Monetary Policy and Global Spillovers: Mechanisms, Effects, and Policy Measures

Enrique G. Mendoza, Ernesto Pastén, and Diego Saravia
editors

Banco Central de Chile / Central Bank of Chile

Monetary Policy and Global Spillovers: Mechanisms, Effects and Policy Measures

Enrique G. Mendoza
Ernesto Pastén
Diego Saravia
Editors

Central Bank of Chile / Banco Central de Chile

Agustinas 1180
Santiago, Chile

Published in Santiago, Chile by the Central Bank of Chile
Manufactured in Chile

ISBN (versión impresa) 978-956-7421-58-9
ISBN (versión digital) 978-956-7421-59-6
Intellectual Property Registration A-287305

ISSN 0717-6686 (Series on Central Banking, Analysis, and Economic Policies)

Production Team

Editors:
Enrique G. Mendoza
Ernesto Pastén
Diego Saravia

Supervisor:
Camila Figueroa

Copy Editor:
María Marta Semberoiz

Designer:
Maru Mazzini

Proof Reader:
Dionisio Vio

Technical Staff:
Carlos Arriagada

Printer:
Andros Impresores

Commodity Connectedness

Francis X. Diebold
University of Pennsylvania

Laura Liu
Federal Reserve Board

Kamil Yilmaz
Koç University

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 and others (2015). Commodities have also emerged as important financial asset classes (e.g., energy, agriculture, metals), with properties different from those of "traditional" asset classes (e.g., stocks, bonds, 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 nominal or financial, and real. In particular, we have in mind elements like connectedness of commodity company stocks (both within and across countries), connectedness of commodity prices, and links between commodity price connectedness and country real output connectedness.

For helpful comments we thank an anonymous referee, as well as Gary Gorton, Alain Kabundi, Danilo Leiva, Fabrizio Perri, and Xiao Qiao. The usual disclaimer applies.

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

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

Monetary Policy and Global Spillovers: Mechanisms, Effects and Policy Measures, edited by Enrique G. Mendoza, Ernesto Pastén, and Diego Saravia, Santiago, Chile.

Moreover, measuring connectedness in real time is of special relevance for policy making. Successful real-time policy (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 and others (2012) use pairwise Granger causality. Bonaldi and others (2013) work with vector autoregressions (VARs), which allow for full multivariate dynamic cross-variable interaction and hence richer connectedness assessment, focusing on connectedness due to cross-lag interactions, as opposed to innovation correlations. Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), and Diebold and Yilmaz (2014) also use VARs, but they use variance decompositions, which account for innovation correlations in addition to dynamic cross-variable interactions[5]. Demirer and others (2016) extend the Diebold-Yilmaz framework to high-dimensional environments, which are increasingly relevant, by incorporating LASSO estimation.

In this paper, we characterize global commodity market connectedness by using the Demirer and others (2016) framework. This is of interest in a variety of contexts. One such key context is private-sector investment management strategies, whose portfolio concentration risk is directly related to connectedness. Another is public-sector monitoring and policy formulation, because connectedness tends to increase during commodity-market crises, which may then spill over into the broader macroeconomy.

We proceed as follows. In section 1, we discuss our commodity price indices, our construction and verification of realized return volatility, and our framework for measuring commodity volatility connectedness.

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 and others (2015).

5. The Diebold and Yilmaz (2014) framework extends earlier variance-decomposition work by Diebold and Yilmaz, including Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012), by using network visualization methods to understand the variance decompositions. Importantly, moreover, as emphasized in Diebold and Yilmaz (2014), the Diebold-Yilmaz framework allows measurement of connectedness at levels ranging from highly granular to highly aggregative, with close connections to marginal expected shortfall or S-risk (Acharya and others, 2010) and CoVaR (Adrian and Brunnermeier, 2016).

In section 2, we provide benchmark results for static connectedness and, in section 3, we provide results for dynamic connectedness. We conclude in section 4, and we explore variations and extensions several appendices.

1. Commodities Data and Volatility

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

1.1 Price 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 so-called "softs" (coffee, cotton, sugar). It is important to note that this category labeling is not ours; rather, it is standard among industry participants, which will subsequently be of interest when interpreting our empirical results[6]. Details on the underlying futures 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, with holidays and weekends dropped. This results in 2,443 observations per series, for a total of 2443x19 = 46,417 observations. We show time-series plots of log sub-indices in figure 1.

6. See Bloomberg (2016).

7. Based on Bloomberg (2016), table 2.

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

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

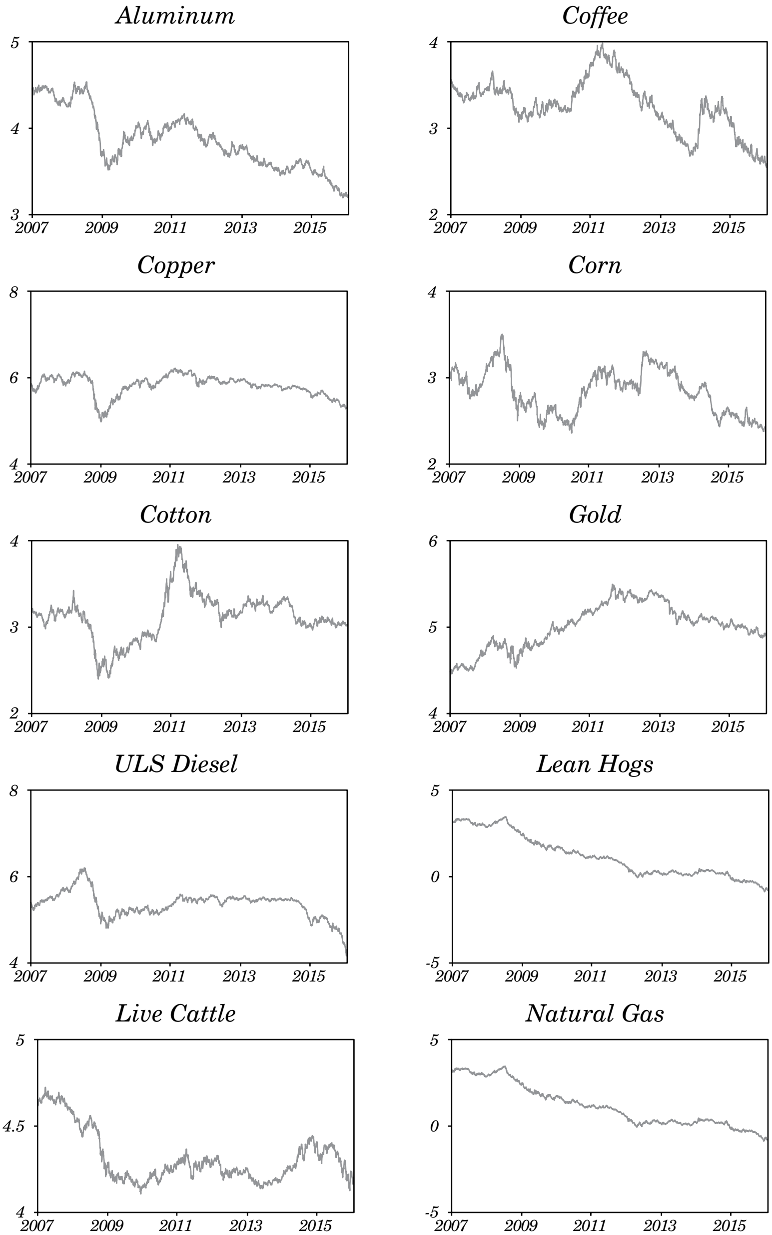


Figure 1. (continued)

