Commodity Connectedness

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Abstract: We use variance decompositions from high-dimensional vector autoregressions to we characterize connectedness in 19 key commodity return volatilities, 2011-2016. We study both static (full-sample) and dynamic (rolling-sample) connectedness. We summarize and visualize the results using tools from network analysis. The full-sample results reveal clear clustering of commodities into groups that match traditional industry groupings, but with some notable differences. The energy sector is most important in terms of sending shocks to others, and energy, industrial metals, and precious metals are themselves tightly connected.

Key Words: network centrality, network visualization, pairwise connectedness, total directional connectedness, total connectedness, vector autoregression, variance decomposition, lasso

JEL codes: G1, C3

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1 Introduction

Commodities and commodity markets play a central role in the global economy.[1] Hence commodity market developments are widely chronicled and followed.[2] Commodities are a key input to all countries' production, and a key output of many emerging economies, so fluctuations in commodity prices may contribute strongly to common business cycle fluctuations in emerging economies and beyond, as emphasized by Fernández et al. (2015). Commodities have also emerged as important financial asset classes (e.g., energy, agriculture, metals), with properties different from those of "traditional" asset classes like stocks, bonds, and foreign exchange, as emphasized by Kat and Oomen (2007a) and Kat and Oomen (2007b).

Understanding *connectedness*, which is central to risk measurement and management, seems particularly important in the commodities context, particularly for emerging economies relying heavily on commodities production. Relevant aspects include connectedness across firms, markets, and countries, both real and nominal/financial. On the real side we have in mind things like connectedness in GDP growth. On the nominal side we have in mind things like connectedness of commodity company stocks (both within and across countries), and connectedness of commodity prices.

Moreover, connectedness measurement in real time may be of special relevance for policy. Successful real-time policy formation and analysis (and *all* policy is real-time) demands real-time monitoring, often exploiting high-frequency data.[3] As we shall later describe in detail, the daily commodity volatilities that we study in this paper are in precisely that tradition, built from key parts of trade-by-trade intra-day price paths.

Several approaches to connectedness measurement have been considered recently.[4] Billio et al. (2012) use pairwise Granger causality. Bonaldi et al. (2013) work with vector autoregressions (VAR's), which allow for full multivariate dynamic cross-variable interaction and hence richer measures than pairwise. Demirer et al. (2015) also use VAR's, but they use variance decompositions, which account for shock correlation in addition to dynamic cross-variable interaction.[5] The Demirer et al. (2015) framework allows measurement of

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[1]For a broad overview from an empirical perspective, see Chevallier and Ielpo (2013).

[2]See, for example, the World Bank Commodity Market Outlook, `http://www.worldbank.org/en/research/commodity-markets`.

[3]See, for example, John Taylor's inaugural Feldstein Lecture at the National Bureau of Economic Research, `http://www.nber.org/feldstein_lecture/feldsteinlecture_2009.html`)

[4]For an interpretive survey see Kara et al. (2015).

[5]The Demirer et al. (2015) framework extends earlier work by Diebold and Yilmaz, including Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014) by using network visualization methods to understand variance decompositions.

connectedness at levels ranging from highly granular to highly aggregative, with close connections to marginal expected shortfall or S-risk (Acharya et al. (2010)) and CoVaR (Adrian and Brunnermeier (2016)).

In this paper, we characterize global commodity market connectedness using the Demirer et al. (2015) framework. This is of interest in a variety of contexts, ranging from private-sector investment management strategies (portfolio concentration risk is directly related to connectedness) to public-sector monitoring and policy formulation (connectedness tends to increase during commodity-market crises, which may then spill over into the broader macroeconomy).

We proceed as follows. In section 2 we discuss our commodity price indexes, our construction and verification of realized return volatility, and our framework for measuring commodity volatility connectedness. In section 3 we provide benchmark results for static connectedness, and in section 4 we provide results for dynamic connectedness. We conclude in section 5, and we explore variations and extensions in several appendices.

2 Commodities Data, Volatility, and Connectedness

In this section we describe our commodities data – prices, returns, and range-based return volatilities – and their properties.

2.1 Spot Indices

We study nineteen sub-indices of the Bloomberg Commodity Price Index: four energy commodities (crude oil, heating oil, natural gas, unleaded gasoline), two precious metals (gold, silver), four industrial metals (aluminum, copper, nickel, zinc), two livestock commodities (live cattle, lean hogs), four grains (corn, soybeans, soybean oil, wheat), and three "softs" (coffee, cotton, sugar). It is important to note that the category labeling is not ours; rather, it is standard among industry participants, which will subsequently be of interest later when interpreting our empirical results.[6] Details on the underlying contracts, and the exchanges on which they are traded, appear in Table 1.[7]

The nineteen sub-indices that we study are those underlying the Bloomberg Commodity Price Index when we obtained our data sample.[8] Our data are daily, 2006/5/11 - 2016/1/25,

[6]See Bloomberg (2016).

[7]Based on Bloomberg (2016), Table 2.

[8]Subsequently Bloomberg (2016) slightly enlarged the set of underlying sub-indices.

Table 1: Commodity Contracts

Commodity	Designated Contract	Exchange	Units	Price Quote
Natural Gas	Henry Hub Natural Gas	NYMEX	10,000 mmbtu	USD/mmbtu
WTI Crude Oil	Light, Sweet Crude Oil	NYMEX	1,000 barrels	USD/barrel
Unleaded Gasoline	RBOB	NYMEX	42,000 gal	U.S. cents/gallon
ULS Diesel (Heating Oil)	ULS Diesel	NYMEX	42,000 gallons	U.S. cents/gallon
Live Cattle	Live Cattle	CME	40,000 lbs	U.S. cents/pound
Lean Hogs	Lean Hogs	CME	40,000 lbs	U.S. cents/pound
Wheat	Soft Wheat	CBOT	5,000 bushels	U.S. cents/bushel
Corn	Corn	CBOT	5,000 bushels	U.S. cents/bushel
Soybeans	Soybeans	CBOT	5000 bushels	U.S. cents/bushel
Soybean Oil	Soybean Oil	CBOT	60,000 lbs	U.S. cents/pound
Aluminum	High Grade Primary Aluminum	LME	25 metric tons	USD/metric ton
Copper	Copper	COMEX	25,000 lbs	U.S. cents/pound
Zinc	Special High Grade Zinc	LME	25 metric tons	USD/metric ton
Nickel	Primary Nickel	LME	6 metric tons	USD/metric ton
Gold	Gold	COMEX	100 troy oz.	USD/troy oz.
Silver	Silver	COMEX	5000 troy oz.	U.S. cents/troy oz.
Sugar	World Sugar No. 11	NYBOT	112,000 lbs	U.S. cents/pound
Cotton	Cotton	NYBOT	50,000 lbs	U.S. cents/pound
Coffee	Coffee 'C'	NYBOT	37,500 lbs	U.S. cents/pound

with holidays and weekends dropped. This results in 2,443 observations per series, for a total of $2443 \times 19 = 46,417$ observations. We show time-series plots of log sub-indices in Figure 1.

2.2 Realized Volatility

We define commodity returns as change in log price, and we study daily range-based realized commodity-return volatility. That is, following Garman and Klass (1980) we construct range-based realized volatility (variance) as:

$$\begin{aligned}\hat{\sigma}^2_{it} &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &\quad -2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2, \end{aligned} \tag{1}$$

where H_{it}, L_{it}, O_{it} and C_{it} are, respectively, the logs of daily high, low, opening, and closing prices for commodity i on day t.

Range-based realized volatility is almost as efficient as realized volatility based on ultra-

