RETURN CONNECTEDNESS ACROSS COMMODITY FUTURES

by

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Abstract

We obtain the connectedness measures in commodity futures by applying the Diebold-Yilmaz connectedness index methodology. We use an extensive data set of 126 commodity futures from July 1997 to January 2019. In the full-sample analysis, our findings show that crude oil, heating oil, copper, soybean have the highest to-connectedness; these are the commodities contributing more to the variance of other ones. Also, the contribution of futures at different maturities to the connectedness at the commodity level varies significantly; we find no significant maturity effect for gold and silver. In the dynamic analysis, we see that connectedness reaches its peak during the Great Recession. To further characterize the dynamic-connectedness, we decompose the connectedness index into within and cross-commodity components. Cross commodity connectedness dominates the within commodity connectedness after 2004, the year after which a significant amount of investment started flowing into commodity index trading. Finally, by focusing on the dynamic behavior of commodity connectedness over time, we show that the global business cycle and the U.S. Dollar index explain the substantial share of the variation in the connectedness and demand for commodities Granger-cause the total return connectedness of commodity futures.

Keywords: Diebold-Yilmaz Connectedness, Commodity Futures, Vector Autoregression

Özet

Bu çalışma, Diebold-Yılmaz bağlanmışlık endeksi metodolojisini uygulayarak emtia vadeli işlemlerinde bağlantılılık ölçülerini elde etmektedir. Temmuz 1997'den Ocak 2019'a kadar 126 emtia vadeli işlemlerinden oluşan kapsamlı bir veri seti kullanılmaktadır. Tam numune analizinde, bulgularımız ham petrolün, kalorifer yakıtının, bakırın, soya fasulyesinin en yüksek bağlanmışlığa sahip olduğunu, yani bu metaların diğer metalarin fiyat varyansına en fazla katkıda bulunan metalar olduğunu göstermektedir . Ayrıca, farklı vadelerdeki vadeli işlemlerin emtia düzeyinde bağlanmışlık derecelerinin önemli ölçüde değiştiğni gözlemlenmiştir; altın ve gümüş için önemli bir vade etkisi bulunamamıştır. Dinamik analizde, bağlanmışlığın 2008-2012 Küresel Ekonomik Kriz sırasında zirveye ulaşmaktadır. Dinamik bağlanmışlığı daha da karakterize etmek için, bağlanmışlık endeksini emtia içi ve emtia arası bileşenlere incelenmektedir. Genel olarak emtia içi bağlanmışlık, emtia arası bağlanmışlığa baskın gelmektedir. Bu baskınlık 2004'ten sonra iyice berlirginleşmektedir. Küresel iş döngüsü ve ABD Doları endeksi bağlanmışlık varyasyonun önemli bir payı açıklamaktadır.

Anahtar Kelimeler: Diebold-Yılmaz bağlanmışlık endeksi, Emtia Vadeli İşlemleri, Vektör Otoregresyon,

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1 Introduction

Commodity markets have experienced a boom and bust in the 2000s in which there existed a broad and sharp co-movement of commodity prices. Two opposite views are explaining the boom-and-bust cycle. One argues that commodity prices experience boom and bust due to the shocks to the supply and demand. Another explanation is that a high level of investment that flows into commodity indices causes the financialization of commodities through which commodity prices become more correlated. Kilian and Murphy (2014) finds that the increase in global oil consumption rather than speculative trading induced the 2003–2008 oil price surge. However, Singleton (2014) argues that the effect of index investments on returns in oil futures was significant and positive. Even though these studies are only on the oil futures, other studies favor the financialization of commodities using the commodity indices. For example, Tang and Xiong (2010) finds that prices of oil and non-energy commodities became increasingly correlated. This correlation is noticeable for the ones that belonged to the Goldman Sachs Commodity Index and Dow Jones-UBS Commodity Index (today known as Bloomberg Commodity Index). Therefore, there is no consensus on what drives the relationship between commodity prices.

In this study, we want to analyze the spillovers across commodity futures by using the Diebold-Yilmaz connectedness index. This methodology uses network estimation measures based on variance decomposition obtained from vector autoregressions. With the Diebold-Yilmaz framework applied to commodity futures data, we have the bilateral connectedness measures across commodity futures at individual and aggregate levels. We use an extensive data set including 18 commodities and seven futures of each one rather than using only commodity indices because of the following reasons.

First, we aim to analyze the spillover effects between commodities. The common assumption of previous studies was that oil prices affected other commodity prices. However, there may exist a reciprocal relationship between them or a factor driving the commodity prices altogether. In this study, we can see whether the prices of other commodities may affect the oil prices. Also, it is necessary to analyze the prices of commodities to conclude whether commodity futures are financialized. For example, one can argue that oil prices affect other commodity prices because of transportation costs. However, the high level of spillovers between non-oil commodities might indicate the financialization of commodities as they belong to tradable commodity indexes.

Second, a major exchange market for commodities is the futures market. Maturity dates vary significantly across commodities. For some, the maturity of a futures contract goes up to even two years. As a result, futures at different maturities can provide particular information as they reflect the expectation of spot prices. To obtain higher levels of information, we prefer to use individual futures rather than commodity indices. A large vector autoregression allows us to estimate the spillovers across commodities and the spillovers across maturities for each one. These estimations are not only static but also dynamic. Therefore, we can trace the connectedness between any two commodity futures for 1997-2018.

Third, we use the individual commodity futures to put equal weight on them rather than having predetermined weights on particular ones. GSCI puts higher weights on energy sector futures, while BCOM has restrictions on how much of the index is composed by a commodity or its derivatives. Also, these indices usually use only 1-month contracts. We use futures contracts with maturities of up to 7 months.

Using an extensive data set, we analyze the connectedness between commodity futures as a static and dynamic one. Static estimation of commodity futures network reveals that the energy sector generates the highest connectedness to other commodities. Among the energy sector, crude oil is the one that has the highest to-connectedness. Soybean, copper, and soybean oil follow the crude oil. Softs and natural gas are the receivers of shocks. Dynamic connectedness analysis shows that the connectedness of commodities reached its peak during the 2008 global crisis. Before the global financial crisis, 2004 was particularly important since it is the beginning of the financialization of commodities. After 2004, spillovers generated to other commodities, which we refer to as cross-commodity connectedness, increases while the within connectedness decreases. To understand the factor that drives the commodity connectedness, we check how business cycles, US Dollar Index, and other financial variables affect the commodity index and whether the Kilian index Granger-causes the connectedness index. We find that the Kilian index Granger causes the commodity connectedness. Moreover, the business cycle and US Dollar Index explains the substantial share of the variation in connectedness.

The remainder of this paper is structured as follows. In section 2, we review the literature on the co-movement of commodity prices and the spillovers across commodity futures. Section 3 describes the data, methodology, and network visualization. In Sections 5 and 6, we present static and dynamic estimation results. Section 7 discusses the possible determinants of commodity connectedness and section 8 concludes.

2 Literature Review

The discussion on the relationship between commodity prices previously focused on the co-movement of commodity prices. Pindyck and Rotemberg (1988) found that even unrelated commodities show a tendency to move together. A more recent study by Ohashi and Okimoto (2016) shows that the degree of co-movement increases for some subset of the commodities after 2000 that coincides with the beginning of index trading of commodities even after filtering out the common fundamental shocks. The analysis of co-movement of commodity prices is important as previously commodities were considered heterogeneous asset classes which attracted the attention for portfolio diversification.

Some studies argue that financialization increased the level of co-movement of commodity prices. Around 2004, a significant amount of investment flow into the commodity index. This process is often referred to as the financialization of commodities. Investment in the commodity index caused the commodity prices to move in the same direction. As a result, the co-movement level increased. As Tang and Xiong (2012) and Cheng and Xiong (2013) argue, one of the implications of the increased level of co-movement is that commodities became susceptible to receive outside shocks. Before financialization, commodity futures were used to hedge out the risk of price changes. With financialization, speculators mostly trade them. Therefore, price volatility originating outside spills over to commodity markets.

From a theoretical perspective, Basak and Pavlova (2016) find that in the presence of institutional investors, futures prices of commodities rise together. In addition to that, they find that the shocks to supply and demand of index commodities are transmitted to other commodities. Commodity spot prices become more prone to outside shocks as a result of financialization. Diebold and Yilmaz (2012) studies the daily volatility spillovers across US stock, bond, foreign exchange and commodity markets. They show that commodity markets are the receiver of shocks from other markets and confirm the theoretical side.

Another argument for the source of co-movement of commodity prices is the economic linkages between them. Casassus, P. Liu, and Tang (2013) show that these linkages between commodities are one of the sources of their long-run price dynamics. They use three categories to describe these linkages between commodities: production, substitution, and complementary relationships. Production relationship occurs when one commodity is produced or extracted from another commodity. For example, both soybean meal and soybean oil are produced from soybean. When two commodities are the substitute of each other in consumption, they call it substitution relationship. If two commodities are complementary in consumption or production, they have a complementary relationship.

Some studies argue that global factors drive the fluctuations in commodity co-movement rather than individual supply and demand shocks. Fattouh, L. Kilian, and Mahadeva (2013) argues that emerging markets and global economic activity drive the increasing correlation of commodity prices. Delle Chiaie, Ferrara, and Giannone (2017) show that there exists a single global factor that is strongly correlated with global economic activity driving commodity prices in the same direction. Chen et al. (2014) studies the common factor driving the prices of 51 commodities and finds the common factor is closely related to U.S. exchange rate.

Above, we mentioned the possible drivers of co-movement of commodity prices. In our study, we focus on return spillovers rather than the co-movement. However, drivers of co-movement are likely the drivers of return spillover as well. Now, we review the literature on spillovers.

