Figure 3.3: Common factor of the agriculture sector and the S&P GSCI index (2006:1 - 2016:3). The figure compares the cumulated common factor of the agriculture sector based on the PANIC approach and the S&P GSCI agriculture index over time. For better comparison, both indices are scaled to one.

3.4 Identification of co-movement's driving factors

Numerous empirical and theoretical studies have investigated how the financialization or commodity index traders affect the long term price development of commodities. However, most of the empirical literature which concludes that their effect is negligible, relies on the argumentation of Masters (2008) who stated that a large increase of commodity index traders during the financial crisis caused a surge in commodity prices. In the following we go one step further and focus on various time periods depending on the relative share of CITs' long open interest.

We examine the main drivers of the common factor within a structural VAR approach based on weekly data for $\boldsymbol{Y}_t = (\Delta op_t, \Delta FX_t, \Delta CIT_t, \Delta F_t)$, where op_t is the logarithmic WTI oil price and FX_t the logarithmic U.S. dollar effective exchange rate. CIT_t is our measure of commodity index traders' long open interest constructed in Section 3.2 and F_t is the common factor or the co-movement of the agriculture sector estimated in Section 3.3. To ensure stationary time series we apply the fist-order difference operator Δ. The structural VAR representation with p lags is

$$\boldsymbol{C}_0 \boldsymbol{Y}_t = \sum_{i=1}^{p} \boldsymbol{C}_i \boldsymbol{Y}_{t-i} + \boldsymbol{\epsilon}_t, \tag{3.2}$$

where $\boldsymbol{\epsilon}_t$ is the vector of serially and mutually uncorrelated structural shocks. The lag length p is determined according to the Schwarz (1978) information criterion. The matrix $\boldsymbol{C}_0^{-1}$ has a recursive structure such that the reduced-form errors $\boldsymbol{u}_t$ can be obtained as $\boldsymbol{u_t} = \boldsymbol{C}_0^{-1}\boldsymbol{\epsilon}_t$:[9]

$$\boldsymbol{u}_t := \begin{pmatrix} u_t^{\Delta op} \\ u_t^{\Delta FX} \\ u_t^{\Delta CIT} \\ u_t^{f} \end{pmatrix} = \begin{bmatrix} c_{11} & 0 & 0 & 0 \\ c_{21} & c_{22} & 0 & 0 \\ c_{31} & c_{32} & c_{33} & 0 \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix} \begin{pmatrix} \epsilon_t^{oil\ price\ shock} \\ \epsilon_t^{U.S. dollar\ shock} \\ \epsilon_t^{investment\ shock} \\ \epsilon_t^{agriculture-specific\ shock} \end{pmatrix} \tag{3.3}$$

The orthogonalization of the VAR relies on a Cholesky decomposition of the covariance matrix of reduced-form errors. This will cause the structural system to be contemporaneously recursive. Accordingly, a shock in the first variable will instantaneously affect all other variables whereas the first variable itself is not contemporaneously affected by the following ones. Agriculture prices are thus contemporaneously responding to changes in oil prices, the U.S. dollar exchange rate, and to index speculators' investment decisions. The set-up of variables is based on the following assumptions:

First, economies are strongly driven by energy input. A shock in oil prices as the main source of energy, will contemporaneously affect the exchange rate of a country, investment decisions and the rest of the commodity markets. Since oil and its derivatives are one of the most important energy inputs and also strongly correlated to natural gas which is a fundamental ingredient for the fertilizer production[10], we follow Byrne et al. (2013) and use the oil price as a proxy for supply shocks.

[9] For a similar approach see for example Kilian (2009) and Wang et al. (2014).

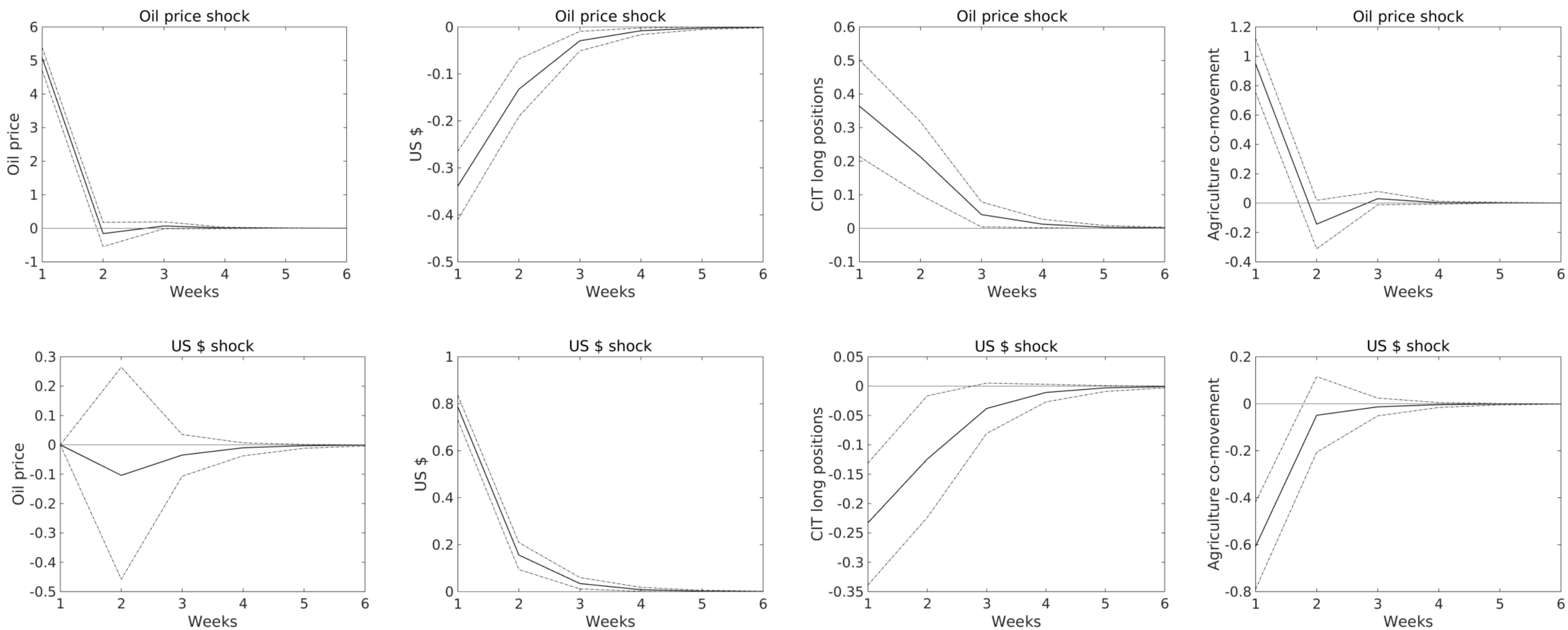
[10] Precursor of all nitrogen fertilizer is ammonia whose key component is methan (natural gas).

Second, most agricultural and energy commodities are traded in U.S. dollar. A change in the U.S. dollar therefore has an immediate impact on these commodities (Akram 2009). Even though a bidirectional causality between US dollar and oil prices exists since 2001 (Fratzscher et al. 2014) we follow Lizardo & Mollick (2010) who show that from 1970 to 2008 an increase in oil prices lead to significant depreciation of the U.S. dollar (USD) against net oil exporter currencies and vice versa for currencies of oil importers.

Third, CITs rather invest according to portfolio allocation decisions than to individual commodity price changes. They react on changes in the financial market in general, not in the commodity market in particular (Masters 2008). However, portfolio allocations are affected by general market situations as proxied by oil price changes or the effective U.S. dollar exchange rate. According to this choice, we assume that index speculation does not instantaneously affect macroeconomic fundamentals like oil prices or U.S. dollar exchange rates but the agriculture commodities which they invest in.

How does the agriculture sector respond to supply, financial market, or investment shocks? Figure 3.4 shows the responses of WTI crude oil prices, the U.S. dollar effective exchange rate, CITs' long open interest, and the co-movement of the agriculture sector to one-standard deviation structural innovations. The 95% confidence bands are estimated from 1000 Monte Carlo simulations.