Figure 1: Time Series Plots of Log Commodity Sub-Indices

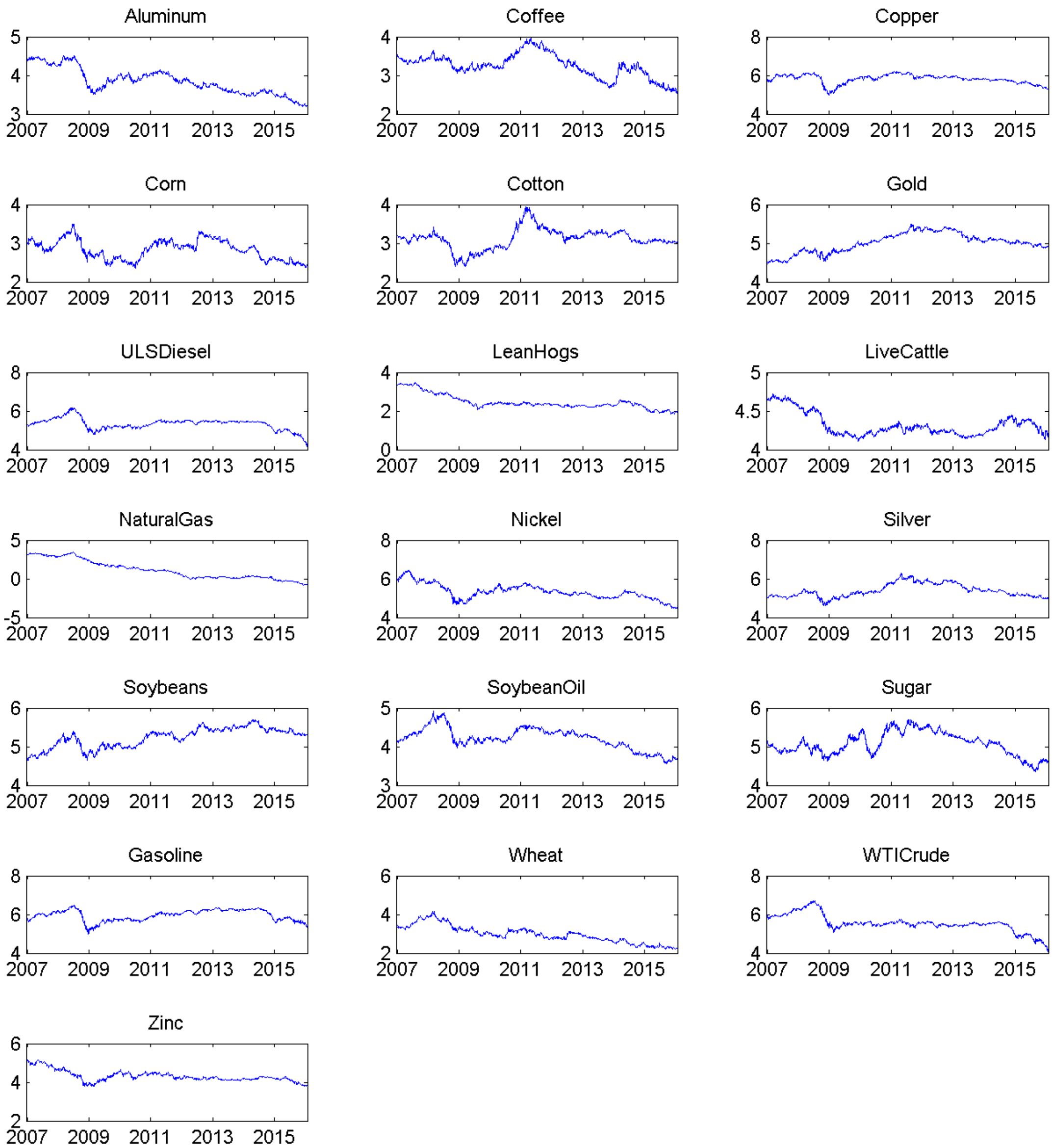


Figure 2: Gaussian Q-Q Plots for Realized Volatilities

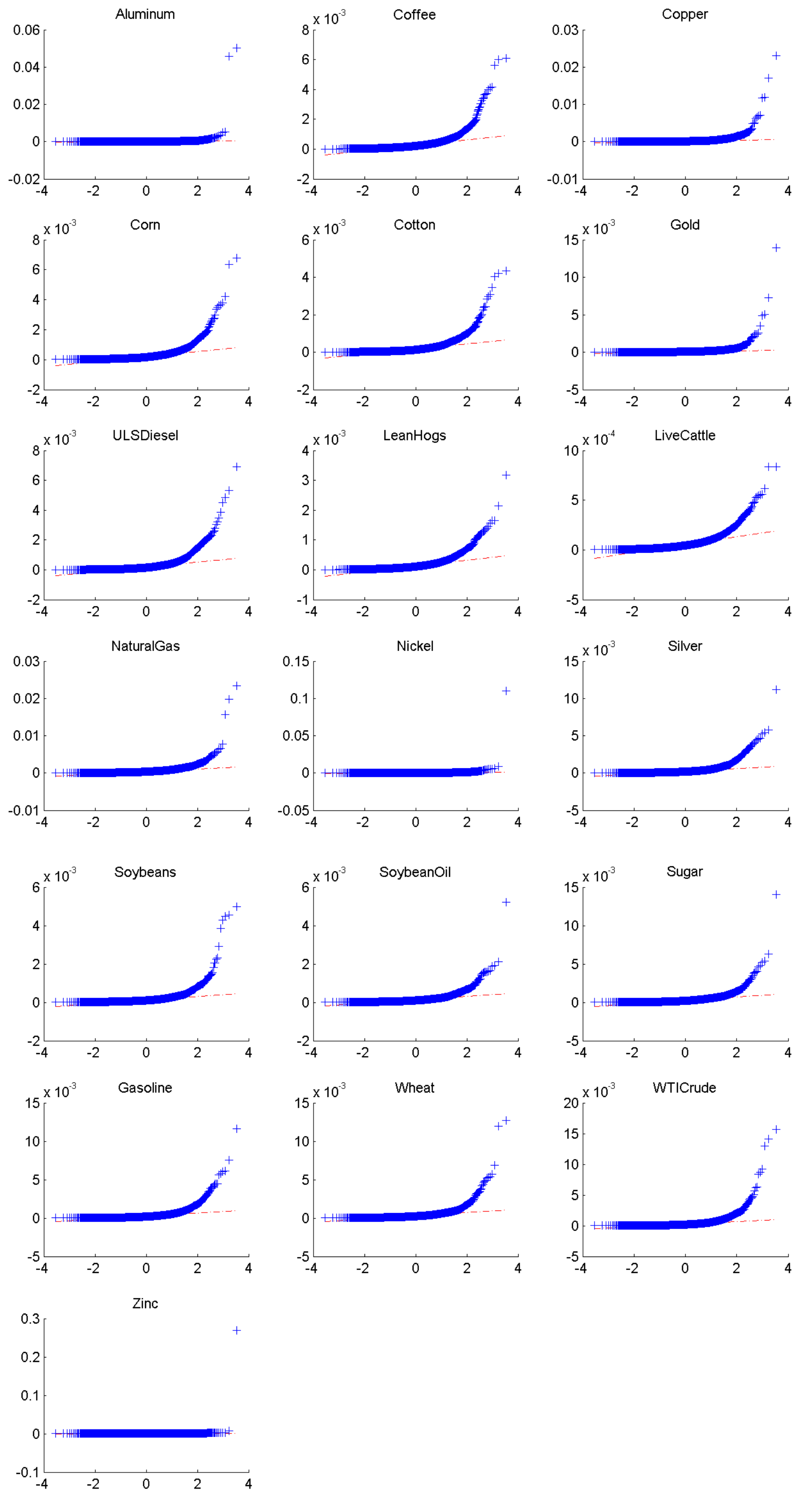
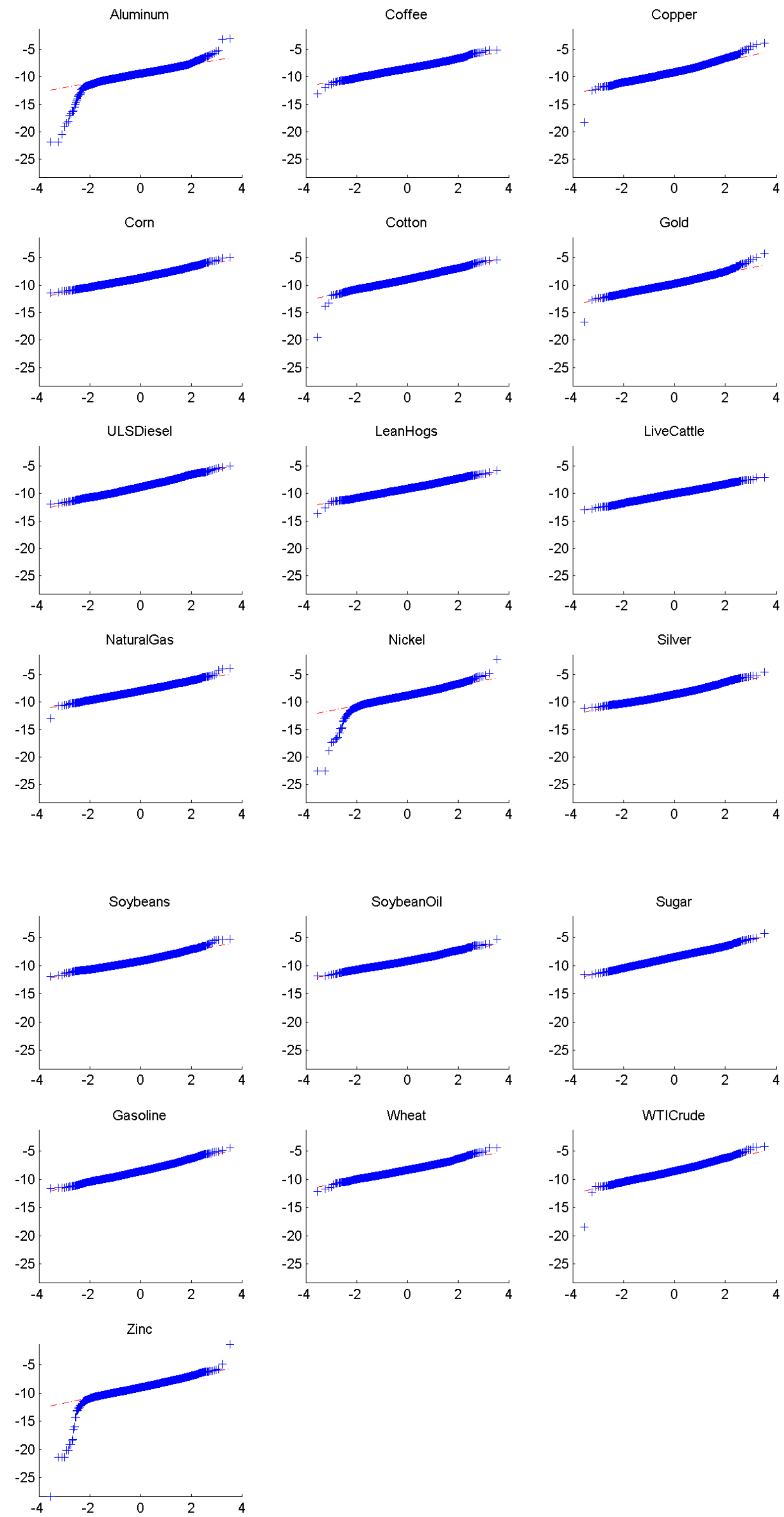


Figure 3: Gaussian Q-Q Plots for Log Realized Volatilities



high-frequency sampling (it is based on the key pieces of the intra-day price path – open, close, high, low), much less tedious to construct, and robust to microstructure noise. The daily range is also very widely available, often for many decades.[9]

2.3 Verification of Key Properties of Realized Volatility

Results for other markets like equities (Andersen et al. (2001a)) and foreign exchange (Andersen et al. (2001b)) indicate that daily realized volatilities are (1) generally distributed asymmetrically, with a right skew, but approximately Gaussian after taking natural logarithms, and (2) very strongly serially correlated. The economics of commodity markets are quite different from those of foreign exchange or equities, however, so we begin with an examination of fundamental distributional and dynamic properties of commodity volatilities.