Diebold, L. Liu, and Yilmaz (2017) studies the return and volatility spillover of 19 commodities by using their spot prices. They find that the energy sector is a strong transmitter of shocks to other commodity groups. They observe a spike in system-wide connectedness during the global financial crisis.

A comprehensive analysis is done by Chevallier and Ielpo (2013) on volatility spillovers in intra-commodity market and commodity market with other assets. In the commodity market only, gold, aluminum, crude oil, and corn are the net givers of volatility spillovers. They observe intra-sector spillover as most of the contribution to spillovers comes from the commodity in the same sector. Across sectors, metals and energy have high levels of spillover while agriculture has lower spillover. They perform volatility spillover analysis on commodity markets with S&P 500, US 10 year rate, and US Dollar to understand the spillovers across different markets. They find a linear trend in the spillover index for 1995-2012 that may indicate the financialization of commodities. Energy sector commodities are a net contributor to the S&P 500 with a contribution of 2.44. Precious metals are the net transmitter to a 10-year rate of 4.62.

Another study on volatility spillover is done by Nazlioglu, Erdem, and Soytas (2013). They focus on the spillovers between oil and agricultural commodities. They find that before the food price crisis, there was no volatility spillover from oil to agricultural commodities. However, after the crisis, wheat, corn, and soybean get transmitted spillovers from oil. Kang, McIver, and Yoon (2017) examines the return and volatility spillovers for gold, silver, WTI, corn, wheat, and rice. They find that return and volatility spillovers follow similar movements over time. During the financial crises, gold and silver are the net givers of spillovers.

What is missing in these studies is the maturity effect. We argue that to obtain more information, not only front-month futures but also distant futures should be included in the data. As futures prices reflect the expectation of future spot prices, the expectation might affect today's prices. Karstanje, Wel, and Dijk (2017) uses commodity futures curves to examine the commonality in the price levels. They find that using the nearest contract overestimates the common factor. Most of the commonality comes from the sector, not from a global one. Therefore, commodities are still a heterogeneous asset class.

3 Data and Methodology

3.1 Data

We focus on 18 commodities: four energy commodities (West Texas Intermediate crude oil, heating oil, gas oil, natural gas); six metal commodities (aluminum, nickel, zinc, copper, gold, silver); eight agriculture commodities (soybean, soybean meal, soybean oil, corn, cotton, coffee, cocoa, sugar). Table 1 shows the commodities, their sector, ticker, and the exchanges on which they are traded. For the sectors and tickers, we follow the Bloomberg categorization and tickers. They subcategorize metals into precious metals (gold and silver) and industrial metals.

In total, we have 126 commodity futures contracts in which there are seven contracts with different maturities for each commodity. These futures contracts are artificial instruments constructed by chaining together individual short-term futures contracts to create a single long-term history. A single futures contract has fixed trading-start and trading-end dates, short lifespans, and variable liquidity. Hence, it is unsuitable for analyzing long-term trends in the data. The simplest form of continuous contract is built by chaining together successive individual contracts which are closest to their expiry date: front-month contracts.

Data taken from Bloomberg is already in the form of continuous futures contracts. For example, CL1 represents WTI Crude Oil futures contract with 1-month maturity. Table 7 in the Appendix shows the descriptive statistics of commodity futures returns. For all contracts, the mean is very close to zero. We observe that as the time to maturity increases, the standard deviation decreases even though the mean is almost the same. That is an important characteristic of futures with distant maturities. They can be used for portfolio balancing.

We restrict our analysis to futures contracts with maturities of up to 7 months even though there are other available futures contracts. Behind this restriction, following reasoning lies. The first one is to analyze across maturity linkages. If we don't take the same number of maturities for each commodity, we put more or less weight on others. To this end, from all available contracts, we set the limit at seven months which is the common largest maturity for all. So we had to exclude futures contracts with an expiration date longer than seven months. For some commodities, even though futures contracts up to 7 months are available, we had to exclude them as there is no change in price for more than 50 consecutive days.

After the eliminations, we end up with 126 contracts for July 1997 -January 2019. We have 5545 observations which are day-end settlement prices. As VAR requires stationary variables, we transform the data by using log differences.

We acknowledge that our data is highly correlated as we use the futures 7 contracts for each commodity. To analyze the linkages across maturities, we need to use different maturities. As we mentioned before, some commodities have economic linkages that lead to higher correlations in their price dynamics. For example, heating oil and gas oil are derivatives of crude oil. Therefore, they have a productive relationship. This also applies to soybean, as soybean meal and soybean oil are the derivatives of soybean. Crude oil and natural are seen as substitutes in the industrial and electric generation sectors. Industrial metals are complementary goods in supply. For the inferences and interpretations, we should take these into account.

Table 1: Commodity Contracts

Sector	Commodity	Ticker	Exchange
Energy	Crude Oil	CL	NYMEX
	Heating Oil	HO	NYMEX
	Natural Gas	NG	NYMEX
	Gasoil	QS	NYMEX
Metals	Gold	GC	COMEX
	Silver	SI	COMEX
	Copper	HG	COMEX
	Aluminum	LA	LME
	Nickel	LN	LME
	Zinc	LX	LME
Grains	Soybean	S	CBOT
	Soybean Meal	SM	CBOT
	Soybean Oil	BO	CBOT
	Corn	C	CBOT
Softs	Cocoa	CC	ICE
	Coffee	KC	ICE
	Cotton	CT	ICE
	Sugar	SB	ICE

3.2 Diebold-Yilmaz Connectedness Framework

In this section, we present the methodology for measuring the connectedness across commodity futures. Our main interest is to investigate how price shocks are transmitted across commodity futures. In particular, we want to learn which commodity contributes more to the variance of other commodities and how much maturity affects the contribution. In order to quantify the level of transmission, we use Diebold-Yilmaz connectedness framework which developed in a series of publications Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), Diebold and Yilmaz (2014).

Diebold-Yilmaz connectedness measures are based on variance decomposition obtained from vector autoregressions. Variance decomposition which indicates how much of i's variance is contributed by the shocks to the j helps us understand the bilateral linkages across variables. Since the Cholesky factor orthogonalization is sensitive to order, we use generalized variance decomposition developed by Pesaran and Shin (1998). With generalized variance decomposition, results are invariant to ordering. We take the lag as three and the horizon as 10.

3.2.1 Pairwise Directional Connectedness

Consider VAR(p) with p lags and N stationary variables,

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t \tag{1}$$

where $\varepsilon_t \sim$ (0,Σ). This process can be represented as moving average process as

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$$

where

$$A_i = \sum_{j=0}^{p} \phi_p A_{i-p} \tag{2}$$

with A_0 $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. Variance decomposition estimated from these coefficients report the contribution of j^{th} variable in h step ahead forecast error variance decomposition of i^{th} variable as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\epsilon_i' A_h \Sigma \epsilon_j\right)^2}{\sum_{h=0}^{H-1} \left(\epsilon_i' A_h \Sigma A_h' \epsilon_j\right)} \tag{3}$$

where σ_{jj} is the standard deviation of ϵ_j and e_i is the selection vector. Selection vector

e_i consists of a diagonal that constructed by ones and zeros on the off-diagonal parts. Also, Σ is the covariance matrix for the error vector ϵ_j .

Note that row sum of variance decomposition matrix is not necessarily one. In order to have the same scale of impulse responses, we normalize each entry by dividing them their respective row sums. Then, this normalization provides the pairwise directional connectedness from j to i:

$$\theta_{ij}^{\sim g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{4}$$

where $\sum_{j=1}^{N} \theta_{ij}^{\sim g}(H)$ =1 and $\sum_{i,j=1}^{N} \theta_{ij}^{\sim g}(H)$ = N.

We call it directional connectedness since connectedness from i to j and j to i are not necessarily the same.

3.2.2 Total Directional Connectedness: To and From

Since we have pairwise measures of connectedness, we can consider the aggregate measures as well. We define total directional connectedness from one variable to all other variables which the contribution of variable i to the variance of all other variables. It is called "to connectedness". Similarly, contribution to the variance of i from all other variables is called "from connectedness".

We estimate total directional "to" connectedness of contract i's price change from future prices of all other contracts:

$$C_{\bullet\leftarrow i} = \frac{\sum_{j=1, j\neq i}^{N} \theta_{ij}^{\sim g}(H)}{\sum_{i,j=1}^{N} \theta_{ij}^{\sim g}(H)} \times 100 = \frac{\sum_{j=1, j\neq i}^{N} \theta_{ij}^{\sim g}(H)}{N} \times 100 \tag{5}$$

Total directional "from" connectedness of contract i's price change to prices of all other contracts:

$$C_{i\leftarrow \bullet} = \frac{\sum_{j=1, j\neq i}^{N} \theta_{ji}^{\sim g}(H)}{\sum_{i,j=1}^{N} \theta_{ji}^{\sim g}(H)} \times 100 = \frac{\sum_{j=1, j\neq i}^{N} \theta_{ji}^{\sim g}(H)}{N} \times 100 \tag{6}$$

Also, net connectedness represents the difference between to and from connectedness as follows:

$$C_i(H) = C_{\bullet \leftarrow i}(H) - C_{i \leftarrow \bullet}(H) \tag{7}$$

One can extend the definitions of total directional connectedness such that we can calculate the "to connectedness" and "from connectedness" of subgroups of variables. In our case, we calculate the directional connectedness by sectors, energy, metals, softs and grains. Similarly, we can calculate the directional connectedness

3.2.3 System-Wide Connectedness

To calculate total spillover, we aggregate the pairwise connectedness measures. It is the average of connectedness measures. Hence, this index provides the overall spillover across contracts of different commodities with different maturities. Therefore, it reflects the significance of price shocks originating in all contracts. Total or system-wide connectedness calculated as:

$$C(H) = \frac{\sum_{j=1, j\neq i}^{N} \theta_{ji}^{\sim g}(H)}{\sum_{i,j=1}^{N} \theta_{ji}^{\sim g}(H)} = \frac{\sum_{j=1, j\neq i}^{N} \theta_{ji}^{\sim g}(H)}{N} \tag{8}$$

3.3 Selecting and Shrinking the Approximating Model

We mentioned in the data section that our sample consists of 126 futures which means that we estimate a high-dimensional VAR. We want to keep the all variables so we don't want to reduce high dimensionality by removing some variables from data. We could use the factor-augmented vector autoregressive approach however it leads to the loss of information coming from the maturities. Therefore, we rely on LASSO which is a hybrid of shrinkage and selection methods.