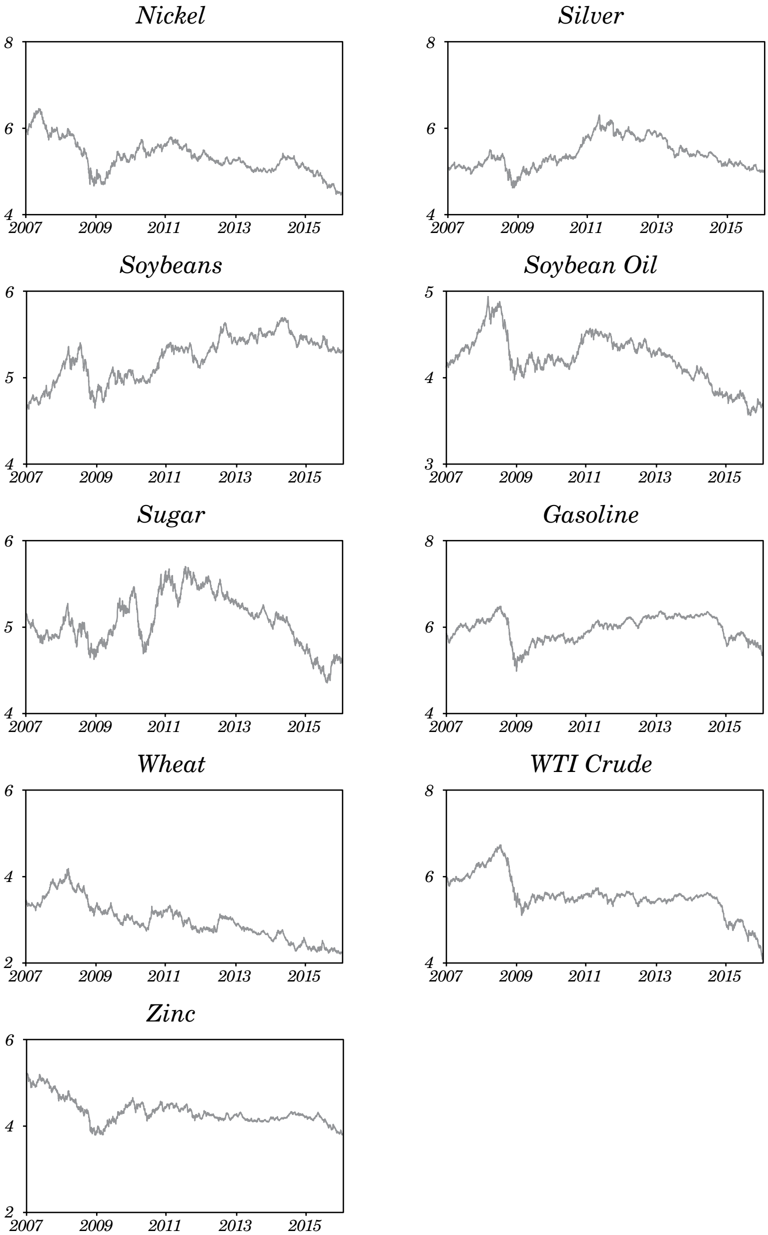


Table 1. Commodity Contracts

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 gal	U.S. cents/gallon
Live Cattle	Live Cattle	CME	40,000 lb	U.S. cents/pound
Lean Hogs	Lean Hogs	CME	40,000 lb	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	5,000 bushels	U.S. cents/bushel
Soybean Oil	Soybean Oil	CBOT	60,000 lb	U.S. cents/pound
Aluminum	High Grade Primary Aluminum	LME	25 metric tons	USD/metric ton
Copper	Copper	COMEX	25,000 lb	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	5,000 troy oz.	U.S. cents/troy oz.
Sugar	World Sugar N°11	NYBOT	112,000 lb	U.S. cents/pound
Cotton	Cotton	NYBOT	50,000 lb	U.S. cents/pound
Coffee	Coffee "C"	NYBOT	37,500 lb	U.S. cents/pound

1.2 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:

$$\hat{\sigma}_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \qquad (1)$$
$$-2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2,$$

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

In appendix 1, we verify the key properties of realized volatility. Results for other markets like equities (Andersen, Ebens, and others, 2001) and foreign exchange (Andersen, Labys, and others, 2001), indicate that daily realized volatilities are (1) generally distributed asymmetrically, with a right skew, (2) approximately Gaussian after taking natural logarithms, and (3) very strongly serially correlated. Despite the fact that the economics of commodity markets are quite different from those of foreign exchange or equities, the results in appendix 1 make clear that all three properties hold for commodity returns. Given property (2), 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). We show time-series plots of the log realized volatilities in figure 2.

9. See Alizadeh and others (2002).

Figure 2. Time Series Plots of Log Realized Volatilities

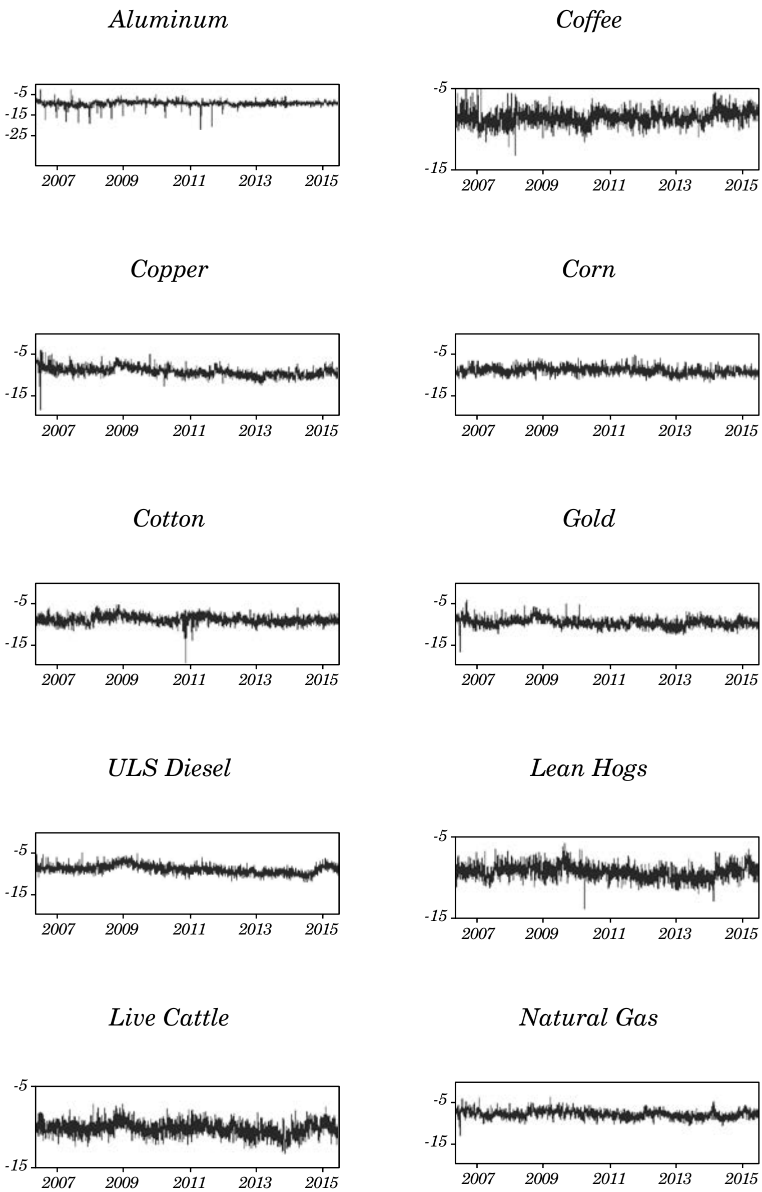
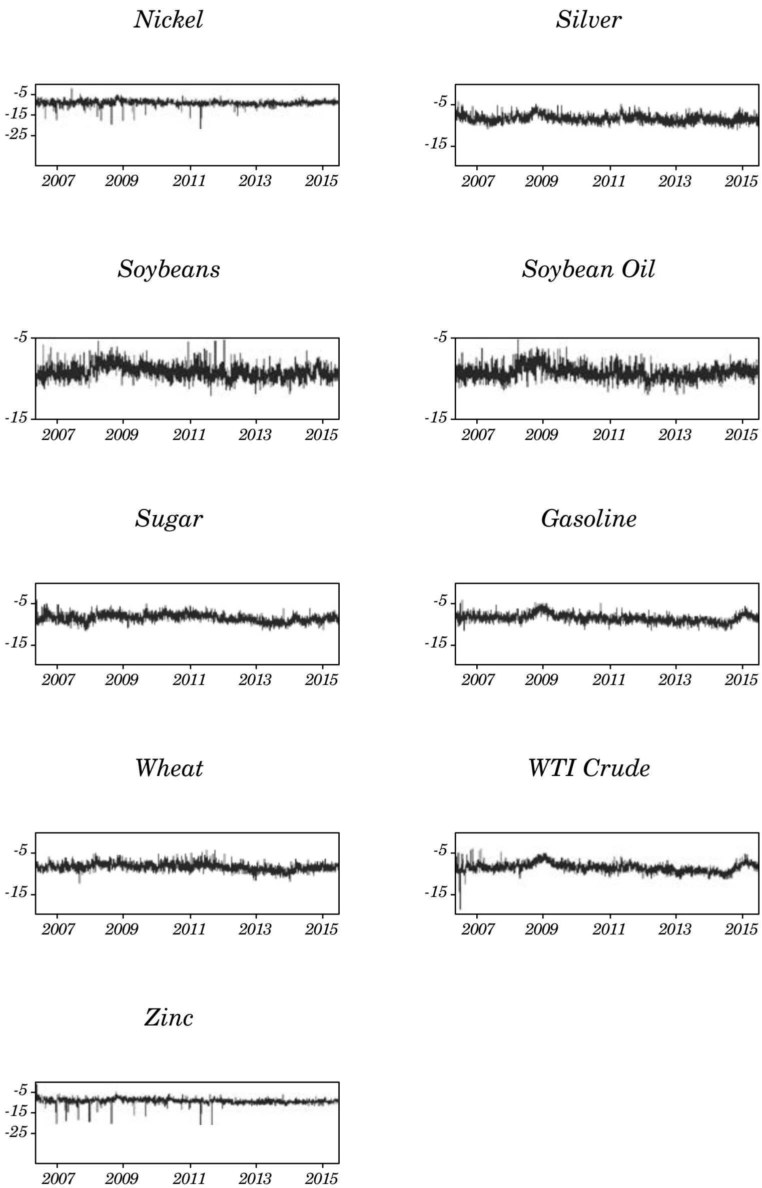


