Commodity markets dynamics: What do cross-commodities over different nearest-to-maturities tell us?

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Abstract

In this paper we investigate cross-commodity futures markets connectedness over different nearest-to-maturities. We thus implement time and time-frequency estimations for two constructed baskets of commodities, classified based on common delivery months. Using daily data spanning the period 1995-2020, we provide a set of stylized facts on the extent to which commodity markets are integrated or segmented. More specifically, our results show that the total connectedness is broadly insensitive to maturity. However, after 2008 financial crisis, the connectedness among commodity futures prices increases when the maturity increases. Furthermore, the overall connectedness amplifies during crises periods compared to tranquil periods. Moreover, certain pairwise markets are comparatively highly linked such as crude oil and heating oil, wheat and corn, corn and soybean, and soybean and soybean oil. The results also demonstrate that crude oil and heating oil are net transmitters all the time and across maturities, while natural gas, gold, and wheat are net receivers all the time and across maturities. More interestingly, the frequency decomposition reveals that most of periods of high total connectedness are driven mostly by high frequency components, which may indicate that commodity markets process information rapidly, except for the COVID-19 crisis period where total connectedness has been driven by lower frequency components.

Keywords: Cross-commodity integration, financialization, energy, agricultural, precious metals, futures, nearest-to-maturities, connectedness, COVID-19.

1. Introduction

In the past three decades, the simultaneous interaction of several factors, particularly financial deregulation and technological innovations, has contributed to the increased integration of financial markets. As increasing financial market integration exacerbates systemic risk[1], and because higher systemic risk threatens the stability of the global financial system as well as the resilience of the global economy (Goldstein, 1998; Summers, 2000)[2], the empirical economic literature has recently extensively investigated how shocks spread from one market to others, to better understand the extent to which financial markets are integrated and interconnected. More integrated markets imply higher interferences among them. Although greater integration of financial markets would allow, in tranquil periods and from an investor perspective, for more efficient portfolio management and diversification strategies (King and Wadhwani, 1990; Arshanapalli et al., 1997; Hsin, 2004; Garcia and Tsafack, 2011; Fengler and Gisler, 2015; Barunik et al. 2017), as well as hedging strategies (Jayasinghe and Tsui, 2008; James et al. 2012), it would contribute, in times of crisis, to decreasing the gains from portfolio diversification (Amonlirdviman and Carvalho, 2010), as well as amplifying the effects of shocks (Black, 1976; French et al. 1987; Tang and Xiong, 2012; Barunik et al. 2017; Ben Amar et al. 2020) as co-jumps across financial assets tend to occur just before or during economic crisis (Lahaye et al. 2011; Chevallier and Ielpo, 2013)[3]. Indeed, it is natural to expect that greater financial integration would not only facilitate and accelerate the transmission of price fluctuations in one market to other markets, but also prolong and intensify their destabilizing effects, which was the case over the past two decades (Forbes and Rigobon, 2002; Aït-Sahalia et al., 2015). Moreover, the increased 'financialization' of commodity markets over the last two decades could further strengthen financial integration and thus amplify both the magnitude and speed of the spread of shocks between markets (Cheng and Xiong, 2013; Adams and Glück, 2015).

For the last two decades, commodity futures markets witnessed several changes and structural breaks, especially around 2002-2003, namely financialization of commodity markets. However, financial investors operate in a basket of commodities, *i.e.*, commodity index funds mimic commodity indices (*e.g.*, Stoll and Whaley, 2010, and Irwin and Sanders, 2011). Consequently, the increase in financial investors participation in commodity markets increase linkage between commodity markets (*e.g.*, Natanelov et al. 2011, Tang and Xiong 2012, Cheng and Xiong, 2013; Adams and Glück, 2015, Basak and Pavlova, 2016, Bruno et al. 2017). As far as we know, the literature investigates cross commodity linkage less than linkage between commodity and equity markets. However, studying the connectedness between commodity markets across different maturities is not taken into consideration. Meanwhile the current research focuses on spot, first, or first two nearest-to-maturities, studying the effect of long-term maturities is neglected. However, financial investors operate in both short- and long-term maturities (*e.g.*, Buyuksahin and Robe, 2014). Thus, in this article, we investigate the connectedness between commodity futures markets and across different nearest-to-maturities.

