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Abstract

In this study, we examine the asymmetric short- and long-run spillover among commodities using realized variances and realized semivariances calculated through 5-min trading data of commodity futures. In doing so, we apply time and frequency domain generalized error variance decomposition approaches and build a network of commodity connectedness. Our findings indicate low inter-group connectedness, distinct group clustering, and high intragroup network-based connectedness in realized volatilities of sample commodities. We find more pronounced inter- and intra-group volatility connectedness for negative realized volatilities than positive ones. Besides, we show that volatility connectedness is a long-run phenomenon. Additionally, the time-varying net directional spillover connectedness reveals that the bad volatility connectedness dictates the good volatility connectedness for the total sample as well as for various frequency domains, both in terms of magnitude and length of time. The implications for investors and policymakers are discussed.

Keywords	asymmetric volatility; time-frequency domain; high-frequency data, commodity connectedness

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HIGHLIGHTS

- Asymmetric short- and long-run spillover among commodities volatilities
- 5-min trading data of commodity futures and frequency domain GFEVD
- Low inter-group, high intragroup network-based connectedness
- Pronounced inter- and intra-group volatility connectedness for negative realized volatilities
- Volatility connectedness is a long-run phenomenon

Asymmetric and time-frequency spillovers among commodities using high-frequency data

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Asymmetric and time-frequency spillovers among commodities using high-frequency data

Abstract

In this study, we examine the asymmetric short- and long-run spillover among commodities using realized variances and realized semivariances calculated through 5-min trading data of commodity futures. In doing so, we apply time and frequency domain generalized error variance decomposition approaches and build a network of commodity connectedness. Our findings indicate low inter-group connectedness, distinct group clustering, and high intragroup network-based connectedness in realized volatilities of sample commodities. We find more pronounced inter- and intra-group volatility connectedness for negative realized volatilities than positive ones. Besides, we show that volatility connectedness is a long-run phenomenon. Additionally, the time-varying net directional spillover connectedness reveals that the bad volatility connectedness dictates the good volatility connectedness for the total sample as well as for various frequency domains, both in terms of magnitude and length of time. The implications for investors and policymakers are discussed.

Keywords: asymmetric volatility, time-frequency domain, high-frequency data, commodity connectedness

JEL Classification: F3, G1

1. Introduction

Commodity markets, just like other financial assets, have become increasingly interconnected since the onset of the global financial crisis (hereafter GFC). The presence of cross-commodity interactions has drawn a great deal of attention from investors, policymakers, and the academic community (Diebold, Liu, & Yilmaz, 2017). Although globalization, financial liberalization, and trade integration have been partly responsible for strengthening the cross-commodity linkages, the financialization of commodities has played a vital role by equipping commodity markets with increased liquidity, ease of trading, and thereby a massive influx of investors (Chong & Miffre, 2010; Silvennoinen & Thorp, 2013). The financialization, on the one hand, transformed commodities such as precious metals into successful diversification/hedging tools (Büyükşahin & Robe, 2014), and on the other, opened the door for speculators to exploit commodity markets, multiplying the transmission of volatility across those markets[1], thereby increasing the complexity of the investment climate. Since the existence of volatility spillovers between commodity markets carries potential challenges for investors and policymakers, a better understanding of these spillovers would be needed to improve the decision making around risk management, portfolio allocation, and business cycle analysis[2] (Baruník & Křehlík, 2018).

In addition to the determinants of volatility connectedness listed-above, the distinctive nature of commodity prices brings with it considerable diversity across commodity groups, leading to diverse interactions in their inter- and intra-group volatility. Unlike other financial assets, commodity prices are determined by forces of demand and supply. Apart from precious metals, which are often regarded as hedge assets, the demand for most commodities tends to follow the aggregate global demand. Energy commodities and industrial metals, for example, provide inputs for global production processes, which render both commodity groups to be reasonably similarly vulnerable to demand shocks; hence their prices are tightly interlinked[3] (Diebold et al., 2017). On

[1] An alarming consequence was the dramatic rise in commodity volatility during and after the GFC, which called into question the role of speculation in commodity markets. Michael Masters, a member of Masters Capital Management, in his testimony to the US Senate, pointed out that speculative trading by hedge funds and investors created a price bubble and induced high volatility in commodity markets (Junttila, Pesonen, & Raatikainen, 2018; Naeem et al., 2020).
[2] Commodities play a pivotal role in the global economy, and thus their price behavior is widely tracked (Chevallier & Ielpo, 2013a). Commodities are a key input into the global manufacturing processes, and a major export of many emerging economies. Hence, commodity price swings are a key driver of business cycle fluctuations globally (Fernández, González, & Rodriguez, 2018).
[3] A sharp decline in the prices of these commodities was witnessed after the GFC.

the contrary, commodity prices behave more idiosyncratically under supply-shocks, as the factors determining the supply of a given commodity (commodity group/class) are often unique. For example, while weather conditions and the policies of the exporting countries dictate the supply of agricultural commodities (Kang et al., 2017), government export decisions determine the supply of industrial and precious metals and oil. Consequently, the inherent differences in supply-shocks result in the price behaviors across the commodity market being divergent, and therefore the connectedness dynamics are more commodity-centric. Aside from the underpinnings of the supply and demand framework, the financialization has also led to more integrated commodity markets, including precious metal, industrial metal, energy, and agriculture. However, energy commodities have become more financialized (Zhang, 2017) than other commodity groups. For this reason, the energy group transmits shocks to other commodity groups, suggesting a close connection with precious and industrial metals, and agricultural commodities (Diebold et al., 2017). Therefore, driven by the differences in supply/demand processes, financialization, and other macroeconomic factors (de Nicola et al., 2016), there is considerable heterogeneity across commodity price movements, which potentially translates into inter- and intra-group volatility connectedness.

Under the given cross-commodity interactions, there is a considerable potential that commodity volatility spills over from one commodity market to another. Pindyck and Rotemberg (1990) found that commodities behave similarly and their prices engage in comovement. Subsequently, numerous studies explored the interdependencies and volatility spillovers among commodity markets (Dimpfl & Jung, 2012) from various perspectives including the inter- and intra-group spillovers across energy and non-energy commodities, and precious metals (Shahzad et al., 2019; Kang, Mclver, & Yoon, 2017). The application of novel econometric models has been used to uncover the complex dynamics of spillovers (Mensi et al., 2014; Filip et al., 2016), and, more recently, the spillover network of commodities (Balli et al., 2019; Tiwari et al., 2020). However, although the commodity market spillovers are well-known under the assumption of symmetric volatility, three relevant aspects remain unexplored: first, the network dynamics of asymmetric volatility spillovers across commodity markets, i.e. by distinguishing between the volatility associated with positive and negative returns; second, the behavior of the asymmetric spillover network over the short and long run, disentangling the two elements by focusing on time-frequency domain analysis; and third, and most important, the asymmetric volatility connectedness heterogeneity of total, short- and long-run spillovers using higher-frequency data of commodity prices. Inspired by the availability of high-frequency data, an emerging strand of research has recently begun to take advantage of the new realized volatility measures, enabling the examination of the relationships among various asset markets at micro level. Compared to the traditional daily or weekly data, high-frequency data carries more detailed information. Specifically, the volatility indicators based on high-frequency data are capable of tracking much smaller intra-day price movements, thereby offering more precise estimations of market risk. This carries a great deal of economic relevance not only for formulating portfolio strategies and mitigating investor risk, but also for devising and implementing appropriate policy initiatives to stabilize the markets. Also, Křehlík & Baruník (2017) suggest that decomposing volatility into positive and negative components allows us to elucidate the commodity connectedness in a detailed manner that is potentially revealing and can be used for trading, portfolio formation, risk preference, and policy framing. Likewise, the relevance of time-frequency analysis of asymmetric spillovers emanates from the fact that different economic agents operate at different investment horizons – expressed in trading frequencies – that are associated with various types of investors, trading tools, and strategies that correspond to these various trading frequencies (Gencay et al., 2010; Conlon et al., 2016; Bredin et al., 2017).

Since asymmetric volatility and its associated spillovers in commodity markets is evident (Cheong, 2009; Shahzad et al., 2018a), one would naturally expect asymmetric volatility to spill over from one commodity market to another. In the energy and agriculture markets, this may be driven by demand/supply shocks (Kilian, 2009; Vacha & Barunik, 2012), while for precious metals, financialization (Bekiros et al., 2017), or factors such as economic and business cycles, financial crises, central bank monetary policy, or geopolitical conflicts could be the underlying channels (Uddin et al., 2019). In the time-frequency domain, the possibility of asymmetric volatility spillovers may arise from the economic linkages among commodity markets (Casassus et al., 2013) or due to the shocks to economic activity which impact variables at various frequencies with various strengths (Baruník and Křehlík, 2018). Building on this literature, the foremost contribution of this study is as part of the much needed and emerging stream of studies using high-frequency data to uncover new stylized facts in certain commodity groups (Luo & Ji, 2018; Křehlík & Baruník, 2017; Baruník & Kocenda, 2019; Lu, Yang, & Liu, 2019). Using high-frequency data, we provide network-based evidence of asymmetric volatility connectedness among a wide range of commodities in the time-frequency domain. To the best of our knowledge, this is the first study to achieve this task. We also contribute to the inter- and intra-group evidence of asymmetric volatility connectedness (Baruník & Kocenda, 2019; Luo & Ji, 2018; Ji et al., 2018; Baruník et al., 2015; Uddin et al., 2019) by documenting the asymmetric volatility spillovers of commodities, thus partly contributing to the previous studies exploring commodity connectedness via network frameworks (Chevallier & Ielpo, 2013b; and Diebold et al., 2017; Balli et al., 2019; Tiwari et al., 2020). By splitting the realized volatility into positive and negative semivariances, this study also contributes to the methodological studies estimating commodity volatility – whether symmetric or asymmetric – using a family of GARCH models (Mensi et al., 2014; Olson et al., 2014; Ji and Fan, 2012; Trujillo-Barrera et al., 2012; Dutta & Noor Md, 2017). Additionally, this study complements the existing literature that captures time-frequency commodity interdependence using the wavelet framework (Connor & Rossiter, 2005; Naccache, 2011; Filip et al., 2016).

Using high-frequency data, we investigate asymmetric volatility connectedness among a wide variety of commodities by implementing a network framework that also accounts for the time-frequency domain. Specifically, we compute the asymmetric volatility connectedness using the asymmetric connectedness model of Baruník, Kočenda, and Vácha (2017), which also encompasses the spillover model of Diebold and Yilmaz (2012) and the frequency connectedness approach of Baruník and Křehlík (2016). From high-frequency data, we calculate realized variance and realized semivariances through the volatility decomposition approach of Barndorff-Nielsen, Kinnebrock, and Shephard (2010).

Our findings indicate low inter-group connectedness, distinct group clustering, and high intra-group network-based connectedness in the realized volatilities of the sample commodities. We find more pronounced inter- and intra-group volatility connectedness for negative realized volatilities than positive ones. We also show that volatility connectedness is a long-run phenomenon. These results suggest that, although diversification prospects for commodity investors are generally curtailed during bearish market conditions, some inter- and intra-group commodity combinations continue to carry such prospects irrespective of the market conditions. In addition, the time-varying connectedness results indicate that the bad volatility connectedness commands the good volatility connectedness for the total sample as well as for various frequency domains. Moreover, the time-varying asymmetries in the volatility connectedness are driven by several financial, economic and political events. Finally, we report time-varying asymmetries for the inter- and intra-group volatility transmission that again shows the dominance of negative volatility transmission, both inter-group and intra-group, in the long-run frequency domain.

The remainder of the paper is structured as follows. Section 2 provides a brief review of the literature. Section 3 describes the methodology. The description of the data is presented in Section 4. Section 5 presents the empirical findings. Section 6 offers concluding remarks.

2. Literature Review

A seminal work by Pindyck and Rotemberg (1990) found that commodity prices behave similarly and therefore engage in comovement (or spillover). With this new information, many researchers began to pay attention to the spillovers among commodity prices, returns, and volatilities as well as across commodity classes (Hammoudeh, Li, & Jeon, 2003; Baffes, 2007). Commodity spillover literature can be categorized into three strands.

