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Examining the Common Dynamics of Commodity Futures Prices

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Abstract

We investigate the extent and dynamic nature of co-movement in daily futures prices of 18 non-energy commodities over the period 1994-2016. Our analysis provides evidence that co-movement between individual commodities and between commodities and outside financial markets varies strongly over time and that economic events play a key role in shaping the dynamics of co-movement. Our main findings suggest a steady rise in the co-movement of commodity returns between 2004 and 2010, with clear peaks during the period of global financial turmoil, but a steep decline in co-movement after 2013. We also find that overall connectedness of commodity futures markets to shocks in financial markets shows an increasing trend after 2004. Using several risk measures we show that financial investors' risk aversion affects the systematic component of commodity futures returns.

JEL Classification: E44, F30, G12, G13, G15

Keywords: Commodity futures markets, connectedness, co-movement, financialization, common factors

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1 Introduction

Over the past 10-15 years, commodity markets have been exposed to high volatility. After decades of relatively stable prices, a broad set of commodities experienced synchronized boom-and-bust periods, in the course of which record highs were soon followed by sudden and pronounced price drops. The Goldman Sachs Commodity Index (GSCI) excluding energy, which summarizes the most important non-energy commodities, more than doubled between 2005 and 2008, then lost almost 50 percent of its value in the second half of 2008, before it reached a new record high in early-2011. This apparent co-movement of numerous commodities in the recent past triggered an active debate about the driving forces behind these developments.[1] Motivated by the rising popularity of commodities as an asset class for financial investors, the so-called "financialization of commodities", one prominent approach is to focus on financial speculation as a possible source for the increase in cross-market correlations and volatility spikes (e.g., Irwin et al. 2009; Tang and Xiong 2012). Other researchers highlight macroeconomic factors as the prime drivers, including strong global demand for raw materials and food, particularly from fast-growing emerging markets, and the strong impact of a volatile oil price on non-energy commodities (Hamilton 2009; Baffes and Haniotis 2010).

This paper provides a new perspective on the empirical analysis of commodity price dynamics. The aim is to disentangle the different sources of co-movement in commodity markets by applying and extending recent techniques to measure connectedness in a system of asset returns. Our empirical approach seeks to measure and explain the systematic component of commodity price fluctuations, going beyond the measurement of simple pairwise relationships. Given that the systematic component is of special relevance to market participants and policy makers in terms of risk management and monitoring, as it represents the non-diversifiable part of market risk, it is essential to have quasi real-time information on its evolution and dependence structure. Our econometric framework accommodates this by ex-

[1] See e.g., Economist (2012, 2014) for a discussion in the popular media.

ploiting *daily* time series data from a broad set of 18 non-energy commodity futures markets, allowing us to track how systematic commodity price movements behave at high-frequency.

The need to analyze the dependencies of commodities at high-frequency can also be viewed as a corollary of the financialization of commodities. As commodities have entered many investment portfolios alongside other asset classes (stocks, bonds, etc.), financial commodity traders concurrently monitor changes in a vast array of commodity markets along with contemporaneous fluctuations in outside financial markets. Under these circumstances, sudden price drops in outside markets may force financial investors to immediately liquidate their commodity futures positions to reduce risk, which increases the sensitivity of commodity markets to overall risk in financial markets (Cheng and Xiong 2014; Cheng et al. 2015). Using the appropriate tools to measure and characterize short-run interconnectedness of commodities with each other and with outside financial markets is therefore an important step toward understanding the consequences of financialization.

Our empirical analysis is divided into two parts. In the first part we implement a simple latent factor model which we estimate through the method of principal components analysis. The principal components can be interpreted as common factors that explain the systematic variation in our set of 18 commodities. To uncover temporal changes in the degree of dependence among commodities, we then employ the framework of Diebold and Yilmaz (2012, 2014) to quantify aggregate co-movement. Specifically, we estimate two variants of their proposed connectedness measure, differentiating between system-wide and idiosyncratic connectedness among commodities. System-wide connectedness summarizes interdependencies arising as a result of common *and* idiosyncratic shocks to the system of commodity returns. Idiosyncratic connectedness, on the other hand, ignores interdependencies that arise because all commodities are hit by the same common shock. By comparing the dynamic behavior of the rolling window (200 days) estimates for both measures, we can precisely gauge how systematic co-movement evolves over time. In the second part of our analysis, our aim is to isolate the determinants of co-movement in commodity futures returns. To this end, we implement a factor-augmented vector autoregression (FAVAR) model that considers the common factor(s) together with a number of potential explanatory variables, including stock market indices, the oil price and the U.S. dollar exchange rate. We also investigate the relation of the common factor(s) to different measures of risk in financial markets.

Our main results document a relatively modest extent of co-movement among non-energy commodities during the first ten years of our sample (1994-2004). In early-2004, however, co-movement starts to increase considerably, reaching a particularly strong degree in the period of economic and financial turmoil from 2008 to 2013. As markets calmed down after these crisis events, we observe a steep decline in the level of commodity co-movement. In our analysis of determinants we find that common price movements in commodity markets are increasingly connected to changes in financial market conditions. Especially the global financial crisis, the European debt crisis and financial market developments in emerging markets are found to have a strong influence on the common price dynamics of non-energy commodities. We can also show that the time-varying risk aversion of financial investors impacts the systematic commodity component. The paper's main findings are confirmed by various robustness checks. Our results are in sharp contrast to the findings of older studies that document little co-movement of commodities among each other (Erb and Harvey 2006) or with other asset classes (Gorton and Rouwenhorst 2006). Instead, the evidence presented in this paper is in line with the findings of more recent studies reporting an increasing integration of commodity markets with outside financial markets (e.g., Tang and Xiong 2012; Büyüksahin and Robe 2014), thereby supporting the view that, as a result of financialization, commodities have become more like a "traditional" financial asset in recent years.

Our results bear a number of important implications for market participants and policy makers. First, the identified pass-through of financial risk to the systematic component of commodity futures prices involves adverse effects for commodity producers relying on futures markets to hedge their price risk. According to the traditional hedging pressure theory (Keynes 1923; Hicks 1939; Hirshleifer 1990), financial traders facilitate the demand for hedging by taking the other side of commodity producers' positions. If financial traders respond to increases in financial risk by reducing their long positions, this leads to lower futures prices and lower short positions of hedgers in equilibrium (Cheng et al. 2015). As a consequence, hedgers are constrained in transferring their price risk to financial speculators. A second implication of our findings is that the diversification benefits of investing in commodities are decreasing as a result of the increasing integration of commodity futures markets, which is consistent with empirical studies that directly assess the diversification effects of commodities (Daskalaki and Skiadopoulos 2011; Bessler and Wolff 2015). Finally, our findings are relevant from a financial stability perspective in that the risk-commodity link represents another contagion channel through which financial distress spills over to the real economy in crisis times. Economies that depend heavily on commodity production are therefore particularly vulnerable to this type of contagion.

The remainder of this paper is organized as follows. In Section 2 we review the literature related to our study. Section 3 describes the methodology and Section 4 the data used in our analysis. In Section 5 we present and discuss our results. This section also includes a series of robustness checks. Finally, we provide a conclusion in Section 6.

2 Related Literature

Our study contributes to a growing body of empirical literature that investigates correlations between commodities and the influence of external shocks on commodity price dynamics. One of the earliest empirical studies on this topic is by Pindyck and Rotemberg (1990) who analyze excess correlation between seven commodities over a period of 25 years (1960-1985). The authors find that commodity prices move together in excess of what can be explained by the effects of common macroeconomic shocks and they interpret their results as evidence against the standard competitive model of price formation in commodity markets. Instead, they argue that herd behavior by financial speculators may serve as one possible explanation for their findings.

As a consequence of the synchronized boom-and-bust cycles in many commodity markets after 2006, academic interest in analyzing patterns and sources of co-movement among commodity prices re-emerged. This literature can be divided into two groups. The first group of studies employs latent factor models to filter out the common component of commodity prices, typically using low-frequency panel data sets (monthly, quarterly or yearly).[2] The second group of research articles resorts to data of higher frequency (daily or weekly), but these studies focus on bi-variate relationships, i.e., the link between commodity 1 and commodity 2, or the relationship between some type of commodity and different asset markets, without aiming to explain the systematic variation of a wide range of commodities.

Studies belonging to the first group include Byrne et al. (2013) who conduct a long-term factor analysis (1900-2008) based on yearly price data for 24 non-energy commodities. The analysis shows substantial co-movement due to a common factor. There is, however, large heterogeneity with regard to the importance of the first common factor across individual commodities. Using monthly prices of energy, metals and agricultural commodities, West and Wong (2014) show that commodity prices display a tendency to revert toward the common factor. Vansteenkiste (2009) provides evidence for a change in the degree of co-movement based on a state-space factor model model, using quarterly data of 32 non-energy commodities over the period 1957-2008. The findings suggest an upward trend in co-movement for the period after 2000, but the level of co-movement is found to be relatively higher in the 1970s and early-1980s. Evidence for a trend toward increasing commodity co-movement in recent years is also presented by Poncela et al. (2014), Yin and Han (2015), and Lübbers and Posch (2016).[3]

Similarly, factor models are used to analyze the macroeconomic determinants of commodity co-movement. Adopting a FAVAR model to a sample of 15 commodities, Lombardi et

[2]The only exception is the study by Lübbers and Posch (2016) in which daily data is used.

[3]Daskalaki et al. (2014) also contribute to the literature by testing the performance of a number of asset pricing models in explaining the cross-section of commodity futures returns. Besides several macro-models and equity-motivated tradable factor models, the authors also analyze the performance of various principal components asset pricing models. The study's results suggest that none of the factors is successful in explaining the cross-section of commodity futures returns.

al. (2012) find that the U.S. exchange rate and economic activity are important drivers of commodity price dynamics. West and Wong (2014) also report a strong correlation of the first factor with economic activity and the U.S. dollar exchange rate. Vansteenkiste (2009) and Kagraoka show that fluctuations in the oil price explain large proportions of the commodity factor. In addition, Byrne et al. (2013) and Poncela et al. (2014) document that commodity prices are negatively related to stock market uncertainty.