Let us start with distributional aspects. As obviously revealed in the Gaussian Q-Q plots of Figure 2, the distribution of realized commodity volatility is strongly skewed right. This is not surprising, because volatilities are bounded below by zero and experience occasional large bursts. The real issue is whether *log* commodity volatilities are approximately Gaussian, as with foreign exchange and equities. As shown in the Gaussian Q-Q plots for log returns in Figure 3, the answer is mostly yes. Hence from this point onward, we work in logarithms. That is, even if we simply say "realized volatility" or "volatility", we mean the natural logarithm of range-based realized volatility as defined in equation (1).

The only exceptions to approximate log-normality are three industrial metals (aluminum, nickel, zinc), as clearly shown in the Gaussian Q-Q plots of Figure 3. All are traded on the London metals exchange (LME), and they are the *only* commodities in our data set traded on that exchange. The LME anomalies are also manifest in Figure 4, in which we show time-series plots. Evidently LME circuit breakers radically reduced volatility on certain days.

Now consider dynamics. In Figure 5, we show the sample autocorrelation functions of log volatilities. They decay, which is consistent with covariance stationarity, but they decay very slowly, indicating highly persistent, if nevertheless mean-reverting, dynamics.

2.4 Measuring Connectedness

We examine commodity return volatility connectedness using precisely the framework of Demirer et al. (2015), which builds on Diebold and Yilmaz (2014). In particular, for the

[9]See Alizadeh et al. (2002).

Figure 4: Time Series Plots of Log Realized Volatilities

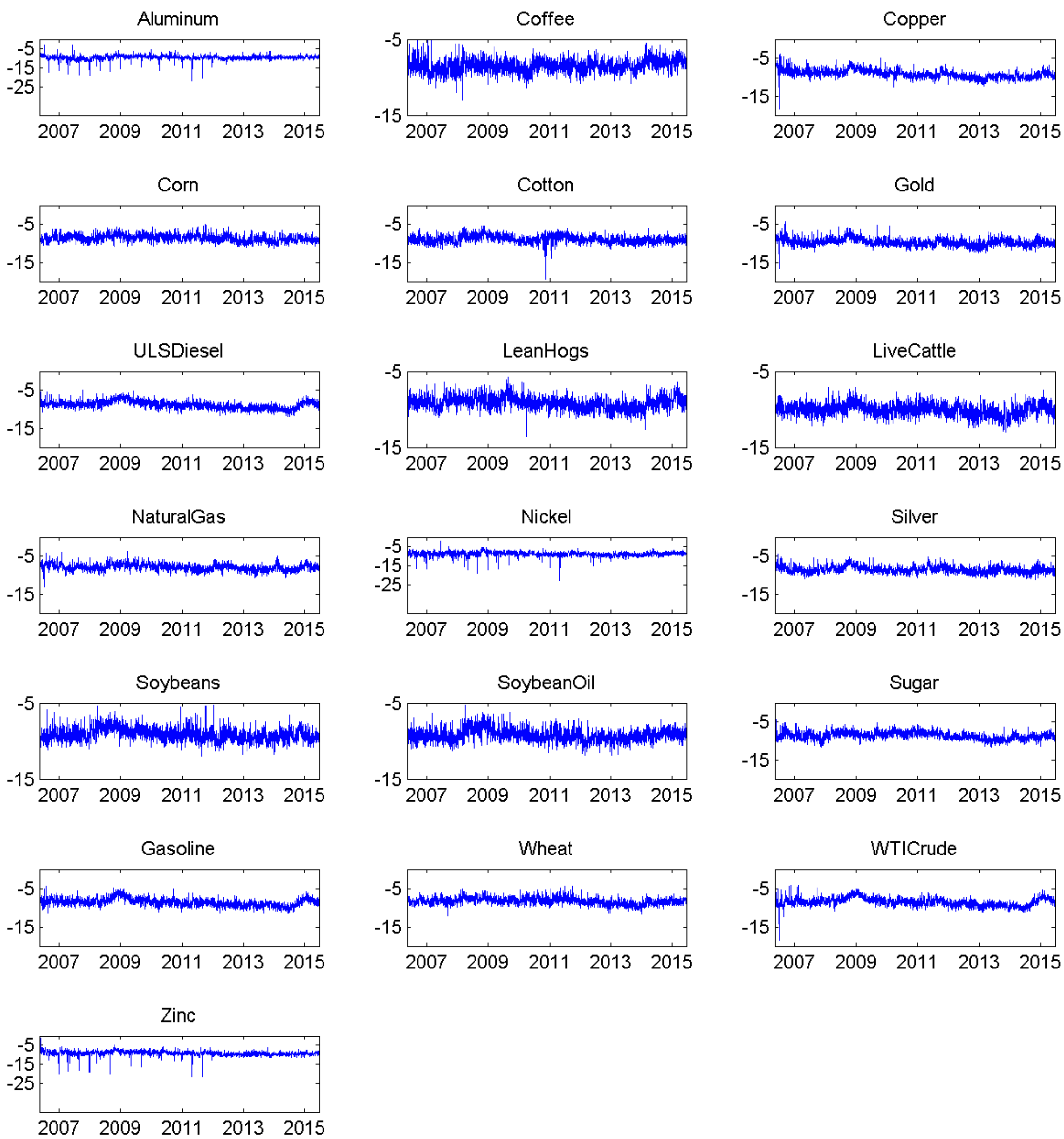
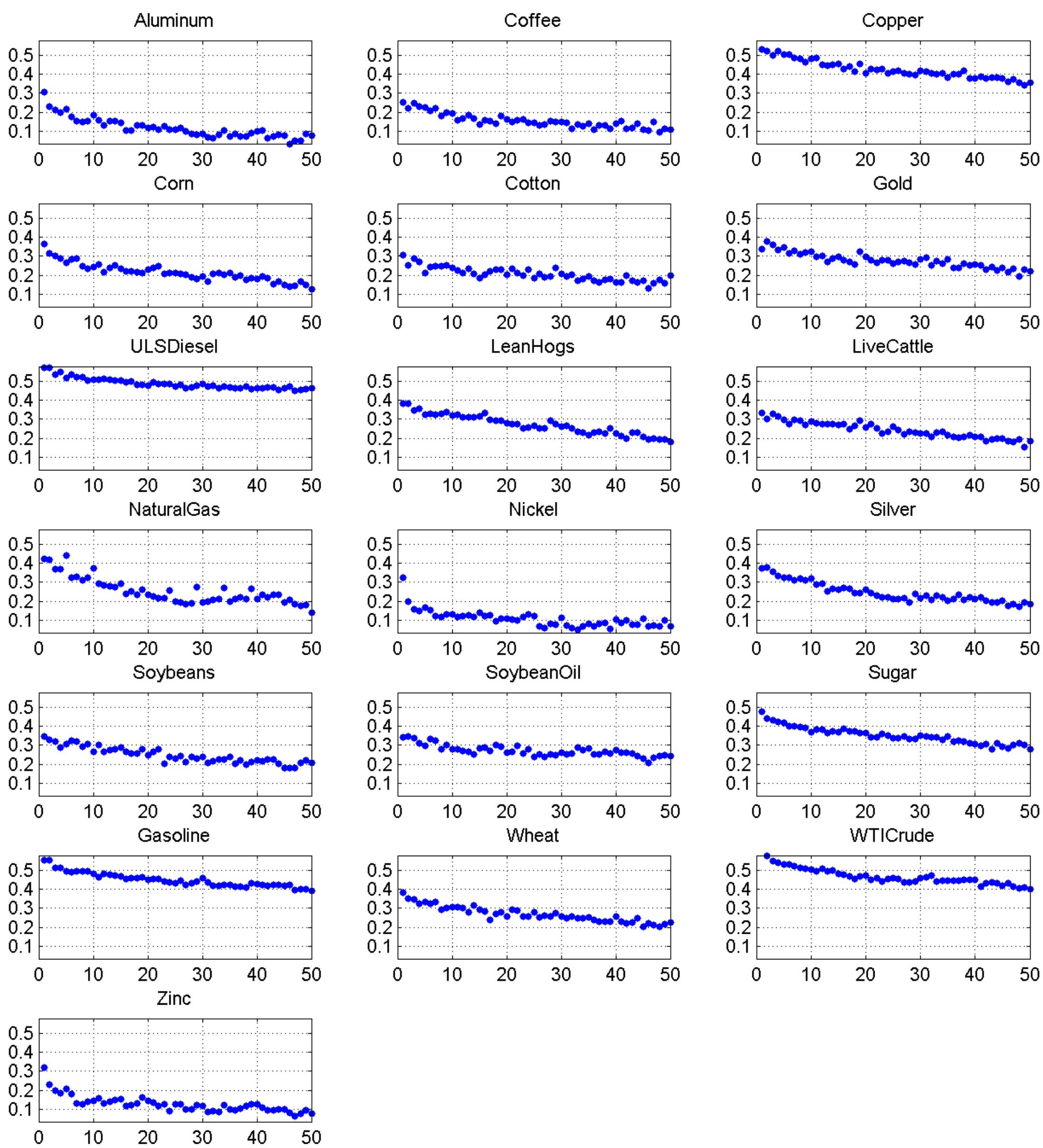


Figure 5: Sample Autocorrelation Functions of Log Realized Volatilities



benchmark results that we report in sections 3 and 4:

1. We use a $VAR(3)$ approximating model, estimated using an adaptive elastic net with penalty parameter chosen by 10-fold cross validation.