The first strand of literature focuses on studying the volatility spillovers between individual commodities or commodity classes. This strand places an overwhelming emphasis on inter- and intra-group volatility connections between energy (oil) and non-energy (agriculture) commodities (McPhail and Babcock, 2012; Qiu et al., 2012), within precious metals (Sensoy, 2013; Batten et al., 2015), and across commodity classes (Chen & Wu, 2016; Mensi et al., 2013; Abderladi & Serra, 2015; Yaya et al., 2016; Shahzad et al., 2019). A key message from this literature is that cross-commodity volatility spillovers display considerable heterogeneity across commodity groups, accounting for which is essential for any spillover analysis concerning commodity markets. In the second strand, scholars uncover the complex dynamics of cross-commodity spillovers by employing novel statistical techniques including co-integration and/or Granger-causality analyses (Chaudhri, 2001; Zhang et al., 2010; Hassouneh et al., 2012; Nemati, 2016; Popp et al., 2018), time-frequency domain analyses, mainly the wavelet approach (Connor & Rossiter, 2005; Naccache, 2011; Kristoufek et al., 2013; Vacha et al., 2013; Filip et al., 2016), and frameworks such as the vector autoregressive (VAR), generalized autoregressive conditional heteroskedasticity (GARCH), and dynamic conditional correlation (DCC) (Beckmann & Czudaj, 2014; Mensi et al., 2014). Overall, these sophisticated modelling exercises produce mixed evidence of volatility spillovers in commodity markets, and there is always a room for new evidence using novel techniques.

With growing concern about commodity connectedness since the GFC, the studies on commodity market spillovers moved to a network framework, constituting the third strand of literature. By viewing commodity markets as a network, Diebold et al. (2017) opened up new avenues of empirical examination. Therefore, another strand of literature started to emerge following their work, spotlighting the various dimensions of the commodity network. Table 1 summarizes all those attempts made since the publication of Diebold et al. (2017).

<< Insert Table 1 about here >>

As can be seen from Table 1, there is growing evidence of the volatility spillover among commodity markets from both network and time-frequency domain perspectives. However, no evidence exists to date that capitalizes on high-frequency data to investigate the presence of asymmetric volatility spillovers among commodity markets in the time-frequency domain, despite the recently documented benefits of high-frequency data from the investment and policy aspects of commodity markets (Luo & Ji, 2018; Křehlík & Baruník, 2017; Baruník & Kocenda, 2019; Lu, Yang, & Liu, 2019). As suggested by Křehlík and Baruník (2017), the short- and long-run dynamics in energy market connectedness have an important bearing for systemic risk, especially when modelling the high-frequency aspects of volatility. To fill this literature gap, we first resort to the studies indicating the presence of asymmetric volatility and its associated spillovers in commodity markets. For instance, consistent with Kilian, (2009), Narayan and Narayan (2007) found asymmetric effects on oil price volatility, induced by demand/supply shocks. The presence of asymmetry, once joined with the prevalence of volatility spillovers across commodity markets, would naturally lead asymmetric volatility to spillover from one commodity market to another, mainly because of volatility asymmetries caused by supply/demand shocks and the financialization of commodities (Bekiros et al., 2015; Kilian, 2009; Baruník et al., 2015; Shahzad et al., 2018b; Apergis, Baruník, & Lau, 2017), and partly because of the asymmetries induced by economic and business cycles, financial crises, central bank monetary policy, and geopolitical conflicts (Uddin et al., 2019). The time-frequency aspect of the asymmetric volatility spillovers may emerge from the notion that economic agents operate at different investment horizons – expressed in trading frequencies – associated with different types of investors, trading tools, and strategies that correspond to different trading frequencies (Gencay et al., 2010; Conlon et al., 2016; Bredin et al., 2017), which is suggested by some recent modelling strategies (Bandi & Tamoni, 2017; Cogley, 2001; and Ortu et al., 2013), as well as by the presence of economic linkages among commodities causing long-term correlation (Casassus et al., 2013). Supporting this aspect are Baruník and Křehlík (2018), who argue that shocks to economic activity impact variables at various frequencies with various strengths, leading to frequency connectedness. In addition to the studies listed above, an emerging strand of literature uses high-frequency data to uncover spillover asymmetry along with new stylized facts for certain commodity groups (Luo & Ji, 2018; Křehlík & Baruník, 2017; Baruník & Kocenda, 2019; Lu, Yang, & Liu, 2019). Reconciling the literature on asymmetric volatility, its associated spillovers in the time-frequency domain, and the related studies using high-frequency data with the network-based evidence of commodity market spillovers (Chevallier & Ielpo, 2013b; Diebold et al., 2017; Balli et al., 2019; Tiwari et al., 2020), we conjuncture about the presence of asymmetric volatility connectedness among commodity markets in the time-frequency domain using high-frequency data, and that this connectedness is different for total, short- and long-run spillovers. In light of this literature, we also hypothesize possible heterogeneity across inter- and intra-group spillovers in terms of their directional asymmetric spillover effects.

3. Methodology

In this section, we describe the computation procedures for the realized volatility and asymmetric volatility. The subsequent section provides details of the asymmetric and time-frequency connectedness approaches adopted for this investigation.

By overcoming the network-based model of Diebold et al. (2017), where the range-based volatility measures of Garman and Klass (1980) are used, we exploit the potential of recently developed realized volatility estimators of Barndorff-Nielsen, Kinnebrock, and Shephard (2010) by taking advantage of high-frequency data. Accordingly, a given spillover analysis becomes much more exciting and informative once the connections between volatilities from both negative and positive returns are spotted through the realized semivariances. What follows is an introduction to the two existing concepts and a subsequent description of how we combine the two concepts to compute asymmetric volatility spillovers using high-frequency measures.

3.1. Realized variance and semivariance

Consider a continuous-time stochastic process for log-prices, p_t, evolving over a time horizon $t \in [0,T]$, which consists of a continuous component and a pure jump component,

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s + J_t, \tag{1}$$

Where μ is a locally bounded predictable drift process, and σ is a strictly positive volatility process, and all are adapted to some common filtration *CF*. The quadratic variation of the log prices p_t is

$$[p_t, p_t] = \int_0^t \sigma_s^2 ds + \sum_{0<s\leq t} (\Delta p_s)^2, \tag{2}$$

where $\Delta p_s = p_s - p_{s-}$ are jumps, if present. A natural measure for quadratic variation has been proposed by Andersen, Bollerslev, Diebold, and Labys (2001) and Barndorff-Nielsen (2002) as the sum of squared returns called "realized variance" (RV). Formally, let us suppose that the intra-day returns $r_i = p_i - p_{i-1}$ defined as a difference between intraday log prices $p_0, \ldots, p_n$ are equally spaced on the interval $[0,t]$, then

$$RV = \sum_{i=1}^n r_i^2 \tag{3}$$

converges in probability to $[p_t, p_t]$ with $n \to \infty$.

Later, Barndorff-Nielsen, Kinnebrock, and Shephard (2010) split the realized variance into realized semivariance for capturing the variation due to negative or positive movements (RV^- and RV^+) in a specific variable[4], defined as:

$$RV^- = \sum_{i=1}^n \mathbb{I}(r_i < 0) r_i^2, \tag{4}$$

[4] The technique was quickly adopted by Feunou, Jahan-Parvar, and Tédongap (2013), Patton and Sheppard (2015), and Segal, Shaliastovich, and Yaron (2015).

$$RV^{+} = \sum_{i=1}^{n} \mathbb{I}(r_i \geq 0) r_i^2 \tag{5}$$

such that the decomposition, $RV = RV^{-} + RV^{+}$, holds exactly for any n. Barndorff-Nielsen, Kinnebrock, and Shephard (2010) contend that the realized semivariance converges to $\frac{1}{2}\int_{0}^{t}\sigma_s^2 ds$ and limits to the sum of the jumps due to negative and positive returns. Consequently, the postitive and negative semivariances correspond to the good and bad state of the realized volatilities. We discuss below that the two states may spill over differently across markets, creating asymmetries in the volatility spillovers.

3.2. Asymmetric spillovers through Diebold and Yilmaz (2012)

To compute the asymmetric volatility connectedness across our sample commodities, we first apply the spillover model of Diebold and Yilmaz (2012). To further explore the time-frequency domain aspect of asymmetric volatility connectedness, we implement the connectedness framework of Brunik and Krehlik (2016). Under the model framework, we consider $RV_t = (RV_{1t},...,RV_{nt})'$ to measure total volatility spillovers, and $RV_t^{-} = (RV_{1t}^{-},..., RV_{nt}^{-})'$ and $RV_t^{+} = (RV_{1t}^{+},..., RV_{nt}^{+})'$ to measure volatility spillovers due to negative and positive returns, respectively, which allows for the measurement of bad and good volatility and hence asymmetric spillovers (Baruník et al., 2016).

According to Diebold and Yilmaz (2012), total and directional spillover measures follow directly from the forecast error variance decomposition associated with an *N*-variable vector autoregression fitted to volatility (semivariance). To begin, consider an *N*-dimensional vector $RV_t = (RV_{1t},...,RV_{nt})'$ holding the realized variance of *N* assets, which is modelled by a covariance stationary vector autoregression VAR (p) as:

$$RV_t = \sum_{i=1}^{p} \phi_i RV_{t-i} + \varepsilon_t, \tag{6}$$

where $\varepsilon_t \sim N(0,\Sigma_\varepsilon)$ is a vector of independently and identically distributed disturbances and ϕ_i, for $i = 1$,...,p coefficient matrices.

Provided that the VAR process is invertible, the moving average (MA) representation is written as:

$$RV_t = \sum_{j=0}^{\infty} A_i \varepsilon_{t-i}, \tag{7}$$

where the $N \times N$ coefficient matrices A_i obey a recursion of the form $A_i = \sum_{j=1}^{p} \phi_j A_{i-j}$, with A_0 being the $N \times N$ identity matrix, $A_0 = I_N$.

From the MA representation, it is possible to recover the system forecasts, the forecast errors, and the forecast error variance. The latter might also be decomposed highlighting the contribution of the system shocks, thus leading to the forecast error variance decomposition (FEVD). Diebold and Yilmaz (2012) define the generalized spillover index as the fraction of the H-step-ahead forecast error variance of RV_i owing to the shocks to RV_j $(i \neq j)$ for $i, j = 1,2,\cdots,N$. Accordingly, the total spillover index takes into account both (a) the i^{th} variable's own share of the H-step-ahead forecast error variance due to its own shocks, for i for $i = 1,2,\cdots,N$, and (b) the cross variance share of the H-step-ahead forecast error variances in the ith variable due to shocks to the j^{th} variable, for $i, j = 1,2,\cdots,N$, such that $i \neq j$. Hence, for $H = 1,2,\cdots$, the H-step-ahead generalized forecast error variance decomposition can be described as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma_\varepsilon e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma_\varepsilon A_h' e_i \right)}, \tag{8}$$

where Σ_ε is the variance matrix of the vector of errors ε. σ_{jj} is the standard deviation of the error term of the j^{th} equation, and e_i is selection vector with a value of one for the i^{th} element and zero otherwise. Following Diebold and Yilmaz (2012), we obtain the generalized FEVD through a VAR system which is independent of variable ordering (Koop, Pesaran, & Potter, 1996; Pesaran & Shin,1998). A_h stands for the $N \times N$ matrix of MA coefficients corresponding to the forecast horizon h. Since the own- and cross-variable variance contribution shares do not sum to one under the generalized decomposition, each entry of the variance decomposition matrix is normalized by its row sum as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)}, \tag{9}$$

Using the contributions from the variance decomposition, Diebold and Yilmaz (2012) define the total spillover index (*SPILL*), which measures the contribution of spillovers from volatility shocks across variables in the system to the total forecast error variance as:

$$SPILL(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100\,. \tag{10}$$

Note that, by construction, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$. Thus the contributions of spillovers from volatility shocks are normalized by the total forecast error variance.