Another strand of the literature examines linkages between pairs of commodities or cross-market linkages between commodities and other asset markets by making use of daily or weekly returns data. While these studies assume a high-frequency perspective, they focus on bi-variate relationships without attempting to explain the systematic dependence structure. Du et al. (2011) and Nazlioglu et al. (2013) document significant volatility spillovers from oil prices to selected agricultural commodities during the (post-2006) high-volatility period in commodity markets. Beckmann and Czudaj (2014) investigate the bi-variate volatility transmission pattern among three U.S. agricultural futures markets (corn, wheat and cotton) and find significant volatility spillover effects. Evidence for causality-in-variance among major agricultural commodities is also presented by Gardebroek et al. (2016), relying on spot price data for corn, wheat and soybeans. Baur (2013) employs a quantile regression approach to analyze the relationship between daily gold returns and returns of the aggregate GSCI commodity index. Conducting a split-sample analysis, the findings suggest a change in the dependence structure for the post-2004 period (i.e., the period of financialization), with a stronger degree of co-movement when gold returns are around their median but a decoupling of gold and the basket of commodities when gold returns are in the extreme tails of the distribution, which can be explained by the role of gold as a safe-haven asset.

Studies focusing on the co-movement of commodity markets with other asset classes include Tang and Xiong (2012) who document a rise in correlation coefficients between the returns of the S&P GSCI and the S&P 500 during the 2008-09 financial crisis. They attribute this finding to increased macroeconomic uncertainty at the time and the process of financialization. Similarly, Adams and Glück (2015) detect a structural change in the bivariate correlation structure between individual commodities and stock markets around the time of the Lehman bankruptcy. Based on multivariate models with time-varying correlations and volatilities, Creti et al. (2013), Silvennoinen and Thorp (2013), and Büyüksahin and Robe (2014) also uncover increasing commodity-equity correlations during and after the financial crisis.

In this paper we combine elements of both literature strands discussed above and add important extensions to previous work. In this way, we produce several novel insights into the nature of commodity price dynamics and the consequences of financialization. Specifically, using a factor model approach to measure the systematic component of daily commodity price fluctuations in conjunction with the connectedness framework introduced by Diebold and Yilmaz (2012, 2014), our econometric setup is suitable to capture in quasi real-time the dynamic behavior of co-movement in commodity markets. Similarly, we are able to explain how co-movement is related to observable financial market conditions outside the commodity sector. One particular empirical relationship that we explore in this context is the impact of investors' risk aversion on commodity price dynamics. A few recent theoretical and empirical studies emphasize that the time-varying risk appetite of financial investors influences the price determination mechanism in commodity futures markets. For example, Cheng et al. (2015) find that during the global financial crisis financial commodity traders, such as commodity index investors and hedge funds, reduced their net long positions in a number of agricultural commodities as a result of heightened risk aversion.

3 Econometric Methodology

Our analysis is divided into two parts. In the first part we analyze the degree of co-movement among commodity returns and its time-varying nature. In the second part we aim to relate the co-movement to key economic and financial variables. We also identify the impact of specific economic events on commodity price dynamics.

3.1 Common Factors and Measurement of Co-Movement

Co-movements of asset prices reflect similar responses to common shocks, where the source of these shocks may be both endogenous and exogenous to the system of asset prices. Without specifying the source of shocks à priori, one can summarize the co-movement of commodity futures returns by a small number of common latent factors.[4] In extracting these factors we follow Stock and Watson (2002) and assume a factor model representation with r common latent factors. The factor model decomposes a vector of N observable commodity returns, $\boldsymbol{Y_t}$, into a $r \times 1$ vector of latent common factors $\boldsymbol{F_t}$ and an idiosyncratic component $\boldsymbol{u_t}$:

$$\boldsymbol{Y_t} = \boldsymbol{\lambda F_t} + \boldsymbol{u_t}, \tag{1}$$

where the latent factors have zero mean and unit variance, $\boldsymbol{F_t} \sim (0, 1)$, and $\boldsymbol{\lambda}$ represents a $N \times r$ matrix of factor loadings. We use the criteria proposed by Bai and Ng (2002) to determine the number of factors and then estimate Eq. (1) by the method of principal components analysis.

Next, we use the estimated common factors in our subsequent analysis of co-movement to control for systematic shocks that affect all commodities simultaneously. Our aim is to quantify co-movement among commodity futures returns in the connectedness-framework of Diebold and Yilmaz (2012, 2014), which builds on variance decompositions in VAR models to assess the interconnectedness of asset returns.[5] Specifically, we estimate two different versions of their proposed connectedness measure, allowing for a decomposition into common and idiosyncratic shocks as a source of interdependence. The first version measures *system-wide connectedness* of all commodity returns in the sample, which includes the interdependencies arising due to both common and idiosyncratic shocks. The second version

[4] An alternative approach would be to use a commodity index to summarize system-wide movements. However, the compilation of any index requires to pre-define the weights that are assigned to each asset in calculating the index. For example, the GSCI is a production-weighted index based on the 5-year average production quantity of each commodity. Hence, in contrast to the index-based approach, our latent factor framework lets the data determine the appropriate weights (namely the factor loadings).

[5] An earlier but less general version of this methodology is outlined in Diebold and Yilmaz (2009).

measures only *idiosyncratic connectedness* in commodity returns by removing the impact of the common factors from the measurement of interdependencies. By comparing both measures, we are able to assess the degree of systematic co-movement in commodity futures markets.

To arrive at the measure of *system-wide connectedness*, we write the following covariance stationary VAR with N endogenous variables:

$$\boldsymbol{Y_t} = \sum_{i=1}^{p} \boldsymbol{\Phi_i} \boldsymbol{Y_{t-i}} + \boldsymbol{\varepsilon_t}, \tag{2}$$

where $\boldsymbol{\varepsilon_t} \sim (0, \sum)$. The vector of endogenous variables $\boldsymbol{Y_t}$ contains the individual commodity returns and $\boldsymbol{\Phi_i}$ is a parameter matrix of dimension $N \times N$. We choose to estimate the VAR with four lags ($p = 4$) of the endogenous variables, but the robustness checks presented later indicate that our results are little affected by changes in the model's lag structure. The remaining residuals $\boldsymbol{\varepsilon_t}$ represent shocks that can be common to all commodities or specific to one particular commodity.

The model in Eq. (2) can be modified to include the r common factors as exogenous variables on the right-hand side of our VAR model, which serves as the basis for our measure of *idiosyncratic connectedness*:

$$\boldsymbol{Y_t} = \sum_{i=1}^{p} \boldsymbol{\Phi_i} \boldsymbol{Y_{t-i}} + \sum_{j=0}^{q} \boldsymbol{\Gamma_j} \boldsymbol{F_{t-j}} + \boldsymbol{\varepsilon_t}. \tag{3}$$

$\boldsymbol{F_t}$ represents the estimated common factors from Eq. (1) as contemporaneous control variables ($q = 0$), and $\boldsymbol{\Gamma}$ is the corresponding parameter matrix of dimension $N \times r$.[6] In Eq. (3), the remaining residuals $\boldsymbol{\varepsilon_t}$ represent idiosyncratic shocks to the system since the common factors remove the impact of the systematic component.

The models in Eqs. (2) and (3) can be expressed in their moving average representation

[6] Including lags of the endogenous variables but contemporaneous values of the exogenous factors ensures that there is no issue with regards to collinearity among the regressors.

as follows:

$$\boldsymbol{Y_t} = \sum_{i=0}^{\infty} \boldsymbol{A_i \varepsilon_{t-i}}, \tag{4}$$

where $\boldsymbol{A_i}$ is the matrix of moving average coefficients at lag i. These moving average coefficients are crucial for assessing the dynamics of the system. Using forecast error variance decompositions for h steps ahead enables to determine how much of the variance of each variable Y_i, for $i = 1, 2, ..., N$, is due to shocks to another variable included in the system. In calculating variance decompositions we adopt the generalized impulse-response framework of Koop et al. (1996) and Pesaran and Shin (1998). This approach accounts for correlated shocks across markets by using the historically observed distribution of the shocks. As a consequence, all estimation results are invariant to the ordering of variables in the VAR.

Defining θ_{ij} as the h-step-ahead error variance in forecasting variable Y_i that is due to shocks to variable Y_j, where $i, j = 1, 2, ...N$, we can obtain the relative contribution (in %) of each variable Y_j to the forecast error of variable Y_i by normalizing by the sum of all row entries in the variance decomposition matrix:

$$\gamma_{ij} = \frac{\theta_{ij}}{\sum_{j=1}^{N} \theta_{ij}} \times 100. \tag{5}$$

Each element γ_{ij} has a value between 0 and 100 and provides a quantitative measure for the pairwise directional connectedness from market j to market i. In this way, Diebold and Yilmaz (2012, 2014) define a connectedness table that contains all variance decompositions and the associated connectedness measures (see Appendix A for a detailed discussion of the derivation and interpretation of this table). Based on the estimates for pairwise directional connectedness, it is possible to construct an overall measure of connectedness among all variables in the system by summing all cross-market elements γ_{ij} $(i \neq j)$:

$$\gamma^{Total} = \frac{\sum_{i,j=1 i\neq j}^{N} \gamma_{ij}}{\sum_{i,j=1}^{N} \gamma_{ij}} = \frac{\sum_{i,j=1 i\neq j}^{N} \gamma_{ij}}{N}. \tag{6}$$

Depending on the underlying VAR model, we will call the measure γ^{Total} either *system-*

wide connectedness (model (2)) or *idiosyncratic connectedness* (model (3)). Comparing the dynamic behavior of both measures allows us to uncover changes in the degree of systematic co-movement over time. Consistent with Diebold and Yilmaz (2012), we use a 200-day rolling window to obtain time-varying parameters for the two variants of γ^{Total}.

3.2 Explaining Co-Movement: A FAVAR model

In the second part of our analysis we aim to determine the drivers of co-movement among commodity futures returns. To this end, we estimate a factor-augmented VAR (FAVAR) which besides the common factors includes a number of potential explanatory variables. As proposed by Bernanke et al. (2005) we first extract the common factors from our set of commodity returns according to Eq. (1) and then estimate the following model:

$$\begin{bmatrix} \boldsymbol{F_t} \\ \boldsymbol{X_t} \end{bmatrix} = \sum_{i=1}^{p} \boldsymbol{\Theta_i} \begin{bmatrix} \boldsymbol{F_{t-i}} \\ \boldsymbol{X_{t-i}} \end{bmatrix} + \boldsymbol{\nu_t}. \tag{7}$$

As before, $\boldsymbol{F_t}$ represents the vector of latent factors and $\boldsymbol{X_t}$ is the $k \times 1$ vector of observed explanatory variables.