Consider the following least-squares estimation:

$$\hat{\beta} = \arg\min_{\beta} \sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2$$

subject to

$$\sum_{i=1}^{K} |\beta_i|^q \leq c$$

which is equivalent to

$$\hat{\beta} = \arg\min_{\beta} \left[\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q \right]$$

Concave penalty functions which are non-differentiable at origin enables selection. Convex penalties produce shrinkage. This estimator can be extended such that it does both shrink and select with the property that if correct coefficients are chosen, bias goes to zero. This estimator is elastic net, given by

$$\hat{\beta}_{Enet} = \arg\min_{\beta} \left[\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} w_i(\alpha|\beta_i| + (1-\alpha)\beta_i^2) \right]$$

where $w_i = 1/|\hat{\beta}_{i,OLS}|$ and λ is chosen equation by equation by 10-fold cross-validation. Elastic net combines the the lasso penalty and ridge penalty. By using the inverse of ordinary least square estimation as weight, it forces small OLS coefficients to zero.

3.4 Network Visualization

By using DY connectedness framework, we have complete and directed pairwise connectedness measures. So, they constitute complete, weighted, directed networks. In order to visualize the networks, we use the open-source Gephi software.[1] In the networks, we have 126 nodes and 126 x 126 edges. We use ForceAtlas2 algorithm developed by Jacomy et al. (2014) to locate nodes in the networks as implemented in Gephi. The algorithm finds a steady state in which repelling and attracting forces

[1]For more information, check https://gephi.github.io/ .

exactly balance, where nodes repel each other, while edges between two nodes attract their nodes. The attracting force of an edge is proportional to average pairwise directional connectedness “to" and “from," which also determines the thickness of the edge between two nodes.

In the network graph, nodes are named based on the contracts. For example, node named CL1 represent the crude oil contract with 1 month maturity.

Node color shows the "to connectedness". It shows how much a contract contributes to the other contracts’ variance. Since we are using the range of one particular color, the darker the node color gets, the higher to connectedness.

Node location shows the average pairwise directional connectedness. Node locations are determined by ForceAtlas2. At the steady state, nodes that generate higher pairwise directional connectedness to each other are expected to be closer. Similarly, nodes generating lower pairwise directional connectedness to each other are placed farther away.

In the return connectedness network, the edge thickness represent the average pairwise “to" and “from" return connectedness between two nodes.

4 Static Analysis of Return Connectedness

4.1 Joint Analysis

In this section, we provide the full-sample analysis of return on futures contracts of commodities. Estimation based on the whole sample provides us with an average connectedness of commodity futures. As connectedness across contracts is likely to change over time, we discuss dynamics of connectedness over time in the following section. We study with 126 contracts, therefore I employ network visualization to analyze linkages across futures contracts rather than reporting the connectedness table of all futures. Return connectedness of commodity futures from 23 July 1997 to 16 January 2019 is presented in Figure 1.

Network visualization of static estimation helps us analyze the clusters among sectors or commodities, the major transmitter, and receiver commodities on average. The clusters are formed by the commodities that generate the highest pairwise connectedness to each other. As expected, each commodity naturally forms a cluster within itself since futures contracts of the same commodity are most correlated with each other. The network graph shows that there are three main clusters: energy, metals, and grains. Softs do not form clustering and they have weak connections with other commodities. These clusters follow the categorization of Bloomberg that we mentioned above with slight differences.

Crude oil, heating oil, and gas oil form a very strongly connected cluster. As heating oil and gas oil are derivatives of crude oil, they have a production relationship. Therefore, it is expected that their price dynamics are strongly correlated. However, natural gas is not in this cluster. Even though natural gas is a part of the energy sector, it exhibits a weak correlation with other energy commodities. Most of the spillovers to natural gas' return come from its price dynamics. Natural gas is closer to this cluster through heating oil. 1-month heating oil generates the highest spillover to natural gas. It is expected as they have a substitution relationship. Within this cluster, crude oil generates the highest level of pairwise connectedness to other commodities. As seen in the graph, each cluster involves a commodity that connects itself to other clusters. It is the crude oil among energy commodities that connects its cluster to other ones.

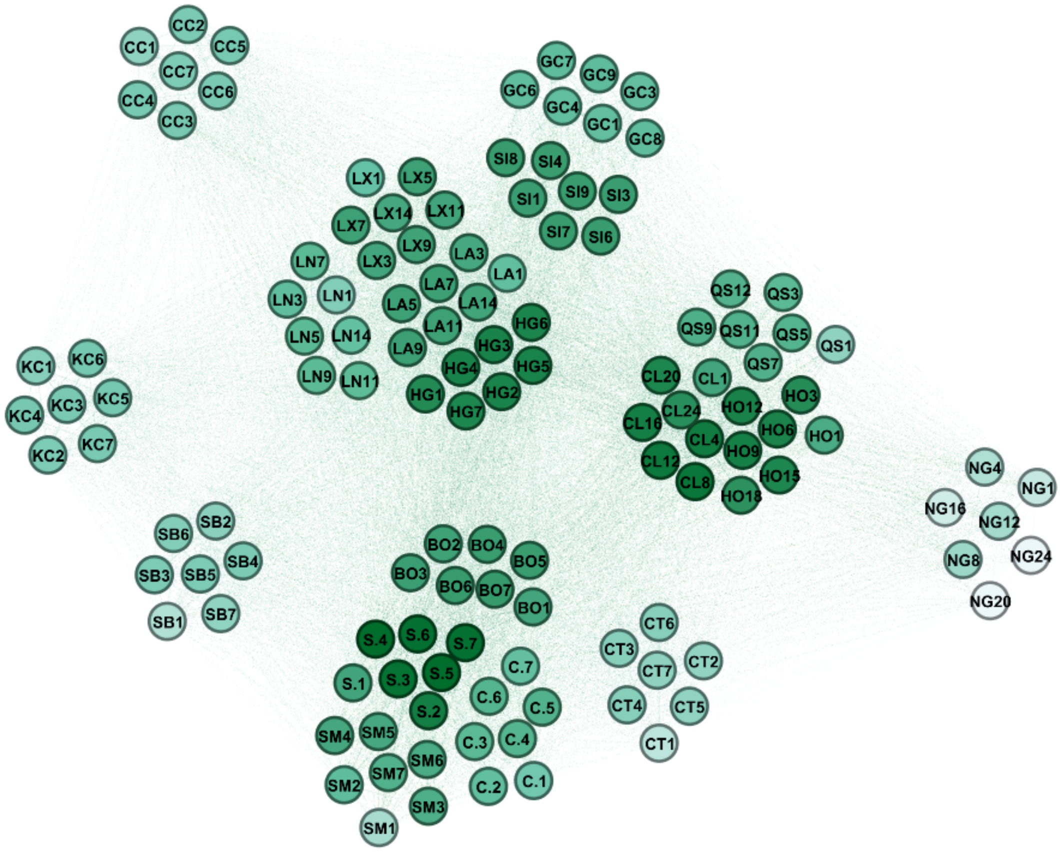

Figure 1: Return Connectedness Network (1998–2019)

Grains form another cluster. Their characteristics are very similar to the energy sector. As soybean oil and soybean meal are the derivatives of soybean, they have a production relationship. Therefore, we observe higher pairwise connectedness among them. Soybean and corn are very connected as well. Both soybean and corn are used in biodiesel and ethanol production. Traditionally soybean and corn are considered substitute commodities as farmers compare futures prices to choose soybean or corn to grow. Thus, production and substitution relationships constitute the correlation in the price dynamics in this cluster. Soybean is the commodity generating the highest connectedness in this cluster as well as among all commodities. However, it is not at the center of the network graph as it is strongly connected to its cluster. In this network, commodities at the center are the ones connecting sectors. Since closest commodity to center reveals the transmission across sectors, grains are connected through soybean oil to other sectors.

Industrial metals have a complementary relationship in the supply as we mentioned before. As expected, they form a cluster in the graph. Copper generates the highest pairwise directional connectedness to other metals as well as other commodities. Gold and silver are under the category of precious metals, and they are closer to industrial metals. Even though gold and silver have a production use, they are often considered as financial assets. It is also possible that they transmit outside shocks to commodity markets.

Among commodities, softs remain as a heterogeneous class as there are no economic linkages between them. Their variance in the returns comes from their price dynamics. They are more likely to be driven by their fundamentals, i.e. supply, demand, and inventory. Commodities with the highest own connectedness are coffee with 73.8 percent, cocoa with 76.9 percent, cotton with 60.6 percent, sugar with 67.2 percent. They all are the net receiver of shocks.