Similarly, we can identify directional spillovers by decomposing the total spillovers into those coming from or going to a particular variable in the system. Diebold and Yilmaz (2012) use the following to measure the directional spillovers received by asset *i* from all other assets *j*:

$$SPILL_{i \leftarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100\,. \tag{11}$$

In a similar fashion, the directional spillovers transmitted by asset *i* to all other assets *j* can be measured as:

$$SPILL_{i \rightarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100\,. \tag{12}$$

3.3. Asymmetric spillovers

Following the spillover model described above, we can not only compute the total spillovers from RV^- ($SPILL^-$) and RV^+ ($SPILL^+$) but also the directional spillovers from RV^- ($SPILL_{i \leftarrow j}^-$, $SPILL_{j \rightarrow i}^-$) and RV^+ ($SPILL_{i \leftarrow j}^+$, $SPILL_{j \rightarrow i}^+$), and this enables us to capture symmetric volatility spillovers. To quantify the extent of asymmetric volatility spillovers, we follow the spillover asymmetry measure of Baruník et al. (2016). If the contributions of RV^- and RV^+ are equal, the spillovers are symmetric, and are expected to be equal to spillovers from RV. On the other hand, the differences in the realized semivariances result in asymmetric spillovers. A bootstrapping procedure tests the null hypothesis $H_0^1: SPILL^- = SPILL^+$ of the spillover asymmetry. Accordingly, the extent of spillover asymmetry (SA) only measures the difference between positive and negative spillovers:

$$SA = SPILL^+ - SPILL^- \quad (13)$$

where $SPILL^+$ and $SPILL^-$ are volatility spillover indices due to RV^+ and RV^-, respectively, with an H-step-ahead forecast at time t. When SA takes the value of zero, spillovers coming from RV^- and RV^+ are equal. When SA is positive (negative), spillovers coming from RV^+ (RV^-) are larger than those from RV^-(RV^+).

3.4. Total, directional, and asymmetric spillovers in the frequency domain

In this section, we lay out details of the spillover framework recently introduced by Barunik and Krehlik (2018). We apply this model to test whether the results of spillover asymmetry continue to hold for short- and long-term horizons. For spillover computations, Diebold and Yilmaz (2012) aggregate information through frequencies while disregarding the possible heterogeneity across frequency responses to shocks, which we highlighted earlier. However, the behavior of asymmetric spillovers could well behave differently over different frequency bands, and be computed by the connectedness framework of Barunik and Krehlik (2018). Relying on the spectral representation of variance decomposition (e.g., Stiassny, 1996; Dew-Becker and Giglio, 2016), this approach is an expansion of Diebold and Yilmaz (2012).

In this framework, the frequency response function plays a central role and is obtained as the Fourier transform of the coefficients A_h, with $= \sqrt{-1}$, which can be defined as:

$$A(e^{-ih\omega}) = \sum_{h=0}^{\infty} e^{-ih\omega} A_h \quad (14)$$

where ω denotes the frequency.

The power spectrum $S_{RV}(\omega)$, which indicates how the variance of RV_t is distributed over the frequency components ω , is computed as:

$$S_{RV}(\omega) = \sum_{h=0}^{\infty} E\left(RV_t RV_{t-h}^{'}\right)e^{-ih\omega} = A\left(e^{-ih\omega}\right)\Sigma A^{'}\left(e^{+ih\omega}\right) \tag{15}$$

According to Krehlik and Barunik (2018), the frequency domain counterparts can be defined by the spectral representation for covariance and can be written as:

$$E\left(RV_t RV_{t-h}^{'}\right) = \int_a^b S_{RV}(\omega)e^{ih\omega}d\omega \tag{16}$$

where $(a,b) = d$ is an arbitrary frequency band such that, $a,b \in (-\pi, +\pi)$ & $a < b$.

The spectral quantities are estimated using standard discrete Fourier transforms. The cross-spectral density on the interval d is estimated as:

$$\sum_{\omega} \hat{A}(\omega)\hat{\Sigma}\hat{A}^{'}(\omega), \text{ for } \omega \in \left\{\left\lfloor\frac{aH}{2\pi}\right\rfloor, \ldots, \left\lfloor\frac{bH}{2\pi}\right\rfloor\right\}, \tag{17}$$

where:

$$\hat{A}(\omega) = \sum_{h=0}^{H-1} \hat{A}_h e^{-2i\pi\omega/H}, \tag{18}$$

and $\hat{\Sigma} = \hat{\varepsilon}^{'}\hat{\varepsilon}/(T - z)$, where z is a correction for a loss of a degree of freedom, which depends on the VAR specification.

The decomposition of the impulse response function at a given frequency band can be estimated as:

$$\hat{A}(d) = \sum_{\omega} \hat{A}(\omega) \tag{19}$$

Finally, the generalized variance decomposition at the desired frequency band is estimated as

$$\hat{\theta}_{ij}(d) = \sum_{\omega} \hat{\Gamma}_i(\omega) \frac{\hat{\sigma}_{jj}^{-1}\left(e_i^{'}\hat{A}(\omega)\hat{\Sigma}e_j\right)^2}{e_i^{'}\hat{A}(\omega)\hat{\Sigma}\hat{A}^{'}(\omega)\, e_i}, \tag{20}$$

where $\hat{\Gamma}_i(\omega) = \frac{e_i^{'}\hat{A}(\omega)\hat{\Sigma}\hat{A}^{'}(\omega)e_i}{e_i^{'}\Omega e_i}$ is an estimate of the weighing function, and $\Omega = \sum_{\omega} \hat{A}(\omega)\hat{\Sigma}\hat{A}^{'}(\omega)$.

Then, the connectedness measures at a given frequency band of interest can be readily derived by substituting $\hat{\theta}_{ij}(d)$ to estimate the traditional measures outlined above.

4. Data and descriptive statistics

The data we use for empirical analysis consists of high-frequency 5-minute prices of 12 commodities from September 30, 2009 to December 31, 2019. The availability of liquid data dictates the start date. The twelve commodity products comprise three categories, energy, metals, and grains. All the data is sourced from the Kibot.com[5] database on a nearly 24-hour basis, so each day there are 288 prices with matched date/time information set at New York time. Consistent with Luo and Ji (2018), Degiannakis (2008), and Andersen and Todorov (2010), we use a high-frequency sample of five minutes as it strikes a logical balance between accurate estimation and microstructure noise.

<< Insert Table 2 about here >>

Table 2 presents the descriptive statistics of the realized volatility measure in three classifications, 1) total realized variance, 2) realized positive semivariance, and 3) realized negative semivariance. As shown in Table 2, natural gas has the highest average realized variance, positive and negative semivariances, and standard deviation, while gold has the lowest estimates for all variance measures. Moreover, in the three commodity groups, natural gas produces the highest realized variance and semivariances in the energy commodities, whereas palladium and wheat dominate the metal and agriculture commodities. These commodities also show the highest standard deviations of realized variance for the respective commodity groups except for agriculture commodities where corn has a higher variation for the total realized and negative semivariance. It is evident from the descriptive analysis that energy commodities produce higher volatilities compared to other commodities, confirming a common finding reported in the commodity literature (Ji, Bouri, Roubaud, & Shahzad, 2018; Kang, McIver, & Yoon, 2017).

5. Empirical results

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[5] This data provider is lesser known than its competitors, but its data quality is comparable to that of the New York Stock Exchange's TAQ database. A limited comparison of the two databases is available upon request.

5.1 Static volatility spillover analysis

First, we employ the Diebold & Yilmaz (2012) spillover approach to analyze the volatility connectedness among twelve commodities under consideration. Fig. 1 presents the volatility connectedness network that shows the volatility spillovers from each commodity to other commodities and vice versa. This spillover table is estimated from the GFEVD with a forecast horizon of H=100 days and lag order of 3 (based on the Schwarz information criterion). Overall, crude oil transmits more volatility spillovers than it receives, making it a leading net transmitter of volatility spillovers. In contrast, natural gas is the leading net receiver as it receives more volatility spillovers than it transmits. Additionally, we observe a robust intragroup volatility clustering for all commodity groups that signifies the importance of related production processes and complement/substitute effect in all commodity groups. Our group-wise volatility clustering findings corroborate Diebold, Liu, and Yilmaz (2017) and Balli, Naeem, Shahzad, and de Bruin (2019), as they also report volatility clustering among commodity groups in their connectedness analysis.

Moreover, in terms of intragroup volatility connectedness, the metal commodities show the highest connectedness followed by agricultural commodities, while the energy commodity group has the lowest intragroup volatility connectedness. Precisely, all the metal group commodities transmit/receive moderate to strong volatility spillovers to/from each other, and two strong commodity pairs, i.e., gold/silver and palladium/platinum emerge in the metal commodity group. In contrast, the only significant connection in the energy commodity group is between crude oil and RBOB gasoline. It is relevant to mention that gasoline is generally refined from crude oil; hence a volatility spillover connection between these two commodities is inevitable. Moreover, for the agriculture commodity group, rough rice is least connected to other commodities, while strong connectedness is present between the wheat/corn pair. Our intragroup commodity pairing concurs with previous studies (Balli et al., 2019; Diebold et al., 2017) and indicates the significance of interdependence in similar commodities.

<< Insert figure 1 about here >>

Furthermore, in the inter-group connectedness, commodities in the metal group transmit/receive substantial spillovers to/from energy and agricultural commodities, while the latter two groups show disconnect from each other. In particular, crude oil and natural gas receive volatility spillovers from gold, platinum, and silver, while the latter transmits the same to gold and silver. Moreover, in the agricultural commodities, corn and wheat receive significant volatility spillovers from metal commodities. Also reported by Barbaglia, Croux, and Wilms (2020), the inter-group volatility transmission highlights the reliance of various commodities on each other's production processes and supply chains.

Overall, the volatility connectedness analysis shows low inter-group connectedness, distinct group clustering, and high intra-group connectedness. These findings imply that commodity volatilities show more connectedness in the same group than inter-group transmissions. Hence, commodity investors can diversify volatility risks by constructing balanced portfolios, and choosing commodities from different commodity groups rather than just sticking to one commodity group. Additionally, we observe the intra-group volatility disconnect between some commodities such as crude oil and ethanol, that offers diversification possibilities for specialized commodity group investors.

Furthermore, studies show that negative shocks generate more spillovers in the commodity market than positive ones, producing asymmetries in the connectedness of volatility spillovers (Luo & Ji, 2018; Shahzad, Hernandez, Al-Yahyaee, & Jammazi, 2018). To determine these asymmetries in the sampled commodity volatility spillovers, we construct a volatility connectedness network using positive and negative semivariance estimates. The positive semivariance connectedness network presented in Fig. 2a shows a relatively weak intra-group connectedness and fewer inter-group spillovers than the negative semivariance connectedness network presented in Fig. 2b, confirming the presence of asymmetries in the volatility spillovers. Moreover, in the negative semivariance connectedness network, ethanol clusters with agricultural commodities instead of energy commodities, which confirm the agriculture-biofuel link reported by Barbaglia et al. (2020) and Shahzad et al. (2018). Nevertheless, intra-group connectedness in the agriculture commodity group is more robust in the positive semivariance network than the negative semivariance network, indicating intra-group diversification possibilities during bearish market times.

<< Insert figure 2 about here >>

Based on the asymmetric volatility spillovers analysis, we observe the dominance of bad volatility transmission over good volatility in the total volatility connectedness for the commodity market. However, dividing total spillover transmission into positive and negative volatility connectedness overlooks the effect of asymmetries when commodity groups experience distinct market conditions. For instance, due to a recent political or economic event, the energy market may face a downturn, while the same event does not affect the other commodity groups. Therefore, to gauge the impact of how good or bad volatility in one commodity spills over to good or bad volatility of other commodities, we construct the volatility connectedness networks shown in Fig. 3, which serve to identify the good/bad volatility spillovers to/from individual commodities. Additionally, we estimate the volatility transmission mechanism in the short and long run, in order to understand the volatility connectedness in various frequency domains.