The measurement of volatility spillovers has recently received particular attention in the literature. However, while the study of the connectedness between financial markets is the subject of a growing strand of the empirical literature, connectedness across different commodity classes at different maturities, and the way it shifts from tranquil periods to crisis ones, have not received comparable attention yet, reason for which we still know little on how commodity markets interact. Understanding the connectedness among commodity markets is central to (**i**) market participants, especially investors and regulators, because it would provide them with a better understanding of the extent and reasons why

[1] Although systemic risk is a "*hard-to-define-but-you-know-it-when-you-see-it*" concept (Benoit et al. 2017), it is widely accepted in the literature that systemic risk is the risk that many market participants are affected by large losses at the same time. See Benoit et al. (2017) for a literature review on systemic risk.

[2] Goldstein (1998) and Summers (2000) argue that a shock in one country can lead to a shift in investors' perceptions of the resilience of other countries.

[3] One of the stylized facts associated with financial markets is that large negative returns, occurring in times of stress, are much more correlated than large positive returns (Longin and Solnik, 2001; Wu, 2001; Barunik et al. 2016).

markets vary together, as well as (**ii**) many areas of research in finance and economics, especially portfolio management and business cycle analysis. From the regulator's point of view, because increasingly integrated markets imply greater systemic risk, and because systemic risk threatens not only the stability of the entire financial system, but also the resilience of the global economy, a better understanding of the causes, the magnitude and the consequences of interdependencies among commodity markets is of paramount importance for policymakers seeking to design appropriate tools to monitor the accumulation of risk and, thereby, to strengthen financial stability and to promote economic growth (Karolyi, 1995; Caporale et al., 2002; Ewing et al., 2002; Xu and Fung, 2005; Gouel, 2013; Lee et al., 2015, Liu et al., 2019). From an investor perspective, a better understanding of the connectedness among commodities would allow for a more efficient portfolio and hedging strategies structuring (Erb and Campbell, 2006).