The color of the nodes reveals the degree of connectedness transmitted to other contracts from that contract. From 1997 through 2018, soybean has the highest to-connectedness followed by crude oil, heating oil, and copper. However, not all contracts of these commodities are the major transmitter of shocks. For example, while three to six soybean month contracts have the highest to-connectedness, one-month soybean contract has the lowest to-connectedness. These show that maturities are also an important determinant of connectedness. Like soybean, most commodities' medium-term maturities have higher to-connectedness compared to short and long-term maturities.

In Table 2, we present the to-connectedness of commodities across maturities. We can observe the maturity effect in the network graph as well. This table shows detailed information on the effect of maturity on commodity connectedness at the individual level.

Table 2: To Connectedness of Commodities Across Maturities

	1-month	2-month	3-month	4-month	5-month	6-month	7-month
CL	98.37	117.31	119.37	118.67	115.91	112.68	108.70
HO	95.64	109.86	113.90	115.30	114.34	112.16	107.25
NG	58.55	65.20	69.99	67.96	56.04	47.71	47.79
QS	73.95	89.62	91.90	93.35	93.95	93.19	92.38
GC	87.15	87.15	87.35	87.79	88.03	88.18	88.51
SI	101.80	101.82	101.99	102.44	102.52	102.65	102.61
HG	110.29	113.78	114.11	114.12	113.72	112.97	112.44
LA	87.30	97.18	100.40	100.74	100.77	100.35	99.04
LX	85.78	98.52	100.26	100.25	99.82	99.14	97.50
LN	77.81	87.90	89.19	89.36	88.95	88.37	86.58
S	98.94	116.18	121.22	123.43	123.67	122.04	121.90
BO	98.24	100.14	101.48	102.16	102.02	102.86	103.15
SM	66.89	88.00	94.46	97.31	96.90	95.79	92.57
CC	74.07	79.69	80.47	80.73	80.65	79.80	78.79
SB	64.28	75.16	78.96	79.72	79.14	77.04	73.69
KC	76.33	79.25	80.31	80.85	81.10	80.92	79.86
C	82.15	87.38	89.41	91.50	92.41	91.70	86.76
CT	60.75	72.77	76.02	76.06	73.58	76.28	73.84

We observe that a 1-month contract of all commodities except natural gas generates the lowest connectedness across maturities. The maturity effect of gold and silver contracts on transmitting spillovers is negligible. All maturities of financial commodities are almost equally important for the variance of commodity prices. Crude oil and heating oil reveal a high variation in connectedness across maturities. For natural gas and gas oil, we observe the same pattern with a lower level of variation. In industrial metals, the importance of maturities is almost the same for copper while for others 2-6 months contracts transmit higher spillover. Among agricultural commodities, we observe that soybean contracts from 3 to 7 months are the most connected. The connectedness of soybean reaches the maximum at a 5-month contract. However, the connectedness of soybean oil increases, the longer the maturity is. The difference in the spillovers across maturities for soybean meal is very high. Connectedness across maturities for soft commodities vary as well.

Table 3: Connectedness Table of Commodities

	BO	C	CC	CL	CT	GC	HG	HO	KC	LA	LN	LX	NG	QS	S	SB	SI	SM
BO	**36.8**	8.9	0.7	3.4	2.4	1.6	3.2	2.8	1.0	2.1	1.5	2.0	0.5	2.2	19.4	1.1	2.6	7.9
C	10.7	**39.4**	0.5	2.1	2.4	1.2	2.1	1.7	1.1	1.5	0.9	1.1	0.5	1.2	16.7	1.6	2.0	13.4
CC	1.4	0.9	**76.9**	1.4	1.0	1.9	1.7	1.1	2.0	1.6	0.9	1.5	0.3	1.5	1.1	1.4	2.6	0.6
CL	3.0	1.6	0.6	**31.5**	1.2	1.6	3.8	26.3	0.7	2.6	2.1	2.1	1.8	14.7	2.0	1.1	2.5	0.9
CT	4.7	3.9	0.9	2.5	**60.7**	1.3	3.3	2.0	1.1	2.1	1.9	1.9	0.3	1.8	4.9	1.7	2.2	3.0
GC	1.9	1.2	1.1	2.1	0.8	**46.5**	4.7	1.9	0.7	3.2	1.9	3.2	0.2	1.7	1.3	0.6	26.2	0.7
HG	2.8	1.6	0.7	3.7	1.5	3.4	**33.3**	3.0	0.9	12.6	9.9	13.0	0.3	3.0	2.3	1.1	5.8	1.2
HO	2.6	1.3	0.5	27.0	0.9	1.5	3.1	**32.1**	0.5	2.1	1.6	1.7	2.2	17.0	1.8	0.9	2.1	0.9
KC	1.9	1.7	1.9	1.4	1.1	1.2	1.9	1.1	**73.8**	1.4	1.2	1.6	0.1	0.9	2.1	3.0	2.3	1.4
LA	2.1	1.3	0.8	3.0	1.1	2.7	14.6	2.4	0.7	**37.4**	9.4	14.0	0.3	2.3	1.7	1.0	4.4	1.0
LN	1.8	0.9	0.5	2.7	1.1	1.9	13.3	2.1	0.7	10.9	**42.7**	12.6	0.1	2.2	1.4	0.8	3.4	0.8
LX	2.0	0.9	0.8	2.4	1.0	2.7	15.2	1.9	0.8	14.0	10.9	**37.3**	0.1	2.3	1.5	0.8	4.6	0.8
NG	1.8	1.4	0.4	6.9	0.5	0.7	1.2	8.0	0.2	0.9	0.4	0.5	**68.0**	4.6	1.7	0.6	0.8	1.2
QS	2.5	1.2	0.7	19.4	1.0	1.5	3.5	21.6	0.5	2.3	1.9	2.2	1.6	**34.8**	1.5	0.8	2.2	0.7
S	17.0	12.2	0.5	1.9	2.2	1.0	2.2	1.6	0.9	1.5	1.1	1.3	0.4	1.1	**29.0**	1.2	1.8	23.1
SB	2.3	2.8	1.3	2.4	1.8	1.1	2.6	1.9	3.1	2.0	1.4	1.7	0.4	1.4	2.8	**67.2**	1.9	1.9
SI	2.6	1.7	1.3	2.9	1.1	22.2	6.7	2.4	1.2	4.4	3.0	4.5	0.3	2.2	2.1	1.0	**39.3**	1.2
SM	8.8	12.5	0.3	1.2	1.7	0.7	1.5	1.0	0.8	1.1	0.7	0.8	0.4	0.6	29.6	1.0	1.3	**35.8**
To	70.1	56.0	13.7	86.5	22.9	47.9	84.6	82.9	16.9	66.2	50.7	65.7	10.0	60.5	94.1	19.6	68.6	60.7
From	63.2	60.6	23.1	68.5	39.3	53.5	66.7	67.9	26.2	62.6	57.3	62.7	32.0	65.2	71.0	32.8	60.7	64.2
Net	6.9	-4.6	-9.4	18.0	-16.4	-5.6	17.9	14.9	-9.3	3.6	-6.6	3.0	-22.0	-4.7	23.0	-13.2	7.9	-3.5

Table **??** shows the to-connectedness of maturities at the aggregate level. This connectedness table is derived from joint analysis by aggregating the spillovers across commodities for each maturity. Net connectedness is -8.97 for 1-month contracts that indicates it is the receiver of shocks. It is consistent with the theory that futures contracts approaching their maturity converge to spot price and react more heavily to the news. However, futures contracts with distant maturity reflect long-term expectations and do not react strongly to current shocks. Medium-term contracts are most connected while 1-month and 7-month contracts are the least.

Table 4: Connectedness Table of Maturities

	1-month	2-month	3-month	4-month	5-month	6-month	7-month
1-month	**17.65**	15.60	14.23	13.91	13.31	12.83	12.47
2-month	13.89	**15.70**	15.10	14.65	14.06	13.45	13.15
3-month	12.52	14.56	**15.67**	15.19	14.60	13.94	13.50
4-month	12.14	13.94	14.98	**15.66**	15.06	14.41	13.82
5-month	11.74	13.51	14.53	15.21	**15.64**	14.94	14.43
6-month	11.57	13.19	14.15	14.84	15.24	**15.81**	15.20
7-month	11.51	13.19	14.01	14.55	15.07	15.59	**16.09**
To	73.38	83.98	87.00	88.35	87.35	85.16	82.57
From	82.35	84.30	84.33	84.34	84.36	84.19	83.91
Net	-8.97	-0.32	2.67	4.00	2.99	0.97	-1.35

We also estimate the static connectedness of commodities for each maturity level. For example, we include only a 1-month contract for each commodity. We find that for 1-month contracts spillover index is 41.6 that is significantly lower compared to other maturities. The spillover index for the rest of the maturities is between 52.1 and 53.2. Major transmitter and receiver commodities remain the same for each maturity. A lower spillover index for 1-month contacts indicates that 1-month contracts contribute less to the variance of other commodities. Medium and long-term futures contracts have higher connectedness.

To conclude, I explore the direction of return spillover across commodities and maturities. Medium-term maturities are the transmitter of shocks to short-term and long-term ones for most commodities. Soybean, crude oil, heating oil, and copper are the commodities that contribute more to the variance of other ones.

5 Dynamic Connectedness Analysis

5.1 Joint Analysis

In the previous section, we provide the average connectedness from July 1997 to January 2019. However, the direction and magnitude of spillover are likely to change over time. The dynamic analysis allows us to observe changing linkages across commodities over time. In this section, we report the results of the time-varying connectedness of futures contracts. Our estimation is performed with a window length of 150 and a 10-day ahead forecast. The window length is 150 due to the high dimension of variables. Even though it is a long window, we have a sample of 5546 daily observations that enables us to capture significant changes. First, we describe the evolution of system-wide connectedness. Then we decompose system-wide connectedness into within and cross index to understand the source and change in system-wide connectedness. Then taking one step further, we analyze the connectedness at maturity and commodity levels separately.