Fig. 3 Panels a and b present the individual commodity-based asymmetric volatility connectedness among all the commodities under consideration in the short and long run. There are various points to note; first, owing to a strong production process link between crude oil and RBOB gasoline, we observe robust volatility transmission in the long-run between these energy commodities, whereas in the metal commodities, gold and silver show moderate volatility connectedness in the long-run regardless of market conditions. In contrast, wheat and corn transmit higher volatility spillovers to each other in the short run when both commodities are in a similar market state, i.e., positive-positive and negative-negative. Second, the metal commodities show higher volatility connectedness with each other than to other commodity groups in all the scenarios considered, eliminating any possible intra-group diversification opportunities. Third, the volatility connectedness is more pronounced in the networks involving analogous volatility spillovers, i.e., positive-positive and negative-negative. This observation indicates the availability of fewer diversification opportunities when overall markets are experiencing negative returns. Fourth, the metal commodities are the only ones transmitting inter-group spillovers to crude oil, wheat, and rough rice when the overall commodity market experiences downturn, i.e., negative to negative spillovers. Lastly, the long-run clustering of ethanol with agricultural commodities under all scenarios reinforces the agriculture-biofuel link. Thus, we confirm the asymmetries in the volatility transmission of individual commodities under various directional spillover scenarios. In another vein, Baruník, Kočenda, and Vácha (2017) and Baruník, Kočenda, and Vácha (2016) report similar asymmetries in volatility spillovers for forex and stock markets, respectively.

<< Insert figure 3 about here >>

Overall, the network connectedness approach discussed above provides essential insights into volatility connectedness among the sampled commodities over time. However, the static network analysis approach overlooks the time-varying feature of the volatility spillovers, which is very important given the vulnerability of commodity prices to the economic, financial, and political events such as the European debt crisis, middle east conflicts, and oil crises. To mitigate this shortcoming of the static spillover analysis approach, in the next sub-section we estimate and analyze time-varying volatility connectedness among sample commodities and commodity groups using the total and asymmetric volatility spillovers. The frequency domain analysis further highlights the importance of using various time horizons.

5.2 Dynamic volatility spillover analysis

Fig. 4 presents the total volatility spillovers among all commodities using the rolling window approach. This dynamic total spillover index is calculated from the GFEVD using a rolling window size of 200 days, a forecast horizon of H=100 days, and lag order of 3 (based on SIC). One can see many spikes and drops in the total connectedness confirming the time-varying nature of the volatility connectedness. The spikes and drops in the total volatility connectedness indicate the impact of economic, financial, or political events on commodity markets. For example, after a stable period from the start of the sample period to late 2011, the volatility connectedness experienced two spikes between 2012 and 2103 that can be attributed to the European debt crisis and political disturbances in the Middle East and North Africa. During the European debt crisis, countries such as Greece, Portugal, and Ireland failed to bail out over-indebted financial institutions or, even worse, were not able to refinance their government debts. Additionally, bigger European economies such as Spain, Italy, and France also experience a drop in their economic activity leading to sharp a decline in commodity demand from the region[6]; consequently, increasing the volatility transmission in the commodity markets. Similarly, political disturbances

[6] See https://www.ft.com/content/e5c80488-20f3-11e1-8a43-00144feabdc0

in the Middle East and North Africa, particularly in Libya and Egypt, increased the volatility connectedness in the commodity markets due to the notable presence of the African continent in the commodity market supply chain[7].

<< Insert figure 4 about here >>

Owing to stable crude oil price and the slowdown of the global economy, the commodity market volatility connectedness started to decrease in the later part of 2013 and reached its second-lowest point by the start of 2015. However, in mid-2015, the Chinese stock market experienced a strong bearish trend as one-third of the total value of A-shares on the Shanghai Stock Exchange was lost within a month (Jayanthakumaran, 2016). The disruption of the Chinese financial market increased uncertainty not only in the financial markets but also in commodity markets globally, leading to increased volatility connectedness among commodities that lasted until the end of 2015.

Post-2015, we observe a gradual decrease in the total volatility spillover connectedness with the index touching its lowest point just before the end of 2017. Owing to increasing US-China trade frictions, the spillover index experienced another sharp increase in the third quarter of 2018. Hence, our time-varying analysis indicates that the commodity markets are highly susceptible to both economic and political global shocks, which corroborates Balli et al. (2019), Barbaglia et al. (2020), Diebold et al. (2017), and Kang et al. (2017).

<< Insert figure 5 about here >>

Fig. 2 confirms the existence of asymmetries for the static spillover analysis, and we further explore these asymmetries in the time-varying framework. Fig. 5 shows asymmetries due to positive/negative shocks plotted in the positive/negative domain. It is apparent that the adverse negative shocks dominate the volatility spillovers both in magnitude and duration, confirming the distinctive asymmetries in the commodity spillovers, and concurring with the findings of Kang et al. (2017) and Luo & Ji (2018). Additionally, we present time-varying asymmetries in various frequency domains in Fig. 6a, and Fig. 6b, for the short and long term, respectively. Both short-

[7] See https://www.weforum.org/agenda/2016/05/which-are-africas-biggest-exports/

and long-term frequencies show a similar pattern of asymmetries in the volatility spillovers; however, long-term spillovers are more pronounced than short-term.

<< Insert figure 6 about here >>

The analysis above confirms asymmetries in the total volatility connectedness among sampled commodities for the total sample and the various frequency domains. To further explore the asymmetries in inter- and intra-group volatility transmission, we estimate and analyze the time-varying asymmetric inter- and intra-group volatility transmission. The short-term time-varying asymmetric volatility connectedness presented in Fig. 7a shows the dominance of bad volatility connectedness over good volatility connectedness for all commodity groups both in terms of magnitude and duration. Although we observe a similar time-varying intragroup volatility transmission pattern, the agriculture commodity group experiences higher intragroup volatility transmission than the metal or energy groups, which could be attributed to the ever-declining prices of agricultural commodities since their 2011 peak. Fig. 7 (b-d) presents inter-group volatility spillovers in the short run. It is evident from the figures that bad volatility spillovers from one group of commodities to other groups are more frequent and more pronounced than good volatility spillovers. Additionally, there is a higher inter-group volatility transmission between energy and agricultural commodities than metal commodities.

<< Insert figure 7 about here >>

Lastly, Fig. 8 (a-d) presents the asymmetric inter- and intra-group volatility transmission for the long-run frequency that reinforces the dominance of bad volatility transmission in the commodity market over good volatility, consequently confirming the asymmetries in the volatility transmission mechanism. Moreover, we observe a higher (lower) volatility transmission between energy and metals (agriculture) commodity groups in the long run than the short run. Overall, the asymmetries in the inter- and intra-group volatility transmission indicate the importance of breaking down volatility connectedness analysis into commodity groups and frequency domains to explore the dynamics of volatility connectedness in the commodity market.

<< Insert figure 8 about here >>

6. Conclusion

This paper examines the asymmetric volatility transmission between twelve commodities belonging to the energy, agriculture and metals commodity groups, using 5-minute trading data of commodity futures. We compute the asymmetric volatility connectedness using the asymmetric connectedness model of Baruník, Kočenda, and Vácha (2017), which encompasses the spillover model of Diebold and Yilmaz (2012) and the frequency connectedness approach of Baruník and Křehlík (2016). Additionally, we investigate the time-varying dynamics of volatility spillovers for all commodities and inter- and intra-group volatility connectedness, which reveal the asymmetries in the volatility connectedness owing to various economic, financial, and political events.

Our empirical results are as follows: First, we report low inter-group connectedness, distinct group clustering, and high intra-group network-based connectedness in realized volatilities of sample commodities. Second, we find more pronounced inter- and intra-group volatility connectedness for negative realized volatilities than positive ones. We show that volatility connectedness is a long-run phenomenon. These findings reveal that commodity investors have fewer diversification opportunities when the overall commodity market is going through bearish trends. However, some inter- and intra-group commodity pairs such as crude oil/ethanol and natural gas/rice still offer diversification opportunities regardless of market conditions. Short-horizon investors can make use of short-term diversification opportunities available in the commodity market.

Based on the dynamic connectedness results, we show time-varying asymmetries in the total spillover transmission between the selected commodities. Additionally, the time-varying net directional spillover connectedness reveals that the bad volatility connectedness dictates the good volatility connectedness for the total sample as well as for the various frequency domains; both in terms of magnitude and duration. We identify various financial, economic and political events such as the European debt crisis, Chinese stock market crash, and political drift in the North African region, as potentially driving time-varying asymmetries in the volatility connectedness of the commodity market. Finally, we report time-varying asymmetries for the inter- and intra-group volatility transmission that again shows the dominance of negative volatility transmission in both inter- and intra-group volatility transmission, being more pronounced in the long-run frequency domain.

References

Abdelradi, F., & Serra, T. (2015). Asymmetric price volatility transmission between food and energy markets: The case of Spain. *Agricultural economics*, *46*(4), 503-513.

An, S., Gao, X., An, H., Liu, S., Sun, Q., & Jia, N. (2020). Dynamic volatility spillovers among bulk mineral commodities: A network method. *Resources Policy*, *66*, 101613.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of financial economics*, *61*(1), 43-76.

Andersen, T. G., & Todorov, V. (2010). Realized volatility and multipower variation. *Encyclopedia of Quantitative Finance*.

Apergis, N., Baruník, J., & Lau, M. C. K. (2017). Good volatility, bad volatility: What drives the asymmetric connectedness of Australian electricity markets?. *Energy Economics*, *66*, 108-115.

Baffes, J. (2007). *Oil spills on other commodities*. The World Bank.

Bahloul, W. (2018). Short-term contrarian and sentiment by traders' types on futures markets. *Review of Behavioral Finance*.

Balli, F., Naeem, M. A., Shahzad, S. J. H., & de Bruin, A. (2019). Spillover network of commodity uncertainties. *Energy Economics*, *81*, 914-927.

Bandi, F. M., & Tamoni, A. (2017). The horizon of systematic risk: a new beta representation. *Available at SSRN 2337973*.

Barbaglia, L., Croux, C., & Wilms, I. (2020). Volatility spillovers in commodity markets: A large t-vector autoregressive approach. *Energy Economics*, *85*, 104555.

Barndorff-Nielsen, O. E., & Shephard, N. (2002). Estimating quadratic variation using realized variance. *Journal of Applied econometrics*, *17*(5), 457-477.

Barndorff-Nielsen, O. E., Kinnebrock, S., & Shephard, N. (2010). Measuring downside risk: realised semivariance. In "Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle"(Edited by T. Bollerslev, J. Russell and M. Watson).

Baruník, J., & Kocenda, E. (2019). Total, asymmetric and frequency connectedness between oil and forex markets. *The Energy Journal*, *40*(Special Issue).

Baruník, J., Kocenda, E., & Vácha, L. (2015). Volatility spillovers across petroleum markets. *The Energy Journal*, *36*(3).

Baruník, J., Kočenda, E., & Vácha, L. (2016). Asymmetric connectedness on the US stock market: Bad and good volatility spillovers. *Journal of Financial Markets*, *27*, 55-78.

Baruník, J., Kočenda, E., & Vácha, L. (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance, 77*, 39-56.

Baruník, J., & Křehlík, T. (2018). Measuring the frequency dynamics of financial connectedness and systemic risk. *Journal of Financial Econometrics*, *16*(2), 271-296.

Batten, J. A., Ciner, C., & Lucey, B. M. (2015). Which precious metals spill over on which, when and why? Some evidence. *Applied Economics Letters*, *22*(6), 466-473.

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, *45*(2), 217-229.

Beckmann, J., & Czudaj, R. (2014). Volatility transmission in agricultural futures markets. *Economic Modelling*, *36*, 541-546.

Bekiros, S., Boubaker, S., Nguyen, D. K., & Uddin, G. S. (2017). Black swan events and safe havens: The role of gold in globally integrated emerging markets. *Journal of International Money and Finance*, *73*, 317-334.

Bredin, D., Conlon, T., & Potì, V. (2017). The price of shelter-Downside risk reduction with precious metals. *International Review of Financial Analysis*, *49*, 48-58.

Büyükşahin, B., & Robe, M. A. (2014). Speculators, commodities and cross-market linkages. Journal of International Money and Finance, 42, 38-70.

Casassus, J., & Higuera, F. (2013). *The Economic Impact of Oil on Industry Portfolios* (Vol. 433). Oficina de Publ..