For instance, Pinduck and Rotemberg (1990) use United States average monthly cash prices from April 1960 to November 1985 to explore the co-movement among a broad spectrum of commodities – wheat, cotton, copper, gold, crude oil, lumber, and cacao – that are largely unrelated, *i.e.*, their supply and demand cross-price elasticities are almost zero. They found that not only commodities prices' have a persistent tendency to move together, but also this co-movement depends, at least in part, on changes in current and expected values of macroeconomic variables. Booth and Ciner (1997) applies a multivariate VAR model on daily data spanning from 1993 to 1995 to investigate the presence of price and volatility spillovers between corn futures traded in Tokyo Grain Exchange (TGE) and Chicago Board of Trade (CBOT), and find that the TGE is dependent on the CBOT. Booth et al. (1998) use a cointegration methodology *à la* Engle and Granger (1987) to explore the relationship between U.S. and Canadian wheat futures markets over the period January 2nd, 1980 to December 31st, 1994. Their results suggest that the Canadian market seems to be dependent on the CBOT. Escribano and Granger (1998) focus on the long-run relationship between gold and silver prices. By using different single-equation estimation techniques, they reveal a strong simultaneous relationship between silver and gold. Lin and Tamvakis (2001) use univariate and bivariate GARCH models to explore the information transmission mechanism between crude and refined oil process traded on New York Mercantile Exchange (NYMEX) and London's International Petroleum Exchange (IPE) over the period January 4, 1994 to June 30, 1997. Their results indicate that IPE open prices appear to be significantly affected by the close prices of the previous day on NYMEX. In the same vein, Xu and Fung (2005) use a bivariate asymmetric GARCH model on daily data to study spillovers across precious metals futures contracts – gold, platinum and silver – traded in both U.S. and Japanese markets over the period November 1994 to March 2001. Their results support that information flows appear to lead from the U.S. market to the Japanese market. Baffes (2007) investigates the effect of crude oil prices on the prices of 35 commodities over the 1960-2005 period, and finds that fertilizers exhibit the largest pass-through, followed by food commodities. Kao and Wan (2009) use daily closing prices (from June 26, 1998 to December 31, 2007) to examine the price discovery process among the U.S. and U.K. natural gas markets. Their main findings suggest (**i**) that the U.S. futures market is the most efficient in processing information, (**ii**) that the U.S. and U.K. spot markets are less efficient than their corresponding futures markets, and (**iii**) that the volatility spillovers across markets exhibit asymmetric responses to news. Zhang and Wei (2010) use a monthly dataset, from January of 2000 to March of 2008, to analyze the cointegration and causality relationships between crude oil and gold markets. Their results suggest a unidirectional Granger causality running from crude oil to gold. Based on panel cointegration and Granger causality methods and a monthly dataset ranging from January 1980 to February 2010, Nazlioglu and Soytas (2012), examine the linkages between oil prices and twenty-four agricultural commodity prices. Their results suggest that oil prices exert a significant impact on agricultural commodity prices. Gardebroek et al. (2016) employ a multivariate GARCH model on different data frequencies to explore volatility transmission among major agricultural commodities returns in the United States over the 1998-2012 period. Their results reveal important volatility spillovers across commodities, particularly at the weekly and monthly frequencies. More interestingly, despite the supposed higher financial market integration of agricultural commodities, their results do not indicate that agricultural markets have become more interdependent in recent years. Le Pen and Sevi (2018) empirically investigate the excess co-movement of commodity prices over the 1993-2013 period. By considering a set of eight unrelated commodities – wheat, copper, silver, soybeans, raw sugar, cotton, crude oil, and live cattle – along with 184 real and nominal macroeconomic variables from developed and emerging markets, they provide insights of time-varying excess co-movements, which are particularly high after the 2007 crisis[1]. They further show that the estimated excess co-movements of commodity prices (**i**) persist even after adjusting for the impact of fundamentals and that they are (**ii**) linked to hedging pressure and speculative intensity, which reflects the significant impact of the financialization of commodity markets. Indeed, the popularity of commodity-related financial instruments, such as commodity indices, has led many observers to conclude that commodity markets are now more intimately connected to financial markets, and so may also co-move more significantly (Tang and Xiong, 2012; Basak and Pavlova, 2016)[2]. Nakajima and Toyoshima (2020) investigate the connectedness among natural gas and wholesale electricity markets at different maturities. They show that, while gas futures market appears to be integrated, the electricity futures market is not. Ben Ameur et al. (2020) have focused on the risk dependence between oil and gas. By applying different extreme risk measures on a 5-minute intraday sample data from November 2014 to October 2017, they found evidence of extreme risk dependence between oil and gas markets, with a relatively higher risk spillover from the oil to the gas market than from the gas to the oil market. Moreover, their results also show that extreme negative shocks produce stronger spillover effect than do extreme positive shocks.

Investigating connectedness on the commodity markets is somewhat special because the commodity markets differ from other financial markets in several ways. First, commodity markets are generally more volatile than other financial markets because commodities are not only more sensitive to supply-demand dynamics and to geopolitics, but also comparatively less liquid. Second, commodity instruments have a fixed expiry date, the "nearby month", on which settlement must take place. Third, the contracts traded in commodity markets cover several maturities, ranging from short-term to long-term. Therefore, they are suitable for short-term and long-term investments. Fourth, open almost 24 hours a day, with a break on weekends, commodity markets are a very important source of information.