Figure 3.4: Responses to one-standard-deviation structural shocks



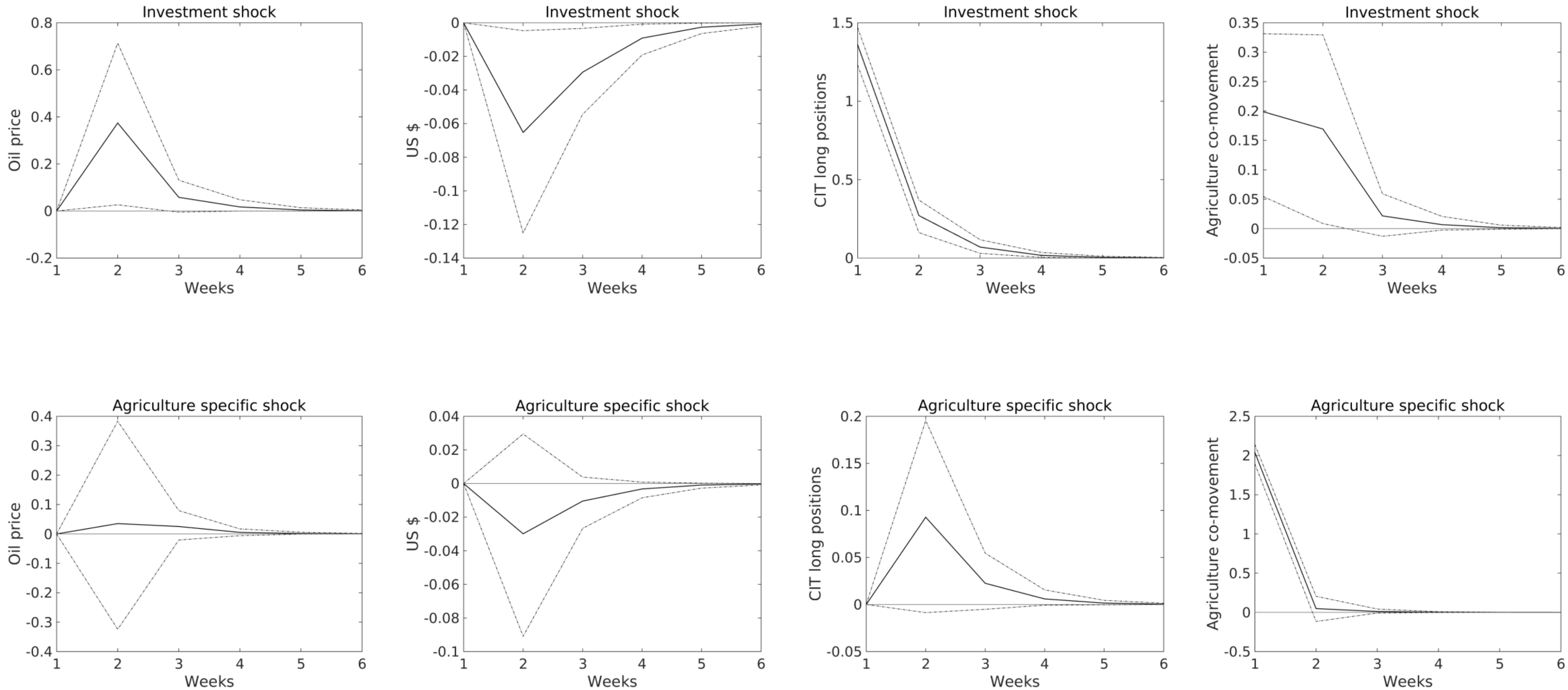


Figure 3.4: Responses to one-standard-deviation structural shocks: The graphs show the response of the oil price, U.S. dollar, long open interest of commodity index traders and the co-movement of the agriculture sector to a generalized one standard deviation innovation in those variables. Also shown are the 95% confidence bands based on 1000 Monte Carlo simulations.

Oil price shock

A shock in oil prices influences all variables in our system. In line with Lizardo & Mollick (2010), an oil price shock negativly affects the U.S. dollar exchange rate. Its effect on the U.S. dollar becomes insignificant only four weeks after the initial shock. Since higher oil prices might be seen as a positive development of the commodity market in general CITs increase their investment in commodity markets in expectation of further increasing commodity prices and vice versa. A shock in oil prices is thus positively related to CITs' long open interest. However, the short-term effect is strongest for the co-movement of agriculture prices, even though it becomes insignifcant after one week. We argue that an increase in oil prices explains the instantaneous increase in the price of food commodities because of cost effects on the energy intensive agriculture sector and substitution effects due to an increasing biofuel production. According to Tang & Xiong (2012) who show that prices of non-energy commodity futures have become increasingly correlated with oil prices since the early 2000s, the effect of oil price shocks on the agriculture sector also helps to explain the large increase in the price volatility of non-energy commodities around 2008 and reflects the financialization of the commodity markets.

U.S. dollar shock

A shock in U.S. dollar negatively affects both the open interest of CITs and the co-movement of agriculture commodities which response becomes insignificant within the first week. From an economic perspective this is reasonable since an increase of the U.S. dollar would lead to rising interests which makes investment in fixed income securities more interesting than investments in risky products like commodities. This migth lead to less demand for commodities and prices of valuable commodities would fall. This is in line with Akram (2009) who shows that a weaker USD leads to higher commodity prices and accounts for substantial shares in commodity price fluctuations.

Investment shock

Our most striking results of Figure 3.4 are related to responses to shocks in open interest of commodity index traders. First, a shock in CITs' open interest positively affects the co-movement of agriculture commodities. The extent is rather weak compared to the effect of oil, but it lasts for almost two weeks. We thus confirm Masters (2008) and Basak & Pavlova (2016) argumentaion how the presence of institutional investors may affect commodity prices and suggest that in the presence of institutional investors futures' prices of all commodities rise. Second, a shock in the investment behaviour of commodity index traders has a positive delayed effect on the oil price. As CITs invest in all commodities of the most famous commodity indices, our financialization index based on the agriculture sector seems to be a good proxy for the financial investment in other commodities, too. Third, since CITs positively affect the co-movement of commodity prices and their prices are negatively related to the U.S. dollar exchange rate, we also measure a small but negative effect of CITs on the U.S. dollar.

What is the explanatory ability of different shocks to the co-movement of agriculture commodities?

In order to quantify the contribution of various shocks to changes in the co-movement of agriculture commodities we apply the forecasting error variance decomposition (FEVD) at forecast horizons of one and four weeks. Since our approach relies on short term movements we not only determine the FEVD based on the entire period (2006:1 – 2016:3), but also focus on five two-year periods which allows us to assess the importance of our variables for the co-movement of agriculture commodities for different market situations. The results are shown in Table 3.3.

For both forecast horizons and the entire period (2006:1 – 2016:3) the contribution of CITs' investment shocks to the variation in the agriculture co-movement is 0.7% and 1.2% which is relatively low compared to oil price shocks accounting for 16.5%. In 2006-07 and after the price peak in 2011, shocks in oil prices, in the U.S. dollar, and in CITs' investment changes contribute only a small fraction to agriculture co-movement's variations. Most variation in the agriculture sector is related to agriculture specific factors and the average contribution of the common factor to commodity price variations only varies around 24%. From 2014 to 2016 agriculture commodities seem to be even more segmented as we do not find a single common factor for the agriculture sector. These results confirm the body of the literature which does not find any significant contribution of the financialization process on commodity futures prices. It is also in line with Lübbers & Posch (2016) who show that the commodity sector seems to be driven by commodity specific factors rather than by macroeconomic variables since 2012.

Table 3.3: Percentage contribution to variations in the co-movement of agriculture commodity prices for various time periods: Focus on CITs' long open interest. This table compares the percentage contribution of different shocks to the agriculture co-movement for various time periods and forecast horizons of one and four weeks. We also add the percentage share of CITs' long position relative to the total open interest in the agriculture sector (See also Figure 3.2) and the average percentage contribution of the common factor to commodity price variations ($1-\bar{R}^2$). Bold numbers indicate periods where a significant share of the variation (greater than 5%) in the co-movement can be explained with shocks in CITs' open interest.

	Oil price shock	US $ shock	CITs' investment shock	Agriculture sector shock	Avg. contribution of common factor to cmdty price variations ($1-\bar{R}^2$)	Average share of CITs' long to total open interest
One week horizon						
2006:1 – 2016:3	16.5	6.7	0.7	76.1	30.0	26.9
2006:1 - 2007:12	0.9	1.1	0.6	97.4	24.2	26.8
2008:1 - 2009:12	33.8	7.5	0.4	58.3	39.0	28.9
2010:1 - 2011:12	20.0	9.4	**5.2**	65.4	38.6	29.2
2012:1 - 2013:12	1.7	0.2	1.0	97.2	23.5	27.3
2014:1 - 2016:3	-	-	-	-	-	23.1
Four weeks horizon						
2006:1 – 2016:3	16.7	6.7	1.2	75.4	30.0	26.9
2006:1 - 2007:12	4.4	1.1	2.4	92.1	24.2	26.8
2008:1 - 2009:12	31.9	7.1	**6.8**	54.3	39.0	28.9
2010:1 - 2011:12	19.9	9.2	**9.9**	61.1	38.6	29.2
2012:1 - 2013:12	1.9	0.3	1.0	96.8	23.5	27.3
2014:1 - 2016:3	-	-	-	-	-	23.1

However, our most striking results from Table 3.3 and the four weeks forecasting horizon are a significant contribution of CITs' investment behaviour on the co-movement variation of commodity prices from 2008 to 2009 and from 2010 to 2011 of 6.8% and 9.9%, respectively. The effect of oil price shocks is even stronger. During this time the share of CITs' long to total open interest rises to 29.2% and the contribution of the common factor to variations in agriculture commodity price variations increases to 39%. The increasing share of commodity index traders thus not only yields higher correlations between agriculture commodity prices but also stronger effects on the variation of futures returns which confirms the theoretical exploration of Basak & Pavlova (2016). Based on our findings we conclude that the dramatic surge in commodity prices in 2008 and 2011 can be related to the surge in the co-movement of agriculture futures prices which in turn is driven by the relative increase of CITs' interest to the total open interest in the agriculture commodity markets.

Robustness checks - To assess the robustness of our results we compare the findings for the CITs' long open interest index with the more commonly used Working (1960) *T* index to proxy speculation in commodity markets[11]. The basic idea of Working's *T* index is to compare positions of all non-commercial commodity futures traders (often called speculators, e.g. index funds and other financial instruments) to net demand from commercial traders (often called hedgers). If long and short hedgers' positions exactly match, no speculators would be needed in that market. However, in practice long and short hedgers wish to trade at different times and quantities and speculators need to fill this gap. The Working *T* index is defined as the ratio of the amount of long speculation (short speculation) to the amount of hedging (hedging long and short)

$$Working's\, T_{i,t} = T_{i,t} = \begin{cases} 1 + \dfrac{SS_{i,t}}{HS_{i,t} + HL_{i,t}} \; if\; HS_{i,t} \geq HL_{i,t} \\ 1 + \dfrac{SL_{i,t}}{HS_{i,t} + HL_{i,t}} \; if\; HL_{i,t} \geq HS_{i,t} \end{cases} \quad i = 1, \dots, N, \qquad (3.4)$$

where *SS* (*SL*) represents speculative or non-commercial short (long) positions and *HS* (*HL*) short (long) commercial/hedged positions. Working's *T* thus measures the extent to which financial speculation exceeds the minimum required to offset unbalanced commercial hedging positions. Averaging individual indices provides a picture of speculative activity in the agriculture futures market:

$$T_t = \sum_{i=1}^{N} w_{i,t} T_{i,t} \qquad (3.5)$$

At each point in time we use equal weights $w_{i,t}$ for each commodity *i* in our sample. All data

[11] For a similar approach see for example McPhail et al. (2012), Etienne et al. (2015), Bruno et al. (2016), and references therein.

are received from CFTC's futures and options combined COT reports covering all contract maturities. The average *T* index and a comparison with CITs' long index determined in Section 3.2 and the common factor of the agriculture sector are given in Figure 3.5.