Figure 2. (continued)



2. Benchmark Results I: Static (Full-Sample) Connectedness

2.1 Measuring Connectedness

We examine commodity return volatility connectedness by using the framework of Demirer and others (2016), which builds on Diebold and Yilmaz (2014). In particular, for the benchmark results that we report in sections 2 and 3:

1. We use a *VAR*(3) approximating model, estimated by using an adaptive elastic net with penalty parameter chosen by ten-fold cross validation.
2. We identify the estimated *VAR* by using the generalized approach of Koop and others (1996) and Pesaran and Shin (1998), and then we examine variance decompositions at horizon $H = 10$ days.
3. We summarize the variance decomposition matrix by using connectedness statistics (pairwise directional, total directional "to" and "from", and system-wide).
4. We visualize the variance decomposition matrix by using network "spring graphs".
5. In appendix 2, we explore different horizons (various h, fixed $p = 3$), and in appendix 3 we explore different approximating models (fixed $h = 10$, various p).

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

Let us elaborate upon our approach to network visualization. Node shading indicates total directional connectedness "to others"; the darker, the stronger. The spring graph 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[10]. Edge thickness also indicates average pairwise directional connectedness. Finally, edge arrow size indicates pairwise directional connectedness "to" and "from".

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.

2.2 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. It is interesting that the 40% system-wide commodity return volatility connectedness is significantly lower than the system-wide equity return volatility connectedness found by Demirer and others (2016) for the world's largest banks. It makes sense, however, as large parts of commodity price movements come from idiosyncratic fluctuations in national and regional macroeconomic fundamentals that drive commodity supply and demand.

2.3 To-Degrees and From-Degrees

It is of interest to know the individual commodity degrees, particularly to-degrees, as we are especially interested in which sectors are sending the most 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. From largest to smallest, the from-degree ranking is: ULS Diesel, WTI Crude Oil, Unleaded Gasoline, Zinc, Gold, Soybeans, Copper, Silver, Corn, Soybean Oil, Aluminum, Wheat, Nickel, Live Cattle, Cotton, Lean Hogs, Sugar, Natural Gas, and Coffee. The rank correlation is 0.9794. Bar charts appear in figure 3, ordered by to-degrees, from largest to smallest. It is interesting to note that the to-degree ordering is almost identical to the from-degree ordering.

In figure 4, 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.

Figure 3. Full-Sample Individual Commodity From/To Degrees

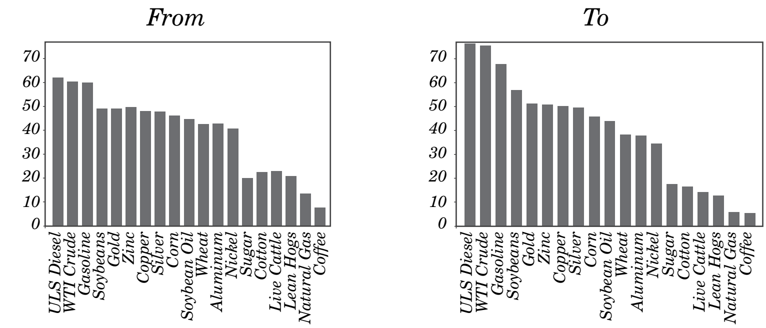
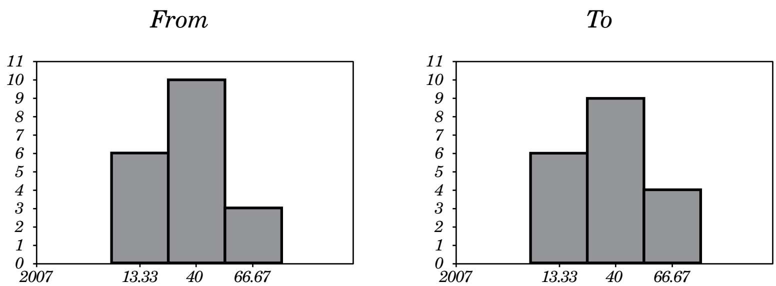


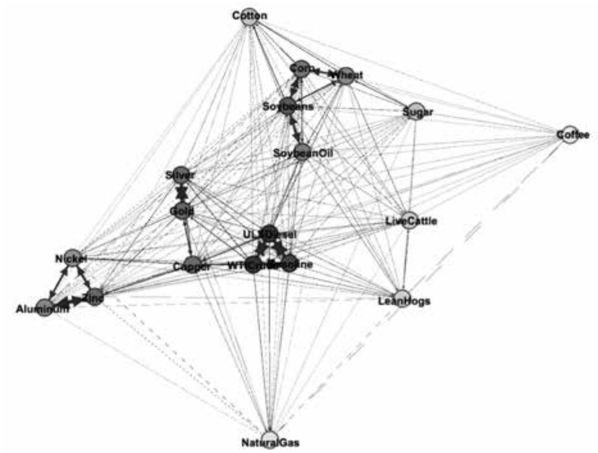
Figure 4. Full-Sample From and To Degree Distributions



2.4 The Network Graph

In figure 5, we show the static (full-sample) network graph. Several aspects are notable. First, there is clear clustering, associated primarily with the traditional industry groupings (energy, industrial metals, precious metals, grains, livestock, and softs), perhaps due to the nature of production processes; e.g., upstream/downstream, substitutes/complements, etc. This implies that a commodity volatility shock is likely to be transmitted to the commodity's sub-group, but not necessarily to all commodities. So we have an interesting situation: rather low system-wide connectedness, but clear group clustering and high within-group connectedness.

Figure 5. Full-Sample Network Graph



a. There is clear clustering in precious metals, grains, and livestock.
b. There is clear clustering in energy and industrial 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 this "copper anomaly" is due to its role in production. Alternatively, perhaps it is not a copper anomaly, but rather an "aluminum-nickel-zinc anomaly" associated with the London Metal Exchange rules mentioned in appendix 1.
c. There is no clustering in softs (coffee, cotton, sugar). Presumably, this is because softs is largely a residual category.

Taken together, (a), (b), and (c) suggest that the traditional commodity groupings are largely, but not entirely, accurate. Natural gas, in particular, is far from the other energy commodities.

2.5 Six-Group Aggregation

We present full numerical results in a six-group (6x6) "connectedness table", or "variance decomposition table" (table 2), obtained by aggregating the original (19x19) connectedness table within the six traditional commodity categories (energy, industrial metals, precious metals, grains, livestock, softs)[11]. 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[12].

We show the associated network graph for the six-group aggregation in figure 6. There are several results. First, the energy, industrial metals, and precious metals groups themselves form a tight cluster. Second, there is a very large amount of total directional connectedness to others from energy. Third, livestock and softs are largely peripheral and net receivers, rather than transmitters, of shocks.

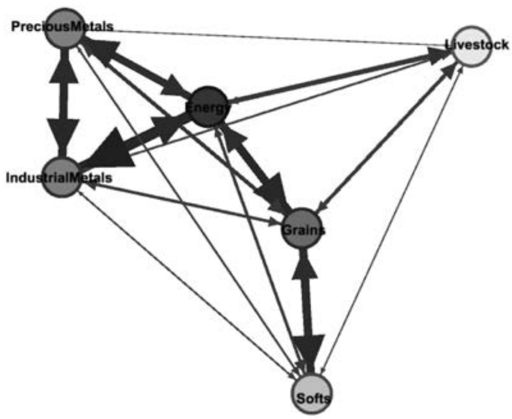
Table 2. Full-Sample Connectedness Table, Six-Group Aggregation

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

11. In principle, we could of course have shown a (19x19) connectedness table earlier, but its size proved unwieldy.

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

Figure 6. Full-Sample Network Graph, Six-Group Aggregation



3. Benchmark Results II: Dynamic (Rolling-Sample) Connectedness

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

3.1 On the Economics of Commodity Connectedness Dynamics

Thus far we have introduced our commodity price index data, constructed the corresponding returns and return volatilities, and provided a basic statistical characterization. Here we delve into more economic aspects.

Commodity prices differ in important ways from those of bonds and stocks. Unlike bonds and stocks, commodity prices are determined more by traditional supply and demand considerations. Perhaps with the exception of precious metals, which in significant part serve as alternative investment vehicles to hedge against global uncertainty, demand for commodities is closely linked to global income. In that regard, at times, commodity prices can be subject to highly-correlated demand-side shocks. This was indeed the case during the global financial crisis, when prices of all major commodities dropped sharply as the near-collapse of global financial markets led to the Great Global Recession of 2009.