To that end, this paper attempts to investigate the time and time-frequency volatility connectedness among different commodities at different maturities, over the period between January 3rd, 1995 to December 11th, 2020, from two different perspectives. First, within a given basket of commodities, how do shocks spread across commodities belonging to different classes? Second, is the propagation scheme of shocks the same regardless of maturity? Our analysis is motivated by relevant questions arising with respect to the connectedness in the commodity markets. How does shocks in one commodity market spread to others? To what extent different commodity markets are integrated or segmented? Is there a commodity market that dominate the others? Is the magnitude of connectedness among commodities sensitive to maturity? Do market participants process information similarly in short-, medium- and long-term financial cycles? The above questions have not been sufficiently explored yet because to the best of our knowledge there are almost no studies addressing the issue of connectedness among different commodities at different maturities in the time and time-frequency domains.

The main goal of this study is to clarify to what extent commodities market is integrated or segmented by examining the connectedness between commodities with different characteristics (energy, precious metal, and agricultural commodities) and maturities. While there is a large lack of agreement in the literature on the methodologies that should be used to measure the connectedness among financial markets, six main approaches are developed and used in the literature: (**i**) Dynamic correlation models (Karolyi and Stulz, 1996; Forbes and Rigobon, 2002; Antonakakis et al. 2018); (**ii**) Copulas (Delatte and

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[1] This result is in line with the results of Bruno et al. (2017).

[2] While a greater number of participants in commodity markets may bring about improved risk sharing, the financialization process has been widely criticized as a potential source of excessive price volatility (Stoll and Whaley, 2010).

Lopez, 2012; Albulescu et al. 2020; Ben Ameur et al. 2020); (**iii**) Markov Switching models (Khalifa et al. 2012; Charlot et al. 2016; Singhal and Biswal, 2019); (**iv**) Causality tests (Marais and Bates, 2006; Ben Amar et al. 2021); (**v**) connectedness measures (Diebold and Yilmaz, 2009, 2012, 2014, 2016; Barunik and Krehlik, 2018); (**vi**) wavelets (Connor and Rossitor, 2005; Vacha and Barunik, 2012; Meng, 2018). In this paper, the recent connectedness measures of Diebold and Yilmaz (2014), which is defined in the time domain, and of Barunik and Krehlik (2018), which is defined in the time-frequency domain, are used to better understand the propagation scheme of volatility shocks among commodities. Studying the connectedness across different commodity classes would help to understand the extent to which commodity markets are segmented or interconnected, thus enabling investors to better diversify their portfolios and manage risk.

This paper contributes to the previous literature in several ways. First, to the best of our knowledge, ours is the first empirical paper that examines the connectedness among different categories of commodities at different maturities. Studies has recently deeply examined (**i**) the financial contagion and volatility transmission among similar commodities, *i.e.,* inside an asset class, traded on different market places (See, among others, Booth and Ciner, 1997; Escribano and Granger, 1998; Booth et al. 1998; Lin and Tamvakis, 2001; Xu and Fung, 2005; Kao and Wan, 2009), as well as (**ii**) the interaction across different commodity classes (See, among others, Baffes, 2007; Chng, 2009; Kaltalioglu and Soytas, 2011; Khalifa et al. 2012; Nakajima and Toyoshima, 2020) and (**iii**) the interaction between commodities and non-commodities assets (See, among others, Chong and Miffre, 2010; Daskaki and Skiadopoulos, 2011; Chevallier and Ielpo, 2013; Antonakakis et al. 2018; Ben Amar et al. 2020; Aziz et al., 2020; Barbaglia et al., 2020), nevertheless, there is still much to say regarding the interaction between different types of commodities, especially when it comes to the connectedness among commodities at different maturities. Selecting different maturities is motivated by Büyükşahin and Robe (2014) and Isleimeyyeh (2020). For instance, Büyükşahin and Robe (2014) demonstrate that excess speculation increases in short-term maturities as well as all maturities. Isleimeyyeh (2020) investigates the integration between commodity futures risk premium and stock market for different maturities. His results show that futures risk premium is attributed to stock market, represented by financial investors, more than to traditional hedging pressure for long-dated maturity. Second, our selected datasets cover critical and important period between 1995 and 2020 (approximately 26 years). Indeed, as the past 26 years witnessed three uneven recessions in the United States and in the Euro area, as well as several well-known episodes of global political and financial concerns that increased uncertainty, and, more importantly, the financialization of commodities, our sample period is informative in terms of market development and, therefore, allows us to investigate the connectedness among commodities during tranquil and stress periods. We thus analyze our results into several steps: first, the connectedness between commodities in each basket over the full sample periods; second, the connectedness between commodities in each basket for different sub-periods; third, the connectedness between commodities in each basket at different frequencies.