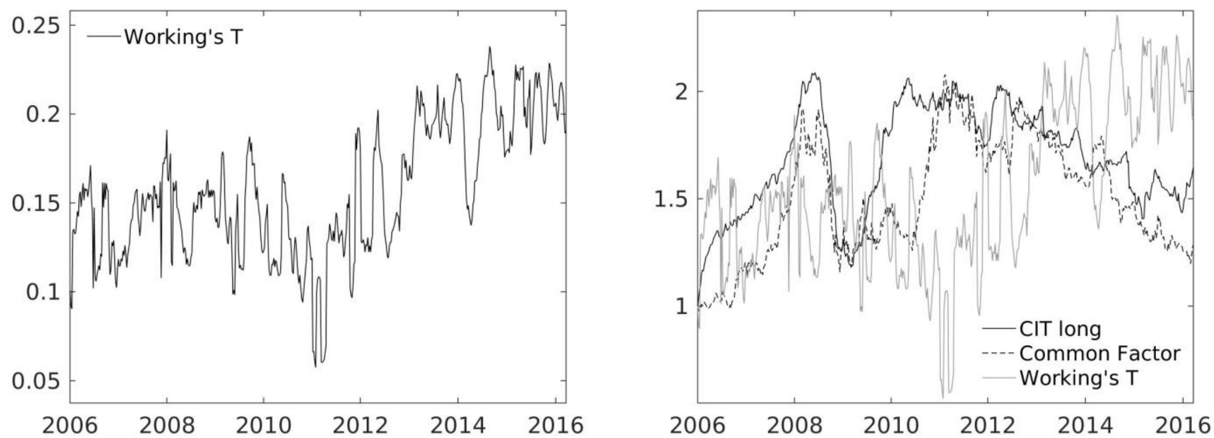


Figure 3.5: Working's T index and a comparison of cumulated growth rates of CITs' long open interest and the agriculture common factor (2006:1 - 2016:3). The figure presents speculative intensity measuresd as Working's *T* index minus 1 (left panel). The cumulated average growth rates of the long open interest of commodity index traders (CIT long), the common factor of the agriculture sector and Working's *T* index are compared over time (right panel). For better comparison, all indices are scaled to one. The weekly raw data are received from the U.S. commodity futures trading commission's commitments of traders (COT) reports.

For easier interpretation, we subtract 1 from the *T* index. (For a similar approach see for example Bruno et al. (2016)). The index of speculative positions thus ranges between 6% and 24% more than what is minimally needed to meet commercial hedging positions. As opposed to CITs' long open interest or the common factor of the agriculture sector the Working's *T* is much more volatile and exhibits an increasing trend since 2011.

Table 3.4 shows the results of the FEVD including Working's *T* index. The percentage contribution of the *T* index to the co-movement of agriculture commodity futures returns is strongest in 2012 and 2013. It explains up to 15.4% of the variation in commodities' common factor. During this period, the *T* index reaches its highest level of 17.3% more than what is minimally needed to meet commercial hedging positions. However, in contrast to the *T* index the average contribution of the common factor to commodity price variations reaches its lowest value of 23%. We thus conclude that Working's *T* index only plays a minor role in explaining the variation in the co-movement of commodity futures returns.

Interestingly, the average contribution of the common factor to individual commodity price variations decreases with decreasing share of CITs and with increasing levels of the Working's T. From 2014 to the beginning of 2016 when the average Working's T reaches its highest value (Table 3.4) and the share of CITs' to total open interest its lowest value (Table 3.3), no single common factor for agriculture commodity futures returns exists. Since Working's T cannot distinguish between index-related speculation and other forms of speculation it is a more general index than the index based on CITs' long open interest. Hence, the CIT index seems to be favorable when measuring the influence of financial institutions on agriculture commodity futures returns.

Table 3.4: Percentage contribution to variations in the co-movement of agriculture commodity prices for various time periods: Focus on Working's T: This table compares the percentage contribution of different shocks to the agriculture co-movement for various time periods and forecast horizons of one and four weeks. We also add the percentage average level of Working's T index (see also Figure 3.5) and the average percentage contribution of the common factor to commodity price variations $(1-\bar{R}^2)$. Bold numbers indicate periods where a significant share of the variation (greater than 5%) in the co-movement can be explained with shocks in Working's T.

	Oil price shock	US $ shock	Working's T shock	Agriculture sector shock	Avg. contribution of common factor to cmdty price variations $(1-\bar{R}^2)$	Average Working's T
One week horizon						
2006:1 – 2016:3	16.5	6.8	0.2	76.4	30.0	15.7
2006:1 - 2007:12	0.4	0.7	0.0	98.8	24.2	13.9
2008:1 - 2009:12	38.2	7.6	0.7	53.6	39.0	14.5
2010:1 - 2011:12	21.6	10.1	0.2	68.1	38.6	12.1
2012:1 - 2013:12	2.1	0.3	**13.6**	84.0	23.5	17.3
2014:1 - 2016:3	-	-	-	-	-	20.0
Four weeks horizon						
2006:1 – 2016:3	16.4	6.7	2.5	74.4	30.0	15.7
2006:1 - 2007:12	3.7	1.4	3.3	91.5	24.2	13.9
2008:1 - 2009:12	37.7	7.5	2.1	52.8	39.0	14.5
2010:1 - 2011:12	21.5	9.7	**5.2**	63.6	38.6	12.1
2012:1 - 2013:12	2.3	0.5	**15.4**	81.9	23.5	17.3
2014:1 - 2016:3	-	-	-	-	-	20.0

Finally, we also include the Fed rate and the S&P 500 which may be crucial since institutional investors typically trade both, the commodity and the equity market. However, the inclusion of both variables does not significantly change the outcome of our results. In addition, the use of CITs' short open interest instead of long open interest does not show any effect.

3.5 Concluding remarks

We adopt the panel analysis of nonstationarity in idiosyncratic and common components of Bai & Ng (2004) to extract the co-movement of seventeen agriculture commodity futures returns. This common factor reflects key characteristics of agriculture prices and is assumed to be driven by fundamental forces, common to all those commodities. In order to assess the effect of financial investors' portfolio allocation on agriculture markets we develop a measure of financialization based on weekly commodity index traders' open interest of the CFTC's Commitments of Traders supplementary reports. To identify the importance of the main drivers of the common factor we use a structural VAR approach and estimate the contribution of shocks in oil prices, the U.S. dollar, and CITs' long open interest to changes in the co-movement of agriculture commodities based on the forecasting error variance decomposition.

Between 2008 and 2011 we find an increased co-movement of agriculture commodities. We show that up to 9.9% of the variation in this co-movement can be explained with changes in CITs' open interest. The effect of CITs on commodity futures returns is strongest when the share of CITs' open interest to the total open interest in the agriculture sector is 29.2%.

The implications of our results are thus twofold. Based on short time periods, our results have implications for the risk management of companies heavily relying on raw materials. As a growing share of commodity index traders increases the correlation or the co-movement between commodities, dynamically measuring the share of commodity index traders' long open interest might help to assess the diversification benefits within commodity markets. Second, our results confirm Master's hypothesis as changes in commodity index traders' open interest lead to variations in the common factor of agriculture commodity prices between 2008 and 2011.

As we do not find significant effects of both indices over long time periods either of the commodity index traders' long open interest or of Working's *T* index, this chapter suggests the influence of index speculation on the common factor of agriculture commodity futures prices is strongest only during agriculture price peaks in 2008 and 2011. During this period, the relative share of commodity index traders' open interest is highest. In order to avoid financial speculation directly affecting commodity price changes, our results thus indicate that the relative share of CITs' long open interest to total open interest should not be significantly higher than 28%. However, as we do not focus on the benefits of commodity index investors who are likely to improve the sharing of commodity price risk, future research is needed from that perspective in view of our results. Future investigations in this area should also focus on further variables such as a proxy for global business activity, weather and inventories.

4 Commodity prices and the EROI of oil: Decreasing surplus energy and it's effect on agriculture and metal prices

Energy plays a major role throughout social and economic development (Hall et al. 2014). However, it is not just the energy produced what matters most, but the relation between the energy that is produced and the amount of energy that is needed in the production process. This ratio of energy returned to energy invested is called *Energy Return On Investment* (EROI). Like all forms of economic output, also the extraction and processing of raw commodities largely depends on amount of surplus energy available to the system. However, since the middle of the last century an increasing proportion of the energy output is diverted to producing that energy (Lambert et al. 2012). As most renewables and non-conventional fossil fuels have substantially lower EROI values than conventional fossil fuels (Lambert et al. 2012) the consequences of an energy transition on economic conditions and especially on commodity price developments are unclear (Court & Fizaine 2017).

Since the oil price boom between 2005 and 2008 and the subsequent market collapse, there are serious concerns among economists as to whether today's energy prices may be sufficient to guide decisions about the energy future (Hall et al. 2009). As proposed in Hall et al. (2009), the analysis of EROI values thus might provide an alternative view for assessing advantages and disadvantages of various energy sources. In addition, considerations of EROI values might provide valuable information on future, fundamental market developments which market prices not account for, cf. Hall et al. (2009) and Hamilton (2012).

In this chapter, we estimate the effect of the decreasing EROI of oil on long-term commodity price developments. Relying on a price-based EROI of Court & Fizaine (2017), we assess the effect of changes in this EROI on both, an index of non-fuel commodities and individual commodity prices between 1900 and 2014. We extend existing literature on long-term commodity assessments like Byrne et al. (2013) to gain a better understanding of long-run movements in commodity prices.

Our main contribution to the literature is twofold. First, to the best of our knowledge, we are the first who examine the long-run effect of declining EROI of oil on an index of non-energy commodity prices. We find evidence that commodity prices depend on the amount of surplus energy available to economies. Since 1938, EROI is the most influential variable compared to world GDP growth rates, interest rates, and uncertainty and explains up to 30% of commodity price fluctuations. The lower the EROI, the higher are commodity prices. During times of strong economic growth, the effect of EROI on commodity prices is lower than in times of weaker economic growth. This might have serious consequences in times of weakening economic growth and decreasing EROI values. Simultaneously considering GDP growth rates and EROI values might thus help to estimate long-term effects of a changing energy supply on commodity price developments.