2. We indentify the estimated VAR using the generalized approach of Koop et al. (1996) and Pesaran and Shin (1998), and then we examine variance decompositions at horizon $H = 10$ days.

3. We summarize the variance decomposition matrix using connectedness statistics (pairwise directional, total directional "to" and "from", and system-wide).

4. We visualize the variance decomposition matrix using network spring graphs.

We perform static (full-sample) analyses in section 3 and dynamic (rolling-sample) analyses in section 4.

Let us elaborate upon our approach to network visualization. Node shading indicates total directional connectedness "to others"; the darker the stronger. The node location layout represents a steady state in which repelling and attracting forces exactly balance, where (1) nodes repel each other, but (2) edges attract the nodes they connect according to average pairwise directional connectedness "to" and "from."[10] Edge thickness also indicates average pairwise directional connectedness. Finally, edge arrow size indicates pairwise directional connectedness "to" and "from".

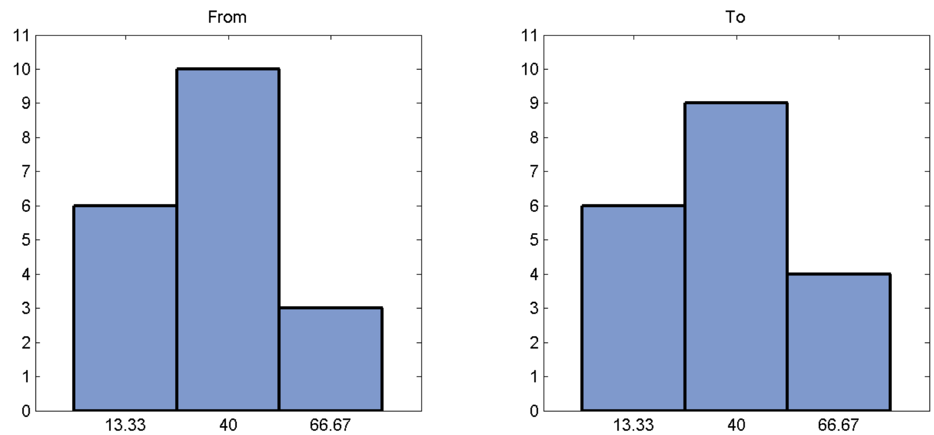
3 Benchmark Results I: Static (Full-Sample) Connectedness

3.1 System-Wide Connectedness

System-wide connectedness is 40%. That is, on average almost half of a commodity's future volatility uncertainty is due to "non-own" shocks.

[10]The steady state node locations depend on initial node locations and hence are not unique. They are, however, topologically unique up to rotation and flipping.

Figure 6: Full-Sample From and To Degree Distributions



3.2 Degree Distributions

In Figure 6, we show estimates of the the static (full-sample) "from" and "to" degree distributions, based on three-bin histograms. Their means are of course equal, and equal to system-wide connectedness (again, 40%). Their shapes are similar but slightly different. The "to" degree distribution has a slightly thicker right tail, consistent with a few commodities sending a rather large amount of future uncertainty to others.

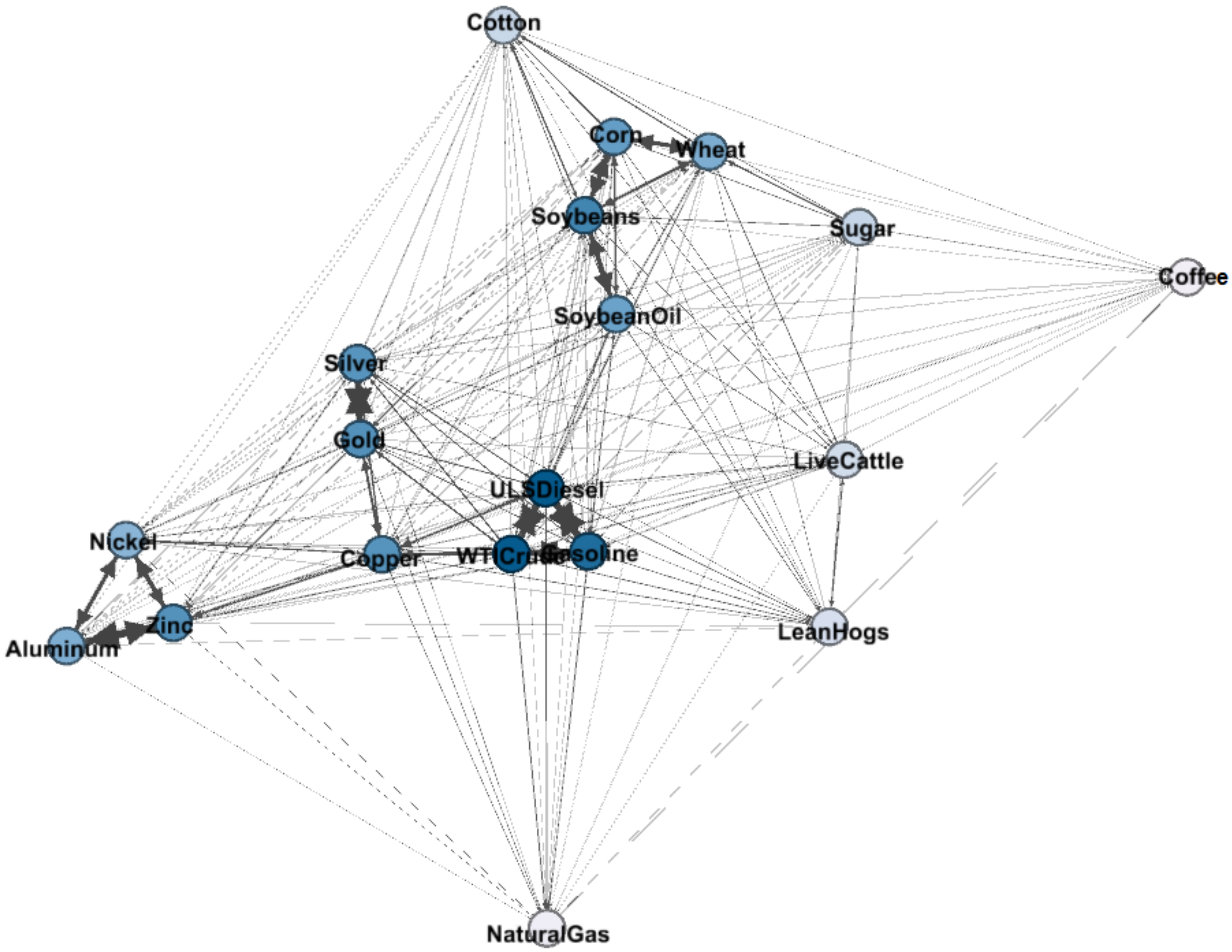
Digging beneath the degree distributions, it is of interest to know the individual commodity degrees, particularly to-degrees as we are especially interested in which sectors are sending uncertainty to others. From largest to smallest, the to-degree ranking is ULS Diesel, WTI Crude Oil, Unleaded Gasoline, Soybeans, Gold, Zinc, Copper, Silver, Corn, Soybean Oil, Wheat, Aluminum, Nickel, Sugar, Cotton, Live Cattle, Lean Hogs, Natural Gas, and Coffee.

3.3 The Network Graph

In Figure 7, we show the static (full-sample) network spring graph. Several aspects are notable.

First, there is clear clustering, associated primarily with the earlier-mentioned traditional industry groupings (precious metals, grains, livestock, energy, industrial metals, and softs). This is perhaps due to the nature of production processes; e.g., upstream/downstream, substitutes/complements, etc. Several remarks are in order: (1) There is complete clustering in precious metals, grains, and livestock; (2) There is clear clustering in energy and industrial

Figure 7: Full-Sample Spring Graph



metals, but in each case with a noteworthy exception. In the energy group, heating oil, crude oil, and gasoline cluster tightly, but natural gas is quite far away. In the industrial metals group, aluminum, nickel, and zinc cluster tightly, but copper is noticeably elsewhere, closer to precious metals and energy, perhaps due to its role in production; (3) There is, however, no clustering in so-called "softs" (coffee, cotton, sugar). Presumably this is because softs is largely a residual category. Taken together, (1), (2), and (3) suggest that the traditional commodity groupings, although largely accurate, are not precisely right.

Second, there are clear differences in transmission intensity, with transmissions to others from energy and precious metals clearly dominant.