The emergence of China as a global economic powerhouse since the early 2000s provides another example of how commodity prices are affected by global consumption demand. From 2001 to 2011, China's industrial production quadrupled, its consumption of industrial metals increased by 330%, and its oil consumption increased by 98% (World Bank, July 2015). China's phenomenal growth in commodity demand is reflected in a broad upward trend in commodities prices that lasted until 2011, but then subsided, as demand from China and other emerging-market economies lessened (World Bank, October 2014).

Unlike commodity demand, which is driven at least in part by a common "global demand" factor, commodity supply is more idiosyncratic. Supplies of energy, industrial metals, precious metals, and agricultural commodities can be affected by very different factors. For example, while the Organization of Petroleum Exporting Countries (OPEC) controls part of the global oil supply, a larger share of it, as well as supplies of metals, can be affected by the decisions of exporting country governments. In the case of agricultural commodities, moreover, weather conditions can play an important role in the short run, while government policies (e.g., export and/or import taxes) can have significant impact in the longer run. Therefore, due to the existence of rather different processes in effect on the supply side, it is quite normal to observe different price movements in different commodity markets.

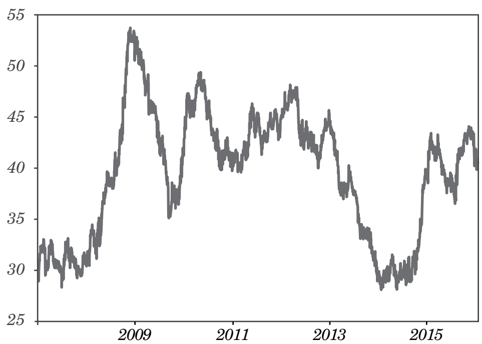
3.2 System-Wide Connectedness

We show total system-wide connectedness in figure 7. It 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 difference. Global bank return volatility shocks, in general, generate higher connectedness, because even though 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 volatility connectedness (and, for that matter, global bond market yield volatility connectedness) indices 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.

Returning to dynamic system-wide volatility connectedness in commodity markets, we observe a spike in total connectedness around late 2008 and early 2009. The U.S. recession that started in the first half of 2008 triggered a global growth slowdown, 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 the world economy accelerated the downward process of commodity prices that lasted until mid-2009.

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

Figure 7. Rolling-Sample System-Wide Connectedness



:

Once it became apparent that the 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 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.

Commodity prices continued to increase until mid-2011; then energy prices stayed more or less steady in the following three years or so, until a sharp drop in oil prices occurred in the second half of 2014. In the meantime, agricultural commodities, as well as 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 dropped by 45% and 52%, respectively, 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 on the demand for other commodities, especially industrial metals. Secondly, the geopolitical risks in some countries in the Middle East and North Africa, as well as in Ukraine, when combined with Saudi Arabia's policy of adjusting its supplies to keep oil price high, played a role in oil prices fluctuating in a band of $80-$105 per barrel for more than three years.

System-wide commodity volatility connectedness reflects the developments over the period. From mid-2010 to early 2013, the system-wide connectedness fluctuated in the narrow band of 40%-45%. System-wide connectedness followed a short-lived upward trend from early 2011 to early 2012, during which period it reached as high as 48%. This increase 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 the 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, system-wide connectedness started to increase from its 30% lows 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, military actions of Russian-backed separatists 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 the 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, 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.

3.3 Total Directional Connectedness

In this section we analyze the dynamics of directional connectedness of individual commodities as well as commodity groups, based on net total directional connectedness graphs ("to" – "from") in figure 8.

Figure 8. Rolling-Sample Net Total Directional Connectedness

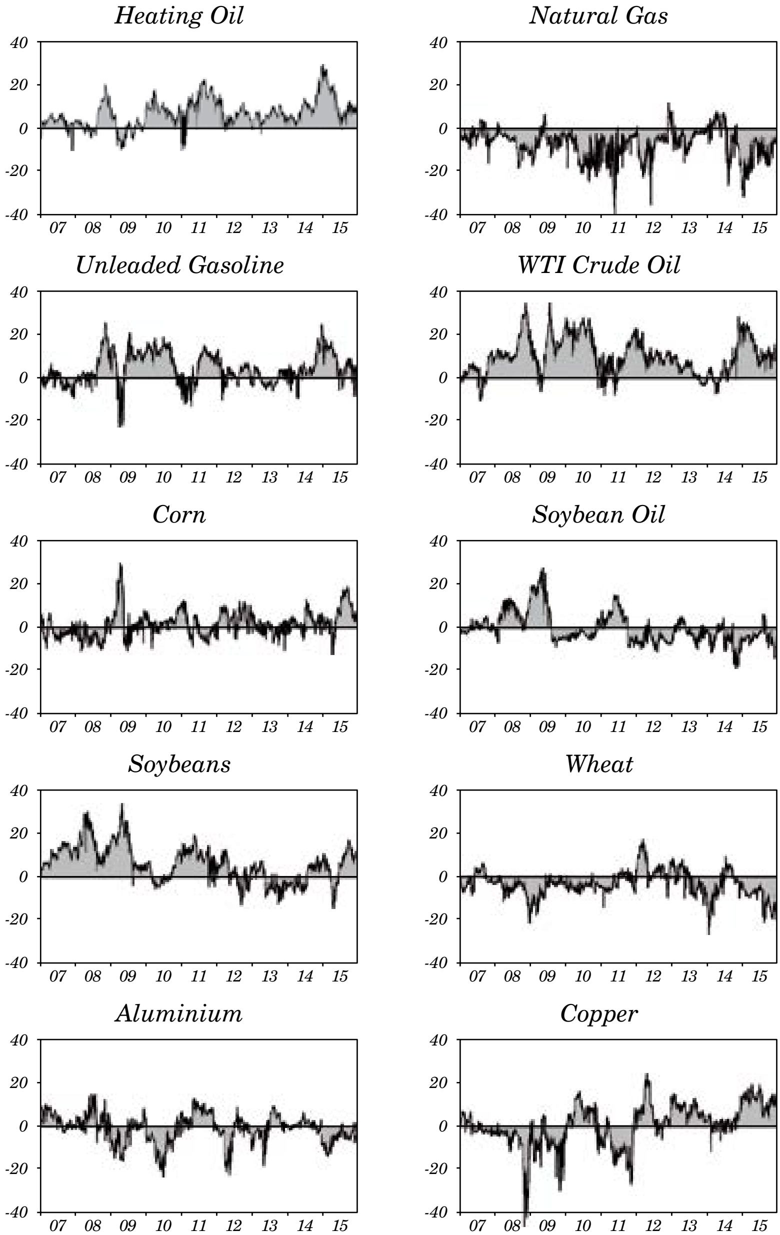
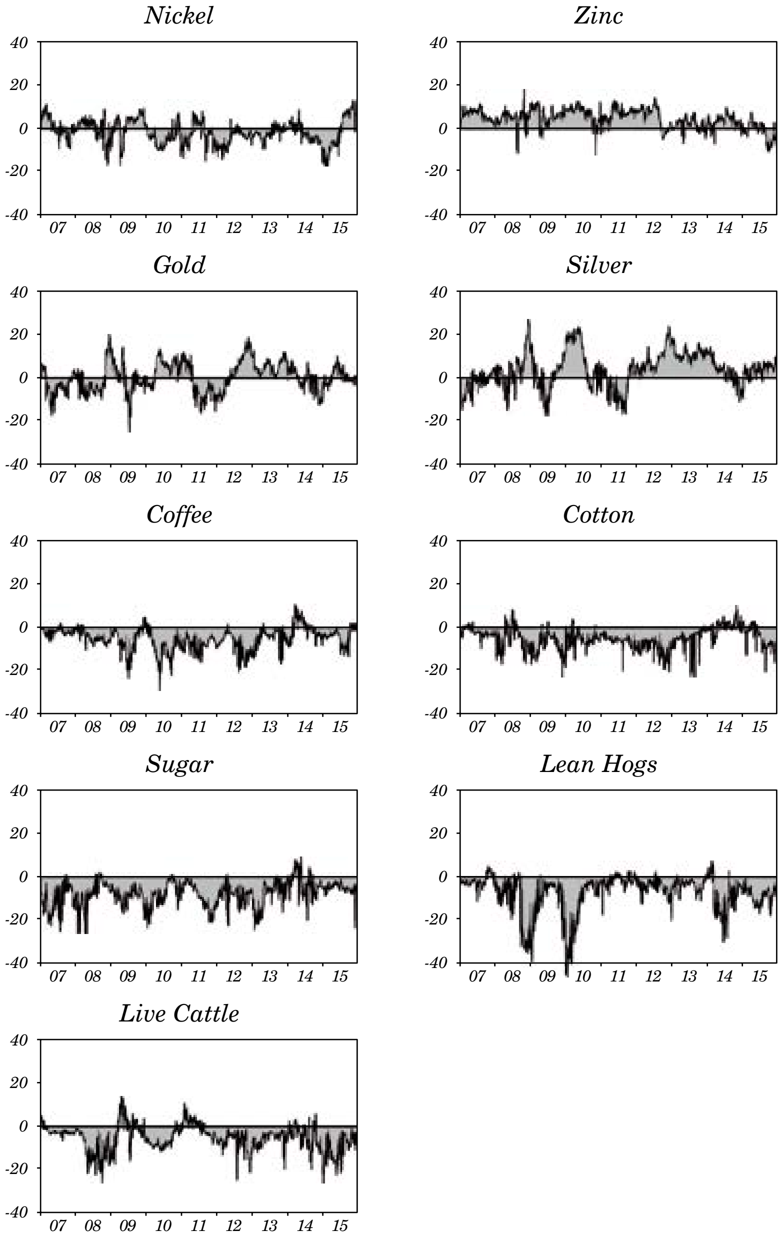