As not all commodities follow the same long-run trends but rather show periods of declining prices followed by long periods of price booms, cf. Arezki et al. (2014) and Jacks (2013), our second contribution is to show how decreasing EROI values affect individual agriculture and metal commodity price variations. Between *1900 and 2014*, variations in wheat, maize, copper, and aluminium prices are to a larger extent driven by individual commodity shocks, rather than by macroeconomic variables. However, variations in GDP growth rates account for 10% of copper price fluctuations over the sample period confirming the importance of copper as an indicator for global economic developments. EROI values are most important for wheat, maize, and copper returns and account for up to 10% of their price variations. The importance of broad market trends and the effect of decreasing EROI values therefore have different effects on individual commodities.

In the remainder of this chapter, we continue with a literature review, followed by an overview of the data used in the model and the determination of the EROI of oil. The penultimate section determines the driving factors of commodity price developments in a structural VAR approach while the final section concludes.

4.1 Literature review

Historically, commodity prices are driven by various factors and determined by long-term trends, long cycles, and short-run fluctuations (Arezki et al. 2014). Focusing on long-run commodity price trends, a large body of literature has been developed based on the Prebisch (1950) and Singer (1950) (PS) thesis. They argue that over the long run, prices of primary commodities exhibit declining trends relative to prices of manufactured goods. These findings might be explained by low-income elasticities of demand for commodities or technological and productivity differentials between industrial and non-industrial countries (Harvey et al. 2017). An excellent overview of most important papers in the field of trend analysis of long-run commodity price series is given in Baffes & Etienne (2016).

Analyzing long cycles, the literature finds strong empirical evidence that global economic growth is one of the key drives of commodity demand (Bruno et al. 2016). For example, Barsky & Kilian (2001) show that commodity prices are influenced by macroeconomic conditions. Especially in the early 1970s, they argue that industrial commodity price increases were consistent with an economic boom driven by monetary expansion. Similarly, Carter et al. (2011) focus on two major commodity booms and busts episodes in 1974 and 2008. As the primary reason behind this development they find contemporaneous supply and demand shocks coinciding with low inventory levels and macroeconomic shocks. Jeffrey A. Frankel (2006) examines connections between monetary policy, agriculture and mineral commodities and claims that low real interest rates lead to high real commodity prices. Jeffrey A. Frankel (2006) suggests various risk factors like supply disruptions related to political uncertainty which might affect individual commodity prices rather than an index of different classes of commodities. Based on a structural VAR model, Akram (2009) confirms that commodity prices increase significantly in response to reductions in real interest rates and a weaker US dollar. Also Lombardi et al. (2012) find exchange rates and economic activity to be important drivers for individual non-energy commodity prices between the 1970s and 2008.

Apart from the aforementioned key drivers of commodity prices another branch of literature focuses on the relation between energy and non-energy commodities. Between 1960 and 2005 Baffes (2007) examines the effect of crude oil prices on the prices of 35 internationally traded primary commodities. He argues that oil prices affect the supply side of commodities due to fertilizer prices, transportation, or any kind of energy intensive production. He finds a strong pass-through of crude oil price changes to an overall non-energy commodity index. Baffes & Etienne (2016) and Baffes & Haniotis (2016) come to similar findings. Additionally, they also show that real income negatively affects real agriculture prices in the long run, whereas energy costs, monetary conditions and inventories are rather short term prices drivers. Similarly, Nazlioglu et al. (2013) suggest dynamic interrelationships between energy and agriculture markets. In contrast, Alghalith (2010) and Chang & Su (2010), and Lombardi et al. (2012) do not find direct price relations between fuel and agriculture commodity prices.

In this chapter, we extend the current literature by adopting the concept of energy return on investment (EROI) and its implications on commodity prices. According to Stern (2011), EROI can be interpreted as the ratio of useful energy produced to the amount of energy invested in extracting that energy. As economic systems heavily rely on available energy, Stern (2011) assumes that when energy is scarce it might impose strong constraints on economic growth. In addition, as energy is a key input variable for the extraction and production of raw commodities, it is of great interest how changing energy availability might affect the supply side of commodities. The economic literature on the concept of EROI and its implications for economic growth has emerged in recent years only. For a good review of the literature see Murphy (2014). He concludes that the EROI of global oil production is declining and that the relation between EROI and the price of oil is inverse and exponential. He thus proposes, that declining EROI impedes long-term economic growth and will come at higher financial, energetic and environmental costs (Murphy 2014). Similar conclusions can be found in Murphy & Hall (2011) and Fizaine & Court (2016). Hall et al. (2014) give a detailed description of different types of EROI analysis and its boundaries. Court & Fizaine (2017) follow up on this analysis and introduce a price based methodology to estimate long-term global EROI of coal, oil, and gas (from 1800 to 2012). Their results are consistent with other existing estimations of global oil and gas production from 1992 to 2006 as in Gagnon et al. (2009) and theoretical models developed in Dale et al. (2012). Most important, Court & Fizaine (2017) conclude that the EROI of global oil productions already reached its maximum value of

80:1 in the 1930s-40s and has declined subsequently[12].

Combining various approaches discussed in the literature, we estimate how a decreasing EROI of oil affects commodity price developments in the following sections.

4.2 Data description and the determination of the EROI of oil

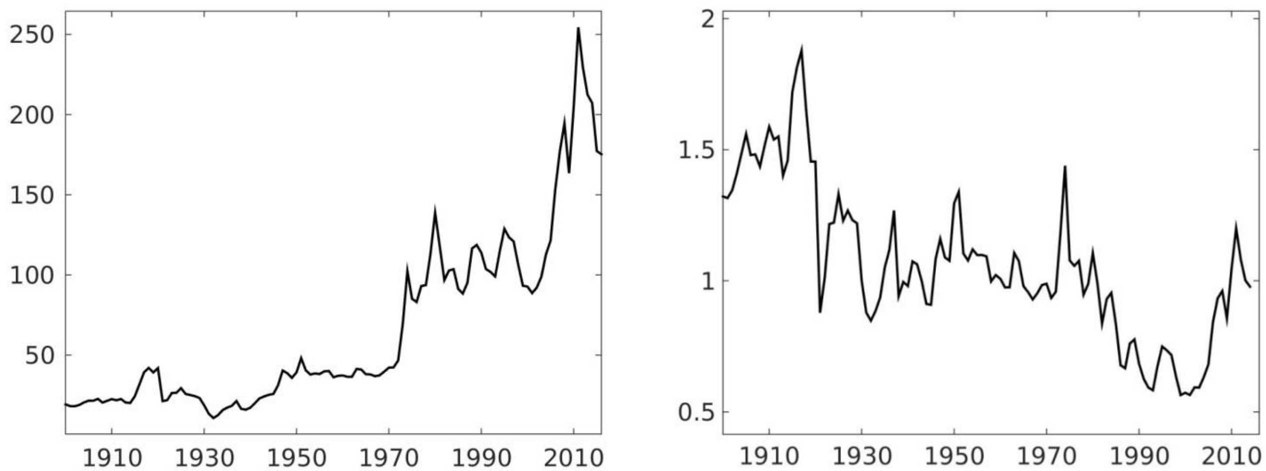
In order to assess long-term effects of decreasing surplus energy on commodity prices we rely on the widely used Grilli & Yang (1988) commodity price index (GYCPI). The trade-weighted index is composed of 24 primary non-fuel commodity prices deflated by the manufacturing unit value index (MUV) for the period 1900 to 1986. The MUV is one of the most frequently used deflator in the literature and is determined as a trade-weighted index of exports of manufactured commodities from France, Germany, Japan, United Kingdom, and United States to developing countries (Pfaffenzeller et al. 2007). We have updated the GYCPI based on commodity price series suggested in Pfaffenzeller et al. (2007) to 2014. Descriptive statistics of the individual commodity return series are shown in Table 4.1 and a detailed summary of the commodities used in our study can be found in Table A4.1.

[12] An EROI of 80:1 indicates that 80 units of energy output require one unit of energy input to produce that energy.

Table 4.1: Descriptive statistics of commodity returns and weightings in the GYCPI between 1900 and 2014. Percentage data on annual commodity prices and weightings are based on Pfaffenzeller et al. (2007) and Grilli & Yang (1988).

Components	Weight	Mean	Standard deviation	Maximum	Minimum
Bananas	0.9	2.8	9.7	33.6	-34.4
Beef	5.1	4.0	21.4	82.6	-60.1
Cocoa	2.7	2.0	26.1	111.0	-60.9
Coffee	10.3	2.7	25.3	78.8	-60.8
Lamb	0.9	4.3	22.7	83.1	-64.6
Maize	6.8	2.1	23.5	70.5	-92.2
Palm oil	8.3	1.9	24.2	72.7	-69.5
Rice	3	1.6	19.5	86.7	-57.8
Sugar	7.3	1.6	35.4	113.5	-134.9
Tea	1.6	1.9	16.2	55.9	-55.8
Wheat	8.1	2.3	19.6	72.5	-51.1
Cotton	4.3	1.6	18.9	50.2	-55.0
Hides	2.3	2.1	26.0	71.5	-100.5
Jute	0.2	2.5	23.4	60.3	-78.3
Rubber	2.8	0.5	29.7	102.3	-96.2
Timber	12	3.3	16.5	55.1	-46.8
Tobacco	2.9	3.5	12.5	50.7	-33.1
Wool	2.7	1.9	21.4	77.0	-63.2
Aluminum	5.1	0.9	16.2	60.6	-45.0
Copper	5.9	2.6	19.4	60.3	-46.9
Lead	1.3	2.7	20.4	69.3	-56.1
Silver	1.7	3.0	21.2	72.0	-67.7
Tin	2.2	3.2	21.1	57.4	-58.0
Zinc	1.6	2.8	21.6	94.7	-54.8
Average		2.4	21.3	72.6	-64.3

Figure 4.1 shows the GYCPI and the GYCPI relative to the MUV index. The GYCPI shows an upward trend over time whereas real commodity prices decline (GYCPI relative to MUV) until the beginning of the 2000s. Both indices exhibit sideways movements between the 1950's and the 1960's and show a commodity price boom during the 1970's. Since the early 2000's we see an increasing trend development corresponding to a second global boom in commodity markets during that period, cf. Carter et al. (2011). In the following analysis we rely on the GYCPI relative to MUV.



a) Grilli-Yang commodity price index

b) Grilli-Yang commodity price index relative to the MUV index

Figure 4.1: Grilli & Yang (1988) index from 1900 to 2014

Which factors drive commodity prices?