To quantify the relationship between common factors and explanatory variables we remain in the connectedness-framework of Diebold and Yilmaz (2012, 2014). Accordingly, we estimate the model in Eq. (7) and conduct forecast error variance decompositions as outlined in the previous section. We then define pairwise directional connectedness from the explanatory variables to the common factor F_{it}, for $i = 1, ..., r$, as the fraction of the h-step ahead forecast error variance of F_{it} that can be attributed to shocks from each of the k explanatory variables. For example, consider a one-factor FAVAR with the factor ordered first and using the same notation as in the previous section, then the connectedness of the factor to variable X_n ($C_{X_n \to F_1}$), for $n = 1, ..., k$, is measured by the $j - th$ element in the first row of the connectedness table:

$$C_{X_n \to F_1} = \gamma_{1j}, \tag{8}$$

where $j = n + 1$. This framework can be easily generalized to a FAVAR with more than one latent factor.

Besides looking at the influence of individual variables on the commodity factor(s), it can be very informative to summarize the overall response of the commodity sector to shocks in other markets. In this vein, we can distill patterns and trends in the exposure of commodities to financial markets. Accordingly, the total directional connectedness from others to factor 1 ($C_{X \to F_1}$) is measured by aggregating all pairwise connectedness measures to factor 1:

$$C_{X \to F_1} = \sum_{j=2}^{N} \gamma_{1j}, \tag{9}$$

where $N = 1 + k$ is the total number of variables in the FAVAR.

4 Data

We use daily first nearby futures returns for all 18 non-energy commodities included in the Goldman Sachs Commodity Index (GSCI). We exclude energy commodities from our sample, because we want to isolate the portion of co-movement not attributable to changes in energy prices. We prefer to use data on futures price over spot prices for two main reasons. First, it is well documented that futures markets lead spot markets in terms of price discovery (see e.g., Yang et al. 2001; Narayan et al. 2013), implying that information is incorporated first into futures prices. Second, we expect that futures markets better capture the potential effects of speculation, since financial traders are typically not active in the underlying spot markets. The contracts included in the GSCI Non-Energy represent the most important futures contracts in terms of overall trading volume for the categories agriculture, livestock and metals. In addition, the commodities included in the GSCI are the most relevant in terms of production volume and consumption.

[Table 1 about here]

Our balanced data set runs from January 3, 1994 to August 31, 2016. The source of our data is Thomson Reuters Datastream. The descriptive statistics for the commodity returns are shown in Table 1. We use log-differences in our analysis to induce stationarity and standardize the data prior to factor extraction.

For our investigation of determinants, we consider the following economic and financial variables in our FAVAR analysis:

1. The U.S. dollar index futures traded at the Intercontinental Exchange (ICE) is used as our variable for the U.S. dollar exchange rate. As shown by Akram (2009), among others, commodity prices react to changes in the dollar exchange rate since most commodities are denominated in U.S. dollar. A weaker U.S. dollar can therefore contribute to higher commodity prices and vice versa.

2. We consider U.S. 10 year treasury bond yields as a measure for the interest rate. A decline in the interest rate increases demand for commodities because speculators shift out of treasury bonds and into commodities. A lower interest rate also decreases the supply of commodities as the cost for firms to carry inventories are lower (Frankel 2006).

3. The Morgan Stanley Capital International (MSCI) World Index of equity prices is used as a proxy for global economic conditions and world demand.

4. The MSCI Emerging Markets Index is taken as a proxy for economic conditions in emerging economies including China, Brazil and Russia. The rapid growth of emerging economies in the past 10-15 years has been identified as one explanation for the recent commodity price boom (Tang and Xiong 2012; Adams and Glück 2015).

5. The ICE Brent Crude Oil futures contract captures fluctuations in the oil price, which is a major component of input costs in processing commodities. Increasing oil prices are therefore equivalent to a supply shock for non-energy commodities. In addition,

the growing demand for biofuels in recent years may have strengthened the link between the oil price and agricultural commodities used in biofuel production (Baffes 2007; Nazlioglu et al. 2013; Baumeister and Kilian 2014).

To investigate whether the financialization of commodities has contributed to a larger sensitivity of commodity markets to overall risk in financial markets, we analyze the response of the common factor(s) to three different risk measures. The first measure is the widely used Chicago Board Options Exchange Volatility Index (VIX), which captures implied volatility of S&P 500 index options. This variable reflects markets' expectations of future stock market volatility and is therefore an indicator of stock market uncertainty.[7] In line with Geyer et al. (2004) and Gerlach et al. (2010), among others, we rely on U.S. corporate bond spreads as a second indicator of financial market risk. Specifically, we use the spread between the Bank of America (BofA) Merrill Lynch U.S. Corporate Master bond index and U.S. treasuries, which can be interpreted as an indicator of financing conditions in the corporate sector and consequently of investors' risk aversion. Finally, we approximate financial risk in emerging economies with corporate bond spreads in emerging markets, as measured by the difference between the BofA Merrill Lynch Emerging Markets Corporate Plus Index and a spot treasury curve.

[Table 2 about here]

We consider all of the above variables in daily log-returns. With the exception of corporate bond spreads, which we obtain from the database of the Federal Reserve Bank of St. Louis (FRED), all data for the explanatory variables are taken from Thomson Reuters Datastream. Consistent with the data on commodity futures returns, the sample period runs from January 3, 1994 to August 31, 2016 for all variables but the corporate bond spreads, for which data

[7] Cheng et al. (2015) use the VIX as a proxy for shocks to financial traders' risk aversion and study how this indicator affects financial traders' net long positions in agricultural futures markets. They find that during the financial crisis, increases in the VIX were associated with a decrease in financial traders' net long positions in 12 agricultural commodities.

are only available from January 4, 1999. Descriptive statistics for the explanatory variables are shown in Table 2 and confirm that all of our series are stationary in first-differences.

5 Empirical Results

In this section we present our main empirical findings along two dimensions. First, we report evidence on the degree and time-varying nature of commodity co-movement. Second, we address the financial drivers of co-movement in commodity markets, where a particular focus is put on the relation to financial risk.

5.1 Extent and Dynamic Nature of Co-Movement in Commodity Markets

We start our analysis by extracting the common latent factors from our panel of 18 non-energy commodities. Applying the Bai and Ng (2002) IC_{p2} information criterion to determine the number of common factors suggests the presence of two factors. Accordingly, we estimate two common factors by the method of principal components. Figures 1a and 1b, respectively, plot the two estimated factors over our sample period (1994-2016). In particular the first factor shows that commodity markets grow increasingly volatile after 2004, with the most notable cluster of large price changes in the period 2008-2010. In Figure 1c we construct indices of the factors by calculating their cumulative sum. The dynamics of both factor indices capture the boom and bust behavior of commodity markets after 2004. A comparison with the S&P GSCI Non-Energy reveals that our factor estimates deviate considerably from this popular index, which highlights that a production-weighted index such as the the S&P GSCI may not accurately reflect the common movements in commodity prices. This supports our empirical strategy to employ a latent factor model framework, because this data-driven approach is more suitable to summarize systematic price movements.

[Figure 1 about here]

Table 3 summarizes some statistics concerning the overall importance of the two factors in explaining the variance of the 18 commodity returns series. Considering the full-sample estimates, the R^2 for the first factor suggests that it can explain 25 percent of the variance in commodity returns and the second factor is able to explain another 13 percent. If we divide our sample in a pre- and post-2004 period (i.e., pre and post financialization period), our estimates show an increase in the R^2 for both factors from 0.32 (1994-2003) to 0.41 (2004-2016). This indicates that the co-movement among commodity futures returns becomes stronger in the period after 2004.

[Table 3 about here]

To gauge the importance of the common factors for individual commodity returns, Table 4 reports the individual R^2 for each of the series over the full-sample and over the sub-samples. As shown by these statistics, there is a large heterogeneity in the influence of the two factors across individual commodities. With regards to some commodities, the two factors explain only a small fraction of the price variations in these series. This includes the commodities coffee, sugar, cocoa, or the group of livestock commodities (lean hogs, live cattle, feeder cattle). It is also noteworthy that the influence of common factors does not increase substantially in the period after 2004 for this group of commodities. By contrast, the results for several other commodities in our sample (wheat, corn, soybean, and the group of metals) indicate a much greater dependence on movements in the common factors. In addition, the proportion of variance explained by the common factors increases in the second period for this group of commodities.

[Table 4 about here]

The results from our first pass of estimations reveal two key features. First, the degree of co-movement among the group of 18 commodities as a whole increases after 2004; and second, the relevance of common factors for individual price dynamics is not distributed equally across the different commodities. The latter finding confirms the heterogeneity of commodity markets reported in previous studies (see e.g., Brooks and Prokopczuk 2013; Daskalaki et al. 2014).

We next turn to the estimation results from our VAR model that includes all 18 commodity returns series. We apply the connectedness methodology proposed by Diebold and Yilmaz (2012, 2014) to quantify the extent and time-varying nature of co-movement among commodities. We therefore concentrate on a dynamic framework based on rolling sample estimations.[8] We employ two different specifications for our underlying VAR. The first specification includes all 18 commodity returns series as endogenous variables, omitting the common factors. This model explicitly allows for the possibility that connectedness arises because all commodities in the sample are hit by the same common shocks (*system-wide connectedness*). The second specification includes both common factors as exogenous variables in the VAR, thereby removing the impact of the systematic component from the measurement of connectedness (*idiosyncratic connectedness*).