Figure 8. (continued)



As our discussion of the dynamic system-wide connectedness in the previous section showed, and as figure 8 confirms, oil played quite an important role in the commodity market connectedness. 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 a 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, the crude oil price skyrocketed from around $60 in February 2007 to reach $141 per barrel by the first week of July 2008. Henceforth, however, the oil price started to come down as the worries about U.S. economic performance intensified, and along with slowdown signs in many countries. As the downturn started in the oil price, oil return volatility increased substantially. Along with the rising oil return volatility, system-wide volatility connectedness increased from around 40% in early July 2008 to 53% by the end of October 2008. Over the same period, net connectedness of West Texas Intermediate (WTI) crude oil increased from 10% to 35%, the highest net connectedness level generated by a commodity for all rolling subsample windows considered (figure 8).

By the end of October 2008, the crude oil price dropped 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, its net connectedness dropped to around 10% by the end of 2008. Once the oil price recovered to reach closer to $60 per barrel, we observe that net volatility connectedness (hence volatility) of oil returns started to increase significantly and reached to 35% by mid-July 2009.

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 that of crude oil.

Soybeans have high net connectedness, not because they are an important consumption item for households around the world, but rather because they are used in the biofuel production. Soybeans' net connectedness reached as high as 28% in March 2008, last quarter of 2008, and first half of 2009. Unlike crude oil, soybeans' net connectedness increased during 2008: in January —exactly around the Federal Open Market Committee's (FOMC's) emergency conference-call on January 22—, late February and early March. 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 of end-October 2008 to a low of -6% in the first week of April 2009, the net connectedness of soybeans increased to reach 28% level during this same period.

Zinc is actually the only commodity that generated net positive connectedness to others throughout the period from 2006 to 2016. During this 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 started to decline significantly in late 2012 to less than 5%, yet continued to stay on the positive side.

As for energy commodities, unleaded gasoline is the third in terms of generating net connectedness to other commodities. Again, its net connectedness followed a behavior over time quite similar to that of crude oil. The only energy commodity that is a net recipient of connectedness from others is natural gas. Natural gas is the energy market with the weakest link to the economic news flow, even when accounting for recession periods. Reflecting this fact, its connectedness to others and from others is much lower than that of other energy commodities. As such, its return volatility is likely to be affected by the return volatilities of other energy commodities. That is why its net connectedness was negative for an overwhelming majority of rolling sample windows, as shown in figure 8.

We also need to focus on the net connectedness of copper. While its net connectedness was negative from the U.S. 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 system-wide connectedness are closely related to the Chinese slowdown in recent years. Other industrial metals, such as zinc, nickel, and aluminum also experienced significant price drops over the period, but none of them had net connectedness as high as copper. We have already covered zinc above. The other two industrial metals, aluminum and nickel, displayed both positive and negative episodes. When considered altogether, industrial metals generated positive net connectedness to other commodity groups (ranging from 5 to 20%) for almost all rolling window samples.

Among 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 (figure 8).

Soft commodities (coffee, cotton and sugar) and livestock (lean hogs and live cattle) all have negative connectedness for almost all rolling sample windows, thus indicating that their prices on average are influenced by other commodities and/or commodity groups (figure 8).

4. Conclusion

We have estimated and examined the network graph for a set of major commodity sub-index volatilities. The 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 tightly interconnected within themselves.

Appendix A

A.1 Verification of Key Properties of Realized Volatility

Results for other markets like equities (Andersen and others, 2001a) and foreign exchange (Andersen and others, 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 here we provide 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 A1, 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 A2, the answer is mostly yes[13].

Finally, we consider dynamics. In figure A3 we show volatility autocorrelations. They decay, which is consistent with covariance stationarity, but they do so very slowly, indicating highly persistent, if nevertheless mean-reverting, dynamics.

13. 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 10. All three of them are traded on the London Metal Exchange (LME), and they are the only commodities in our data set traded on that exchange.

Figure A1. Gaussian Q-Q Plots for Realized Volatilities

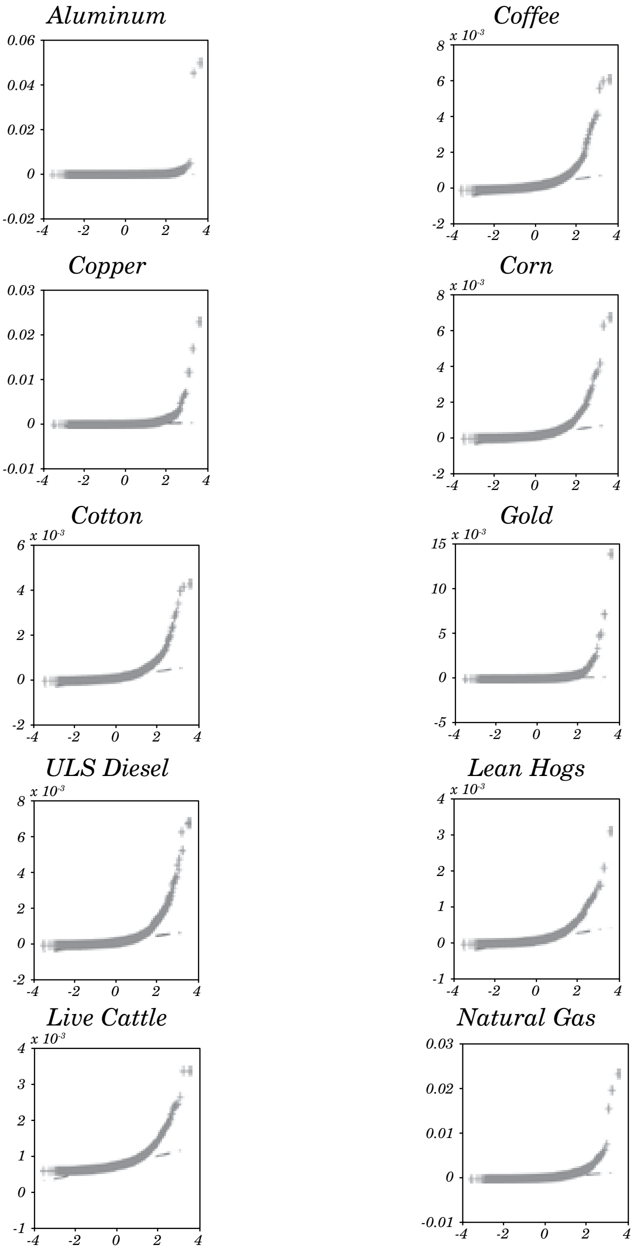


Figure A1. (continued)