We define system-wide connectedness as the percentage of forecast error attributed to shocks that originated in other contracts. Figure 2 shows that system-wide connectedness varies over time. The initial value of system-wide connectedness is 88 % which is also the lowest level of connectedness for our sample. One should be cautious when interpreting the magnitude of the index, as our futures contracts are highly correlated. Rather than magnitude, ups and downs in the index would be informative about the transmission of shocks. The sample covers two recessions: the 2001 USA recession and the Great Recession. The first one is relatively short and is shown as the

Figure 2: Dynamic Connectedness - Window 150

first shaded area. The second crisis is the second shaded area. Right before the recession, there is a sudden decrease in system-wide connectedness whereas during the recession we observe a gradual increase. There has been an upward trend between the two recessions. The upward trend coincides with the commodity boom and bust. During the global financial crisis, connectedness increases rapidly and reaches its peak at 97 %. We might say that business cycles might explain the variation in the system-wide connectedness, at least partially. In addition to that, in 2004, we observe a rapid increase in spillovers. Index investment in commodities might cause an increase in the total connectedness. After the index investment, an upward trend is observed until the recession. The highest increase in return connectedness takes place at the beginning of a recession. That might indicate that commodity prices are more responsive to external or macro shocks. After 2009, connectedness tends to decrease. There are two sudden decreases in system-wide connectedness. The first one takes place at the end of 2010 and it is followed by a quick recovery with almost going back to its initial value. This drop might be related to the increase in agriculture and metals prices. The second decrease is greater in size compared to the first one and it takes place in 2013-2014.

This coincides with the period in which the price of crude oil decreases rapidly. Therefore, negative price shocks might decrease the level of connectedness.

5.2 Index Decomposition

In the previous section, we analyzed the system-wide connectedness index. System-wide connectedness can be decomposed into within and cross-commodity indexes. When we order the contracts by commodities, each block diagonal of the connectedness table represents the connectedness of maturities of a given commodity. The sum of the pairwise connectedness across maturities for the same commodity that is the sum of elements of block diagonals gives the within maturity connectedness. Off-diagonal blocks represent the transmission across commodities. The sum of pairwise connectedness across maturities of different commodities that is the sum of elements of off-block diagonals gives the cross-commodity index. The sum of within and cross-commodity index is a system-wide index by construction. Figure 3 shows the decomposed system-wide index.

Figure 3: Within and Cross Commodity

Until 2004, the within commodity index is higher than the cross-commodity index that shows that commodities' connectedness is higher than the connectedness generated to them on average. It implies that linkages across commodities are weaker before 2004. However, after 2004, the cross-commodity index is higher than the within commodity index. Spillovers across commodities are becoming stronger after 2004. The increase in the cross-commodity index is consistent with the literature of financialization of commodities and their tendency to move together as 2004 is referred to as the beginning of significant inflow of investment into commodity investment. Commodity index investment is the main reason for the increase in the cross-commodity index after 2004. The major contributor to the system-wide index is the cross-commodity index rather than the within-commodity index. In particular, during financial crisis more than 80% of system-wide connectedness is caused by spillovers between commodities. Cross commodity index decreases after global financial crisis while within commodity index increases. At the end of 2014, we observe that the within commodity index is higher than the cross-commodity index. As we mentioned before, in that period there is a sharp decrease in crude oil price. A negative shock to crude oil price can be considered a commodity-specific shock since a sharp price decline is observed only for crude oil. We argue that when there is commodity-specific shock, within commodity index are more likely to increase which leads the cross-commodity index to decrease. We observe a similar pattern for 2011 in which prices of soybean, cotton, corn, and sugar increase rapidly.

The index can also be decomposed into within and cross maturity by following the same steps after futures are ordered by maturities. Figure 4 shows that how within maturity and cross maturity evolves. The values of cross maturity are on the right-hand side and the values of within maturity are on the left-hand side. Cross maturity connectedness is more than eight times within maturity connectedness. In that sense, the major contributor to system-wide connectedness is the spillovers between maturities. As connectedness between maturities is very high, we want to analyze how maturities transmit shock among each other and their behavior over time. For example, we want to learn how much 1-month contracts transmit shocks to 3 or 5 months contracts.

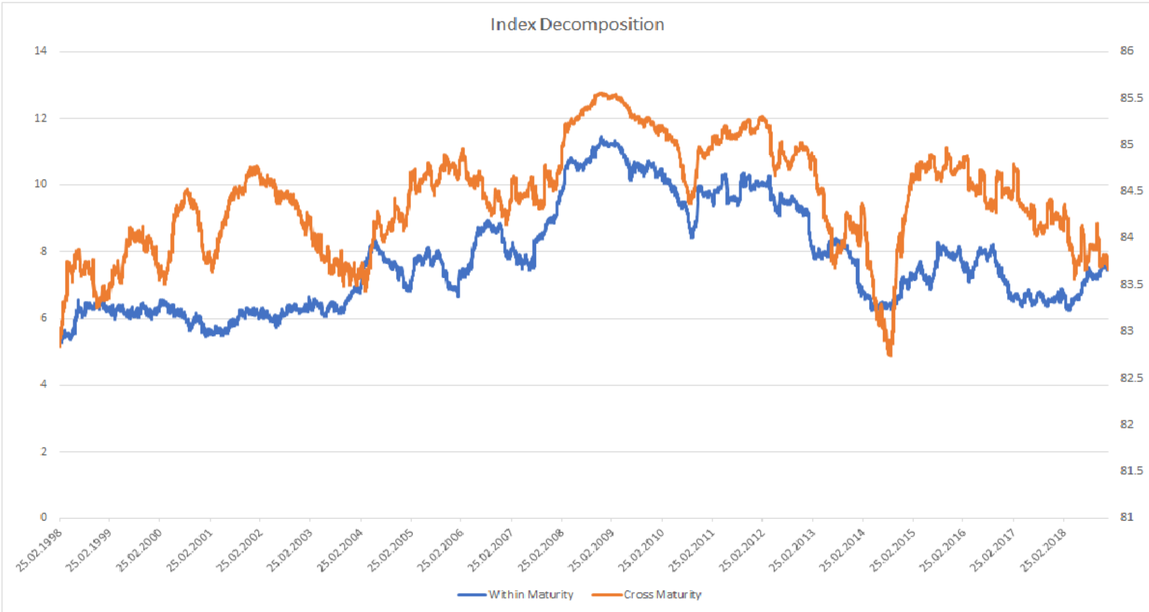

Figure 4: Within and Cross Maturity

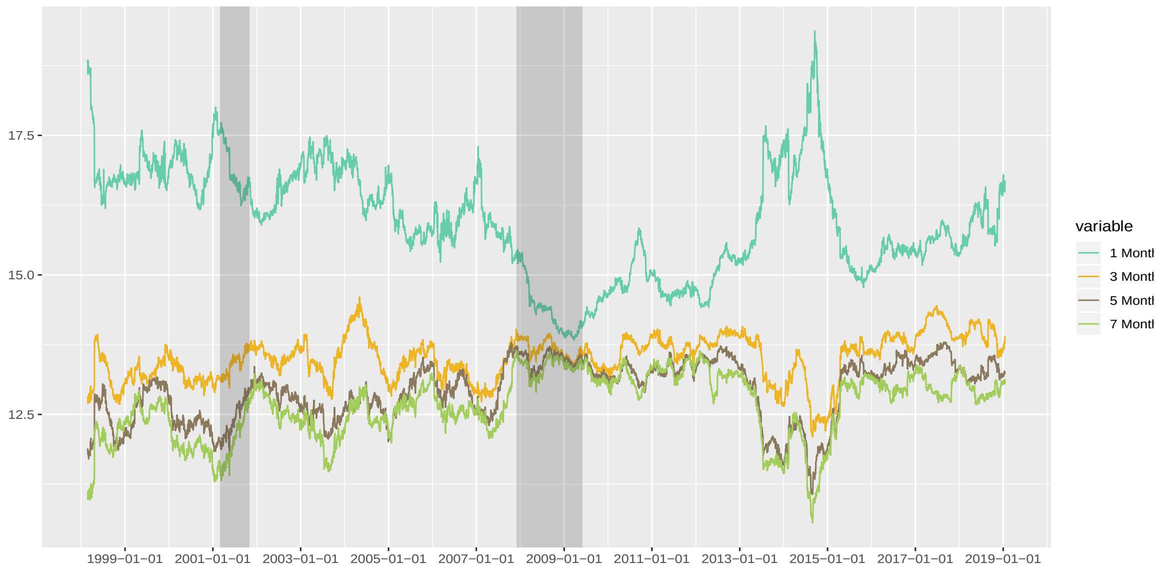

Figure 5: To Connectedness from 1 Month Contracts to others

Figure 5 shows to-connectedness from 1-month contracts to others. For the sake of simplicity, we only visualize four different maturities instead of seven. Similar results hold for the maturities that are not presented here. 1-month contracts generate the highest connectedness to themselves all the time. Then, it generates the second-highest connectedness to 3-month contracts and the lowest connectedness to 7-month contracts. It is a common pattern for maturities to generate the highest connectedness to maturities that are close to themselves. However, during the global financial crisis, spillovers generated to other maturities become almost equal. In the presence of high levels of uncertainty, maturities no longer provide additional information. In Figure 6, we see that the same pattern is observed for 3-months contracts as well. During the Great Recession, to-connectedness generated to other contracts converges. It may indicate that external factors such as business cycles might be one of the sources of spillovers in commodity futures. Similarly, in the 2001 recession, there is a decrease in the own connectedness while to-connectedness to others increases. Since it is prior to financialization, the effect of recession on the convergence is smaller. Another important point is the spike in the own connectedness in 2014. This spike is due to the commodity-specific shock in which crude oil prices decrease rapidly. Commodity-specific shocks decrease the level of connectedness generated to other contracts. To connectedness of 5-months and 7-months contracts are presented in the Appendix.