Chang, C. L., Liu, C. P., & McAleer, M. (2019). Volatility spillovers for spot, futures, and ETF prices in agriculture and energy. *Energy Economics*, *81*, 779-792.

Chaudhuri, K. (2001). Long-run prices of primary commodities and oil prices. *Applied Economics*, *33*(4), 531-538.

Chen, S., & Wu, X. (2016). *Comovements and Volatility Spillover in Commodity Markets* (No. 333-2016-14312).

Cheong, C. W. (2009). Modeling and forecasting crude oil markets using ARCH-type models. *Energy policy*, *37*(6), 2346-2355.

Chevallier, J., & Ielpo, F. (2013b). Volatility spillovers in commodity markets. Applied Economics Letters, 20(13), 1211-1227.

Chevallier, J., & Ielpo, F. (2013a). The economics of commodity markets. John Wiley & Sons.

Chong, J., & Miffre, J. (2010). Conditional return correlations between commodity futures and traditional assets. Journal of Alternative Investments, 12(3), 61-75.

Chuliá, H., Guillén, M., & Uribe, J. M. (2017). Measuring uncertainty in the stock market. *International Review of Economics & Finance*, *48*, 18-33.

Cogley, T. (2001). A frequency decomposition of approximation errors in stochastic discount factor models. *International Economic Review*, *42*(2), 473-503.

Conlon, T., Cotter, J., & Gençay, R. (2016). Commodity futures hedging, risk aversion and the hedging horizon. *The European Journal of Finance*, *22*(15), 1534-1560.

Connor, J., & Rossiter, R. (2005). Wavelet transforms and commodity prices. *Studies in Nonlinear Dynamics & Econometrics*, *9*(1).

de Nicola, F., De Pace, P., & Hernandez, M. A. (2016). Co-movement of major energy, agricultural, and food commodity price returns: A time-series assessment. *Energy Economics*, *57*, 28-41.

Degiannakis, S. (2008). ARFIMAX and ARFIMAX-TARCH realized volatility modeling. *Journal of Applied Statistics, 35*(10), 1169-1180.

Dew-Becker, I., & Giglio, S. (2016). Asset pricing in the frequency domain: theory and empirics. *The Review of Financial Studies*, *29*(8), 2029-2068.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*(534), 158-171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57-66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119-134.

Diebold, F. X., Liu, L., & Yilmaz, K. (2017). *Commodity connectedness* (No. w23685). National Bureau of Economic Research.

Dimpfl, T., & Jung, R. C. (2012). Financial market spillovers around the globe. *Applied Financial Economics*, *22*(1), 45-57.

Dutta, A., & Hasib Noor, M. (2017). Oil and non-energy commodity markets: An empirical analysis of volatility spillovers and hedging effectiveness. *Cogent Economics & Finance*, *5*(1), 1324555.

Fernández, A., González, A., & Rodriguez, D. (2018). Sharing a ride on the commodities roller coaster: Common factors in business cycles of emerging economies. *Journal of International Economics*, *111*, 99-121.

Ferrer, R., Shahzad, S. J. H., López, R., & Jareño, F. (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Economics*, *76*, 1-20.

Feunou, B., Jahan-Parvar, M. R., & Tédongap, R. (2013). Modeling market downside volatility. *Review of Finance*, *17*(1), 443-481.

Filip, O., Janda, K., Kristoufek, L., & Zilberman, D. (2016). Dynamics and evolution of the role of biofuels in global commodity and financial markets. *Nature Energy*, *1*(12), 16169.

Garman, M. B., & Klass, M. J. (1980). On the estimation of security price volatilities from historical data. *Journal of business*, 67-78.

Gençay, R., Gradojevic, N., Selçuk‖, F., & Whitcher, B. (2010). Asymmetry of information flow between volatilities across time scales. *Quantitative Finance*, *10*(8), 895-915.

Guhathakurta, K., Dash, S. R., & Maitra, D. (2020). Period specific volatility spillover based connectedness between oil and other commodity prices and their portfolio implications. *Energy Economics*, *85*, 104566.

Hammoudeh, S., Li, H., & Jeon, B. (2003). Causality and volatility spillovers among petroleum prices of WTI, gasoline and heating oil in different locations. *The North American Journal of Economics and Finance*, *14*(1), 89-114.

Hassouneh, I., Serra, T., Goodwin, B. K., & Gil, J. M. (2012). Non-parametric and parametric modeling of biodiesel, sunflower oil, and crude oil price relationships. *Energy Economics*, *34*(5), 1507-1513.

Jayanthakumaran, K. (2016). *Industrialization and Challenges in Asia*: Springer.

Ji, Q., & Fan, Y. (2012). How does oil price volatility affect non-energy commodity markets?. *Applied Energy*, *89*(1), 273-280.

Ji, Q., Bahloul, W., Geng, J. B., & Gupta, R. (2020). Trading behaviour connectedness across commodity markets: Evidence from the hedgers' sentiment perspective. *Research in International Business and Finance*, *52*, 101114.

Ji, Q., Bouri, E., Roubaud, D., & Shahzad, S. J. H. (2018). Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model. *Energy Economics*, *75*, 14-27.

Junttila, J., Pesonen, J., & Raatikainen, J. (2018). Commodity market based hedging against stock market risk in times of financial crisis: The case of crude oil and gold. Journal of International Financial Markets, Institutions and Money, 56, 255-280.

Kang, S. H., McIver, R., & Yoon, S. M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics*, *62*, 19-32.

Kang, S. H., Tiwari, A. K., Albulescu, C. T., & Yoon, S. M. (2019). Exploring the time-frequency connectedness and network among crude oil and agriculture commodities V1. *Energy Economics*, *84*, 104543.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053-69.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, *74*(1), 119-147.

Křehlík, T., & Baruník, J. (2017). Cyclical properties of supply-side and demand-side shocks in oil-based commodity markets. *Energy Economics*, *65*, 208-218.

Kristoufek, L., Janda, K., & Zilberman, D. (2013). Regime-dependent topological properties of biofuels networks. *The European Physical Journal B*, *86*(2), 40.

Lu, Y., Yang, L., & Liu, L. (2019). Volatility spillovers between crude oil and agricultural commodity markets since the financial crisis. *Sustainability*, *11*(2), 396.

Luo, J., & Ji, Q. (2018). High-frequency volatility connectedness between the US crude oil market and China's agricultural commodity markets. *Energy Economics*, *76*, 424-438.

McPhail, L. L., & Babcock, B. A. (2012). Impact of US biofuel policy on US corn and gasoline price variability. *Energy*, *37*(1), 505-513.

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling*, *32*, 15-22.

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Yoon, S. M. (2014). Dynamic spillovers among major energy and cereal commodity prices. *Energy Economics*, *43*, 225-243.

Mensi, W., Tiwari, A., Bouri, E., Roubaud, D., & Al-Yahyaee, K. H. (2017). The dependence structure across oil, wheat, and corn: A wavelet-based copula approach using implied volatility indexes. *Energy Economics*, *66*, 122-139.

Naccache, T. (2011). Oil price cycles and wavelets. *Energy Economics*, *33*(2), 338-352.

Naeem, M. A., Farid, S., Balli, F., & Hussain Shahzad, S. J. (2020). Hedging the downside risk of commodities through cryptocurrencies. *Applied Economics Letters*, 1-8.

Nemati, M. (2017). Relationship among Energy, Bioenergy and Agricultural Commodity Prices: Re-Considering Structural Changes. *International Journal of Food and Agricultural Economics (IJFAEC)*, *5*(1128-2018-031), 1-8.

Olson, E., Vivian, A. J., & Wohar, M. E. (2014). The relationship between energy and equity markets: Evidence from volatility impulse response functions. *Energy Economics*, *43*, 297-305.

Ortu, F., Tamoni, A., & Tebaldi, C. (2013). Long-run risk and the persistence of consumption shocks. *The Review of Financial Studies*, *26*(11), 2876-2915.

Patton, A. J., & Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics*, *97*(3), 683-697.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters*, *58*(1), 17-29.

Popp, J., Oláh, J., Farkas Fekete, M., Lakner, Z., & Máté, D. (2018). The relationship between prices of various metals, oil and scarcity. *Energies*, *11*(9), 2392.

Prasad, A., Narayan, P. K., & Narayan, J. (2007). Exploring the oil price and real GDP nexus for a small island economy, the Fiji Islands. *Energy Policy*, *35*(12), 6506-6513.

Qiu, C., Colson, G., Escalante, C., & Wetzstein, M. (2012). Considering macroeconomic indicators in the food before fuel nexus. *Energy Economics*, *34*(6), 2021-2028.

Rehman, M. U., Shahzad, S. J. H., Uddin, G. S., & Hedström, A. (2018). Precious metal returns and oil shocks: A time varying connectedness approach. *Resources Policy*, *58*, 77-89.

Rotemberg, J. J., & Pindyck, R. (1990). The excess co-movement of commodity prices.

Segal, G., Shaliastovich, I., & Yaron, A. (2015). Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics*, *117*(2), 369-397.

Sensoy, A. (2013). Dynamic relationship between precious metals. *Resources Policy*, *38*(4), 504-511.

Shahzad, S. J. H., Hernandez, J. A., Al-Yahyaee, K. H., & Jammazi, R. (2018a). Asymmetric risk spillovers between oil and agricultural commodities. Energy policy, 118, 182-198.

Shahzad, S. J. H., Mensi, W., Hammoudeh, S., Rehman, M. U., & Al-Yahyaee, K. H. (2018b). Extreme dependence and risk spillovers between oil and Islamic stock markets. Emerging Markets Review, 34, 42-63.

Shahzad, S. J. H., Rehman, M. U., & Jammazi, R. (2019). Spillovers from oil to precious metals: Quantile approaches. Resources Policy, 61, 508-521.

Silvennoinen, A., & Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. Journal of International Financial Markets, Institutions and Money, 24, 42-65.

Stiassny, A. (1996). A spectral decomposition for structural VAR models. *Empirical Economics*, *21*(4), 535-555.

Tiwari, A. K., Nasreen, S., Shahbaz, M., & Hammoudeh, S. (2020). Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. *Energy Economics*, *85*, 104529.

Trujillo-Barrera, A., Mallory, M., & Garcia, P. (2012). Volatility spillovers in US crude oil, ethanol, and corn futures markets. *Journal of Agricultural and Resource Economics*, 247-262.

Uddin, G. S., Shahzad, S. J. H., Boako, G., Hernandez, J. A., & Lucey, B. M. (2019). Heterogeneous interconnections between precious metals: Evidence from asymmetric and frequency-domain spillover analysis. *Resources Policy*, *64*, 101509.

Vacha, L., Janda, K., Kristoufek, L., & Zilberman, D. (2013). Time–frequency dynamics of biofuel–fuel–food system. *Energy Economics*, *40*, 233-241.

Yaya, O. S., Tumala, M. M., & Udomboso, C. G. (2016). Volatility persistence and returns spillovers between oil and gold prices: Analysis before and after the global financial crisis. *Resources Policy*, *49*, 273-281.

Yip, P. S., Brooks, R., Do, H. X., & Nguyen, D. K. (2020). Dynamic volatility spillover effects between oil and agricultural products. *International Review of Financial Analysis*, 101465.

Zhang, D. (2018). Energy finance: background, concept, and recent developments.

Zhang, D., & Broadstock, D. C. (2018). Global financial crisis and rising connectedness in the international commodity markets. *International Review of Financial Analysis*.

Zhang, Z., Lohr, L., Escalante, C., & Wetzstein, M. (2010). Food versus fuel: What do prices tell us?. *Energy policy*, *38*(1), 445-451.

Zhen, Z., Tian, L., & Lu, J. (2019). Analysis of oil prices' interaction in the USA based on complex networks. *Energy Sources, Part B: Economics, Planning, and Policy*, *14*(1), 1-12.