Table 2: **Full-Sample Connectedness Table, Six-Group Aggregation**

	Energy	Grains	Ind. Metals	Prec. Metals	Softs	Livestock	From
Energy	0.00	17.11	21.59	16.49	6.01	5.43	66.63
Grains	23.05	0.00	7.23	10.57	18.06	7.02	65.93
Ind. Metals	30.67	8.35	0.00	22.88	2.94	3.05	67.88
Prec. Metals	20.78	9.38	20.28	0.00	3.26	1.11	54.80
Softs	8.33	22.88	4.75	5.67	0.00	3.63	45.25
Livestock	13.48	10.39	6.09	3.09	4.22	0.00	37.26
To	96.30	68.10	59.94	58.70	34.48	20.23	56.29

3.4 Six-Group Aggregation

We present full numerical results in a "connectedness table" (Table 2). The individual entries are pairwise directional connectedness, the row sums are total directional connectedness "from", the column sums are total directional connectedness "to", and the grand sum in the lower right corner is system-wide connectedness.[11] We show the associated spring graph for the six-group aggregation in Figure 8. The major result is the huge amount of total directional connectedness to others from energy.

4 Benchmark Results II: Dynamic (Rolling-Sample) Connectedness

Here we study time series of connectedness, estimated using a rolling window with a width of 150 days. We study both total system-wide and total directional (to and from) connectedness.

4.1 System-Wide Connectedness

Total system-wide connectedness fluctuated between 28.3% and 53.8% over the sample period from the end of 2006 to the end of January 2016. Commodity return volatilities tend to generate lower connectedness than the global bank return volatilities, global stock market return volatilities and bond yield volatilities. There are several reasons for this degree difference. Global bank return volatility shocks, in general, generate higher connectedness, because even they are located in different countries, big global banks are subject to shocks to global banking as well as to international financial markets. Global stock market return

[11] All sums exclude the main diagonal, because we are interested in non-own transmissions.

Figure 8: Full-Sample Spring Graph, Six-Group Aggregation

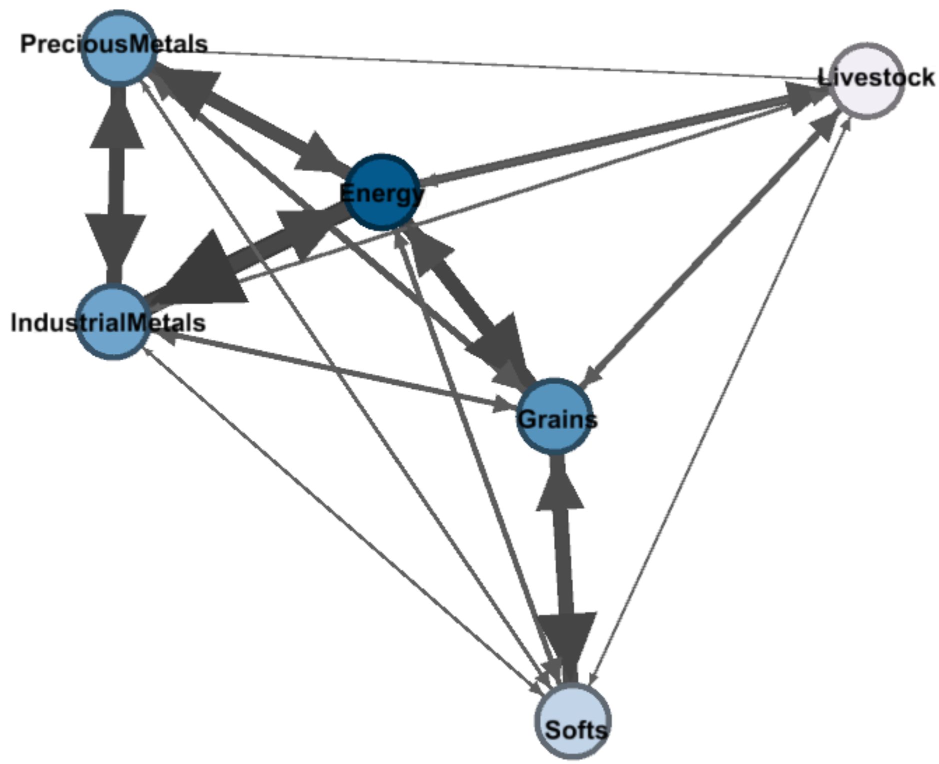
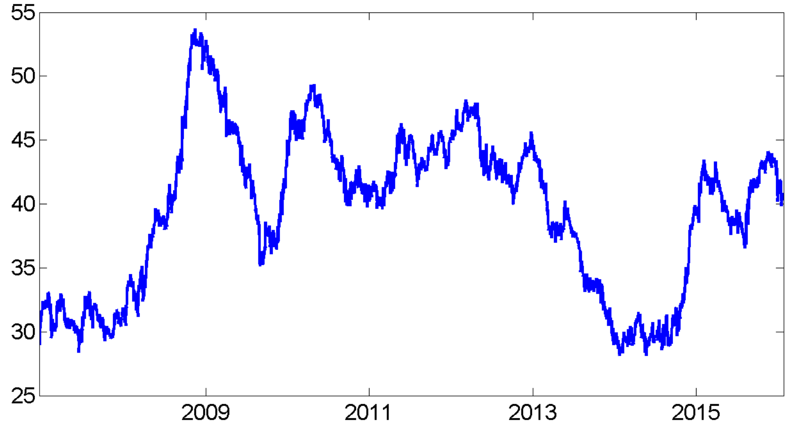


Figure 9: Rolling-Sample System-Wide Connectedness



volatility connectedness (and for that matter global bond market yield volatility connectedness) index tend to be higher because return volatility shocks are likely to be transmitted within the same asset class across countries. When there is an idiosyncratic shock to one of the major stock markets or a shock common to a subset of stock markets it is likely to be transmitted to others rather significantly.

Commodities in large part are different from bonds and stocks. Unlike bonds and stocks they are more than assets: Commodity prices cannot differ substantially from their intrinsic values that are determined by the interaction of the real demand and supply conditions. Perhaps with the exception of precious metals (gold, silver and platinum) that are mostly viewed as alternative investment vehicles to hedge against global uncertainty, demand for commodities is likely to be affected by the changes in the global income. In that regard, at times commodity prices can be subject to similar or highly-correlated demand-side shocks. Indeed, this was the case during the global financial crisis. Prices of all major commodities dropped sharply in a short-period of time as the near-collapse of global financial markets led to the Great Global Recession of 2009. As the commodity prices declined sharply in response to the global financial crisis, commodity return volatilities increased (see World Bank (July 2014)).

The emergence of China as a global economic powerhouse since early 2000s provides us with an example of how commodity prices are affected by rapidly growing global consumption demand. From 2001 to 2011, China's industrial production quadrupled. Along with its industrial production China's consumption of industrial metals increased by 330%, whereas its oil consumption increaed by 98% (see World Bank (July 2015)). Thanks to the increase in China's demand for these commodities, world demand for oil increased by 15% and that of industrial metals increased by 330%. As of 2014, China accounted for 47% of global industrial metal consumption, 24% of global energy consumption and 12% of global oil consumption. China's consumption of most agricultural commodities, on the other hand, grew 25% broadly in line with the rest of the world.

This rather phenomenal growth in the consumption of industrial metals and primary energy, oil and agricultural other commodities is reflected in an upward trend of a commodities super cycle that lasted until the peak of 2011. As a result, precious and industrial metal prices in 2014 were 80 and 210% higher in 2014 than their corresponding average of 2000-2002, respectively. Over the same period, energy and food prices increase by 150 and 60%, respectively. However, as the Chinese economic growth started to subside down since 2012 along with other emerging market economies, the growth rate of the global demand for major commodities also subsided down (see World Bank (October 2014)).

Things are quite different on the supply side. Supplies of energy, industrial and precious metals and agricultural commodities can be affected by very different factors. For example, while OPEC controls part of the global oil supply, a larger share of global oil supply as well as supplies of metals can be affected by the decisions of exporting country governments. In the case of agricultural commodities, on the other hand, weather conditions can play an important role in the short run, while government policies to tax exports or subsidize investment can have significant impact on new plantations and extraction facilities and, for that matter, on the long run supply of these commodities. Therefore, due to the existence of rather different processes in effect on the supply side, it is it is quite normal to observe different price dynamics in commodity markets.

This in turn implies that when there is a volatility shock to a commodity return, it is likely to be transmitted to the sub-group to which the commodity in question belongs, but not necessarily to all commodities. Indeed this was what we observed in the case of the static, full-sample volatility connectedness graph presented in Figure 7. The connectedness among the commodity groups is rather low in the full sample. Most of the volatility shocks are transmitted to other commodities within the same commodity group, rather than the commodities in other groups.

It is also possible that the commodity price dynamics is also affected from the inclusion of the particular commodity in commodity indices that are widely used. Literature has shown that, once a commodity is included in the overall commodity index widely used to gauge the commodity market conditions, then there is more interest for trading that commodity.

Unfortunately, we are not in a position to measure the impact of the index inclusion, as we are not working directly with commodity prices, but rather with the index formed by Bloomberg.

Coming back to the dynamic analysis of system-wide volatility connectedness in commodity markets, we observe a spike in total connectedness around late 2008 and early 2009. Recession that started in the U.S. in the first half of 2008 triggered a slow down of the global growth, which in turn prompted commodity prices to start falling in mid-2008, several months before the climax of the crisis was reached in the last quarter of 2008. The transformation of the U.S. financial crisis into a global one and the resulting downward spiral in world economy accelerated the downward process of commodity prices which lasted until mid-2009.