[Figure 2 about here]

The estimation results are depicted in Figure 2 and provide strong evidence for a change in the degree of co-movement over time. Our sub-sample analysis of the factors in Table 3 has already signalled an increase in the importance of common factors in explaining movements of commodity returns. Our time-varying analysis confirms this trend and gives us a more detailed picture on the exact timing of the changes. While there is a very narrow gap between both measures of connectedness in the first ten years of our sample, indicating a modest extent of systematic co-movement, the gap widens considerably from early-2004 onwards, which illustrates the growing importance of common market shocks for commodity returns. The gap becomes particularly large between 2008 and 2013, corresponding to the

[8]For the sake of completeness and illustration of the methodology, we present the static connectedness table resulting from the VAR with both common factors as exogenous variables (Eq. (3)) for the full-sample period (1994-2016) in Appendix B (Table A.2).

period of high volatility in commodity markets. This suggests that system-wide shocks are an important source of overall connectedness between non-energy commodities in this period. It is also worth noting that co-movement weakens considerably from mid-2013, as evidenced by the very narrow gap between both measures in the last years of the sample.

5.2 The Drivers of Co-Movement in Commodity Markets

In the second part of our analysis we seek to isolate the determinants of commodity co-movement. In other words, our objective is to empirically determine the linkages between the commodity factor(s) and observable market conditions. To do so, we conduct 200-day rolling window estimations of the FAVAR model as detailed in Eq. (7) and quantify both pairwise and aggregate directional connectedness to the first commodity factor.[9]

5.2.1 The influence of financial and economic variables

In Figure 3 we present the results for the directional connectedness of the first commodity factor to shocks in each of the six explanatory variables.[10] In general, we see a great deal of variation in connectedness over the sample period, highlighting that commodity markets underwent different stages characterized by varying degrees of external influences. With a few exceptions, we find that connectedness is relatively low until 2004, but increases thereafter. Before 2004, there are two short-lived spikes in connectedness that stand out from the plots in Figure 3. The first is in 1997-1998 amid growing tensions in international financial markets due to the outbreak of the Asian financial crisis. Directional connectedness increases most visibly to the U.S.-dollar whose value appreciated because of its "safe-haven" status. Connectedness of commodities to emerging equity markets also jumps, showing that market participants feared the Asian crisis would translate into lower demand for commodities from

[9]We repeated the rolling window estimations with a FAVAR that includes both commodity factors and calculated the corresponding connectedness measures. As Figures A.1 and A.2 in Appendix C illustrate, the dynamic pattern is very similar since the second factor shows rather little exposure to shocks from other markets, indicating that the first factor absorbs the bulk of effects from shocks to the explanatory variables.

[10]We include only the VIX (stock market uncertainty) as a measure of risk in the baseline analysis due to data availability. We extend the analysis to other risk measures in Section 5.3.

emerging markets. The second spike in connectedness, particularly from equity markets and the U.S.-dollar, occurs in 2001 during the collapse of the dot-com bubble. However, in both cases connectedness returns quickly to its pre-crisis level in 2002. This changes at the end of 2003 as connectedness begins to rise to a persistently higher level, indicating that commodities showed a trend towards increasing integration with financial markets. Connectedness is particularly high during the 2007-09 global financial crisis and during the European sovereign debt crisis (2010-12).

[Figure 3 about here]

5.2.2 Aggregate connectedness and economic events

The changing nature of interactions between non-energy commodities and markets outside the non-energy commodity sector becomes all the more evident when looking at Figure 4. It depicts our aggregate connectedness measure summarizing the dynamic behavior of connectedness of the first commodity factor to all six explanatory variables. In the first ten years of the sample (1994-2003) aggregate connectedness fluctuates around a stable mean of around 20 percent. Starting in late-2003, however, we observe a steep upward trend that lasts until early-2010 as a result of which the level of connectedness roughly triples to a value of around 70 percent. Connectedness then remains at this high level for the next three years, before there is a rapid decline in mid-2013. At the end of the sample period, linkages between the commodity factor and explanatory variables start to increase again. Taken together, our dynamic connectedness analysis reveals that the systematic component of commodity returns, which is represented by the first common factor, is strongly linked to observable conditions in financial markets in the period after 2004.

[Figure 4 about here]

To shed more light on the driving forces underlying this trend, we provide a modified version of the connectedness plot that concentrates on the period from November 2003 until the end of the sample (Figure 5). It highlights a number of key economic events that have an influence on our measure of connectedness. We see that in the early stages (2004-2005), the prolonged weakness of the U.S. dollar is a major contributor to systematic price movements in commodity markets. Later, economic developments in emerging markets become increasingly important for commodity markets, as the strong growth rates of emerging economies lead to an all-time-high for the MSCI Emerging Markets in December 2007, thereby providing a reliable signal to market participants that the demand for commodities would remain solid. At the same time, oil prices experienced an unprecedented boom period, surpassing the 100 dollar threshold in March 2008 and peaking at more than 140 dollars in July 2008. Our results suggest that non-energy commodities were strongly connected to this oil price boom.

[FIGURE 5 about here]

The prolonged period of favorable economic conditions with strong demand for commodities was soon followed by market turmoil due to the outbreak of the global financial crisis in 2008. In the wake of the financial crisis, oil prices plunged by more than 50 percent within less than six months, further contributing to the rising level of aggregate connectedness. With the European sovereign debt crisis erupting in late-2009, uncertainties and risks over the course of the world economy remained high, which heavily impacted commodity price dynamics.[11] As financial markets calmed down in 2013 connectedness decreased visibly, putting an end to the long-lasting cycle of high and steadily rising connectedness of commodities to financial market events that had started in 2004. However, we observe another rise in connectedness in mid-2014 when sharp decreases in the price of oil and tensions in Chinese financial markets were important sources of shocks to the commodity factor.

[11]Our finding of high spillovers from stock markets to commodity markets after the Lehman bankruptcy is in line with the results of the related literature (see e.g., Creti et al. 2013; Adams and Glück 2015).

5.2.3 The impact of financial risk

The growing presence of financial investors in commodity markets may lead to a stronger exposure of commodities to risk in financial markets. The reason is that financial investors have a time-varying risk appetite, which may cause them to unwind positions during crisis periods (Cheng and Xiong 2014). In order to investigate the transmission of financial risk to commodity markets, we analyze the impact of three different risk measures on the commodity factor. Panel A of Figure 6 reports the results for the connectedness of the commodity factor to risk. The influence of stock market uncertainty increases markedly in 2007/08 with the beginning of the global financial crisis. Moreover, it continues to be a major contributor to commodity dynamics during the European sovereign debt crisis from 2010 until 2012. The connectedness to our second measure of financial risk, U.S. corporate bond spreads, also spikes in 2008 and even more in 2012. The pattern is somewhat different for our proxy of emerging markets' risk, as our estimates suggest a relatively modest degree of connectedness during the global financial crisis but a high level between 2012 and 2014. The financial turmoil in Chinese stock markets in 2015 and 2016 has also transmitted risk to commodity markets. Our results are consistent with Cheng et al. (2015) who find a strong correlation between weekly returns of the VIX and a set of individual commodity futures returns during the crisis period.

[FIGURE 6 about here]

To further investigate the link between financial risk and commodity markets, we present impulse response functions that show the response of the first commodity factor to a shock in each of the risk measures (Panel B of Figure 6).[12] The results for all three measures consistently indicate a negative response of the commodity factor to a shock in financial risk. In other words, commodity prices decrease as a result of heightened risk in global financial markets.

[12]We limit our sample for this analysis to the post-2004 financialization period.

5.3 Robustness Checks

We conclude our empirical analysis with an assessment of the sensitivity of our main results to changes in the model parameters. Figure 7 shows the plots for a number of robustness checks concerning both versions of the total connectedness measure. The first row shows the plots resulting from a VAR without common factors as exogenous variables (system-wide connectedness) and the second row shows the plots resulting from a VAR that includes the first two common factors (idiosyncratic connectedness). We explore robustness along three dimensions. First, we use alternative forecast horizons over the range from 6 to 12 days (column (a)). Second, in addition to a window size of 200 days, we also consider sample windows of 150, 175, 225 and 250 days in the rolling regressions (column (b)). Third, we also experiment with different lag structures in column (c), using a VAR with 2, 3, 4, 5, and 6 lags of the endogenous variables. Figure 7 reveals that the forecast horizon has little influence on the outcome, as the estimation results for the alternative horizons are in a very narrow band. The variation is larger with respect to the window size and the underlying lag structure. Nevertheless, the dynamic behavior of the total connectedness measures remain practically unaltered. In all cases system-wide connectedness starts to increase in 2004 and decreases in 2013 relative to idiosyncratic connectedness. The robustness checks hence confirm our baseline findings.

[Figures 7 and 8 about here]

Finally, in Figure 8 we implement the same set of robustness checks for the calculation of total directional connectedness of the first commodity factor to explanatory variables. As before, the forecast horizon has little impact, while results are in a slightly broader range when we change the window size or the lag structure. The dynamic pattern of the connectedness measure, however, does not change. This shows that our discussion in the previous section is still valid when we choose alternative model parameters.

6 Conclusions

Several commodity markets have recently experienced pronounced price spikes and crashes after decades of low volatility. At the same time, commodities have been increasingly regarded as a financial asset by portfolio investors. These developments raise the question as to whether the co-movement of commodity prices has increased in the past years and to what degree external financial factors have contributed to commodity dynamics. In this paper we provide a new perspective on this research question by combining a factor model approach with recent techniques to measure connectedness among asset returns. Our empirical investigation is based on daily data of 18 non-energy commodity futures returns over the period from January 1994 to August 2016. The results in the first part of our analysis reveal that co-movement starts to increase markedly in 2004 and reaches a particularly high level during the period of economic and financial turmoil from 2008 to 2013. Thereafter, the degree of commodity co-movement drops substantially, returning almost to its pre-2004 level.

In the second part of our analysis, we seek to isolate the determinants of co-movement in commodity markets. Our findings suggest that outside financial markets contribute strongly to commodity co-movement in the post-2004 period. The most influential variables are the price of oil, the global stock market index, the emerging markets stock index, and the U.S. dollar exchange rate. We also show that financial risk, proxied by three different measures, played an important role for commodity markets over the past decade. Connectedness of the commodity factor(s) to our set of financial variables is especially large during periods of market turmoil, indicating that the process of financialization led to a greater integration of commodities with outside financial markets. Our findings have important implications for the risk-transfer function of commodity futures markets, the diversification benefits of commodity investments, and the financial stability of commodity-producing economies.