Table 1. Summary of Literature

No	Author(s)	Method(s)	Sample Period	Variables	Main Findings
1	Diebold et al. (2017)	VAR; FEVD	2011–2016 Daily	Energy, livestock, agricultural commodities, precious and industrial metals	Clustering of commodities into groups; high overall connectedness; energy group as the main transmitter.
2	Kang et al. (2017)	DECO-GARCH	2002–2016 Daily	Oil, agricultural commodities; and precious metals	Strong spillover during crisis; gold and silver are transmitters to other commodities.
3	Rehman et al. (2018)	SVAR	1989–2015 Daily	Crude oil, and precious and industrial metals	Structural oil shocks impact precious metal returns tails except for gold.
4	Zhang and Broadstock (2018)	VAR; FEVD	1982–2017 Daily	Crude oil, beverage, fertilizers, food, precious metals, and raw materials	Codependence in price-changes among seven major commodity classes; the spillover from food commodities increases after GFC.
5	Ferrer et al. (2018)	VAR; FEVD	2003–2017 Daily	Crude oil, US renewable energy stocks, high technology stocks, conventional energy stocks, US 10-year Treasury bond yields	Return and volatility is mostly connectedness in the short-term; crude oil prices are not the key driver of renewable energy companies' performance.
6	Křehlík and Baruník (2017)	Asymmetric Connectedness	1987-2014 5-Minutes Data	Crude oil, heating oil, and gasoline	Shocks to volatility with response shorter than one week are increasingly important; demand-side shocks to volatility are becoming increasingly important in creating short-run connectedness.
7	Luo and Ji (2018)	MHAR with DCC-GARCH	2006-2015 5-Minutes Data	US crude oil futures and China's agricultural commodity futures	Volatility spillover from the US oil to China's agricultural markets is verified; asymmetric volatility spillover exists between positive and negative volatilities.

8	Mensi, Tiwari, Bouri, Roubaud, and Al-Yahyaee (2017)	Wavelet and Copula methods	2012-2016 Daily	Implied volatility indexes of oil, wheat, and corn	Time-varying asymmetric tail dependence was found; the dependence structure is sensitive to time horizons.
9	Ji, Bouri, Roubaud, & Shahzad (2018)	Dependence-Switching CoVaR-Copula model; CoVaR; ΔCoVaR	2000-2017 Daily	Crude oil, natural gas, maize, rice, soybean, and wheat, as well as IGC's grains and oilseeds index	Agricultural commodities are more sensitive to shock from oil than from gas.
10	Shahzad, Hernandez, Al-Yahyaee, and Jammazi (2018a)	CoVaR; ΔCoVaR	2000-2017 Daily	WTI crude oil and IGC's wheat, maize, soybeans, and rice	Asymmetric tail dependence between oil and all agricultural commodities was found; bilateral and asymmetric upside and downside spillovers from oil to agricultural commodities were witnessed.
11	Guhathakurta, Dash, and Maitra (2020)	Structural Breaks Test; DY (2009, 2012, 2014); Baur and Lucey (2010)	1996-2018 Daily	Prices of agro-commodities (cocoa, coffee, rubber, soybeans, soya oil, sugar, wheat, palm oil, oats, and corn), six metal commodities (aluminum, copper, silver, gold, palladium, and platinum), and oil price of WTI index	Overall spillovers peaked during the oil price boom of 2007–08 and crash of 2015–16; oil contributes most to the volatility of agro and metal commodities; generally, agro commodities are net receivers; strong volatility connection between oil price and agro commodities is consistent with the demand for biofuels.
12	Kang, Tiwari, Albulescu, and Yoon (2019)	BK (2018)	1990-2017 Monthly	Crude oil price and five agriculture commodity price indexes (meat, dairy, cereals, vegetable oils, and sugar)	Vegetable oil contributes most to the volatility of oil; bidirectional and asymmetric connectedness between oil and agriculture markets at all frequency bands were found; volatility spillover between oil and agriculture commodities increased in the long run.
13	Yip, Brooks, Do, and Nguyen (2020)	FIVAR	2012-2017 Daily	CBOE commodity implied volatility indices of crude oil,	Net volatility spillover from oil to agricultural commodities decreased during the low regime and more so during relatively high volatility regime of oil; a regime-dependent trading strategy can be beneficial to oil futures investors.

				corn, soybean, and wheat	
14	Lu, Yang, and Liu (2019)	HAR	2008-2017 5-Minutes Data	Future contracts on crude oil, corn, soybean, and wheat	Bidirectional spillovers of short-term volatilities between crude oil and agricultural commodity markets in the crisis period, compared to mid-term and long-term volatilities of corn being transmitted to the crude oil volatility in the post-crisis period.
15	Barbaglia, Croux, and Wilms (2020)	DY (2012) using t-LASSO VAR	2012-2016 Daily	Agricultural (corn, wheat, soybean, sugar, cotton, coffee), energy (crude oil, gasoline, natural gas) and biofuel (ethanol) commodities	Volatility spillovers between energy and agricultural commodities were found.
16	Balli, Naeem, Shahzad, and de Bruin (2019).	Uncertainty Measurement (Chuliá et al. (2017); DY (2014); BK (2018)	2007-2016 Daily	Commodity uncertainty indicators computed by using daily spots and futures price of 22 commodities which are traded globally, namely WTI crude oil, Brent crude oil, gasoline, heating oil, gas oil, natural gas, gold, silver, platinum, palladium, aluminum, copper, zinc, lead, nickel, wheat, corn, soybean, coffee, sugar, cocoa, and cotton.	Uncertainty spillovers increased during the GFC and 2014–16 oil price collapse; intra-group spillover are more pronounced; the safe-have role of precious metsls; commodity uncertainties are more connected in the long-run.
17	An, Gao, An, Liu, Sun, and Jia (2020)	Dynamic Complex Network; GARCH-BEKK	2011-2019 Daily	Future prices of energy commodities (natural gas, crude oil, RBOB regular	The dynamic evolutionary feature of overall structure of the spillover network was found.

				gasoline, heating oil, coal), precious metals (gold, palladium, platinum, silver) and industrial metals (aluminum, copper, zinc, lead, nickel, tin, cobalt, uranium, iron ore, U.S. steel)	
18	Uddin, Shahzad, Boako, Hernandez, and Lucey (2019)	DY (2012);BK (2018)	1999-2019 Daily	Tradable futures of silver, gold, platinum, and palladium	Asymmetric spillovers are pronounced during crisis periods; silver and gold are the highest transmitter in both the short and long run while palladium and platinum are receivers.
19	Ji, Bahloul, Geng, and Gupta (2020)	Sentiment Measure (Bahloul, 2018); DY (2009, 2012, 2014)	2008-2016 Daily	Market sentiments computed from hedgers' positions on agricultural, energy commodities, metals, and live-stocks	Sentiments in agricultural and energy markets were mainly engaged in cross-hedging in the futures market by benefiting from the safe-haven potential of metals; country-specific geopolitical risk drives sentiments' connectedness through energy markets.
20	Tiwari, Nasreen, Shahbaz, and Hammoudeh (2020)	Wavelet Coherency; Phase-Difference; DY (2012);	1990-2017 Monthly	Food Price Index, Beverage Price Index, Industrial Inputs Price Index, Agricultural Raw Materials Index, Metals Price Index, the Fuel (Energy) Index	The agriculture sector is mostly the spillover receiver; industrial inputs are the primary source of volatility transmission at all frequencies.

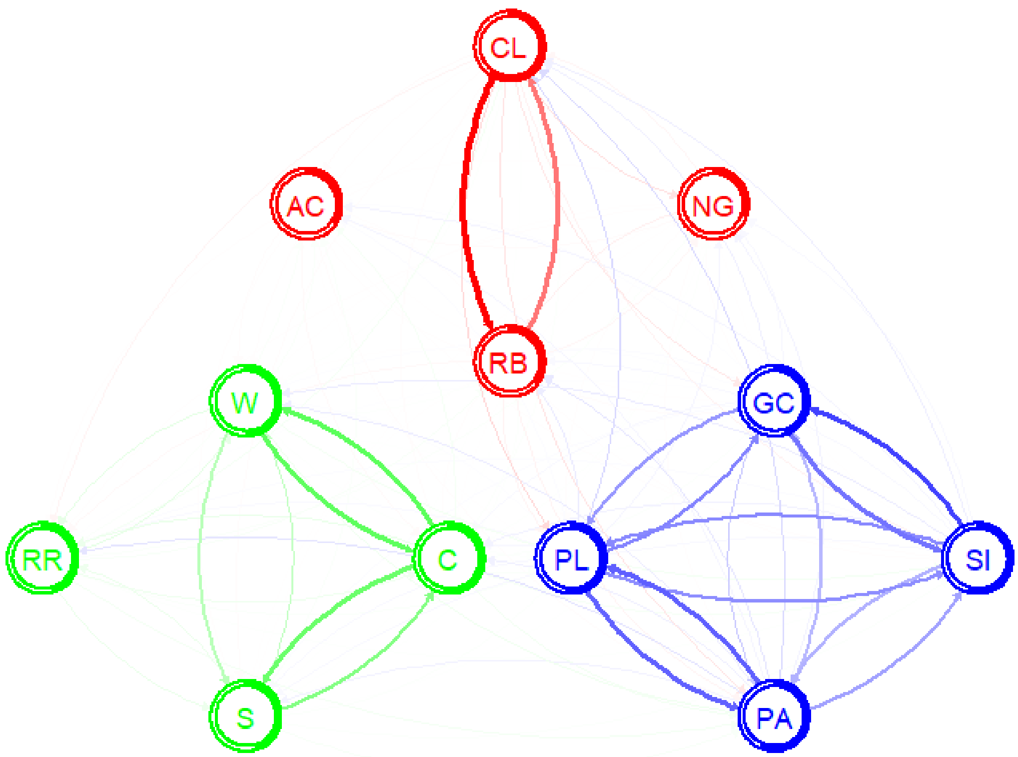
Notes: VAR = Vector Auto-Regression; FEVD = Forecast Error Variance Decomposition; GARCH = Generalized Autoregressive Conditional Heteroskedasticity; DCC = Dynamic Conditional Correlation; SVAR = Structural Vector Auto-Regression; DECO = Dynamic Equi-Correlation; MHAR = Multivariate Heterogeneous Auto-Regressive; HAR = Heterogeneous Auto-Regressive; FIVAR = Fractionally Integrated Vector Auto-Regressive; CoVaR = Conditional Value-at-Risk; BEKK = Baba, Engle, Kraft, and Kroner; GFC = Global Financial Crisis; DY = Diebold & Yilmaz; BK = Barunik & Krehlik; CBOE = Chicago Board Options Exchange.

Table 2. Descriptive stats of realized volatility measures.

Class	Symbol	Commodity	Mean	Minimum	Maximum	Std. Dev.
a). Realized variances						
Energy	CL	Crude oil	3.68	0.15	35.29	3.77
	NG	Natural Gas	6.27	0.47	64.56	5.73
	RB	RBOB gasoline	3.47	0.26	46.21	3.59
	AC	Ethanol	2.24	0.00	85.51	4.33
Metals	GC	Gold	0.89	0.05	12.77	0.94
	SI	Silver	2.95	0.14	35.80	3.27
	PA	Palladium	3.56	0.31	28.98	3.10
	PL	Platinum	1.59	0.23	14.12	0.99
Grains	W	Wheat	3.22	0.00	44.32	3.02
	C	Corn	2.50	0.15	52.15	3.08
	S	Soybeans	1.47	0.15	42.50	1.80
	RR	Rough rice	2.04	0.00	27.47	2.30
b). Realized positive semivariances						
Energy	CL	Crude oil	1.84	20.99	0.09	2.05
	NG	Natural Gas	3.20	56.37	0.28	3.78
	RB	RBOB gasoline	1.69	43.59	0.09	2.00
	AC	Ethanol	1.06	29.42	0.00	1.83
Metals	GC	Gold	0.44	6.38	0.03	0.49
	SI	Silver	1.48	26.09	0.08	1.78
	PA	Palladium	1.77	20.33	0.16	1.57
	PL	Platinum	0.79	6.93	0.11	0.50
Grains	W	Wheat	1.64	36.66	0.00	1.98
	C	Corn	1.25	30.95	0.05	1.65
	S	Soybeans	0.70	10.92	0.00	0.67
	RR	Rough rice	1.00	12.95	0.00	1.25
c). Realized negative semivariances						
Energy	CL	Crude oil	1.84	17.90	0.06	1.91
	NG	Natural Gas	3.11	42.95	0.20	2.94
	RB	RBOB gasoline	1.79	44.22	0.12	2.32
	AC	Ethanol	1.19	64.36	0.00	3.30
Metals	GC	Gold	0.45	7.09	0.02	0.52
	SI	Silver	1.53	34.31	0.06	2.10
	PA	Palladium	1.79	17.09	0.13	1.67
	PL	Platinum	0.80	7.20	0.11	0.55
Grains	W	Wheat	1.57	30.30	0.00	1.53
	C	Corn	1.22	51.63	0.04	2.01
	S	Soybeans	0.76	41.77	0.07	1.35
	RR	Rough rice	1.02	20.44	0.00	1.33

Note: Std. Dev. indicates the standard deviation.