6 Factors Driving the Spillover Index

In the previous chapters, we examined the times series behavior of the commodity connectedness. One of the main findings was that the connectedness of commodity futures reaches a peak during the Great Recession that raises the question of how business cycles affect the spillover index. In addition to business cycles, we test how much the US Dollar exchange rate explains the variation in the spillover index. Akram (2008) show that shocks to the US Dollar exchange rate explain substantial shares of the change in

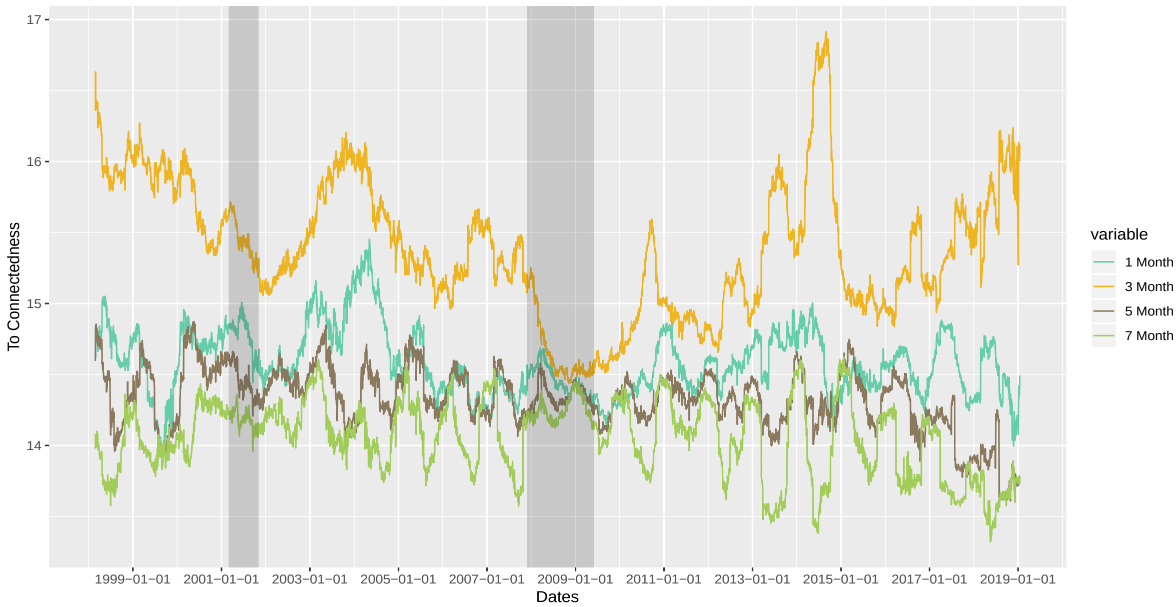

Figure 6: To Connectedness from 3 Month Contracts to others

commodity prices. We also perform a regression with S&P 500, Dow Jones Industrial Average, Fed Funds, and 10-year bonds to analyze the effects of financial variables on the spillover index. Individual levels of supply and demand might drive the connectedness between them. However, due to the lack of data on demand for each commodity, we are unable to test how a change in the demand for commodities affects the shocks transmitted from one commodity to another. We use A Monthly Measure of Global Real Economic Activity which is developed in L. Kilian (2009). This index is a measure of worldwide real economic activity that drives demand for industrial commodities in global markets.

Dynamic connectedness index increases during 2001 and 2007 recessions as shown in Figure 2. We want to investigate the presence of a causal relationship between commodity connectedness and business cycles. For business cycles, we use Chicago Fed National Activity Index which we refer to as CFNAI from now on. CFNAI is derived by taking the weighted average of 85 economic indicators. These indicators are categorized as production, income, employment, unemployment, personal consumption, housing, sales, orders, and inventories. CFNAI MA3 is used to track economic expansions and contractions. [2]

The US Dollar Index tracks the performance of a basket of 10 global currencies against the US dollar. Data is taken from Bloomberg. Commodity futures prices are denominated in US Dollars. As mentioned before, we expect that a shock to the US Dollar exchange rate would be transmitted to commodity prices. We analyze how much US Dollar Index explains the variation in the spillover index.

We also have the data of S&P500, Dow Jones Industrial Average, Fed Funds Rate, and 10-year bonds. Considering the discussion of the financialization of commodities, we expect that at least some financial variables explain the variation in the spillovers. In addition to financial variables, we also have US industrial production. We report the regression results in Table 5. Since some of the data is available at the monthly level, regression is performed at the monthly level. For spillover connectedness, we simply take the average of the spillovers in the corresponding month.

Table 5: Regression Results

VARIABLES	(1) index	(2) index	(3) index	(4) index	(5) index	(6) index	(7) index
CFNAI_MA3	-1.365***			-1.304***	-1.258***	-1.160***	-1.151***
	(0.118)			(0.069)	(0.074)	(0.077)	(0.082)
US Dollar Index		-0.120***		-0.117***	-0.117***	-0.0864***	-0.0930***
		(0.007)		(0.006)	(0.006)	(0.006)	(0.008)
S&P 500			-0.925***		-0.265*	-3.747***	-5.001***
			(0.220)		(0.152)	(0.728)	(0.977)
Dow Jones						5.174***	8.658***
						(1.244)	(1.867)
10 Year Bond						-0.217***	-0.305**
						(0.065)	(0.125)
Fed Funds Rate							0.103
							(0.080)
Industrial Production							-0.0939***
							(0.032)
Constant	91.86***	103.1***	93.49***	102.5***	102.9***	57.31***	36.27**
	(0.113)	(0.717)	(0.419)	(0.570)	(0.584)	(11.11)	(14.47)
Observations	247	247	247	247	247	247	247
R-squared	0.245	0.470	0.044	0.694	0.697	0.731	0.742

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is the same in all seven regressions: spillover index. The

[2] For more information, check https://www.chicagofed.org/research/data/cfnai/historical-data

first three regressions contain a single independent variable for comparison purposes. The coefficient of business cycles is -1.365 and statistically significant. Expansion of the economy might be associated with lower levels of spillovers. It explains the biggest share of the variation in spillover. Adding more variables to regression decreases the effect of business cycles. US Dollar Index is another important variable affecting the spillover index. Consistent with Akram (2008), we observe that increase in the US Dollar index would decrease the level of spillover index. Regarding the financialization of commodities, an increase in the Dow Jones Industrial Average is associated with higher levels of spillover while the increase in the S&P 500 is, on the contrary, lower levels. The coefficient of the Fed Funds rate is not statistically significant. A 10-year bond has a negative and significant effect on spillovers. The effect of industrial production is negative and significant.

6.1 Kilian Index

As our sample consists of various commodities, DY methodology allows us to observe pairwise connectedness between commodity futures. For a deeper analysis of pairwise connectedness, one way would be to compare the demand and supply ratio of commodities to see how a change in the ratio affects connectedness. Due to a lack of available data and measurement, we cannot find demand for commodities. So instead of individual demand for commodities, a proxy for demand for commodities at the aggregate level can be used.

We use the index developed by Kilian for a measure of demand for industrial commodities that are driven by worldwide real economic activity. This index is based on dry cargo single voyage ocean freight which captures the shift in demand for industrial commodities. The change in demand for commodities certainly affects the prices of commodity futures but rather we want to analyze the change in commodity connectedness due to change in demand. As we mentioned, we use this index since the demand for commodities is not available at the individual level.

Table 6: Granger Causality

	Dependent Variable: Index		Dependent Variable: Kilian	
Lag	Chi-Square	P-value	Chi-Square	P-value
1	9.8334	0.002	0.90262	0.342
2	9.403	0.009	0.14206	0.931
3	10.307	0.016	1.6571	0.647
4	9.5719	0.048	1.6645	0.797
5	13.215	0.021	2.0915	0.836
6	13.925	0.03	1.814	0.936

We test whether there is any statistically causal relationship between the spillover index and Kilian index by performing a Granger-causality test. We repeat the vector autoregression for the lags up to 6 months. The results are presented in Table 6. In the first one, the dependent variable is the spillover index and the independent variable is the Kilian index. In the second, it is the other way around. Based on the p-value, we say that we are unable to reject the hypothesis that the Kilian index does not cause the spillover index. In particular, even up to 6 months lag, the demand for commodities Granger-causes the connectedness across futures contracts.

7 Conclusion

As commodity futures prices reflect the expectation of future spot prices, commodity futures are central to risk measurement and management in commodity markets. We apply lasso methods to estimate variance decomposition from high-dimensional vector autoregression. We obtain the measures of connectedness in commodity markets. We use an extensive data set of 126 commodity futures of 18 commodities from July 1997 through January 2019. Our analysis provides a comprehensive measure of the level of return connectedness across commodities and maturities. In the full-sample analysis, our findings show that crude oil, heating oil, copper, soybean have the highest to-connectedness, that is they are the commodities contributing more to the variance of other commodities. In addition, we show that except for the so-called 'softs', each sector forms a cluster itself. In the dynamic analysis, we see that the connectedness of commodity futures reaches a peak during the 2008 financial crisis. To further characterize the dynamic connectedness, we decompose the connectedness index into within and cross-commodity components. Cross-commodity connectedness dominates the within commodity connectedness after 2004, the year after which a significant amount of investment started flowing into commodity index trading. Following the same steps to analyze the within and cross maturity index, we find that the cross maturity index is always higher than the within maturity. The connectedness across maturities converges to similar levels during times of recession in the global economy. However, commodity-specific shocks (for example, the crude oil price shock in 2014) causes connectedness measures across maturities to diverge from each other. The contribution of futures at different maturities to the connectedness at the commodity level varies significantly; we find no significant maturity effect for gold and silver. In the case of soybean and crude oil, the contribution of the one-month future contracts to the connectedness varies substantially over time. Finally, focusing on the dynamic behavior of commodity connectedness over time, we show that the global business cycle and the U.S. Dollar index explain the substantial share of the variation in the connectedness and demand for commodities Granger-cause the total return connectedness of commodity futures.