Empirical evidence suggests that commodity prices are influenced by macroeconomic conditions, geopolitical uncertainty, and monetary policy, see for example Barsky & Kilian (2001), Jeffrey A. Frankel (2006), or Bruno et al. (2016). Hence, to approximate global uncertainty affecting commodity prices we rely on stock market risk calculated as annualized standard deviations of daily Dow Jones index data from Williamson (2017a). For a similar approach see Byrne et al. (2013) and references therein. Second, to estimate the relation between monetary policy and commodity prices as suggested in Frankel (2006) we add real interest rates of the US to our model. As a proxy variable we use short-term interest rates from Officer (2017). Until 1930 they consist of ordinary funds rates from the Federal Reserve and from 1931 to present they are in the form of 3-months treasury bills of the US. Intuitively, rising interest rates lead to an increase of investments in fixed income securities as they get more interesting than risky products like commodities. This in turn reduces the demand for commodities and thus leads to falling commodity prices.

Most important drivers of long-term commodity price developments are supply and demand. As already noted in Bruno et al. (2016), there is overwhelming empirical evidence that global economic growth is a key driver of commodity demand, see also for example Alquist &

Coibion (2014), Kilian (2009). We thus use world GDP growth rates as measure of global demand effects on commodities and obtain the data from Maddison (2013) and World Bank. Similar to Byrne et al. (2013), we estimate missing data for world GDP between 1900 and 1950 by linearly interpolating the GDP series of China, USA, India, 12 Western European countries, Latin America, Australia, New Zealand, Canada, and Japan. On the supply side, we focus on the importance of energy availability as it is the most important input factor for non-fuel commodities due to fertilizer prices, transportation, or any kind of energy intensive production (Baffes 2007). Motivated by Hall et al. (2009) we focus on the EROI of oil as fundamental measure of the effect the decreasing energy availability might have on non-fuel commodity prices. This analysis is particularly important in the light of the fact that EROI of conventional fossil fuels is not only decreasing but the EROI of most renewable and non-conventional energy alternatives is substantially lower than the EROI of conventional fossil fuels (Hall et al. 2014).[13]

Determination of the EROI

Basically, EROI is measured as the energy output E_{out} divided by the energy input E_{in}.

$$EROI_{oil} = \frac{energy\ produced[EJ]}{energy\ invested[EJ]} = \frac{E_{out}}{E_{in}} \tag{4.1}$$

The higher the EROI, the greater is the amount of surplus energy accessible to society (Hall et al. 2014). Until today, there is no single accepted procedure how to estimate EROI for different sources of energy. Hence, in order to estimate long-term EROI of oil we follow Court & Fizaine (2017) and King & Hall (2011) and use a price-based methodology. The EROI based on Court & Fizaine (2017) represents the ratio of annual gross energy produced to annual energy invested and can be seen as *gross power return ratio* which is explained in the following:

The output or production boundary of the EROI is at the well-head and is estimated based on historical production data for oil. The input side covers direct energy expenditures, indirect

[13] We do not consider storage costs explicitly as data is not available for the period considered in this chapter. However, parts of these costs might be related to energy usage and thus partly covered in our EROI-factor.

energy expenditures from physical capital investments, and direct energy embodied in what workers purchase with their payback. Most important variables for the energy input side thus are oil prices, the global primary energy mix, monetary-return-on-investment (MROI) of the energy sector and energy intensity of capital expenditures in the primary fossil energy sector. The final estimation of the global EROI of oil is as follows [14]:

1. Energy E_{in} invested in global oil system corresponds to the quantity of money M_{in} invested in the sector multiplied by the average energy intensity EI of capital and services installed and used.
2. For M_{in} only few data exist. M_{in} is thus estimated as the quantity of energy produced E_{out} by the oil sector multiplied a proxy for annual (not levelized) production cost of oil.
3. The production cost of oil is estimated as the unitary price P of oil divided by the monetary-return-on-investment (MROI) of the oil sector. According to Court & Fizaine (2017) and Damodaran (2015), the US fossil energy sector's MROI is roughly following US long-term interest rates with a 10% risk premium.
4. Further assumption: The energy intensity EI is the same for all energy sectors and corresponds to the average energy intensity of the global economy. EI is estimated as the sum of the entire energy output from coal, oil, gas, nuclear, and renewables divided by the gross world product GWP.
5. The global EROI for oil reads as follows:

$$EROI = \frac{E_{out}}{E_{in}} = \frac{E_{out}}{M_{in} * EI} = \frac{E_{out}}{\frac{P}{MROI} * E_{out} * EI} = \frac{MROI}{P * EI} = \frac{MROI}{P * \frac{\sum_j E_{out,j}}{GWP}}, \tag{4.2}$$

$$for\ j \in (coal, oil, gas, nuclear, renewables)$$

A description of the data sources used in our study is shown in Table A4.2. For a more detailed view on data and estimation procedure, the interested reader should have a look at Court & Fizaine (2017). Figure 4.2 shows the annual price-based global EROI of oil from 1900

[14] All US $ values are expressed in the international Geary-Khamis $1990

to 2014 compared with the GYCPI deflated by MUV. It is clear to see, that both series develop in opposite directions. Periods of high EROI values coincide with periods of low real commodity prices and vice versa.

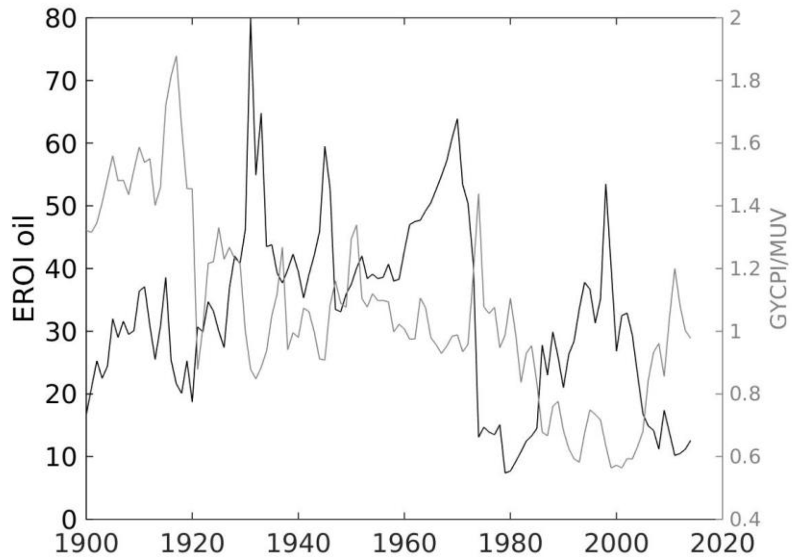


Figure 4.2: Price-based global EROI of oil (black) according to Court & Fizaine (2017) compared to Grilli-Yang commodity price index relative to the MUV index (grey) from 1900 to 2014.

The period from *1900 to 1937* was characterized by intensive use of coal and traditional biomass energy. Oil production was only about to start growing but increased rapidly since the late 1930s. EROI levels for oil reached its all-time high in 1931.

During the period from *1938 to 1976* the production of oil surged. Coal and oil were used for the production and use of war machinery. After WWII, the importance of global manufacturing and transportation increased and oil became even more important (Hall et al. 2014). The EROI of oil reached its highest average level during this period and its second peak in 1970. US oil production peaked in the same year. From this year on, OPEC oil has gained increasing importance for world supply. Hence, the EROI of oil decreased and oil prices rose subsequently reflecting the increased amount of energy needed to acquire this fuel, cf. Hall et al. (2014) and Hall & Klitgaard (2012).

In the beginning of the period from *1977to 2014* the Iranian revolution (1978/79) and Iran-Iraq war (beginning of 1980) caused high oil prices and the oil price shock in 1979. Oil extractions which were uneconomic before became economic during this period, leading to lower EROI values, cf. Guilford et al. (2011) and Hall et al. (2014). The following years between mid 80s and early 90s can be described as a period of abundant oil and falling prices which resulted in less oil explorations. Since the oil price peak in 2008 the introduction of new drilling techniques again rapidly increased the oil production in the US. However, over the past two decades the EROI of oil is decreasing as shown in Murphy & Hall (2011) and Tverberg (2012).

In the following section we investigate if and to what extend the level of EROI not only affects an index of non-fuel commodity prices but also individual commodity prices of different sectors.