As a result of these developments, the system-wide connectedness index started to increase from 32% at the end of February 2008 to close to 40% by the end of May of that year. After a brief respite, the system-wide connectedness started to increase again. Following Lehman's bankruptcy, however, towards the end the index increased at a much faster pace from around 47% to 53.8% by mid-November.

Once it became apparent that global financial crisis would not lead to a complete meltdown of the financial system, commodity prices gradually turned upwards in early 2009, which in turn led the system-wide commodity connectedness turn downwards. The decline in connectedness was at first gradual, but it gained momentum in a couple of months time, dropping as low as 35% by the end of August 2009. The system-wide connectedness did not stay around 35% for a long time. After the a significant correction due to the global financial crisis, commodity prices started to recover from September 2009 onwards, as markets continued their upward journey, the volatility connectedness started to go up reaching as high as 48% by April 2010. During this upswing, there was not a widespread trend in the commodity return volatilities, but increased volatility in precious metals, especially in silver, caused the system-wide connectedness to increase slightly.

The commodity prices continued to increase until mid-2011. Afterwards, the energy prices stayed more or less steady in the next three years or so, followed by a sharp drop in oil prices in the second half of 2014. In the meantime, agricultural commodities, as well as the industrial and precious metals followed a downward trend that lasted until the end of our sample. While the agricultural commodities' prices declined by an average of 35%, that of precious and industrial metals respectively dropped by 45 and 52% over this period. Oil prices did not decline as fast as other major commodities because the impact of China on oil demand was more limited than the case in other commodities, especially in industrial metals. Secondly, the geopolitical risks in some countries in the Middle East and North Africa as well as Ukraine when combined with the policy of Saudi Arabia's policy of adjusting its supplies to keep oil price high together played a role in oil prices fluctuating in a band of $80-105 per barrel for more than three years.

The commodity volatility connectedness index reflects the price and volatility developments over the period. From the mid-2010 to early 2013 the system-wide connectedness fluctuated in the narrow band of 40-45%. The system-wde connectedness index followed a short lived upward trend early 2011 to early 2012, during which it reached as high as 48%. This bout of increase in the index was mostly due to the worries about the political upheavals in the Middle East and North Africa. In particular, the worries about the Suez Canal due to the civil conflict in Egypt and the sharp cut in Libya's oil production due to the civil war in the country fed into the oil price volatility which in turn contributed to the system-wide connectedness in commodity markets. After the overthrow of Qaddafi regime in Libya 2011, the political crisis in Egypt was resolved with a coup d'etat in mid-July 2013. Following the turn of events in Egypt, volatility in oil prices subsided and the system-wide connectedness started to decline from around 37% in mid-July 2013 to 28.5% within six months.

After fluctuating around 30% for several months, the index started to increase from its lows of 30% in July 2014 to reach 43% by the early 2015. The latest upward move in system-wide connectedness was due to worries about the civil war in Ukraine and whether it would lead to the temporary suspension of oil supplies from the Russian Federation to the world market.

At the same time, the military actions of Russia backed seperatists, increased confrontation between Russia, on the one side, and the U.S. and the EU, on the other side. It is speculated that as the tensions between the two sides increased, Saudi Arabia decided to change its policy of playing the marginal supplier which aims to keep oil prices high. With this policy change Saudi Arabia wanted to push high cost shale frackers out of business. Thanks to high global oil prices shale frackers were able to profitably increase global supply of oil, which threatened the dominant position of OPEC and in particular, Saudi Arabia, in the long-run. Secondly, Saudi Arabia helped the U.S. to increase pressure on the Russian government, which had become increasingly belligerent not only in Ukraine but in other civil unrests in parts of the world. As a result, the oil price was almost halved from around $100 at the end of July 2014 to around $50 by the end of the year.

After staying above 40% for several months, the system-wide connectedness dropped to

37% in the summer of 2015, as the oil price ended its downward spiral and settled around $50 per barrel . However, news about China's financial market troubles in August 2015 increased tensions and system-wide connectedness not only in commodity markets but in all financial markets. As a result, system-wide connectedness increased by more than five percentage points within a month and later reached 44% by the end of October 2015.

4.2 Total Directional Connectedness

In this section we are going to analyze the dynamics of directional connectedness of individual commodities as well as commodity groups. In Figures 10, 11 and 12, we present total directional connectedness to others, total directional connectedness from others and total directional net connectedness of each commodity. Even though, we present all three graphs, our main results will be mostly based on net connectedness graph, in Figure 12.

As our discussion of the dynamic system-wide connectedness in the previous section showed, oil played quite an important role in the commodity market connectedness (see Figure 12). Its net connectedness is higher than all other commodities for an overwhelming majority of the rolling sub-sample windows considered. Both in earlier and later parts of the period, net connectedness of oil reached as high as 30-35% range. The only sub-periods during which the net connectedness of crude oil was lower are the first half of 2007, and the period from the second half of 2013 to July 2014.

Starting in the first quarter of 2008, WTI crude oil price skyrocketed from around $60 in February 2007 to reach $141 per barrel by the first week of July 2008. After that moment, however, the oil price started to come down as the worries about the US economic performance intensified along with the signs of slowdown in many countries. As the downturn started in the oil price, the oil returns volatility increased substantially. Along with the rising oil returns volatility, the system-wide volatility connectedness index went up; from around 40% in early July 2008 to 53% by the end of October 2008. Over the same period net connectedness of WTI crude oil increased from 10% to 35%, the highest net connectedness level generated by a commodity for all rolling subsample windows considered (see Figure 12).

By the end of October 2008, WTI oil price went down to $60 per barrel. However, the downward spiral in the price of oil continued until the third week of December, with a minimum price of $31 per barrel. As the oil price lost its downward momentum, the net connectedness of oil dropped to around 10% by the end of 2008. Once the oil price recovers to reach closer to $60 per barrell, we observe that net volatility connectedness (hence volatility) of oil returns started to increase significantly and reached to 35% by mid-July 2009.