References

Akram, Q. Farooq (Aug. 2008). *Commodity prices, interest rates and the dollar.* Working Paper 2008/12. Norges Bank.

Basak, Suleyman and Anna Pavlova (2016). "A Model of Financialization of Commodities". In: *The Journal of Finance* 71.4. Publisher: [American Finance Association, Wiley], pp. 1511–1555.

Casassus, Jaime, Peng Liu, and Ke Tang (2013). "Economic Linkages, Relative Scarcity, and Commodity Futures Returns". In: *The Review of Financial Studies* 26.5, pp. 1324–1362.

Chen, Shu-Ling et al. (2014). "What Drives Commodity Prices?" In: *American Journal of Agricultural Economics* 96.5, pp. 1455–1468.

Cheng, Ing-Haw and Wei Xiong (Nov. 2013). *The Financialization of Commodity Markets.* Working Paper 19642. National Bureau of Economic Research.

Chevallier, J. and F Ielpo (2013). "The Economics of Commodity Markets". In:

Delle Chiaie, Simona, Laurent Ferrara, and Domenico Giannone (2017). *Common Factors of Commodity Prices.* Working papers. Banque de France.

Diebold, Francis X, Laura Liu, and Kamil Yilmaz (Aug. 2017). *Commodity Connectedness.* Working Paper 23685. National Bureau of Economic Research.

Diebold, Francis X and Kamil Yilmaz (2009). "Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets*". In: *The Economic Journal* 119.534, pp. 158–171.

— (2012). "Better to give than to receive: Predictive directional measurement of volatility spillovers". In: *International Journal of Forecasting* 28.1, pp. 57–66.

— (2014). "On the network topology of variance decompositions: Measuring the connectedness of financial firms". In: *Journal of Econometrics* 182.1. Causality, Prediction, and Specification Analysis: Recent Advances and Future Directions, pp. 119–134.

Fattouh, Bassam, Lutz Kilian, and Lavan Mahadeva (2013). "The Role of Speculation in Oil Markets: What Have We Learned So Far?" In: *The Energy Journal* 34.3, pp. 7–33.

Jacomy, Mathieu et al. (June 2014). “ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software”. In: *PLOS ONE* 9.6, pp. 1–12.

Kang, Sang Hoon, Ron McIver, and Seong-Min Yoon (2017). “Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets”. In: *Energy Economics* 62, pp. 19–32.

Karstanje, Dennis, Michel van der Wel, and Dick van Dijk (2017). “Common Factors in Commodity Futures Curves”. In:

Kilian, Lutz (2009). “Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market”. In: *The American Economic Review* 99.3, pp. 1053–1069.

Kilian and Murphy (2014). “The Role Of Inventories and Speculative Trading in the Global Market for Crude Oil”. In: *Journal of Applied Econometrics* 29.3. Publisher: Wiley, pp. 454–478.

Nazlioglu, Saban, Cumhur Erdem, and Ugur Soytas (2013). “Volatility spillover between oil and agricultural commodity markets”. In: *Energy Economics* 36, pp. 658–665.

Ohashi, Kazuhiko and Tatsuyoshi Okimoto (2016). “Increasing trends in the excess comovement of commodity prices”. In: *Journal of Commodity Markets* 1.1, pp. 48–64.

Pesaran, H.Hashem and Yongcheol Shin (1998). “Generalized impulse response analysis in linear multivariate models”. In: *Economics Letters* 58.1, pp. 17–29.

Pindyck, Robert S and Julio J Rotemberg (July 1988). *The Excess Co-Movement of Commodity Prices*. Working Paper 2671. National Bureau of Economic Research.

Singleton, Kenneth J. (2014). “Investor Flows and the 2008 Boom/Bust in Oil Prices”. In: *Management Science* 60.2. Publisher: INFORMS, pp. 300–318.

Tang, Ke and Wei Xiong (Sept. 2010). *Index Investment and Financialization of Commodities*. Working Paper 16385. National Bureau of Economic Research.

— (2012). “Index Investment and the Financialization of Commodities”. In: *Financial Analysts Journal* 68.6, pp. 54–74.

A Appendix

Table 7: Descriptive Statistics of Commodity Futures

Contracts	Mean	Min	Max	SD	Skewness	Kurtosis
CL1	0.00018	-0.165	0.164	0.024	-0.075	4.220
CL2	0.00018	-0.123	0.115	0.020	-0.197	2.979
CL3	0.00018	-0.104	0.100	0.018	-0.212	3.208
CL4	0.00018	-0.091	0.100	0.016	-0.229	3.311
CL5	0.00018	-0.087	0.098	0.015	-0.254	3.415
CL6	0.00018	-0.086	0.094	0.015	-0.258	3.416
CL7	0.00018	-0.085	0.091	0.014	-0.250	3.787
HO1	0.00023	-0.210	0.104	0.022	-0.508	5.947
HO2	0.00022	-0.106	0.097	0.020	-0.074	2.160
HO3	0.00021	-0.089	0.092	0.018	-0.110	2.116
HO4	0.00022	-0.095	0.085	0.016	-0.105	2.141
HO5	0.00023	-0.094	0.081	0.016	-0.129	2.339
HO6	0.00022	-0.089	0.087	0.015	-0.096	2.498
HO7	0.00022	-0.087	0.112	0.015	-0.047	2.856
NG1	0.00009	-0.199	0.324	0.034	0.483	5.449
NG2	0.00004	-0.377	0.186	0.025	-0.545	13.803
NG3	0.00004	-0.208	0.116	0.019	-0.156	6.115
NG4	0.00008	-0.181	0.119	0.016	-1.125	13.702
NG5	0.00003	-0.212	0.087	0.015	-1.674	21.955
NG6	0.00003	-0.287	0.072	0.014	-2.382	43.009
NG7	0.00007	-0.221	0.084	0.013	-2.112	31.352
QS1	0.00022	-0.151	0.121	0.020	-0.065	3.467
QS2	0.00022	-0.137	0.103	0.018	0.014	2.506

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Table 7 – continued from previous page

Contracts	Mean	Min	Max	SD	Skewness	Kurtosis
QS3	0.00021	-0.126	0.096	0.017	0.013	2.497
QS4	0.00022	-0.109	0.090	0.016	0.014	2.369
QS5	0.00022	-0.099	0.084	0.015	0.005	2.306
QS6	0.00022	-0.097	0.082	0.015	0.006	2.301
QS7	0.00022	-0.096	0.079	0.015	0.009	2.249
GC1	0.00025	-0.098	0.089	0.011	-0.102	6.673
GC2	0.00025	-0.098	0.087	0.011	-0.103	6.688
GC3	0.00025	-0.099	0.086	0.011	-0.119	6.676
GC4	0.00025	-0.099	0.086	0.011	-0.136	6.655
GC5	0.00025	-0.099	0.086	0.011	-0.151	6.653
GC6	0.00025	-0.099	0.086	0.011	-0.164	6.677
GC7	0.00024	-0.099	0.145	0.010	0.871	28.180
SI1	0.00023	-0.195	0.122	0.019	-0.826	7.750
SI2	0.00023	-0.195	0.125	0.019	-0.850	7.877
SI3	0.00023	-0.195	0.124	0.019	-0.849	7.925
SI4	0.00023	-0.195	0.124	0.018	-0.859	8.011
SI5	0.00023	-0.196	0.124	0.018	-0.865	8.077
SI6	0.00023	-0.196	0.123	0.018	-0.867	8.120
SI7	0.00024	-0.350	0.269	0.018	-1.289	48.263
HG1	0.00016	-0.117	0.116	0.017	-0.231	4.770
HG2	0.00017	-0.115	0.116	0.017	-0.138	4.408
HG3	0.00017	-0.113	0.114	0.016	-0.140	4.549
HG4	0.00018	-0.113	0.115	0.016	-0.127	4.627
HG5	0.00018	-0.113	0.114	0.016	-0.135	4.691

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Table 7 – continued from previous page

Contracts	Mean	Min	Max	SD	Skewness	Kurtosis
HG6	0.00018	-0.112	0.114	0.015	-0.125	4.686
HG7	0.00018	-0.112	0.114	0.015	-0.122	4.726
LA1	0.00002	-0.114	0.093	0.014	-0.276	4.350
LA2	0.00002	-0.082	0.059	0.013	-0.191	2.799
LA3	0.00002	-0.083	0.058	0.012	-0.225	2.735
LA4	0.00002	-0.080	0.057	0.012	-0.232	2.754
LA5	0.00002	-0.077	0.056	0.012	-0.241	2.778
LA6	0.00003	-0.075	0.056	0.012	-0.240	2.784
LA7	0.00003	-0.071	0.055	0.011	-0.239	2.814
LN1	0.00010	-0.313	0.242	0.024	-0.500	16.857
LN2	0.00010	-0.182	0.131	0.022	-0.165	3.750
LN3	0.00010	-0.175	0.130	0.022	-0.174	3.744
LN4	0.00010	-0.160	0.129	0.021	-0.141	3.491
LN5	0.00010	-0.150	0.128	0.021	-0.134	3.427
LN6	0.00010	-0.142	0.128	0.021	-0.127	3.376
LN7	0.00009	-0.131	0.127	0.021	-0.109	3.308
LX1	0.00008	-0.317	0.210	0.020	-0.993	23.285
LX2	0.00008	-0.129	0.098	0.018	-0.228	3.445
LX3	0.00009	-0.113	0.096	0.017	-0.226	3.347
LX4	0.00009	-0.104	0.095	0.017	-0.206	3.267
LX5	0.00010	-0.103	0.095	0.017	-0.202	3.302
LX6	0.00010	-0.101	0.094	0.017	-0.207	3.341
LX7	0.00010	-0.098	0.093	0.016	-0.203	3.340
S 1	0.00003	-0.174	0.076	0.016	-1.026	8.096