4.3 The effect of decreasing EROI on commodity prices

We examine the effect of changing net energy availability on commodity prices within a structural VAR approach based on yearly data for $\boldsymbol{Y_t} = (\Delta EROI_t, Risk_t, \Delta GDP_t, IR_t, \Delta GYCPI_t)$. Within this model, $EROI_t$ is the log energy returned on investment for oil, $Risk_t$ measures the risk of geopolitical and monetary uncertainty as annualized standard deviations of daily Dow Jones index data, GDP_t corresponds to log world GDP. Until 1930, IR_t are the real US interest rates based on ordinary funds rates from the Federal Reserve and from 1931 to present IR_t are 3-months treasury bills of the US. $GYCPI_t$ is the log of the Grilli-Yang commodity price index deflated by MUV. To ensure stationary time series we apply the fist-order difference operator Δ. We define the structural VAR approach with p lags as follows

$$\boldsymbol{C}_0\boldsymbol{Y}_t = \sum_{i=1}^{p} \boldsymbol{C}_i\boldsymbol{Y}_{t-i} + \boldsymbol{\epsilon}_t \tag{4.3}$$

$\boldsymbol{\epsilon}_t$ is the vector of serially and mutually uncorrelated structural shocks and we determine the lag length p according to the Schwarz (1978) information criterion. The matrix $\boldsymbol{C}_0^{-1}$ given in Equation 4.3 has a recursive structure with reduced-form errors $\boldsymbol{u}_t$ which are obtained as $\boldsymbol{u_t} = \boldsymbol{C}_0^{-1}\boldsymbol{\epsilon}_t$:

$$u_t := \begin{pmatrix} u_t^{\Delta EROI} \\ u_t^{Risk} \\ u_t^{\Delta GDP} \\ u_t^{IR} \\ u_t^{\Delta GYCPI} \end{pmatrix} = \begin{bmatrix} c_{11} & 0 & 0 & 0 & 0 \\ c_{21} & c_{22} & 0 & 0 & 0 \\ c_{31} & c_{32} & c_{33} & 0 & 0 \\ c_{41} & c_{42} & c_{43} & c_{44} & 0 \\ c_{51} & c_{52} & c_{53} & c_{54} & c_{55} \end{bmatrix} \begin{pmatrix} \epsilon_t^{EROI\ shock} \\ \epsilon_t^{risk\ shock} \\ \epsilon_t^{economic\ growth\ shock} \\ \epsilon_t^{interest\ rate\ shock} \\ \epsilon_t^{commodity\ specific\ shock} \end{pmatrix} \tag{4.4}$$

As we rely on the orthogonalization of our VAR system based on a Cholesky decomposition of the reduced-form error's covariance matrix, our structural system is contemporaneously recursive[15]. The set-up of the variables is based on the following assumptions:

First, economies and commodities are strongly driven by energy input. Hence, a shock in the EROI of oil will not only have implications on GDP growth rates but also on commodity prices. In addition, changing EROI of oil might simultaneously affect global economic uncertainty and risk in financial markets due to changing energy prices. Second, risk and uncertainty simultaneously affect economic growth, monetary policies and commodity prices as argued in Frankel (2006). Third, as noted in Bruno et al. (2016), there is overwhelming empirical evidence that global economic growth is a key driver of commodity demand. A shock in world GDP growth rates thus changes global demands for raw commodities and thereby its prices. Fourth, monetary policies are adapted to changes in economic conditions. As suggested in Frankel (2006) and Akram (2009), changes in interest rates thus simultaneously affect commodity prices. Rising interest rate might therefore reduce the demand for commodities and lead to falling commodity prices. Finally, commodity prices are simultaneously affected by all other variables.

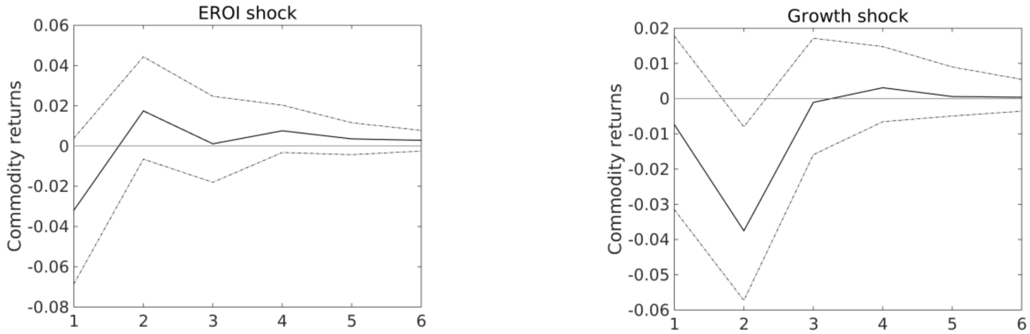
How do commodity prices react to shocks in EROI and GDP growth rates?

We start by estimating the structural VAR for $\boldsymbol{Y_t} = (\Delta EROI_t, Risk_t, \Delta GDP_t,\ IR_t, \Delta GYCPI_t)$ for various sample periods to evaluate the effect of varying EROI levels over time. Figure 4.3a shows the responses of the GYCPI to shocks in the EROI of oil and world GDP growth rates as we focus on supply and demand shocks. The impulse responses of the GYCPI to real interest rates and uncertainty shocks are shown in Figure 4.3b. The 95% confidence bands are estimated from 1000 Monte Carlo simulations.

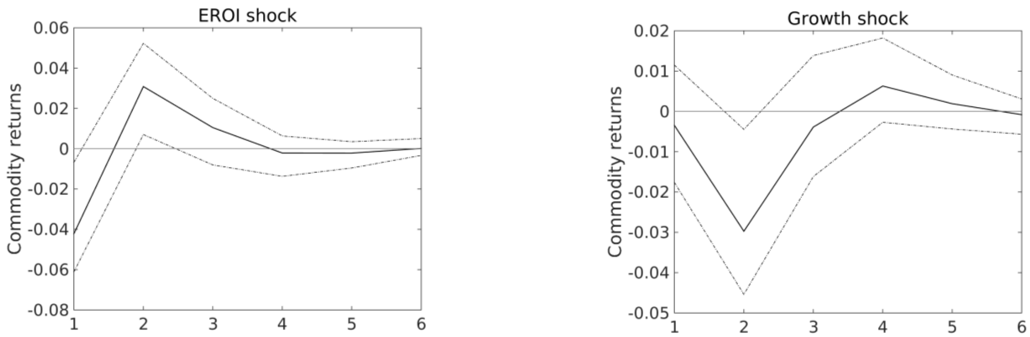
[15] A similar model set up can be found in Kilian (2009), Wang et al. (2014), and Lübbers & Posch (2016)

From *1900 to 1937*, oil's EROI shocks on GYCPI do not have significant effects on commodity returns as this period of time can be characterized by intensive use of coal and traditional biomass energy rather than oil. Similarly, a shock in economic growth rates mostly does not have significant effects on commodity returns.

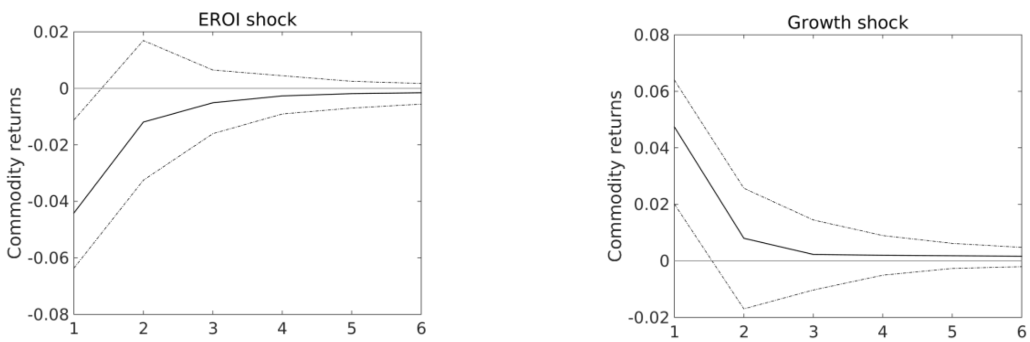
1900 – 1937



1938 – 1976



1977 – 2014



1900 – 2014

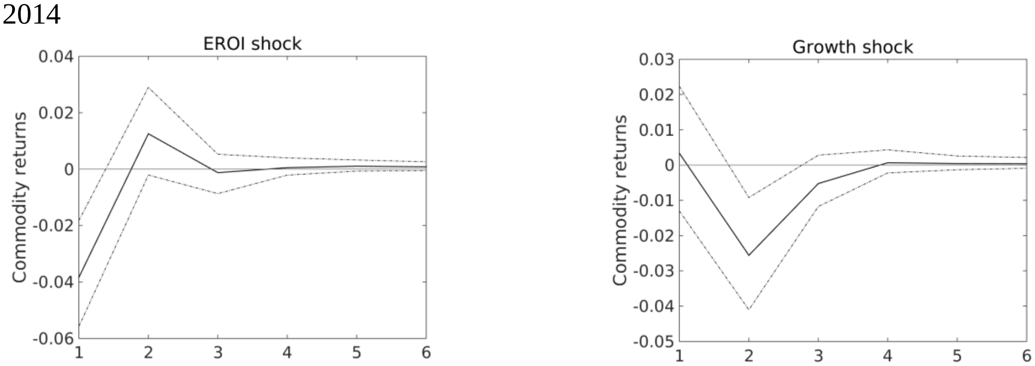
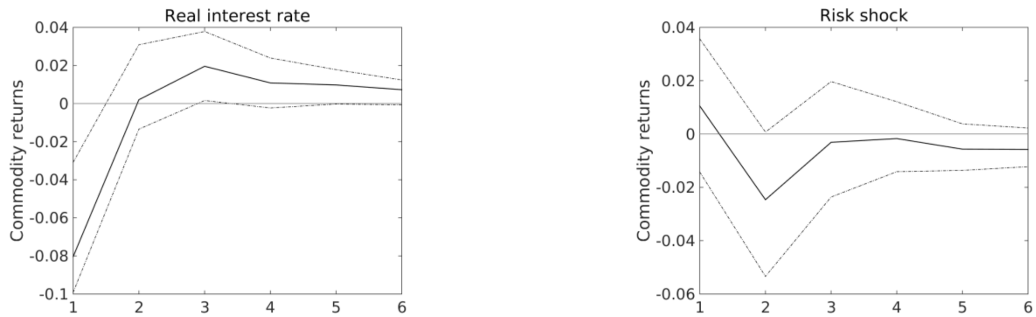
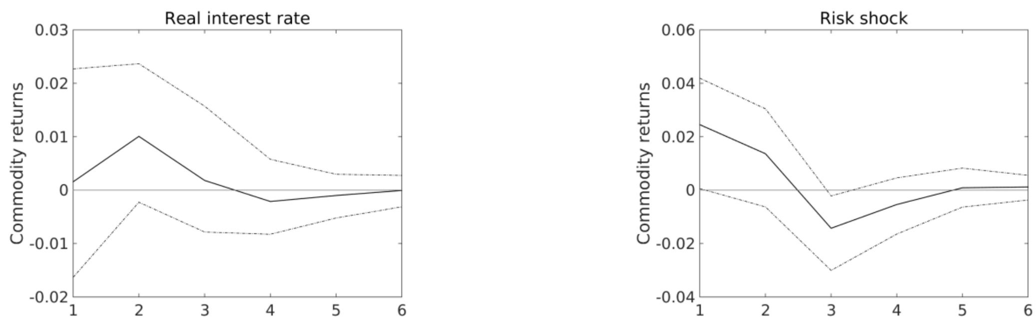


Figure 4.3a: Responses of GYCPI to structural demand and supply shocks. The graphs show the response of the Grilli-Yang index to a generalized one standard deviation innovation in the EROI of oil and world economic growth for different periods of time. Also shown are the 95% confidence bands based on 1000 Monte Carlo simulations.