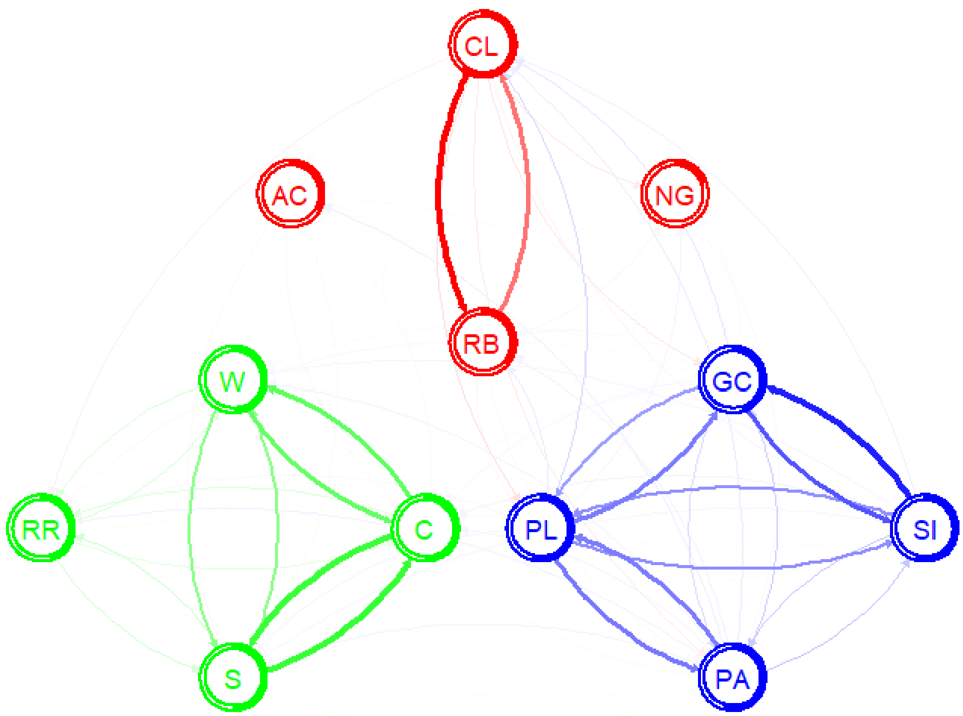
Figure 1. Spillover network of commodities realized volatilities using DY (12) approach.



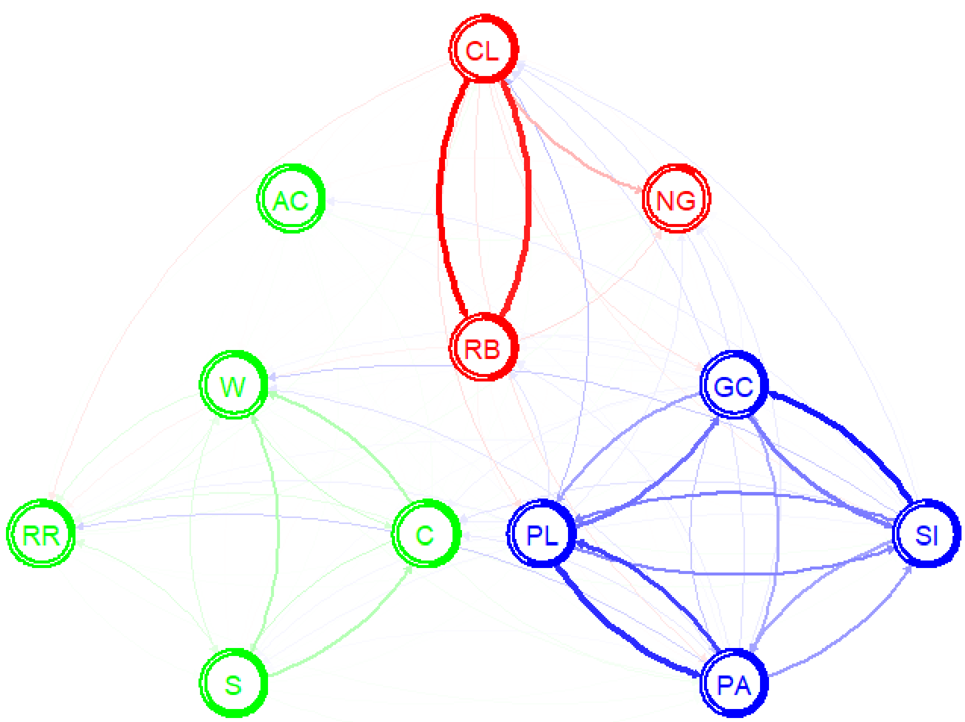
Note: This figure depicts the network graphs of the pairwise directional volatility connectedness across the 16 commodities under consideration computed using the approach of Diebold and Yilmaz (2012). The size of edges shows the magnitude of pair-wise directional spillover. The color of node shows the hierarchical cluster. The pie on the border of node shows the net position of that node, filled area shows net transmission position relative to reception.

Figure 2. Spillover network of commodities realized semivariances using DY (12) approach.

a). Positive realized semivariances



b). Negative realized semivariances



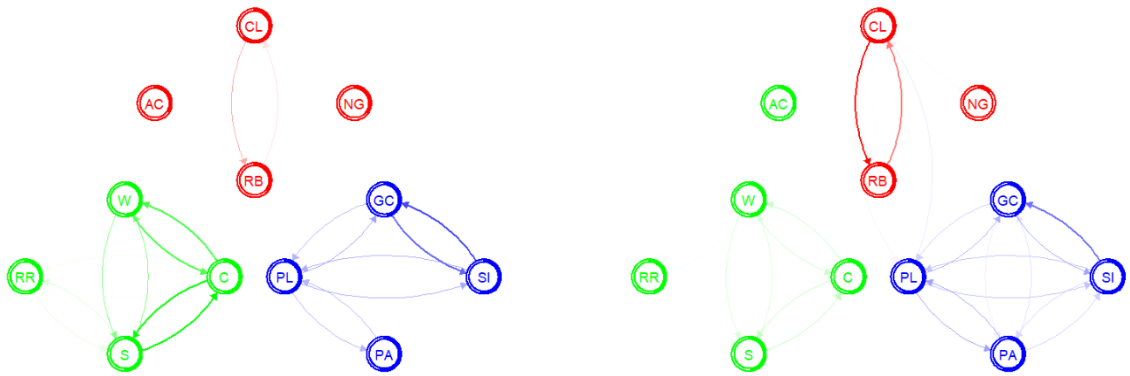
Note: This figure depicts the network graphs of the pairwise directional volatility connectedness across the 16 commodities under consideration computed using the approach of Diebold and Yilmaz (2012). The size of edges shows the magnitude of pair-wise directional spillover. The color of node shows the hierarchical cluster. The pie on the border of node shows the net position of that node, filled area shows net transmission position relative to reception.

Figure 3. Spillover network of commodities realized semivariances using BK (18) approach.

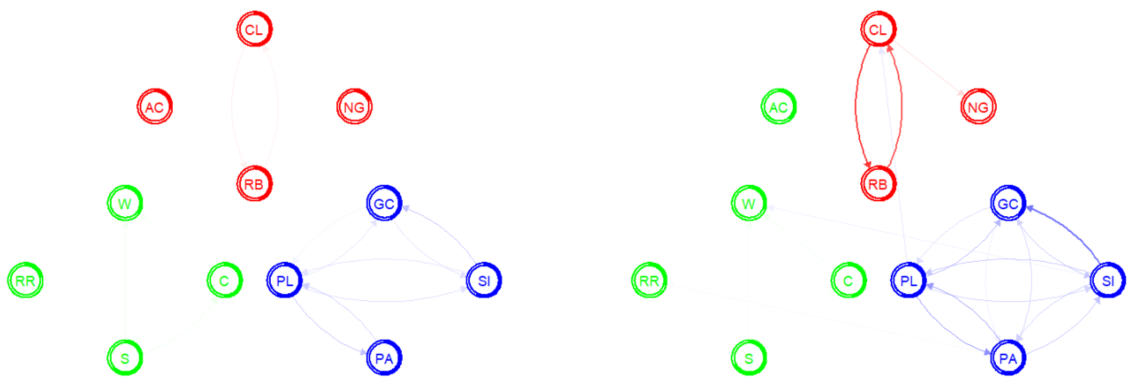
a). Short-run (1-5 days)

b). Long-run (more than 5 days)

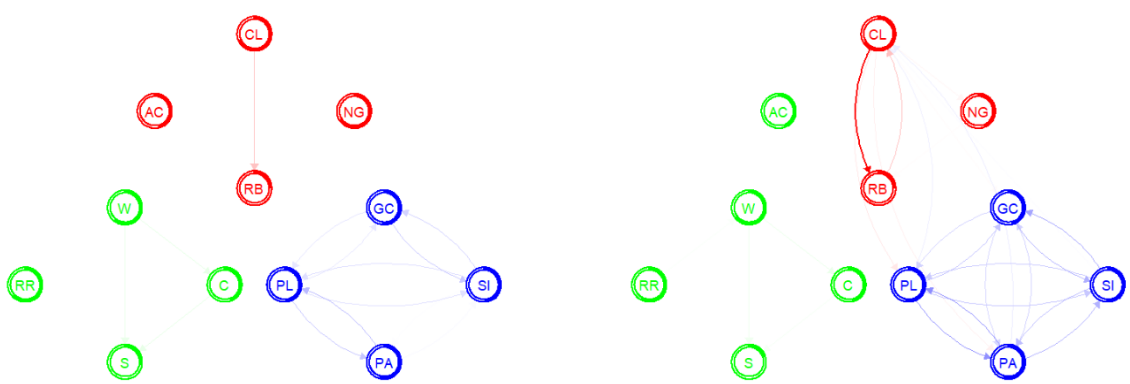
Positive to positive realized semivariances



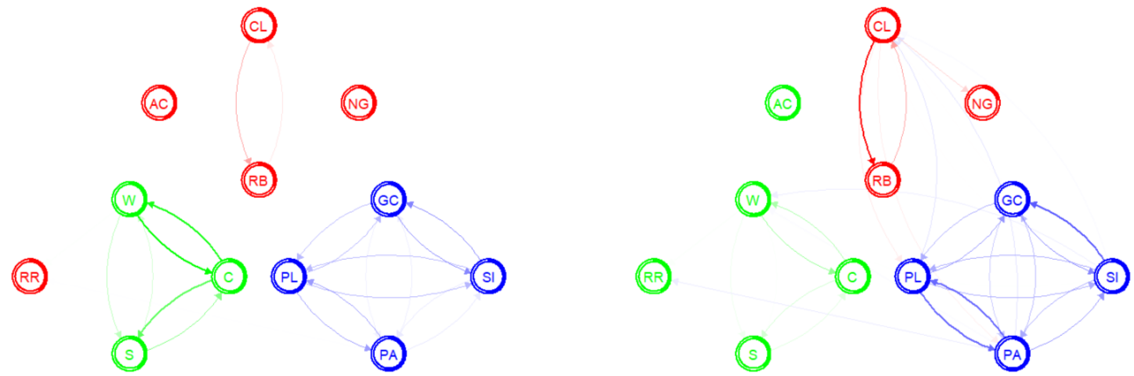
Positive to negative realized semivariances