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Table 7 – continued from previous page

Contracts	Mean	Min	Max	SD	Skewness	Kurtosis
S 2	0.00006	-0.165	0.067	0.015	-0.598	5.784
S 3	0.00008	-0.142	0.068	0.015	-0.447	4.562
S 4	0.00008	-0.092	0.071	0.014	-0.335	3.423
S 5	0.00008	-0.081	0.070	0.014	-0.283	3.446
S 6	0.00007	-0.096	0.071	0.013	-0.319	3.815
S 7	0.00007	-0.102	0.069	0.013	-0.408	4.569
SM1	0.00004	-0.205	0.103	0.019	-1.300	12.001
SM2	0.00006	-0.168	0.078	0.017	-0.485	4.655
SM3	0.00008	-0.153	0.076	0.016	-0.384	4.186
SM4	0.00009	-0.117	0.088	0.016	-0.292	3.349
SM5	0.00009	-0.132	0.084	0.016	-0.352	4.452
SM6	0.00009	-0.129	0.085	0.015	-0.228	3.751
SM7	0.00009	-0.112	0.089	0.015	-0.215	3.612
BO1	0.00005	-0.078	0.080	0.014	0.122	2.413
BO2	0.00005	-0.071	0.081	0.014	0.154	2.102
BO3	0.00005	-0.070	0.078	0.014	0.149	2.227
BO4	0.00005	-0.081	0.077	0.014	0.109	2.484
BO5	0.00005	-0.069	0.077	0.014	0.135	2.509
BO6	0.00005	-0.069	0.073	0.013	0.139	2.530
BO7	0.00005	-0.069	0.072	0.013	0.117	2.546
C 1	0.00007	-0.269	0.128	0.018	-0.526	12.453
C 2	0.00008	-0.147	0.124	0.017	0.020	4.063
C 3	0.00008	-0.174	0.108	0.016	-0.200	5.694
C 4	0.00007	-0.130	0.103	0.015	-0.141	4.651

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Table 7 – continued from previous page

Contracts	Mean	Min	Max	SD	Skewness	Kurtosis
C 5	0.00007	-0.145	0.097	0.014	-0.224	5.238
C 6	0.00008	-0.093	0.097	0.014	-0.110	4.194
C 7	0.00008	-0.075	0.118	0.013	0.090	6.084
CC1	0.00008	-0.100	0.100	0.019	-0.108	2.252
CC2	0.00007	-0.100	0.099	0.018	-0.119	2.458
CC3	0.00007	-0.100	0.095	0.017	-0.127	2.619
CC4	0.00007	-0.100	0.092	0.017	-0.125	2.725
CC5	0.00007	-0.099	0.087	0.017	-0.139	2.741
CC6	0.00007	-0.100	0.085	0.016	-0.136	2.880
CC7	0.00007	-0.102	0.083	0.016	-0.198	3.089
KC1	-0.00011	-0.128	0.212	0.022	0.262	5.105
KC2	-0.00008	-0.115	0.201	0.021	0.266	4.819
KC3	-0.00005	-0.110	0.190	0.020	0.267	4.751
KC4	-0.00004	-0.108	0.183	0.019	0.244	4.780
KC5	-0.00003	-0.105	0.175	0.019	0.212	4.696
KC6	-0.00002	-0.103	0.170	0.018	0.191	4.649
KC7	-0.00001	-0.102	0.164	0.018	0.174	4.694
CT1	0.00000	-0.156	0.136	0.018	0.008	4.455
CT2	0.00000	-0.092	0.092	0.016	0.092	2.551
CT3	0.00000	-0.225	0.100	0.015	-0.521	10.703
CT4	-0.00001	-0.172	0.078	0.014	-0.470	7.921
CT5	-0.00001	-0.113	0.077	0.013	-0.123	4.418
CT6	0.00000	-0.063	0.084	0.012	-0.002	3.787
CT7	0.00000	-0.060	0.068	0.012	0.027	3.541

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Table 7 – continued from previous page

Contracts	Mean	Min	Max	SD	Skewness	Kurtosis
SB1	0.00003	-0.171	0.131	0.021	-0.185	3.605
SB2	0.00002	-0.132	0.143	0.019	-0.152	3.725
SB3	0.00003	-0.137	0.124	0.017	-0.247	4.318
SB4	0.00003	-0.134	0.112	0.016	-0.287	5.081
SB5	0.00004	-0.118	0.083	0.015	-0.404	4.909
SB6	0.00004	-0.113	0.080	0.014	-0.443	5.105
SB7	0.00004	-0.100	0.081	0.013	-0.307	4.122

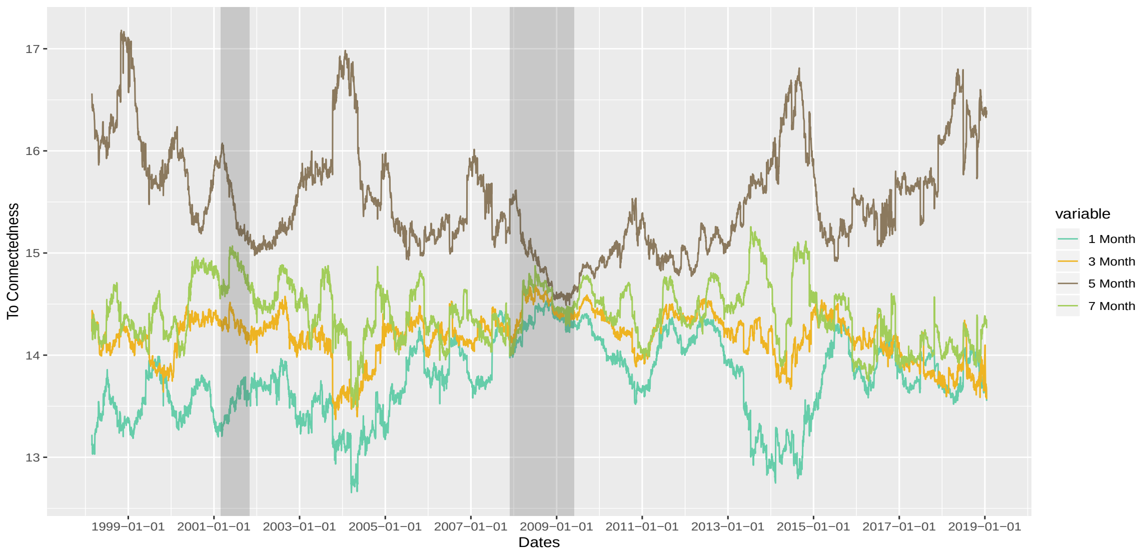

Figure 7: To Connectedness from 5 Month Contracts to others

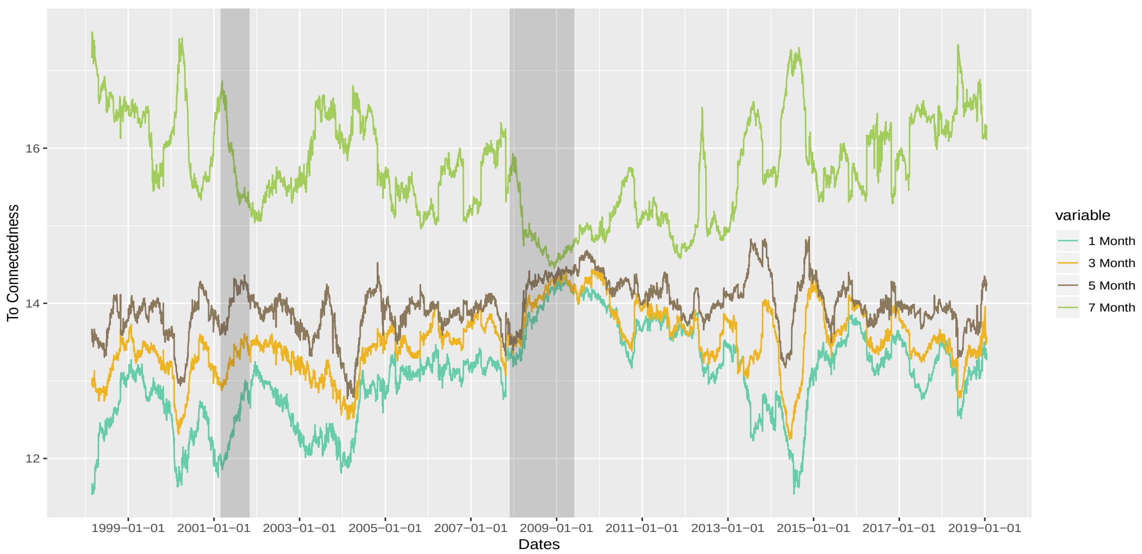

Figure 8: To Connectedness from 7 Month Contracts to others