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Table 1: Descriptive statistics of commodity returns

	Mean	Median	Std. Dev.	Skewness	Kurtosis	ADF Test
Agriculture						
CBT Wheat	-0.0501	-0.0005	1.9308	0.2098	5.5442	-74.0584***
KBT Wheat	-0.0004	0.0000	1.7373	0.0381	5.4150	-72.4183***
Corn	-0.0003	0.0000	1.7752	-0.4230	12.7516	-71.6135***
Soybean	0.0054	0.0461	1.5745	-0.8290	10.2290	-75.0972***
Coffee	0.0124	0.0000	2.4700	0.4001	9.6461	-76.0823***
Sugar	0.0110	0.0000	2.1477	-0.2861	6.6786	-75.8035***
Cocoa	0.0164	0.0000	1.8926	-0.0449	6.0918	-75.1530***
Cotton	-0.0006	0.0000	1.8895	-1.1205	25.6310	-72.0218***
Livestock						
Lean Hogs	0.0000	0.0058	2.1373	0.9911	33.4148	-73.6332***
Live Cattle	0.0068	0.0000	1.0598	-0.1108	9.7034	-71.9561***
Feeder Cattle	0.0099	0.0000	0.9416	-0.2235	7.2491	-68.0713***
Metals						
Aluminum	0.0065	0.0000	1.3190	-0.1685	5.3723	-76.5326***
Copper	0.0170	0.0054	1.6567	-0.1507	7.7190	-78.3647***
Lead	0.0246	0.0121	1.9320	-0.1889	6.6388	-71.2680***
Nickel	0.0109	-0.0250	2.2352	-0.1280	6.7372	-74.6871***
Zinc	0.0146	0.0000	1.7708	-0.1887	6.7973	-76.2545***
Gold	0.0213	0.0000	1.0788	-0.0719	9.9045	-75.3051***
Silver	0.0226	0.0587	1.9208	-0.7502	10.4135	-76.9674***

Note: The table reports descriptive statistics for the log-differences (multiplied by 100) of all sample commodities in the period January 3, 1994-August 31, 2016. "ADF Test" refers to the Augmented-Dickey-Fuller (ADF) test where we include a constant in each test equation and select the lag structure based upon the Schwarz criterion. Critical values are taken from MacKinnon et al. (1999). *, **, *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

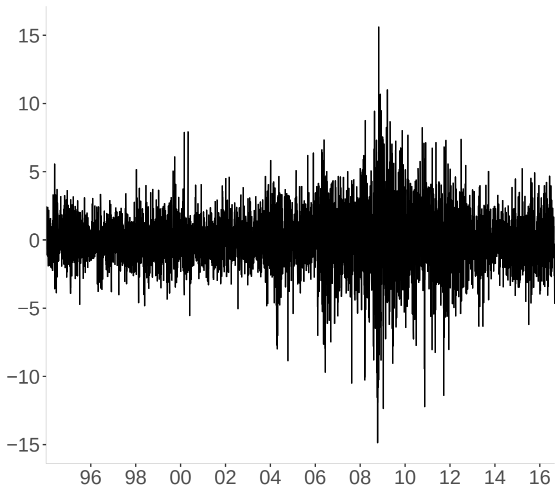
Table 2: Descriptive statistics of financial and economic variables

	Mean	Median	Std. Dev.	Skewness	Kurtosis	ADF Test
Standard explanatory variables						
US-Dollar	-0.0003	0.0000	0.5302	-0.0726	4.7074	-76.9340***
US 10yr Bond	-0.0236	-0.0407	1.7690	-0.012	7.8180	-75.3319***
MSCI World	0.0188	0.0646	0.9890	-0.3777	10.5361	-52.6392***
MSCI EM	0.0089	0.0726	1.2212	-0.5403	10.3957	-59.5928***
Oil Price	0.0226	0.0742	2.2121	-0.1572	6.0307	-79.2599***
Financial risk measures						
VIX	0.0011	-0.3323	6.4217	0.6455	6.7485	-39.1259***
U.S. bond spreads	0.0035	0.0000	1.1621	0.8404	19.7197	-19.9066***
EM bond spreads	-0.0002	0.0000	0.0132	0.2723	11.5082	-23.5614***

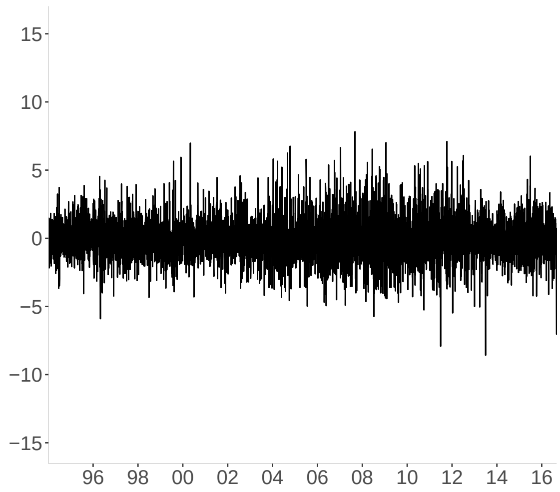
Note: The table reports descriptive statistics for the log-differences (multiplied by 100) of all financial and economic variables used in the FAVAR analysis. The sample period runs from January 3, 1994 to August 31, 2016 for all variables but U.S. corporate bond and EM bond spreads, where data availability limits the beginning of the sample period to January 4, 1999. "ADF Test" refers to the Augmented-Dickey-Fuller (ADF) test where we include a constant in each test equation and select the lag structure based upon the Schwarz criterion. Critical values are taken from MacKinnon et al. (1999). *, **, *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

Figure 1: Factor estimates of commodity returns

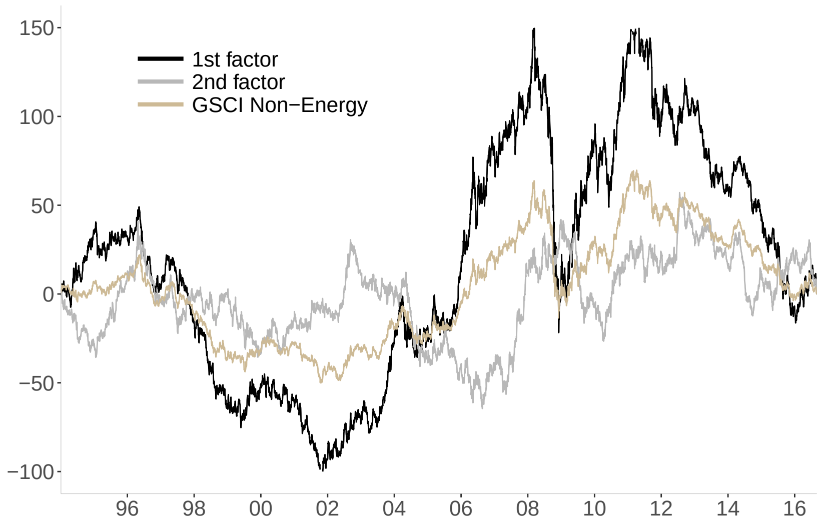
(a) First factor



(b) Second factor



(c) Cumulative factor returns



Note: Figures (a) and (b) plot the estimates of the first and second common factor, respectively, as defined by the model outlined in Eq. (1). Figure (c) depicts the cumulative sum of the two common factors along with the cumulative sum of the (standardized) returns of the GSCI Non-Energy.

Table 3: Overall importance of common factors for index-commodities

Sample period	Number of factors	R^2	Marginal R^2
1994-2016	1	0.25	0.25
	2	0.38	0.13
1994-2003	1	0.17	0.17
	2	0.32	0.15
2004-2016	1	0.28	0.28
	2	0.41	0.13

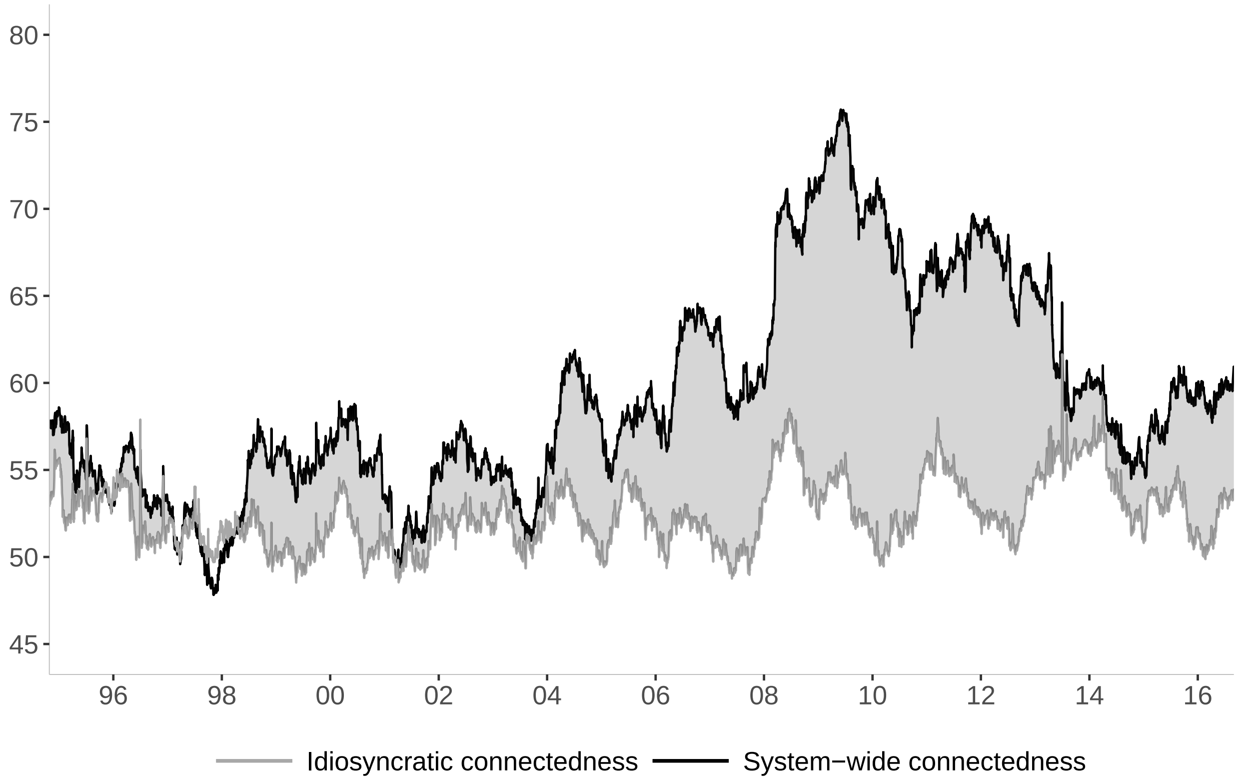
Note: This table shows how much of the variance of all 18 commodity series is explained by the two common factors over different sample periods.