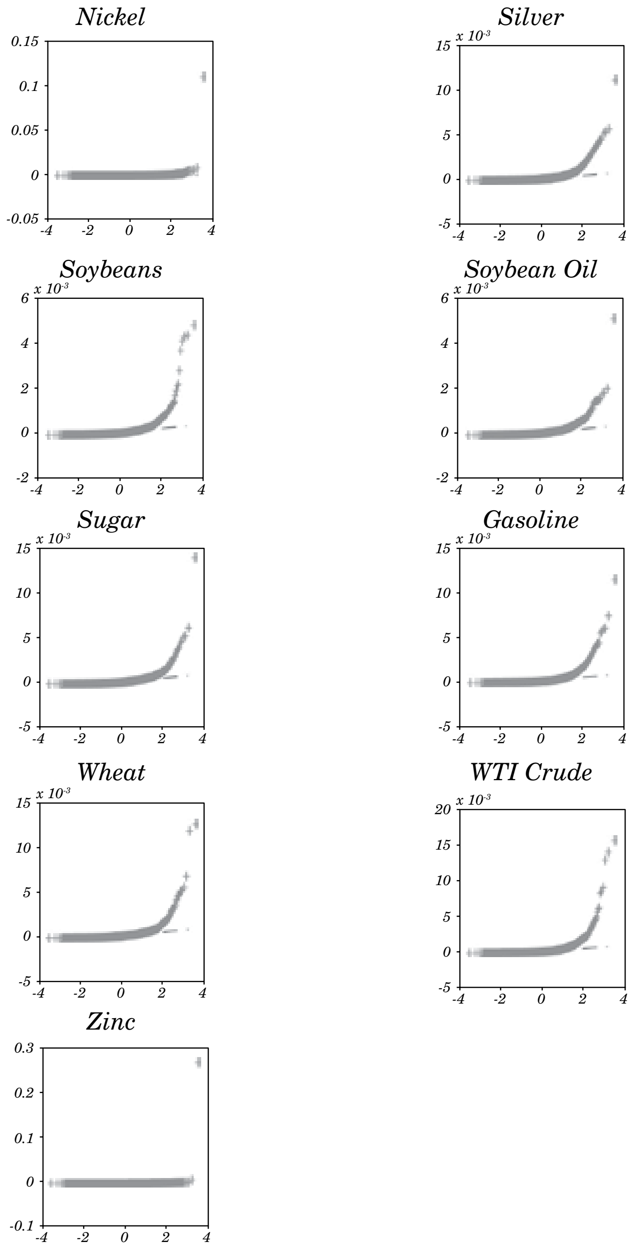


Figure A2. Gaussian Q-Q Plots for Realized Volatilities

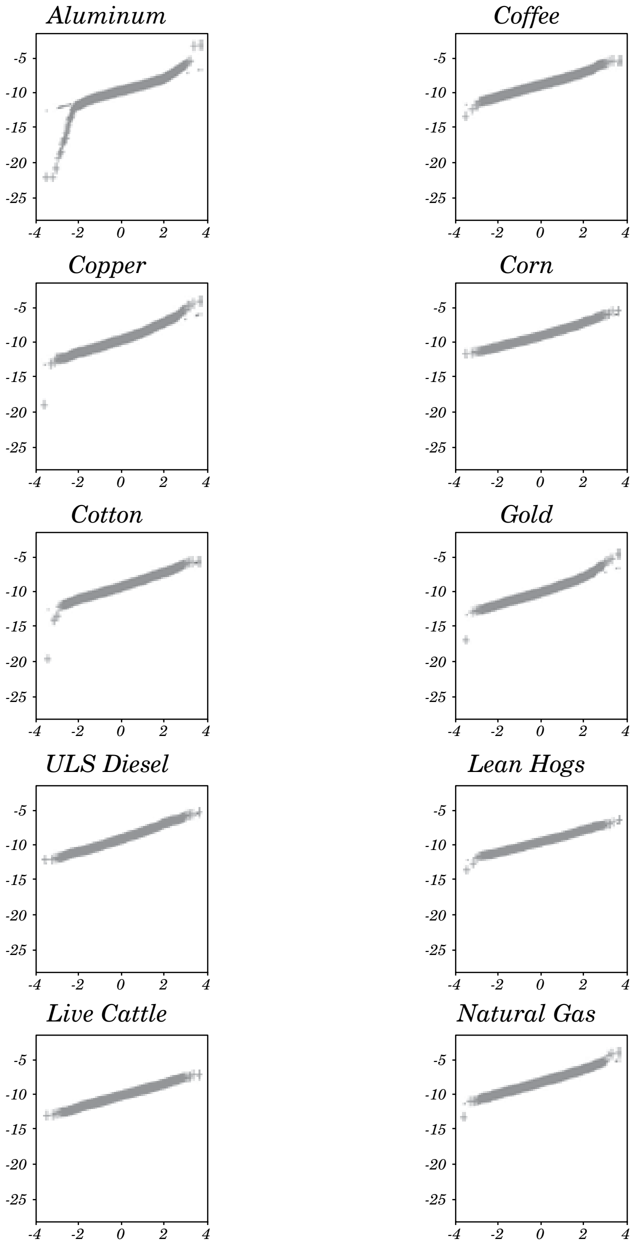


Figure A2. (continued)

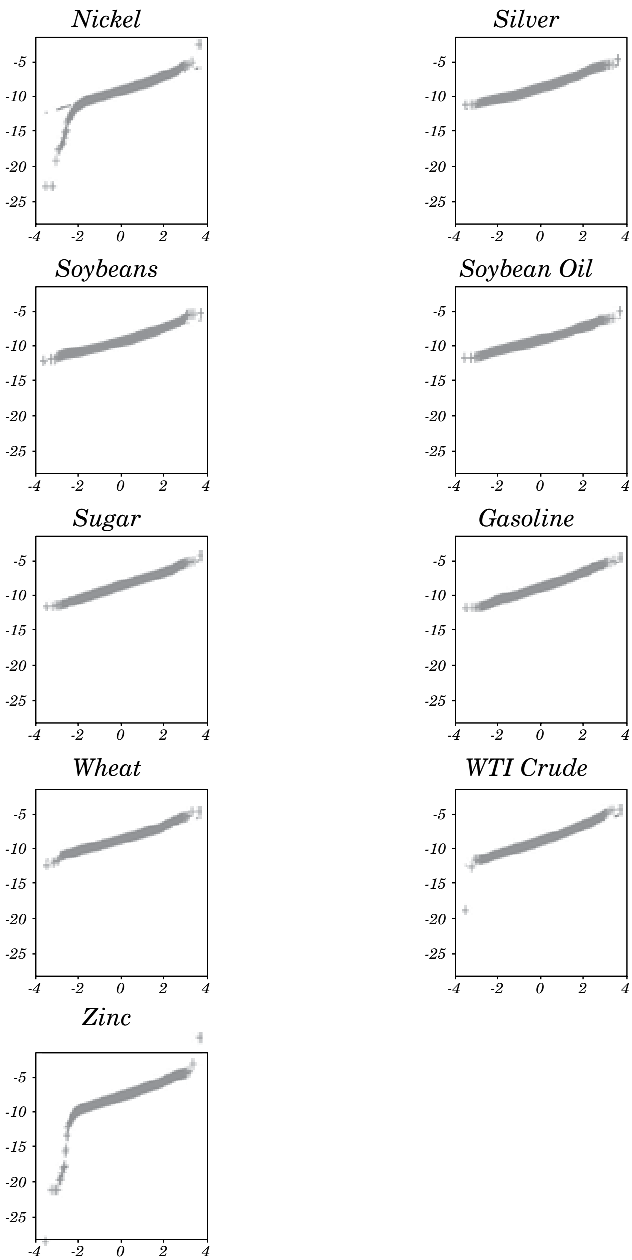
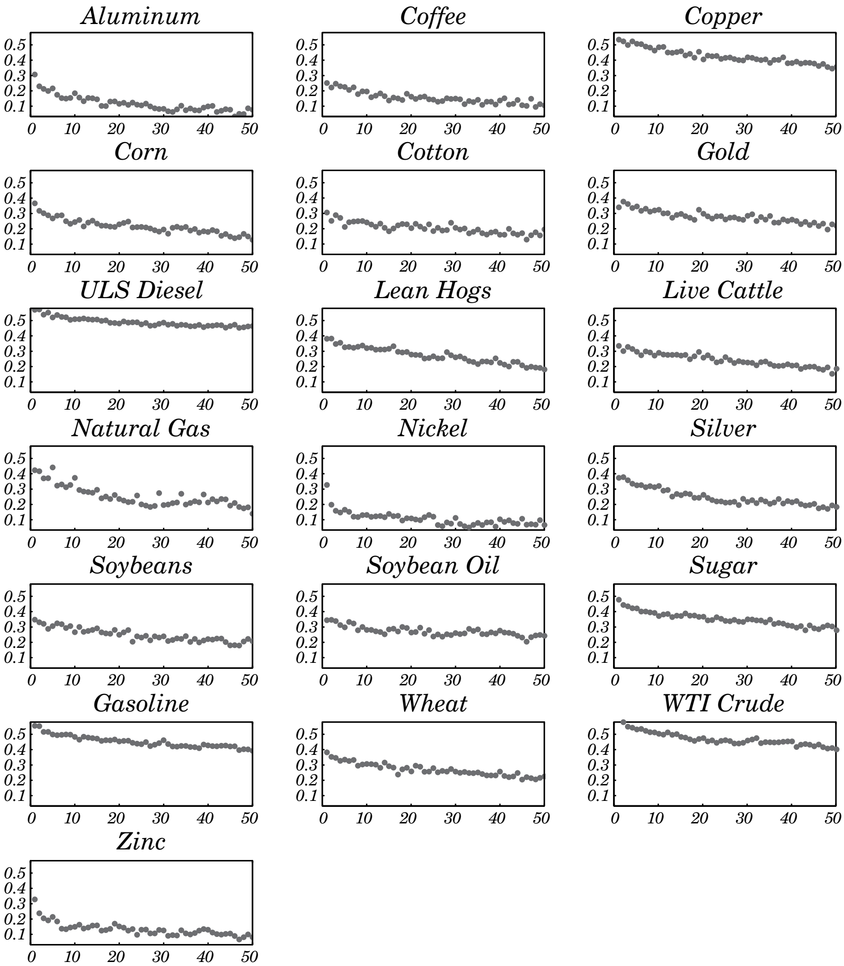