Negative to positive realized semivariances

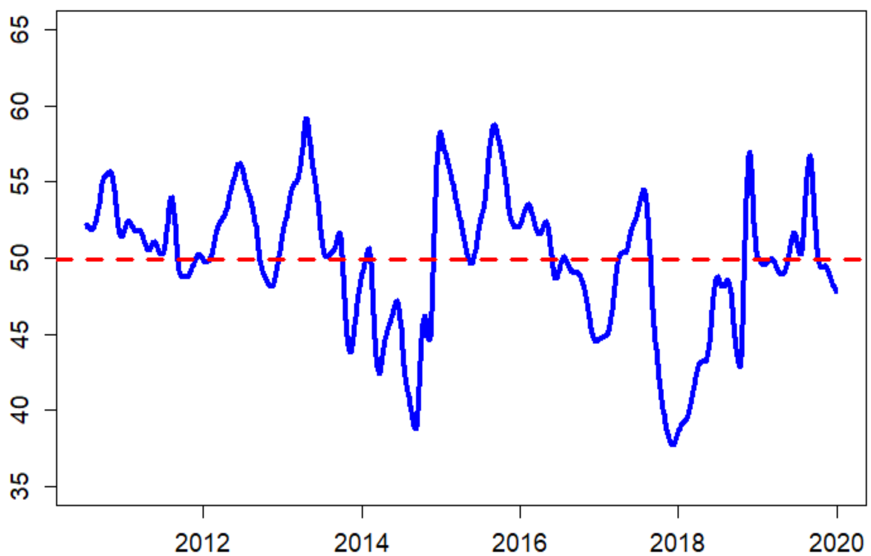


Negative to negative realized semivariances



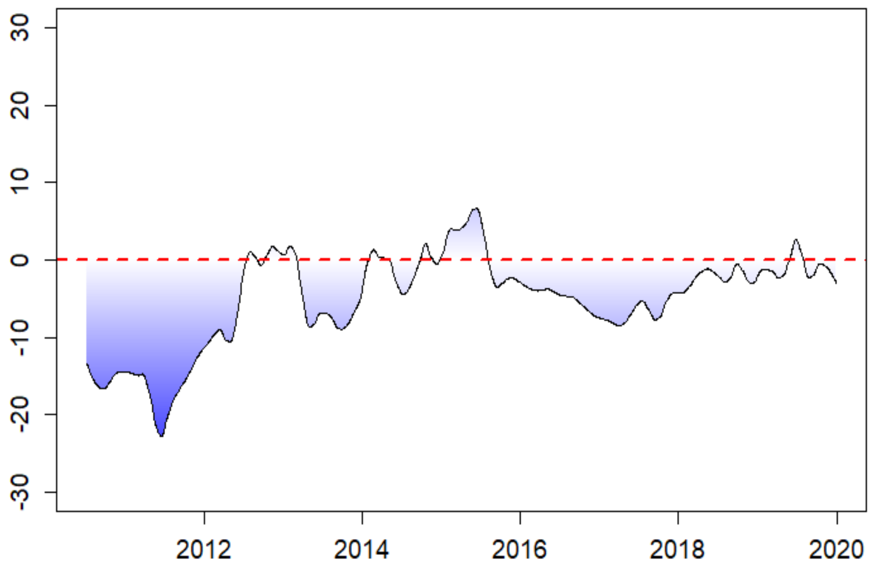
Note: These figures display the network graphs of net directional volatility connectedness across 16 commodities considered and estimated using the method of Barunik and Krehlik (2016). The size of edges shows the magnitude of pair-wise directional spillover. The color of node shows the hierarchical cluster. The pie on the border of node shows the net position of that node, filled area shows net transmission position relative to reception.

Figure 4. Total volatility spillover among all commodities using DY (12)



Note: This figure displays the time-varying behavior (blue line) of the total volatility spillover index among the 16 commodities considered computed using the approach of Diebold and Yilmaz (2012). This dynamic total spillover index is calculated from the generalized forecast error variance decompositions using a rolling window size of 200 days and a forecast horizon of H=100 days and lag order of 3 (based on SIC). The average spillover is shown using dotted red line.

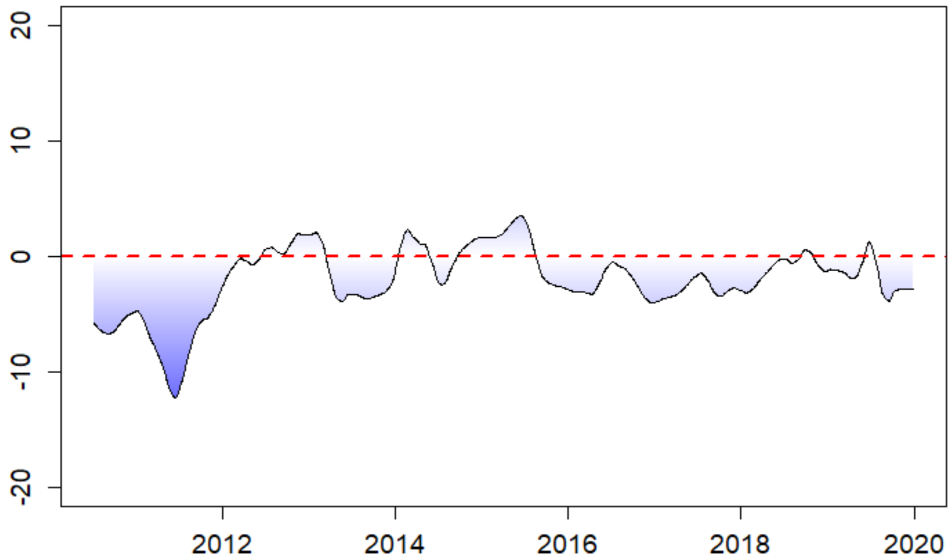
Figure 5. Asymmetric volatility spillover among all commodities using DY (12)



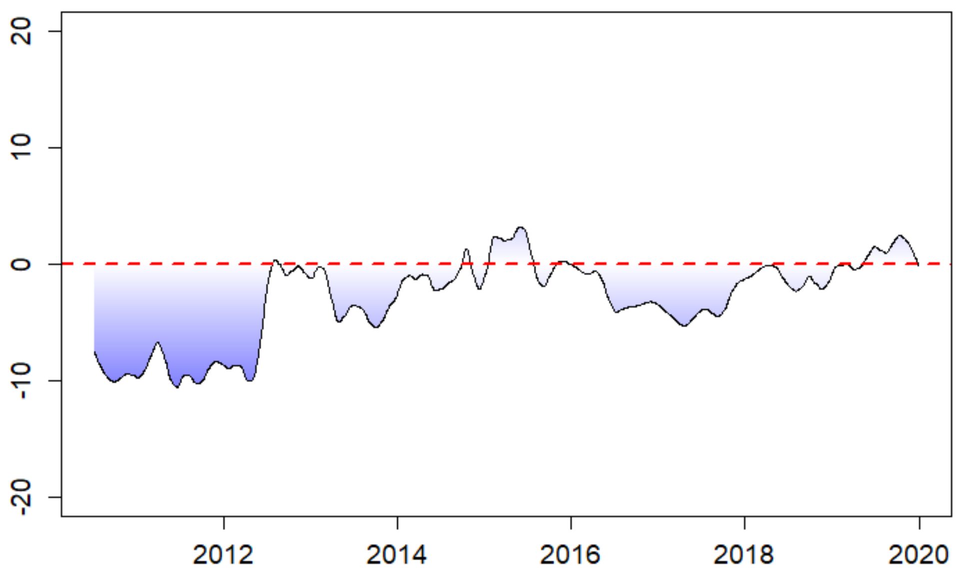
Note: This figure displays the time-varying behavior (black line) of the difference between total positive volatility spillover index and total negative spillover index among the 16 commodities considered computed using the approach of Diebold and Yilmaz (2012). The dynamic total asymmetric spillover indices are calculated from the generalized forecast error variance decompositions using a rolling window size of 200 days and a forecast horizon of H=100 days and lag order of 1 (based on SIC).

Figure 6. Asymmetric volatility spillover among all commodities using BK (18)

a). Short-run (1-5 days)



b). Long-run (more than 5 days)



Note: These figure displays the time-varying behavior (black line) of the difference between total positive volatility spillover index and total negative spillover index among the 16 commodities considered computed using the approach of Barunik and Krehlik (2016). The dynamic total asymmetric spillover indices are calculated from the generalized forecast error variance decompositions using a rolling window size of 200 days and a forecast horizon of H=100 days and lag order of 1 (based on SIC).

Figure 7. Short-run volatility spillover asymmetries among and across commodity classes.

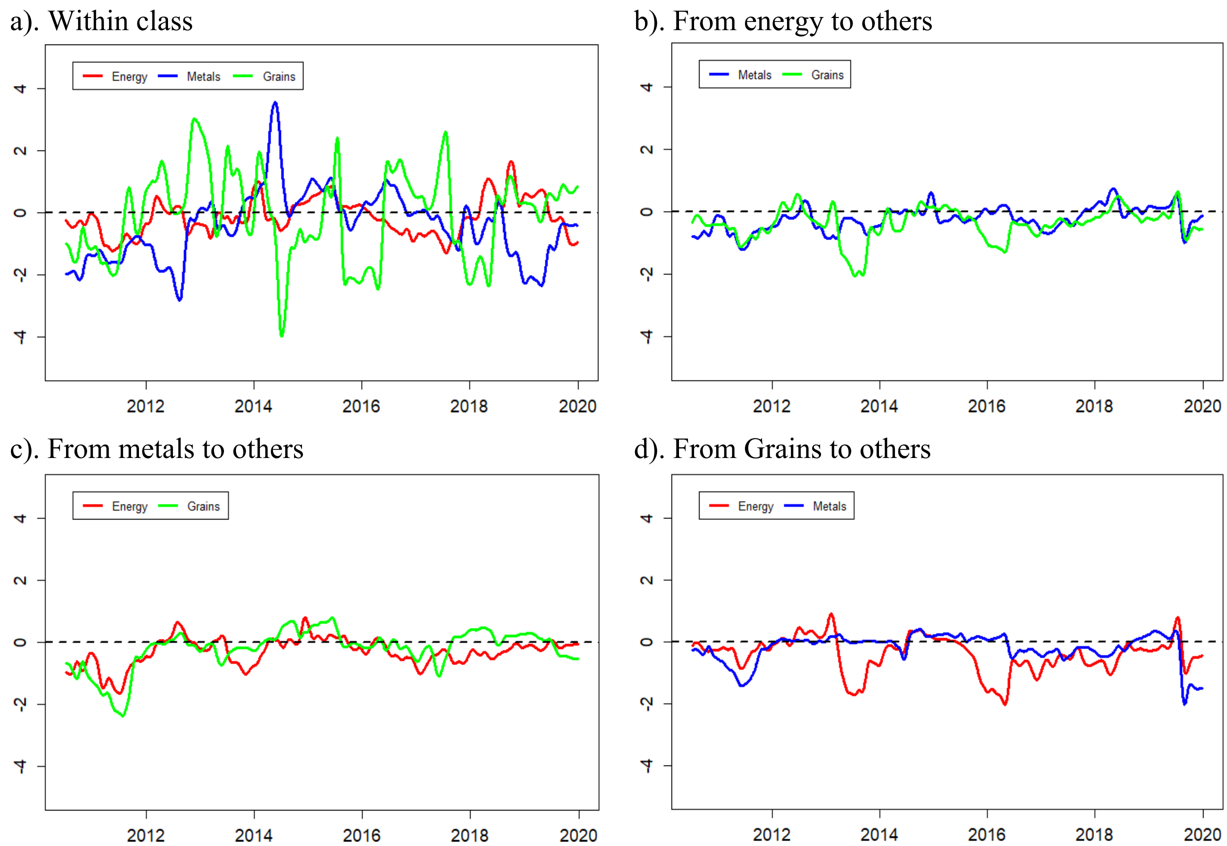


Figure 8. Long-run volatility spillover asymmetries among and across commodity classes.