Table 4: Importance of common factors for individual commodities

	R^2		
	1994-2016	1994-2003	2004-2016
CBT Wheat	0.79	0.74	0.80
KBT Wheat	0.76	0.71	0.77
Corn	0.67	0.63	0.68
Soybean	0.47	0.46	0.47
Coffee	0.09	0.03	0.17
Sugar	0.10	0.01	0.17
Cocoa	0.08	0.03	0.12
Cotton	0.13	0.05	0.19
Lean Hogs	0.01	0.01	0.02
Live Cattle	0.03	0.02	0.05
Feeder Cattle	0.06	0.10	0.04
Aluminum	0.61	0.57	0.64
Copper	0.69	0.57	0.74
Lead	0.58	0.47	0.61
Nickel	0.51	0.52	0.53
Zinc	0.68	0.55	0.71
Gold	0.26	0.10	0.31
Silver	0.35	0.13	0.42

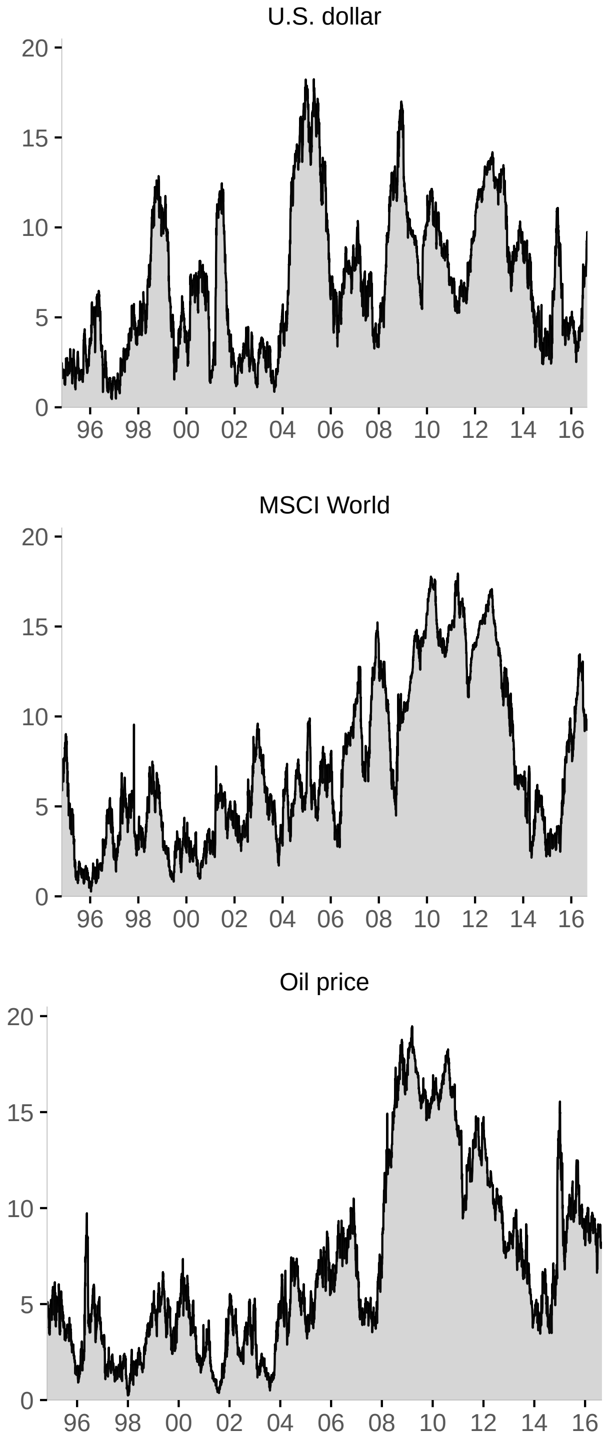
Note: The R^2 statistic measures the fraction of the variation in each individual series explained by the common factors. A higher R^2 indicates a larger link between the individual series and the common components.

Figure 2: Total connectedness of commodities



Note: The above figure shows the results from calculating time-varying parameters of the overall connectedness measure written in Eq. (6), using a rolling-window of 200 days and a forecast horizon of 10 days for the underlying variance decomposition. Two specifications are used for the underlying VAR: The black line refers to the model which omits the common factors from the system of VAR equations (see Eq. (2)), the gray line refers to the model which includes the two common factors as exogenous variables (see Eq. (3)).

Figure 3: Time-varying connectedness of first commodity factor to explanatory variables

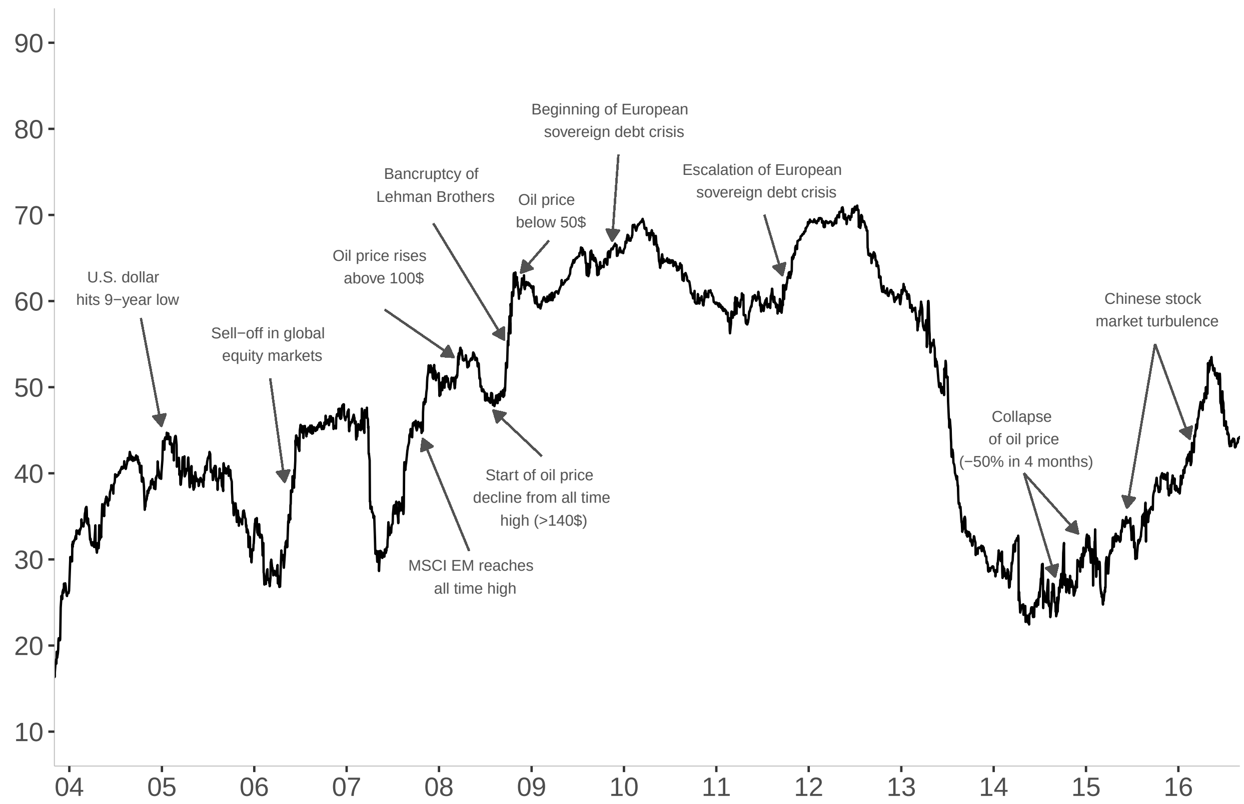


Note: The graph depicts pairwise directional connectedness of the first commodity factor to shocks from each of the FAVAR variables as defined in Eq. (8), using a rolling window size of 200 days and a forecast horizon of 10 days for the underlying variance decomposition.

Figure 4: Time-varying total connectedness of first commodity factor to explanatory variables

Note: The graph shows the sum of pairwise directional connectedness of the first commodity factor to shocks from the explanatory variables, using a rolling window size of 200 days.

Figure 5: Total directional connectedness and economic events: 11/2003-08/2016

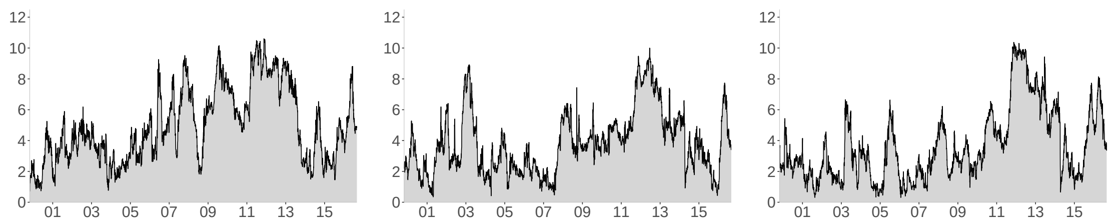


Note: The graph shows the sum of pairwise directional connectedness from the explanatory variables to the first commodity factor starting in November 2003. FED: Federal Reserve System; MSCI EM: MSCI Emerging Markets stock index; PBC: People's Bank of China.