Figure A3. Sample Autocorrelation Functions of Log Realized Volatilities



Appendix B

B1. Different Horizons (Various h, Fixed p = 3)

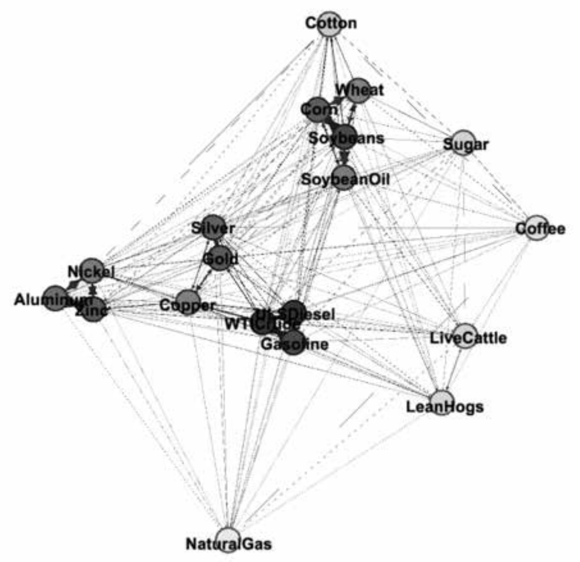
It is of interest to explore connectedness at different horizons h. On the one hand, one might hope for results robust to horizon. On the other hand, upon further consideration, it is not obvious why the results should be robust, or whether such robustness is “desirable”. This point is related to different 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 B1, 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[14].

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

Figure B1. Full-Sample Connectedness, *VAR(3)*, Different Horizons

h=2



h=10

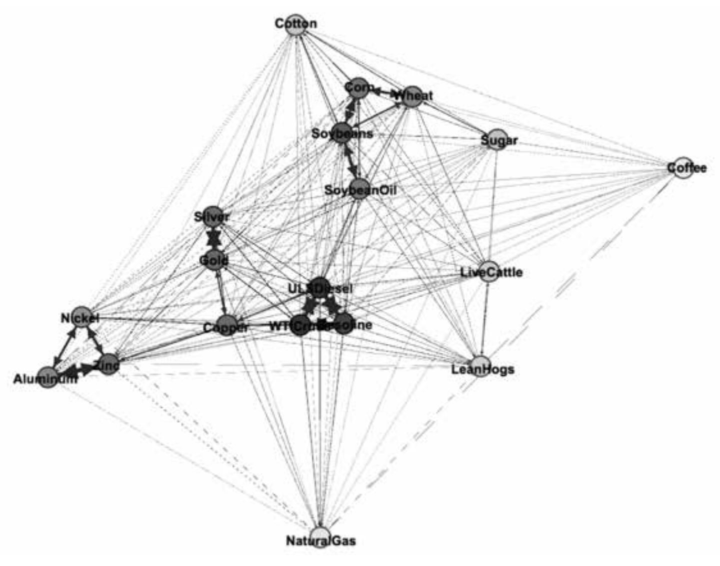
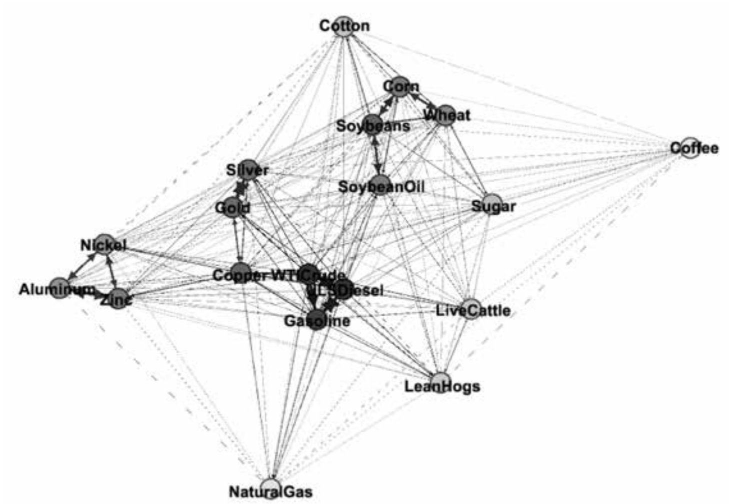


Figure B1. (continued)

h=20



h=30

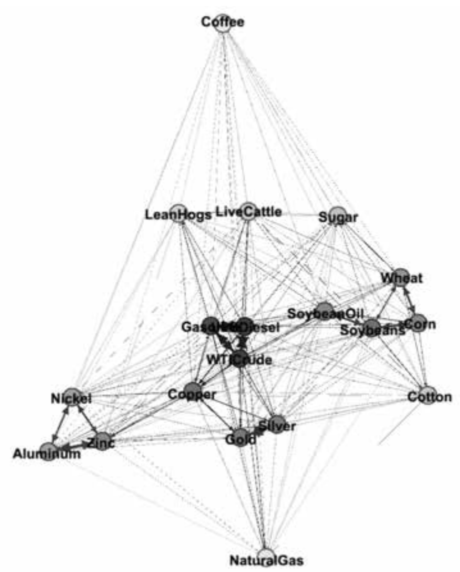
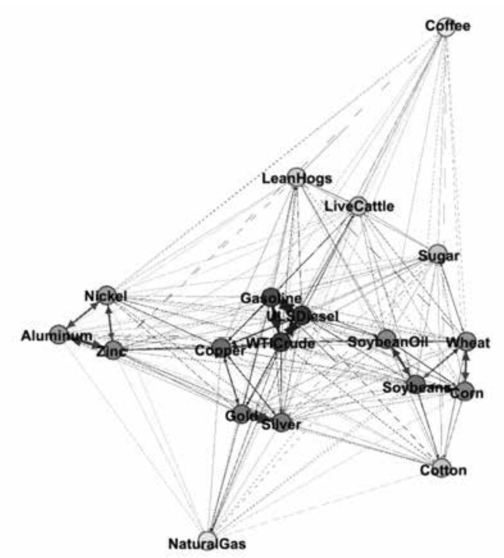
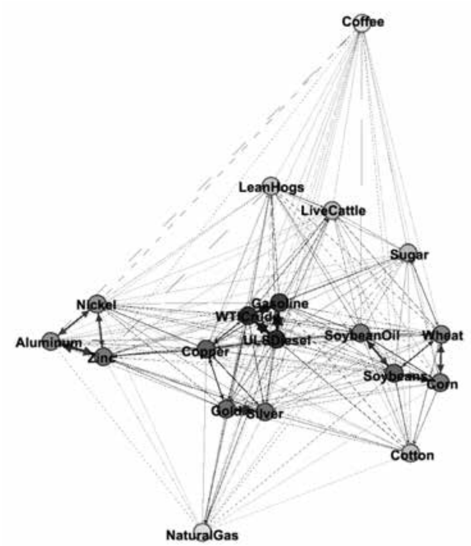


Figure B1. (continued)

h=40



h=50



Appendix C

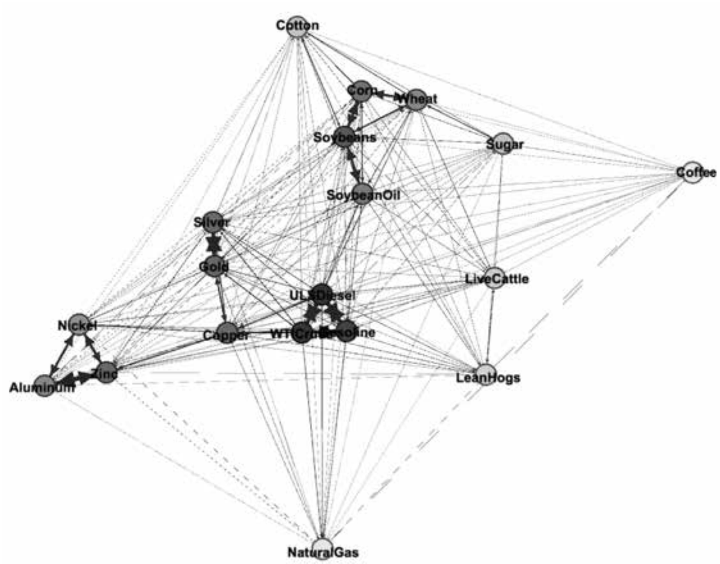
C1. Different Dynamics (Fixed *h* =10, Various *p*)

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 and others (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 C1, 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.