Figure 10: Rolling-Sample Total Directional Connectedness To Others

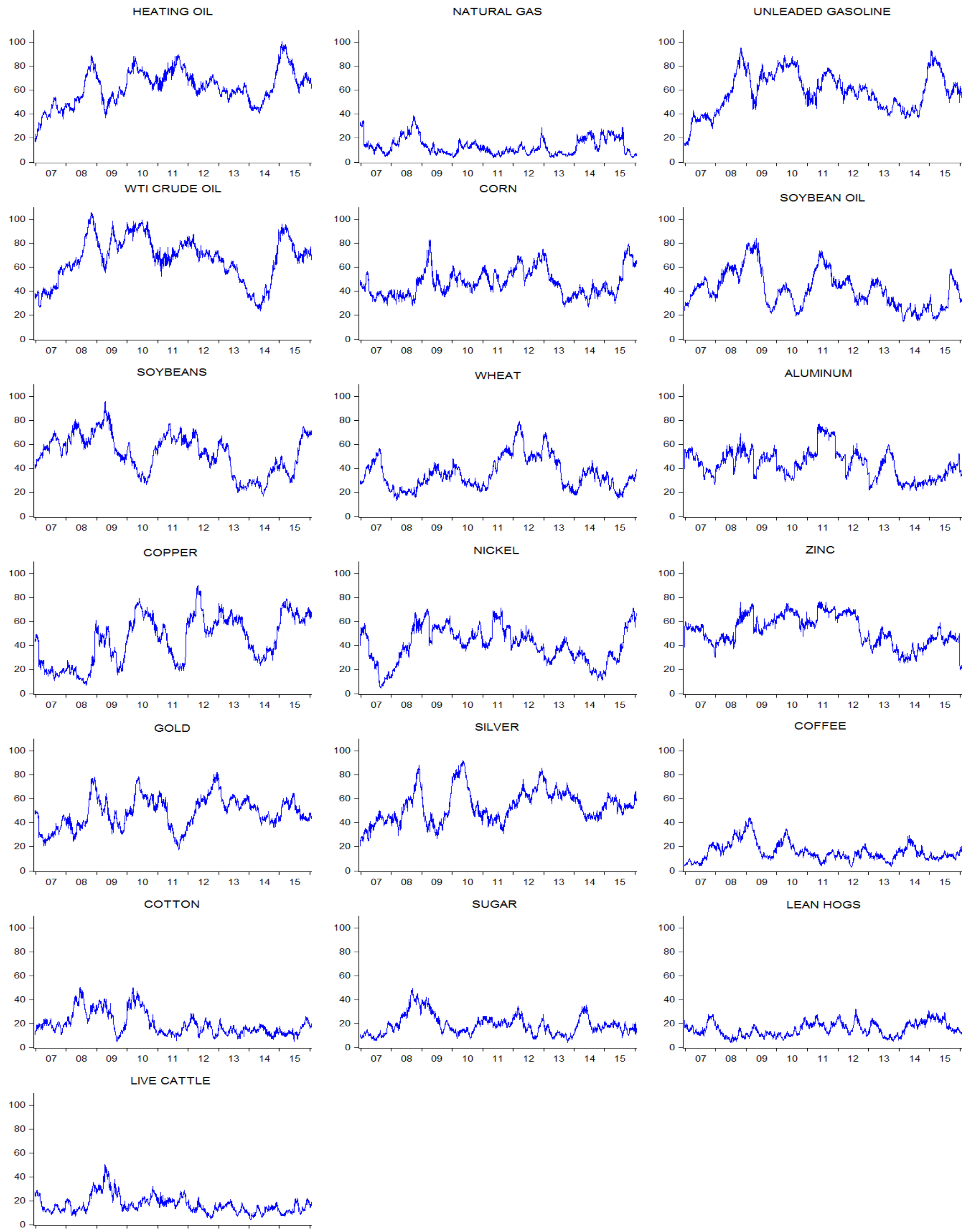


Figure 11: Rolling-Sample Total Directional Connectedness From Others

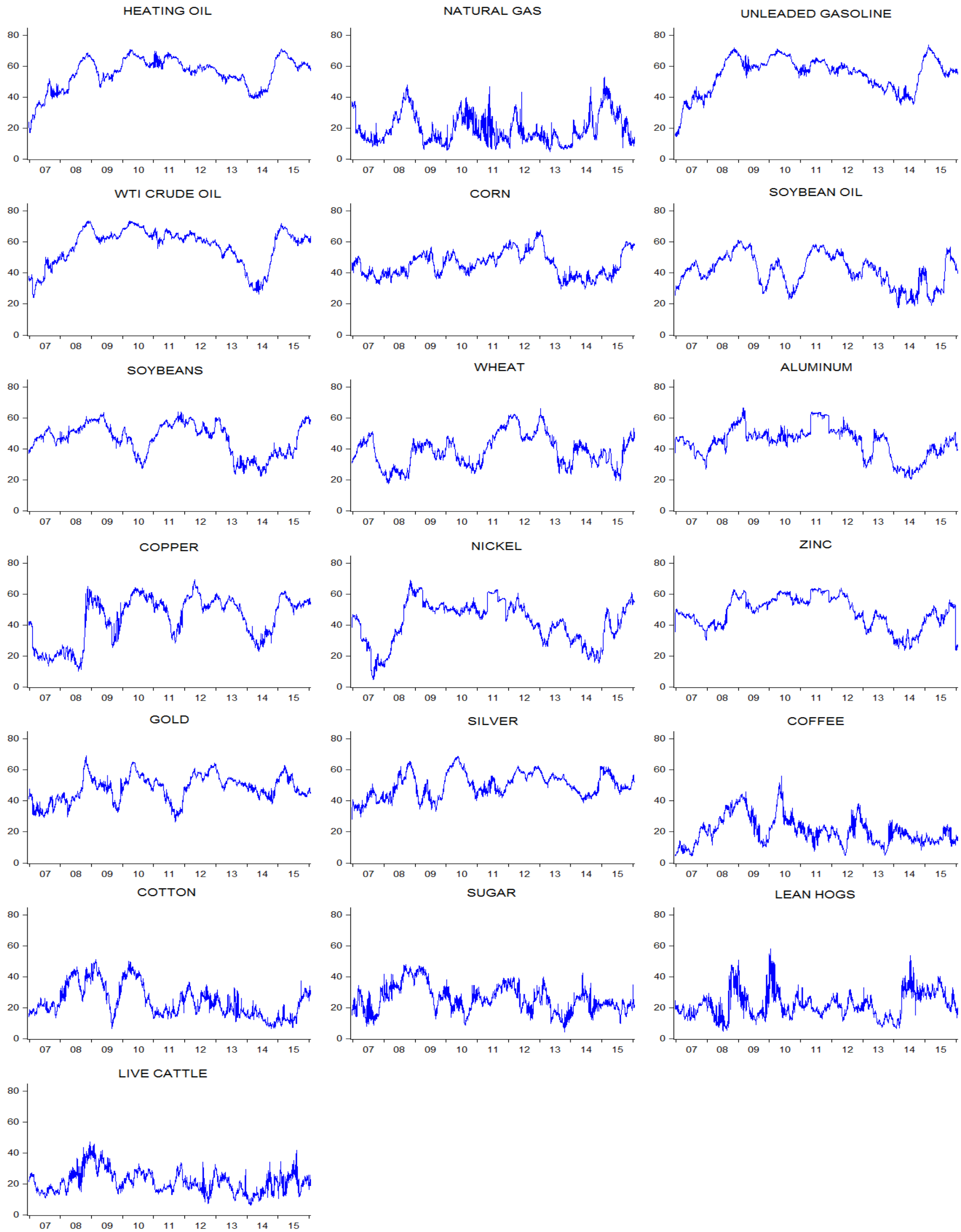
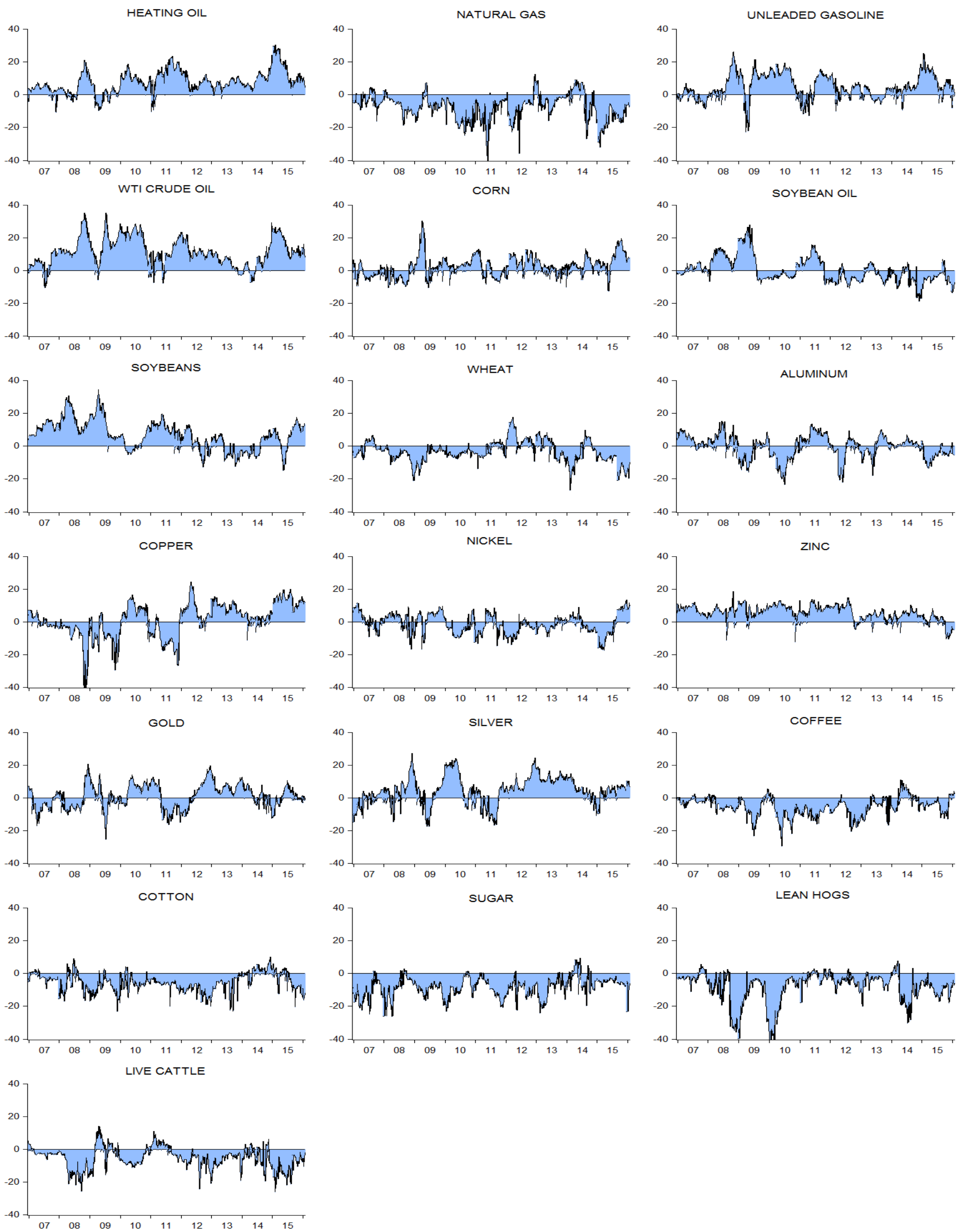


Figure 12: Rolling-Sample Net Total Directional Connectedness



Heating oil, soybeans and zinc are the three commodities that followed crude oil in generating very high levels of net connectedness to other commodities over all subsamples considered. Heating oil is also in the energy commodities group. Its net connectedness to others follows a trajectory which resembles to that of crude oil.

Soybeans is an agricultural commodity that generates high net connectedness, not because it is an important consumption item for households around the world. Rather it is an important generator of connectedness because it is used in the biofuel production, which is an alternative source of energy. Soybeans' net connectedness reached as high as 28% in March 2008 and last quarter of 2008 and first half of 2009. Unlike the crude oil, soybeans' net connectedness increased in January 2008 (exactly around FOMC's emergency conference call meeting on January 22) and at the end of February and beginning of March 2008. During this period, crude oil prices were still on an upward move with a net connectedness of only around 10%. A similar asymmetric move between the net connectedness of crude oil and soybeans occurred in the first half of 2009. While crude oil's net connectedness declined from its peak at the end of October 2008 to a low of -6% in the first week of April 2009, during this period the net connectedness of soybeans increased to reach 28% level.

Zinc is actually the only commodity which generated net positive connectedness to others throughout the period from 2006 to 2016. Throughout the period, zinc had small but positive (between 5 to 10%) net connectedness from the beginning of the sample to the end of 2012. Its net connectedness declined significanly since late 2012 to less than 5%, yet continued to stay on the positive side.