Figure 6: Impact of financial risk measures on commodity factor

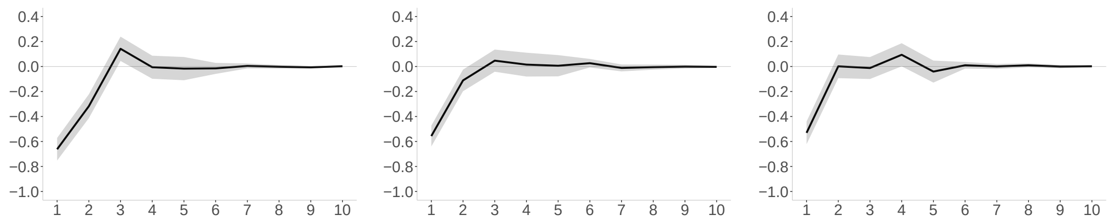
Panel A: Connectedness to risk

(a) Stock market uncertainty (b) U.S. corporate risk (c) Emerging markets risk



Panel B: Impulse responses

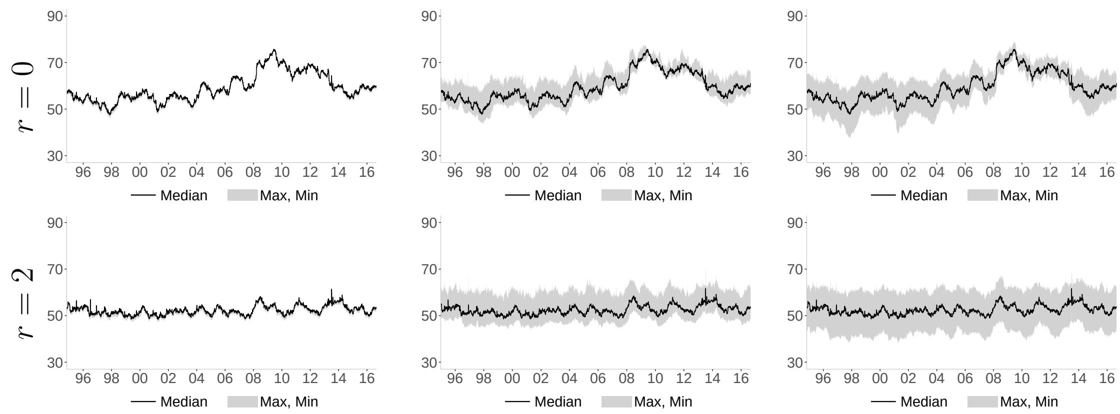
(a) Stock market uncertainty (b) U.S. corporate risk (c) Emerging markets risk



Note: This table reports the impact of three different financial risk measures on the first commodity factor. Stock market uncertainty is captured by the VIX, U.S. corporate risk is represented by U.S. corporate bond spreads, and emerging market risk is proxied by corporate bond spreads in emerging economies. The first row (Panel A) shows pairwise directional connectedness of each of the risk measures to the first commodity factor. Due to data constraints, the sample period for the second and third risk measure begins on January 4, 1999. The second row (Panel B) shows the generalized impulse responses (Pesaran and Shin 1998) of the commodity factor to a one standard deviation shock in each of the risk measures (the shaded area represents the corresponding two standard deviation error bands). The sample period for the impulse response analysis is from January 2, 2004 to August 31, 2016 (i.e., the period of financialization). Along with the commodity factor and the respective risk measure, the FAVAR model used in each of the estimations includes the five explanatory variables from the previous sections to control for other influences.

Figure 7: Robustness checks for total connectedness measure

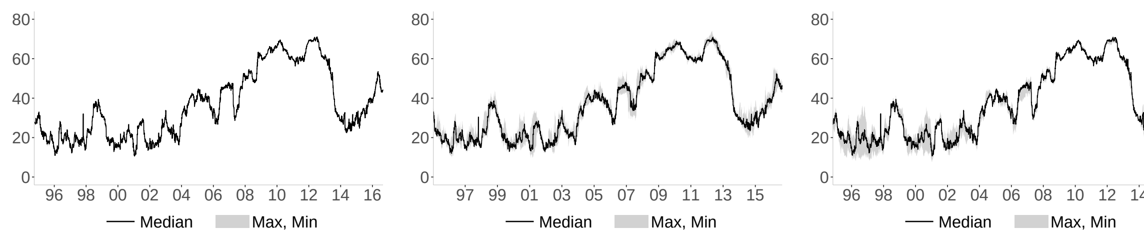
(a) Forecast horizon (b) Window size (c) Lag structure



Note: The robustness checks are conducted for the VAR model without common factors as exogenous variables ($r = 0$: system-wide connectedness) and for the model with two common factors ($r = 2$: idiosyncratic connectedness). In (a) we use a range of different forecast horizons from 6 to 12 days; in (b) we experiment with changing the window size in our rolling regressions (150, 175, 200, 225, and 250 days); and in (c) we test the impact of changes in the lag structure (from 2 to 6 lags). In each graph, the solid line corresponds to the median values and the shaded area depicts the minimum and maximum values across the variety of specifications.

Figure 8: Robustness checks for directional connectedness of the first factor

(a) Forecast horizon (b) Window size (c) Lag structure



Note: The robustness checks are conducted for the FAVAR model as specified in Eq. (7). In column (a) we use a range of different forecast horizons from 6 to 12 days; in column (b) we experiment with changing the window size in our rolling regressions (150, 175, 200, 225, and 250 days); and in column (c) we test the impact of changes in the lag structure (from 2 to 6 lags). In each graph, the solid line corresponds to the median values and the shaded area depicts the minimum and maximum values across the variety of specifications.

Appendix A: Description of connectedness table

Table A.1: The connectedness table

from variable	Y_1	Y_2		Y_N	From others
to variable					
Y_1	γ_{11}	γ_{12}	$\cdots$	γ_{1N}	$\sum_{\substack{j=1\\j\neq 1}}^{N} \gamma_{1j}$
Y_2	γ_{21}	γ_{22}	$\cdots$	γ_{2N}	$\sum_{\substack{j=1\\j\neq 2}}^{N} \gamma_{2j}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$		$\vdots$
Y_N	γ_{N1}	γ_{N2}	$\cdots$	γ_{NN}	$\sum_{\substack{j=1\\j\neq N}}^{N} \gamma_{Nj}$
To others	$\sum_{\substack{i=1\\i\neq 1}}^{N} \gamma_{i1}$	$\sum_{\substack{i=1\\i\neq 2}}^{N} \gamma_{i2}$	$\cdots$	$\sum_{\substack{i=1\\i\neq N}}^{N} \gamma_{iN}$	$\frac{1}{N}\sum_{\substack{i,j=1\\i\neq j}}^{N} \gamma_{ij} = \gamma^{Total}$

Note: The table illustrates the construction of the connectedness measures as proposed by Diebold and Yilmaz (2012, 2014), where γ_{ij} has a value between 0 and 100 and provides a quantitative measure for the connectedness of market i to shocks in market j. N denotes the number of variables in the system of VAR equations.

Based on forecast error variance decompositions in VAR models, Diebold and Yilmaz (2012, 2014) define a connectedness table, alternatively called a "spillover matrix", that is illustrated in Table A.1. The first row of Table A.1, for example, contains all γ_{1j}, for $j = 1, 2, ..., N$, and can be interpreted as the connectedness of market 1 to shocks in other markets. For example, the pairwise directional connectedness from market 2 to market 1 ($C_{Y_2 \to Y_1}$) is captured by γ_{12}. The first column of Table A.1 includes all γ_{i1}, for $i = 1, 2, ..., N$, and measures the connectedness of other markets to shocks in market 1. The entries on the diagonals measure how much a market's own shocks contribute to its forecast error variance (*own connectedness*). By summing all off-diagonal entries of the connectedness table either across rows or across columns, we can summarize total directional connectedness of each variable to shocks from all others (row sums) and the total directional connectedness to others from each variable (column sums). To obtain the total connectedness measure (γ^{Total}) in the last row and column of Table A.1, we sum all cross-market variance shares and normalize through dividing by the number of variables N.

Appendix B: Static estimation of the connectedness table

Table A.2 is the empirical counterpart to Table A.1 in Appendix A. For the purpose of facilitating the interpretation of the connectedness table, we illustrate pairwise directional connectedness by means of different color levels. The overall pattern that emerges from Table A.2 is that connectedness is strong between commodities of the same sector, for example, between wheat and soybean or between gold and silver, whereas connectedness across sectors is generally weak. This is expected given that the common factors remove the impact of shocks that are common to all markets. In addition, there is a large heterogeneity in the strength of own connectedness (diagonal values) across markets. The commodities with the highest own connectedness, including coffee (89.88), sugar (88.15), cocoa (90.05) and lean hogs (93.30), are relatively isolated from shocks in other markets. The value in the last column and row (27.90) is the measure for total connectedness (γ^{Total}). Since the connectedness table above is derived from the VAR model in Eq. (3), which includes two common factors as exogenous variables, this is the static measure for *idiosyncratic connectedness*.

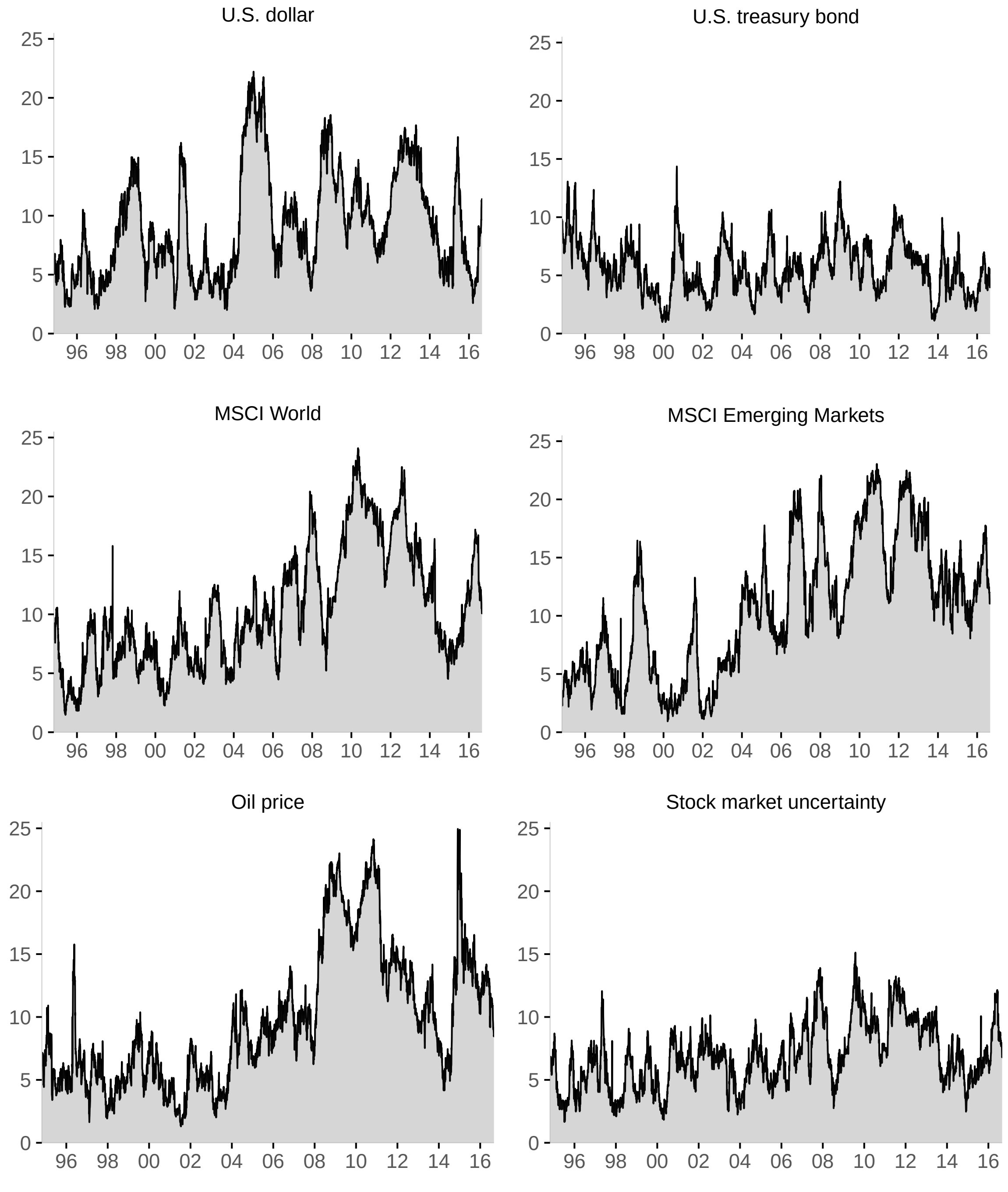
Table A.2: Empirical connectedness table