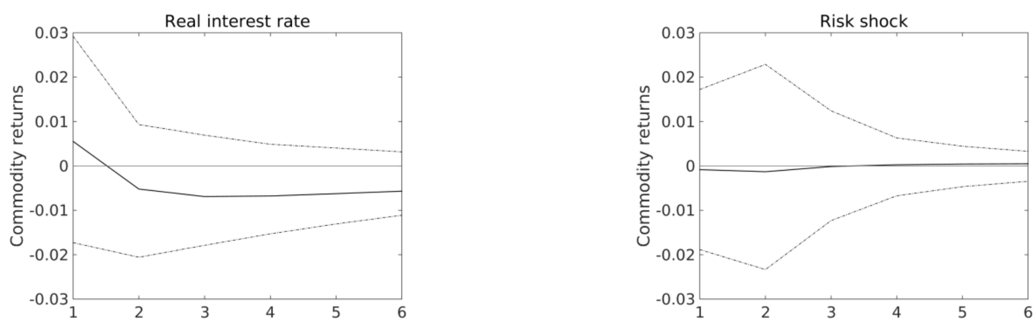
1900 – 1937



1938 – 1976



1977 – 2014



1900 – 2014

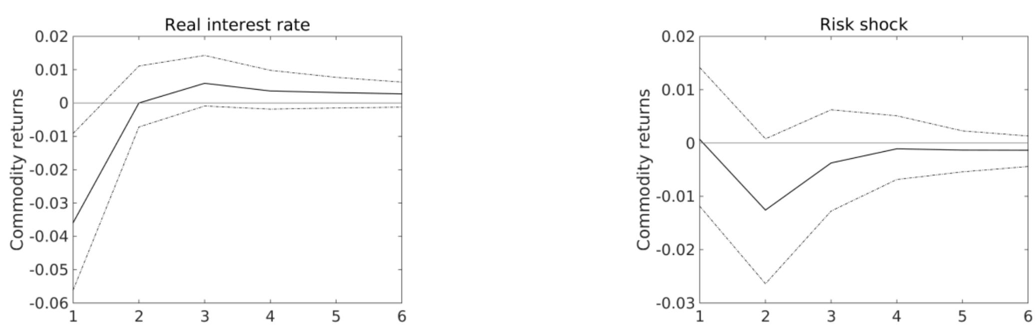


Figure 4.3b: Responses of GYCPI to structural real interest rate and uncertainty shocks. The graphs show the response of the GYCPI to a generalized one standard deviation innovation in real interest rates and risk for different periods of time. Also shown are the 95% confidence bands based on 1000 Monte Carlo simulations.

Its effect on the GYCPI only becomes significant for s short period of time after two years. One possible explanation might be the mixed economic conditions and WWI during this period. The following years from 1938 to 1976 can be described as a period of cheap and abundant fossil energy. The total energy consumption per person has more than doubled (Figure 4.3a) and the average level of the EROI of oil reached its highest values (Figure 4.2). Therefore, a shock in EROI negatively affects the GYCPI. Intuitively, falling EROI values lead to less surplus energy and increasing energy costs which in turn results in higher commodity prices. However, commodity prices seem to overreact on EROI shocks as its effect becomes significantly positive after two years and insignificant subsequently. Shocks in economic growth show only little to no significant effects on the GYCPI.

The most striking results of Figure 4.3a are the distinct negative responses of commodity prices to shocks in oil EROI values during the last period from *1977 to 2014*. This period is characterized by the strongest economic growth (Figure 4.4) and the lowest average EROI (Figure 4.2) of the entire period. We conclude, that decreasing EROI values have a distinct and significant effect on commodity prices. Intuitively, the lower the EROI the less surplus energy is available and the more expansive are commodity prices.

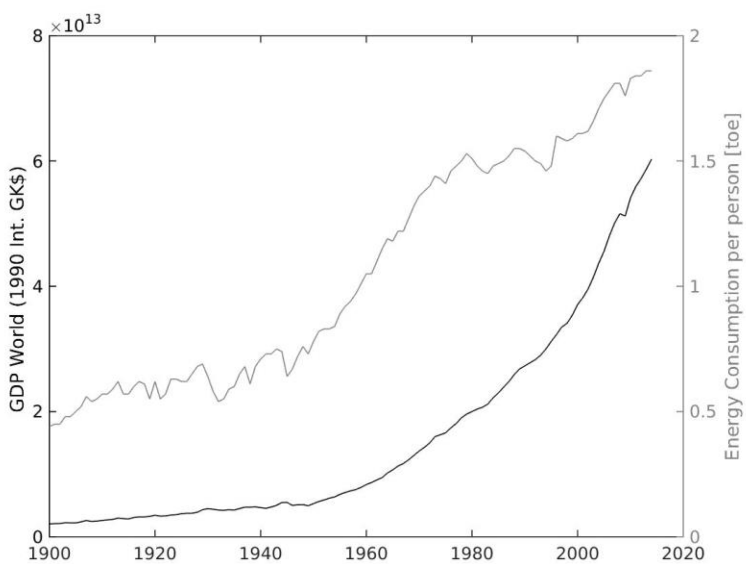


Figure 4.4: World total GDP (black) compared to world energy consumption per person (grey). The world total GDP values are expressed in the international Geary-Khamis 1990$ and energy consumption is given in tons of oil equivalent (toe) per person. Data sources: BritishPetroleum (2017) and United Nations population division.

In contrast, the effect of a shock in world GDP growth rates on GYCPI is significantly positive. The impact of EROI and GDP on GYCPI appears to be about the same level and the time to recover from a shock in EROI and GDP growth rates is approximately 6 months. Over the entire period (*1900 to 2014*) GDP shocks are less influential than shocks in net energy availability. Hence, supply shocks seem to be more important than demand shocks on commodity prices.

What is the explanatory ability of our main drivers' shocks on commodity prices?

In the next step we examine the amount of information each variable of our system contributes to the other variables in our VAR model. Table 4.2 shows the results of the Forecast Error Variance Decomposition (FEVD) at forecast horizons of one and five years. From *1900 to 1937* real interest rate shocks account for more than half of the variation in commodity prices which confirms the findings of Jeffrey A. Frankel (2006) who claims that

Table 4.2: Percentage contribution of fundamental factors to variations in the GYCPI. This table compares the percentage contribution of different shocks to the Grilli-Yang index for various time periods and forecast horizons of one and five years.

Period	Average EROI	Forecast horizon [years]	Shocks in				
			EROI	Risk	GDP growth rate	Interest rate	Commodity prices (GYCPI)
1900 - 1937	32.8	1	9.2	1.0	0.5	58.6	30.7
		5	9.8	5.4	10.4	49.9	24.5
1938 - 1976	40.0	1	27.7	9.4	0.2	0.0	62.8
		5	30.7	11.0	10.3	1.2	46.7
1977- 2014	20.5	1	19.4	0.0	22.5	0.3	57.8
		5	19.9	0.0	21.8	1.8	56.5
1900 - 2014	31.3	1	13.6	0.0	0.1	12.0	74.3
		5	13.6	1.5	5.8	11.2	68.0

low real interest rates lead to high real commodity prices, cf. Figure 4.3b. EROI, risk, and GDP growth are less important for commodity prices during that period of time. However, demand shocks and supply shocks both almost account for 10% of commodity price variations over the five-year forecast horizon. In the second period (*1938 to 1976*), the most important variables are EROI (30.7%), risk (11%), and GDP growth rates (10.3%) which account for 52% of the variations in commodity prices. The importance of these variables reflects macroeconomic and political developments during these years. After WWII strong economic growth, increased manufacturing, and transportation drove demand not only for fossil energy products (Hall et al. 2014) but also for raw commodities.

From *1977 to 2014* economic growth has surged (Figure 4.4). From our FEVD analysis we conclude that demand shocks (GDP growth rates) account for more variation in real commodity price changes than supply shocks. Together, shocks in EROI and GDP growth rates almost account for half of the variation in commodity prices. Interest rates and uncertainty of financial markets only play a minor role. Interestingly, the low impact of financial risk on commodity price fluctuations also suggests that financial markets are not important for long-run commodity price fluctuations. These findings are in line with parts of the literature examining the effect of financial speculation on commodity prices. While the correlation between commodity and equity returns surged during the financial crisis in 2008, Bruno et al. (2016) could not find a significant long-run correlation between those two markets.

Over the entire period (*1900 to 2014*) and in line with Frankel (2006) we find that real interest rates play a dominant role for the fluctuation of commodity prices. However, its effect was strongest during the beginning of the 20th century and became less important over the years. In accordance with Barsky & Kilian (2001) who argue that industrial commodity price increases in early 1970s were consistent with an economic boom driven by monetary expansion, our results show GDP growth rates to be important for commodity price variations only since the early 1970s. As EROI is the most influential variable for commodity price variations since 1938 explaining more than 19% of commodity price fluctuations, our results also confirm Carter et al. (2011) mentioning the importance of supply and demand shocks for commodity price booms in 1974 and 2008. Our findings thus contradict the results of Alghalith (2010), Chang & Su (2010), and Lombardi et al. (2012) who all do not find direct relations between fuel and agriculture commodity prices.

Hence, commodity prices depend on the amount of surplus energy available to society. The lower the EROI, the higher are commodity prices, see Figure 4.2 and 4.4. During times of strong economic growth, the effect of EROI on commodity prices is lower than in times of weaker economic growth (see Table 4.2 and Figure 4.3a and A4.2). This might have serious consequences in times of weakening economic growth and decreasing EROI values. Simultaneously considering GDP growth rates and EROI values might thus help to estimate the effect of a changing energy supply mix on commodity price developments.