Figure C1. Full-Sample Connectedness, Different *VAR* Orders, h = 10

VAR(3)



VAR(5)

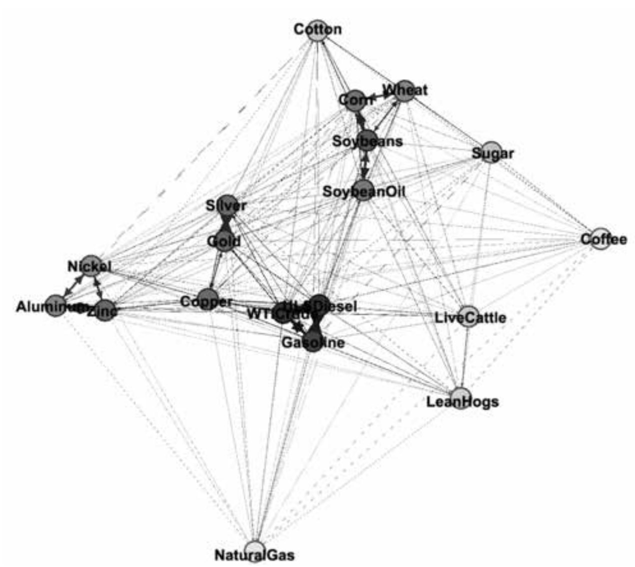
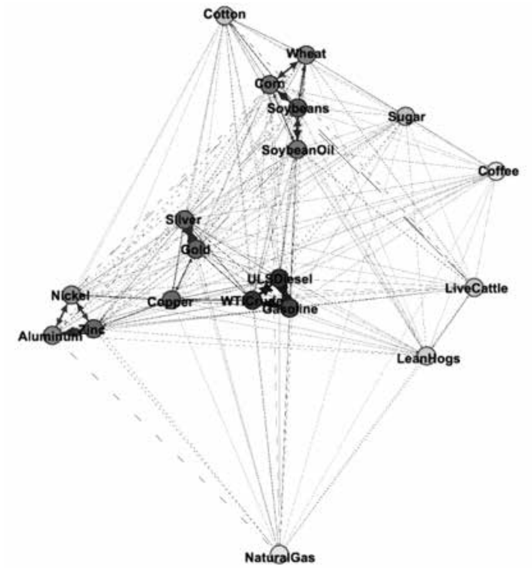


Figure C1. (continued)

VAR(10)



VAR(15)

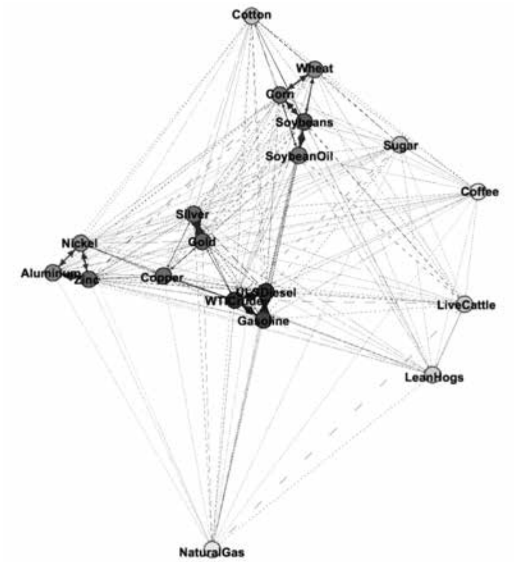
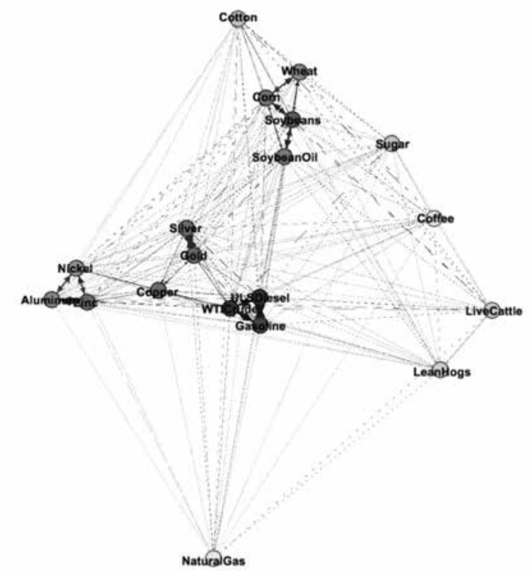
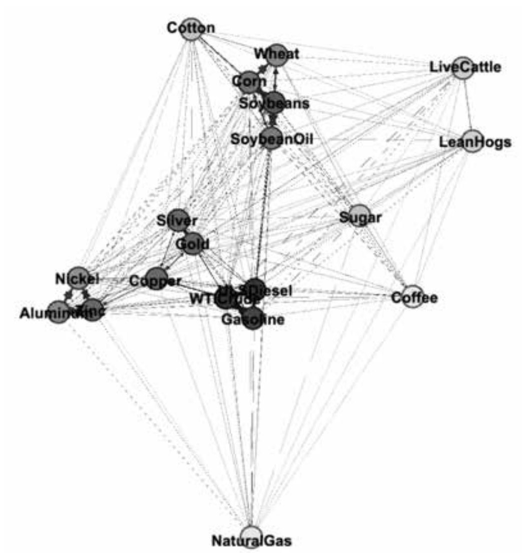


Figure C1. (continued)

VAR(20)



VAR(25)



References

Acharya, V.V., L. Pedersen, T. Philippon, and M. Richardson. 2010. "Measuring Systemic Risk." Manuscript, New York University.

Adrian, T. and M. Brunnermeier. 2016. "CoVaR." *American Economic Review* 106: 1705–41.

Alizadeh, S., M.W. Brandt, and F.X. Diebold. 2002. "Range-Based Estimation of Stochastic Volatility Models." *Journal of Finance* 57: 1047–91.

Andersen, T.G., T. Bollerslev, F.X. Diebold, and H. Ebens. 2001. "The Distribution of Realized Stock Return Volatility." *Journal of Financial Economics* 61: 43–76.

Andersen, T.G., T. Bollerslev, F.X. Diebold, and P. Labys. 2001. "The Distribution of Realized Exchange Rate Volatility." *Journal of the American Statistical Association* 96: 42–55.

———. 2003. "Modeling and Forecasting Realized Volatility." Econometrica 71: 579–625.

Billio, M., M. Getmansky, A.W. Lo, and L. Pelizzon. 2012. "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors." *Journal of Financial Economics* 104: 535–59.

Bloomberg. 2016. "Index Methodology: The Bloomberg Commodity Index Family." Available at https://www.bbhub.io/indices/sites/2/2016/05/BCOM-Methodology-April-2016.pdf.

Bonaldi, P., A. Hortacsu, and J. Kastl. 2013. "An Empirical Analysis of Systemic Risk in the Eurozone." Manuscript, University of Chicago.

Chevallier, J. and F. Ielpo. 2013. *The Economics of Commodity Markets.* Hoboken, NJ: John Wiley & Sons.

Demirer, M., F.X. Diebold, L. Liu, and K. Yilmaz. 2017. "Estimating Global Bank Network Connectedness", *Journal of Applied Econometrics*, in press.

Diebold, F.X. and K. Yilmaz. 2009. "Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets." *Economic Journal* 119: 158–71.

———. 2012. "Better to Give than to Receive: Predictive Measurement of Volatility Spillovers (with discussion)." *International Journal of Forecasting* 28: 57–66.

———. 2014. "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms." *Journal of Econometrics* 182: 119–34.

Fernández, A., A. González, and D. Rodriguez. 2015. "Sharing a Ride on the Commodities Roller Coaster: Common Factors in Business Cycles of Emerging Economies." Inter-American Development Bank Working Paper Series No. IDB-WP-640. Available at http://www.iadb.org/en/research-and-data/publication-details,3169.html?pub_id=IDB-WP-640.

Garman, M.B. and M.J. Klass. 1980. "On the Estimation of Security Price Volatilities From Historical Data." *Journal of Business* 53: 67–78.

Kara, G.I., M.H. Tian, and M. Yellen. 2015. "Taxonomy of Studies on Interconnectedness." SSRN Working Paper No. 2704072. Available at http://ssrn.com/abstract=2704072.

Kat, H.M. and R.C.A. Oomen. 2007a. "What Every Investor Should Know About Commodities, Part I." *Journal of Investment Management* 5(1): 4–28.

———. 2007b. "What Every Investor Should Know About Commodities, Part II: Multivariate Return Analysis." *Journal of Investment Management* 5(3)_ 16–40.

Koop, G., M.H. Pesaran, and S.M. Potter. 1996. "Impulse Response Analysis in Nonlinear Multivariate Models." *Journal of Econometrics* 74: 119–47.

Pesaran, H.H. and Y. Shin. 1998. "Generalized Impulse Response Analysis in Linear Multivariate Models." *Economics Letters* 58: 17–29.

World Bank. 2015. Commodity Market Outlook, July.

World Bank. 2014. Commodity Market Outlook, October.