TO \ FROM	CBT Wheat	KBT Wheat	Corn	Soybean	Coffee	Sugar	Cocoa	Cotton	Lean Hogs	Live Cattle	Feeder Cattle	Aluminum	Copper	Lead	Nickel	Zinc	Gold	Silver	From others
CBT Wheat	46.04	18.39	8.28	13.45	1.06	1.55	0.72	2.06	0.06	0.15	1.42	0.53	0.37	0.99	0.65	1.03	1.34	1.92	53.96
KBT Wheat	18.35	45.72	11.56	12.14	1.03	1.27	0.79	1.91	0.14	0.26	0.99	0.40	0.73	0.72	0.51	0.85	1.04	1.60	54.28
Corn	11.68	16.36	65.14	0.42	0.83	0.80	0.46	0.93	0.11	0.17	0.07	0.28	0.11	0.30	0.25	0.47	0.88	0.75	34.86
Soybean	18.24	16.58	0.45	62.14	0.42	0.53	0.07	0.27	0.17	0.09	0.21	0.08	0.03	0.03	0.01	0.07	0.44	0.18	37.86
Coffee	2.09	2.09	1.11	0.78	89.88	0.45	0.58	0.01	0.06	0.05	0.14	0.54	0.53	0.55	0.35	0.55	0.19	0.04	10.12
Sugar	2.89	2.28	1.13	0.70	0.37	88.15	0.23	0.46	0.12	0.06	0.05	0.65	0.75	0.69	0.38	0.76	0.19	0.13	11.85
Cocoa	1.35	1.58	0.66	0.14	0.58	0.25	90.05	0.10	0.11	0.09	0.09	0.84	1.34	0.50	1.16	1.08	0.04	0.03	9.95
Cotton	3.93	3.66	1.27	0.34	0.02	0.46	0.05	86.90	0.13	0.05	0.16	0.31	0.73	0.42	0.13	0.88	0.31	0.25	13.10
Lean Hogs	0.08	0.24	0.08	0.32	0.07	0.21	0.07	0.14	93.30	0.08	3.52	0.32	0.51	0.15	0.11	0.26	0.30	0.22	6.70
Live Cattle	0.22	0.44	0.21	0.05	0.02	0.09	0.03	0.15	0.03	67.06	27.04	0.53	0.76	0.98	0.70	1.21	0.33	0.16	32.94
Feeder Cattle	1.95	1.40	0.09	0.06	0.10	0.08	0.01	0.13	2.33	25.40	63.07	0.74	0.92	0.96	0.64	1.39	0.47	0.25	36.93
Aluminum	0.89	0.73	0.34	0.04	0.47	0.56	0.77	0.35	0.25	0.66	1.11	79.35	0.10	2.79	1.19	0.74	4.64	5.02	20.65
Copper	0.66	1.30	0.11	0.03	0.49	0.70	1.16	0.64	0.36	0.95	1.11	0.07	79.51	1.44	0.50	0.52	4.91	5.53	20.49
Lead	1.64	1.22	0.31	0.06	0.39	0.58	0.51	0.36	0.13	1.03	1.16	2.60	1.54	77.04	1.20	0.18	4.69	5.37	22.96
Nickel	1.05	0.96	0.29	0.09	0.27	0.33	1.03	0.21	0.06	0.91	0.96	1.21	0.64	1.17	79.01	1.20	4.88	5.74	20.99
Zinc	1.83	1.33	0.55	0.13	0.48	0.72	0.97	0.79	0.22	1.33	1.67	0.75	0.57	0.19	1.15	75.77	5.49	6.05	24.23
Gold	1.58	1.26	0.79	0.40	0.09	0.13	0.04	0.25	0.18	0.32	0.40	3.19	3.45	3.37	3.34	4.04	55.34	21.82	44.66
Silver	2.22	1.92	0.65	0.17	0.04	0.12	0.01	0.16	0.12	0.10	0.27	3.34	3.71	3.80	3.88	4.30	21.28	53.90	46.10
To others	70.64	71.74	27.88	29.32	6.72	8.83	7.51	8.92	4.58	31.71	40.37	16.37	16.80	19.04	16.15	19.52	51.43	55.08	**27.90**

Note: The above table shows the results from estimating the VAR written in Eq. (3) over the full sample (1994-2016) and using the connectedness measurement methodology proposed by Diebold and Yilmaz (2012, 2014). The intensity of directional connectedness between variables is indicated by the color of the corresponding cell (white signifies no connectedness and bright red signifies very strong connectedness). The parameters within the black frame represent connectedness between commodities in the same sector (*intra-sectoral connectedness*), namely agriculture, livestock and metals.

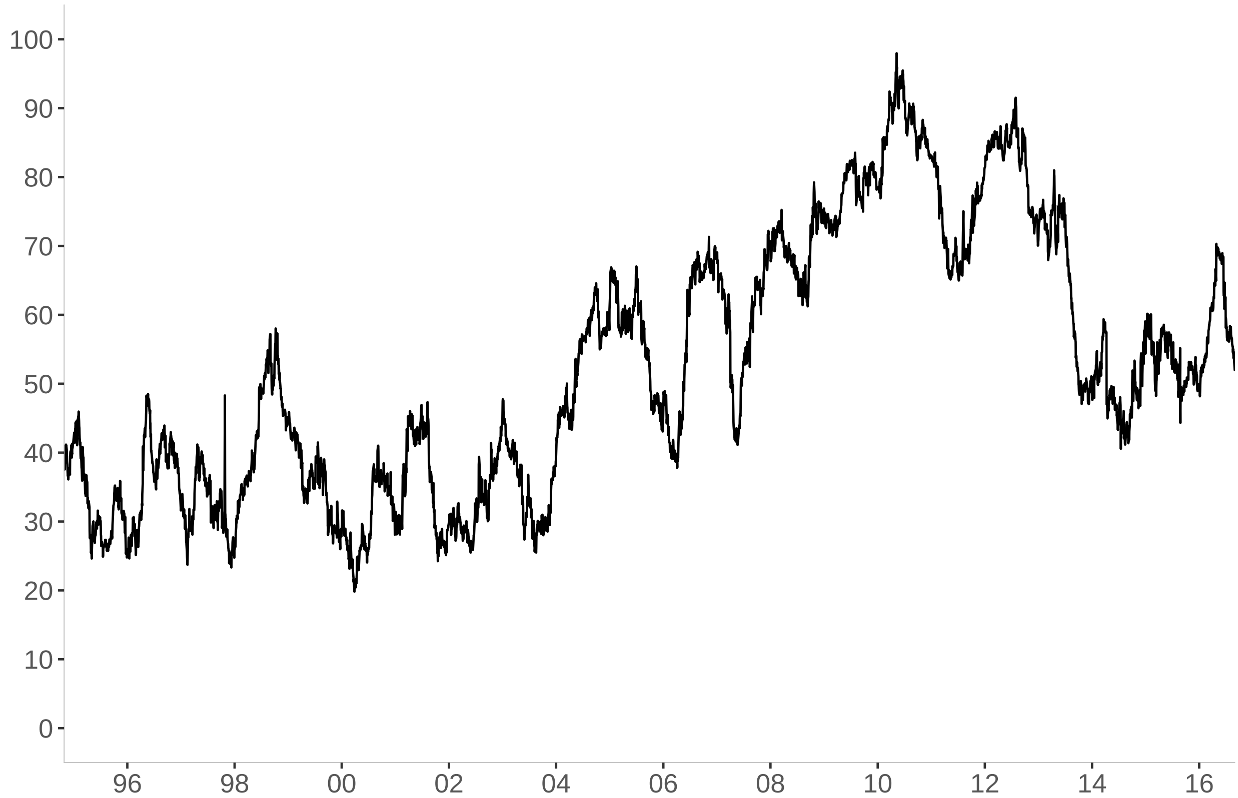
Appendix C: Estimation results for FAVAR with two common factors

Figure A.1: Connectedness of first and second commodity factor to explanatory variables



Note: The graph depicts the sum of directional connectedness of the first and second commodity factor to shocks in each of the explanatory variables as defined in Eq. (8), using a rolling window size of 200 days and a forecast horizon of 10 days for the underlying variance decomposition.

Figure A.2: Total directional connectedness from explanatory variables to first and second factor: 1994-2016



Note: The graph shows the sum of pairwise directional connectedness from the explanatory variables to the first and second commodity factor over the full-sample period.