Model extensions – As Frankel (2006) suggests various risk factors to affect individual commodity prices rather than an index of commodities we now focus on individual agriculture and metal commodities. Table 4.3 summarizes the results of the FEVD. Until *1937* real interest rates account for most of the variations in wheat and maize return fluctuations and GDP growth rates are most important for wheat and copper variations. Similarly to results for the GYCPI (Table 4.2) the EROI values gain importance for all commodity price fluctuations in the following period from *1938 to 1976* and explain up to 21% and 17% of copper and wheat price variations, respectively. From *1977 to 2014* GDP growth rates account for large parts of copper's and aluminum's price fluctuations. The EROI of oil remains most important for variations in maize and copper but decreased for wheat prices.

Over the entire period between *1900 and 2014*, variations in GDP growth rates almost account for 10% of copper price fluctuations which confirms the importance of copper as proxy for global economic growth. On the supply side, EROI values are most important for wheat, maize, and copper returns and account for 5 to 10% of the variation in these commodities. These findings confirm the results of our analysis based on the GYCPI (Table 4.2). However, as can be seen in Table 4.3 and in line with Hamilton (2012), the importance of broad market trends is different for different commodities and variations in all four commodity prices are to a large extent driven by individual commodity shocks, rather than by macroeconomic variables.

Table 4.3: Percentage contribution of fundamental factors to variations in individual commodity prices. This table compares the percentage contribution of different shocks to selected real commodity prices for various time periods and a forecast horizon of five years.

Forecast horizon: 5 years			Shock in			
Period	Average EROI	Effect on	EROI	Risk	GDP growth rate	US interest rates
1900 - 1937	32.8	Wheat	11.4	0.9	15.4	18.8
		Maize	6.6	4.1	0.3	49.6
		Copper	2.5	18.5	16.0	1.1
		Aluminium	18.2	9.6	4.9	5.3
1938 - 1976	40.0	Wheat	17.2	19.7	1.1	2.3
		Maize	16.3	12.4	6.2	2.8
		Copper	21.3	3.8	12.1	4.5
		Aluminium	11.4	8.7	2.5	10.8
1977- 2014	20.5	Wheat	6.1	1.3	4.9	1.3
		Maize	14.0	0.5	4.5	0.8
		Copper	21.4	4.2	28.5	2.4
		Aluminium	4.3	7.4	43.3	6.7
1900 - 2014	31.3	Wheat	6.0	2.4	3.2	3.8
		Maize	4.6	1.2	0.8	12.3
		Copper	9.9	2.5	9.5	0.2
		Aluminium	0.6	1.0	4.9	1.1

When comparing the price-based EROI to EROI values proposed in Gagnon et al. (2009) and to a theoretical model proposed in Dale et al. (2011), it can be shown that the price-based approach is consistent with the literature and follows the same trend as the one of Gagnon et al. (2009), cf. Court & Fizaine (2017). To further assess the robustness of our findings we also tested the sensitivity of the price-based EROI and our results to changes in the monetary-return-on-investment (MROI) as suggested in Court & Fizaine (2017). Based on a document of the American Petroleum Institute (API 2016) quoting an average annual profit assumption of the entire US oil and gas industry between 5 and 15% we follow King & Hall (2011), King et al. (2015), and Court & Fizaine (2017) and also assume a constant MROI equal to 1.1.

However, variations of the MROI did not significantly change the outcome of our results.

4.4 Concluding remarks

Based on a price-based EROI of oil we assess the effect of changes in the EROI on both, an index of non-fuel commodities and individual commodity prices between 1900 and 2014. By applying a structural vector autoregressions model and forecasting error variance decompositions for different subsamples we differentiate from prior literature and get a deeper understanding how economic growth and EROI affect commodity prices during different economic growth periods. The most important finding of this chapter is that a changing EROI of oil accounts for up to 30% of the variation of a commodity price index and up to 21% and 17% of copper and wheat price variations, respectively. We conclude that commodity prices depend on the amount of surplus energy available for society. The lower the EROI, the higher are commodity prices. We show that during times of strong economic growth, the effect of EROI on commodity prices is lower than in times of weaker economic growth. In addition, we find that the importance of broad market trends and the effect of decreasing EROI values have different effects on individual agriculture and metal commodities. As an energy transition from fossil fuels to unconventional fossil fuels and to renewable technologies implies a shift from higher to lower EROI supply energy mix (Court & Fizaine 2017), our findings might have serious consequences in times of weakening economic growth. Simultaneously considering GDP growth rates and EROI values might thus help to estimate the effect of a changing energy supply mix on long-term commodity price developments. Based on the idea of Hall et al. (2009) who focus on the question what a minimum EROI for sustainable societies is, future research may extend our results in this direction and focus on the question whether a critical EROI for sustainable commodity price developments exists.

5 Conclusion

This thesis contributes to three important topics of the literature on commodity and energy markets. Chapter 2 adopts a one-sided representation of the generalized dynamic factor model to extract the common movement of thirty-one commodity futures' returns. It shows that the importance of this common factor increased during the 2008 financial crisis and that this factor is increasingly correlated to changes in gold and oil prices. Even more important, first indications of an asset pricing model for individual commodity futures returns have been found based on common factors of the energy and agriculture sector. These results suggest a recent weakening of the heterogeneity assumption of commodity prices and expand recent findings of the commodity pricing literature.

Based on a panel analysis of nonstationarity in idiosyncratic and common components Chapter 3 extracts the co-movement of seventeen agriculture commodity futures returns and develops a measure of financialization based on weekly commodity index traders' long open interest. It suggests that the influence of index speculation on the common factor of agriculture commodity futures prices is strongest during agriculture price peaks in 2008 and 2011. To avoid financial speculation directly affecting commodity price changes, the relative share of commodity index traders' long open interest should not be significantly higher than 28%.

In contrast to existing literature, Chapter 4 focuses on the Energy Return On Investment (EROI) of oil, to identify fundamental drivers of non-fuel commodity prices. Relying on a price-based EROI of oil, Chapter 4 assesses the effect of changes in the EROI on both, an index of non-fuel commodities and individual commodity prices between 1900 and 2014. It suggests that commodity prices depend on the amount of surplus energy available to economies. The lower the EROI, the higher are commodity prices. During times of strong economic growth, the effect of changes in the EROI of oil on commodity prices is lower. However, this might have serious consequences in times of weakening economic growth and decreasing EROI. Simultaneously considering GDP growth rates and the EROI of main energy sources might help to estimate long-term effects of a changing energy supply mix on commodity price developments.

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Appendix

Table A4.1: Data sources of commodity price series

Commodity	Description of price series	Data source
Aluminum	London Metal Exchange (LME), unalloyed primary ingots, high grade, minimum 99.7% purity	World Bank Development Prospects Group's primary commodity price database
Banana	Central and South American, U.S. import price, free on truck (f.o.t.) gulf ports	World Bank Development Prospects Group's primary commodity price database
Beef	Australian and New Zealand 85% lean fores	IMF commodity price tables series PBEEF
Cocoa	International Cocoa Organization daily price, average of the first three positions on the terminal markets of New York and London, nearest three future trading months	World Bank Development Prospects Group's primary commodity price database
Coffee	International Coffee Organization, other mild Arabica	World Bank Development Prospects Group's primary commodity price database
Copper	LME grade A minimum 99.9935% purity, cathodes and wire bar shapes, settlement price	World Bank Development Prospects Group's primary commodity price database
Cotton	Cotton Outlook A Index, middling 1 3/32 inch staple, Europe cost, insurance, and freight (c.i.f.)	World Bank Development Prospects Group's primary commodity price database
Hides	Heavy native steers, over 53 pounds	IMF commodity price tables series PHIDE
Jute	Raw white D, free on board (f.o.b.) Chittagong	World Bank and quoted on the Pink Sheets and FAO
Lamb	New Zealand, frozen whole carcasses, wholesale price, London	World Bank Development Prospects Group's primary commodity price database
Lead	LME refined, 99.97% purity, settlement price	World Bank Development Prospects Group's primary commodity price database
Maize	U.S. No.2 yellow, f.o.b. gulf port	World Bank Development Prospects Group's primary commodity price database
Palm oil	5% bulk, Malaysian, c.i.f. NW Europe	World Bank Development Prospects Group's primary commodity price database
Rice	Thai 5%, milled, indicative price based on weekly surveys of export transactions, government standard, f.o.b. Bangkok	World Bank Development Prospects Group's primary commodity price database

Rubber	RSS no.1 Rubber Traders Association spot New York	World Bank Development Prospects Group's primary commodity price database
Silver	Handy & Harman 99.9% New York	World Bank Development Prospects Group's primary commodity price database
Sugar	International Sugar Agreement daily price, raw, f.o.b. and stowed at greater Caribbean ports	World Bank Development Prospects Group's primary commodity price database
Tea	Three-auction average (Kolkata, Colombo, Mombasa)	World Bank Development Prospects Group's primary commodity price database
Timber	UK import unit values, SITC Rev.2 series 2482 (sawn wood, coniferous species)	OECD international trade by commodities statistics through ESDS International
Tin	LME 99.85% purity, settlement price	World Bank Development Prospects Group's primary commodity price database
Tobacco	U.S. import unit values, unmanufactured leaves	World Bank Development Prospects Group's primary commodity price database
Wheat	No.1 Canadian western red spring, in store, St. Lawrence, export price	World Bank Development Prospects Group's primary commodity price database
Wool	wool, coarse, 23 micron, Australian Wool Exchange spot quote	IMF commodity price tables series PWOOLC
Zinc	LME, special high grade, minimum 99.995% purity, weekly average bid/asked price, official morning session	World Bank Development Prospects Group's primary commodity price database

Table A4.2: Data sources of the EROI of oil

Item	**Source**
World primary energy production	
Coal, oil, gas, nuclear, hydro, other renewables	The Shift Project (2015), built on Etemad & Luciani (1991) and EIA (2014)
Biofuels (wood fuel, crop residues, modern biofuels)	Smil (2016)
Oil prices	British Petroleum (2017)
CPI US	Williamson (2017b)
MROI, long-term interest rate (US LTIR)	Officer (2017)