In the energy group of commodities, unladed gasoline is the third in terms of generating net connectedness to other commodities. Again its net connectedness followed quiet a similar behavior over time to that of the crude oil. The only energy commodity that is a net recipient of connectedness from others is natural gas. Literature on energy markets pinpoints natural gas as the only energy market with the weakest link to the economic newsflow, even when accounting for periods of recession. Reflecting this fact, its connectedness to others and from others are much lower than those of other energy commodities (see Figures 10 and 11). As such its return volatility is likely to be affected from the return volatilities of other energy commodities. That is why its net connectedness was negative for an overwhelming majority of rolling sample windows (see Figure 12).

We also need to focus on the net connectedness of copper. While its net connectedness was negative during the US and global financial crisis in 2007 through 2009 and during the 2011 European debt crisis, copper has generated positive net connectedness since early

2012. Copper prices declined by more than 50% since the end of 2010, from a high of \$9,800 per ton to a low of \$4,700 per ton at the end of 2015. The decline in the price of copper and its increasing contribution to the system-wide connectedness is closely related to the slowing down of the Chinese economy in recent years. Other industrial metals, such as zinc, nickel, and aliminum also experienced significant price drops over the period, but none of them had as high a net connectedness as copper. We have already covered zinc above. The other two industrial metals, aluminum and nickel, displayed both positive and negative When considered all together industrial metals, industrial metals generated positive net connectedness to other commodity groups (ranging from 5 to 20%) for almost all rolling window samples.

Among the precious metals, silver has higher net connectedness than gold for most of the period covered. During the global financial crisis, in the second half of 2009 and first half of 2010, and since the end of 2011, silver's net connectedness is much higher (sometimes as high as 20%) than that of gold (see Figure 12).

Soft commodities (coffee, cotton and sugar) and livestock (lean hogs and live cattle) all have negative connectedness for almost all rolling sample windows, indicating that their prices on average are influenced by other commodities and/or commodity groups (see Figure 12).

5 Conclusion

To be supplied...

Appendices

A Different Horizons (Various h, Fixed $p = 3$)

It is of interest to explore connectedness at different horizons h. On the one hand, one might hope for results robust to horizon. On the other hand, upon further consideration, it is not obvious why the results *should* be robust, or whether such robustness is "desirable". This point is related to different notions of network centrality; one can assess 1-step through the adjacency matrix A, 2-step through A^2, and so on to ∞-step (eigenvalue centrality).

First consider static connectedness. In Figure 13, we show static (full-sample) $VAR(3)$ network connectedness graphs for six variance decomposition horizons: $h = 2, 10, 20, ..., 50$ days. The different subgraphs are rotated to enhance multiple comparisons. The topology appears strongly robust to horizon.[12]

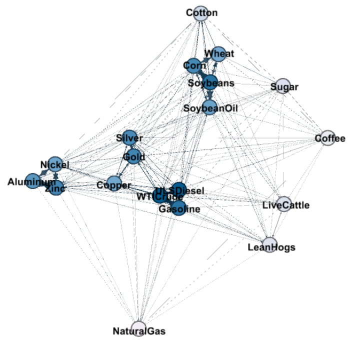
B Different Dynamics (Fixed $h = 10$, Various p)

We already noted the very high persistence in commodity return volatilities, as is common across many assets and asset classes. Indeed there may even be long memory, as emphasized in Andersen et al. (2003). To allow for that possibility, we also explored a variety of higher-order approximating models, estimation of which is feasible despite profligate parameterizations, given the regularization achieved by the lasso.

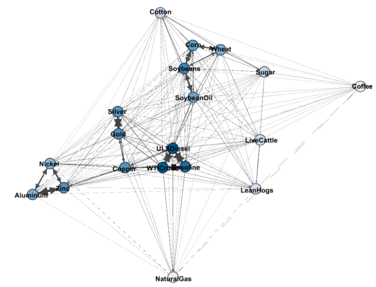
In Figure 14, we show static (full-sample) $h = 10$ network connectedness graphs for six VAR lag orders, $p = 3, 5, 10, 15, 20, 25$. The different subgraphs are rotated to enhance multiple comparisons. The topology appears strongly robust to lag order. (***frank will supply more. The result in interesting insofar as everyone talks about long memory, yet allowing for it seems inconsequential.)

[12] The scaling, however, differs across the subgraphs; otherwise the small-h graphs would be tiny and the large-h graphs would be huge.

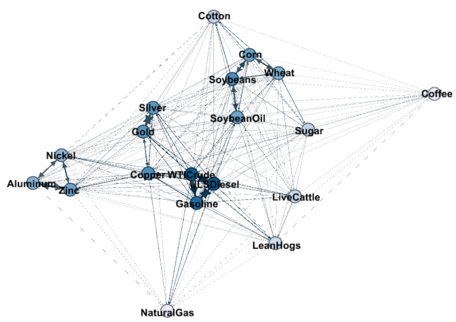
Figure 13: Full-Sample Connectedness, $VAR(3)$, Different Horizons



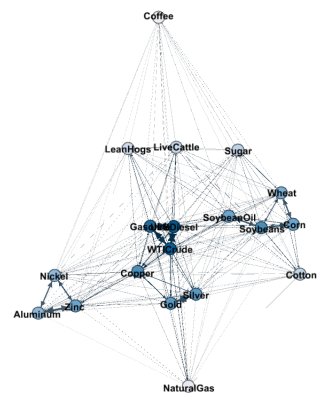
$h = 2$



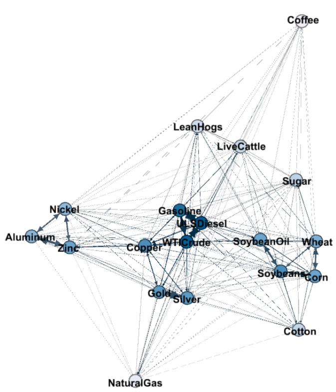
$h = 10$



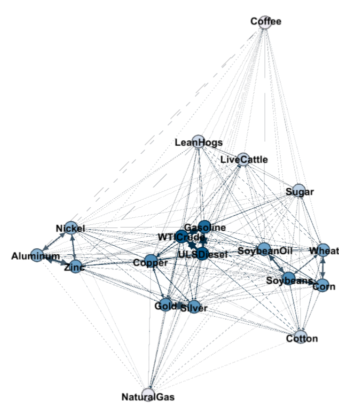
$h = 20$



$h = 30$

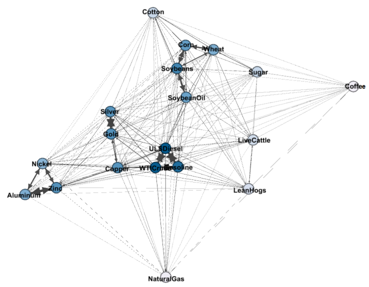


$h = 40$

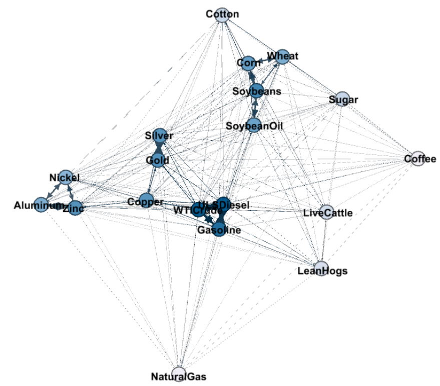


$h = 50$

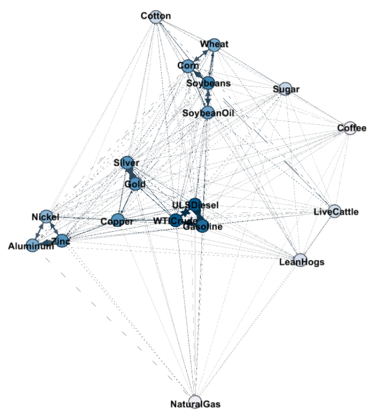
Figure 14: Full-Sample Connectedness, Different VAR Orders, $h = 10$



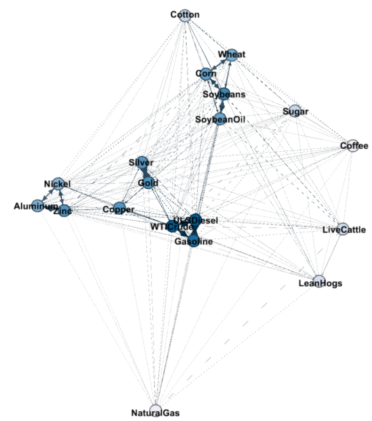
$VAR(3)$



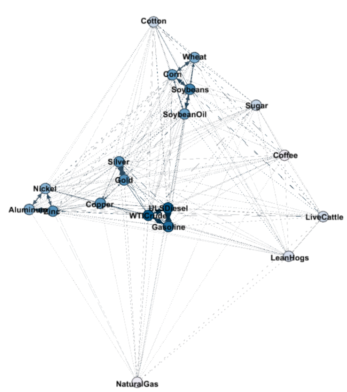
$VAR(5)$



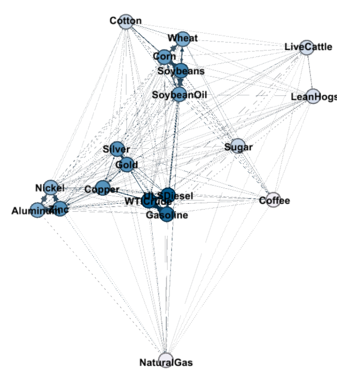
$VAR(10)$



$VAR(15)$



$VAR(20)$



$VAR(25)$

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