We uncovered several results that may be summarized as follows. First, we show several noticeable and comparatively high pairwise linkages between commodities in both selected baskets such as oil and heating oil, wheat and corn, corn and soybean, and soybean and soybean oil. Second, the static total average connectedness over the full sample period is insensitive to maturity. However, after 2008 financial crisis, the connectedness between commodity futures prices increases when the maturity increases, which could be attributed to the role of financial investors in commodity futures markets who operate in short- and long-term maturities, while the hedgers activities decrease when the maturity increases. Therefore, financial investors effect increases as a consequence to the financialization of commodities (*e.g.*, Isleimeyyeh, 2020). Since financial investors overwhelmingly operate in a basket of commodities, the increase of financial investors causes a greater information transmission between commodity markets, and thus higher connectedness. Third, the overall connectedness amplifies during crises periods compared to calm periods. The connectedness between energy and agricultural commodities during the financial crisis 2008 witnessed a significant jump in which it recorded a peak higher than other crises. Fourth, the results demonstrate that crude oil and heating oil are net transmitters all the time and across maturities. Inversely, natural gas, gold, and wheat are net receivers all the time and across maturities. For all sub-periods and maturities, soybean is net transmitter, except for the 2001 and 2020 crisis sub-periods in which it was converted to net receiver. Regarding soybean oil, it is net receiver for all sub-periods and maturities, except for the 2008 financial crisis period in which it was converted to net transmitter. Corn is an example of non-stable commodity. Furthermore, the results show that the net connectedness amplified during tension periods. Thus, net connectedness seems to indicate that both the energy commodities market and the agricultural commodities market are segmented, and that the transmission of shocks, in terms of direction and magnitude, could vary substantially from one maturity to another. Fifth, the connectedness among commodities is not stable over time and across frequency bands. Moreover, the frequency decomposition reveals that most of periods of high total connectedness are driven mostly by high frequency components, which may indicate that commodity markets process information rapidly, except for the COVID-19 crisis period where total connectedness has been driven by lower frequency components.

Our findings are important for market participants, both investors and policy makers. Indeed, in a context of increasing economic openness and financial integration, a better understanding of the magnitude of the interdependence among commodities as well as of the transmission mechanisms of shocks among them is crucial for investors and regulators to deal with financial risks.

The remainder of this paper is organized as follows. Section 2 explains the empirical strategy and describes the dataset; section 3 presents the results; section 4 concludes this study.

2. Empirical Strategy and Data

2.1. Empirical Strategy

To investigate the question of how commodity markets are connected at different maturities, our empirical strategy consists of two complementary measures of connectedness. First, to examine spillovers in volatilities[1] among different types of commodities and for different maturities in the time domain during the period between the January 3rd, 1995 to December 11th, 2020, we use the Diebold and Yilmaz's (2014) connectedness index which is based on variance decomposition matrix of vector autoregressive (VAR) approximating models.[2] The Diebold and Yilmaz's (2014) index, which captures how the variables in a system mutually influence each other, is based on the estimation of an N-variable VAR(p) model $x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t$, with $\phi_1, \dots, \phi_p$ coefficient matrices, and $\varepsilon_t \sim (0, \Sigma)$. The moving-average process representation (i.e., MA(∞)) of this VAR(p) is given by $x_t = \sum_{i=0}^{\infty} A_i\, \varepsilon_{t-i}$, where $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with A_0 is an identity matrix and $A_i = 0$ for $i < 0$. Since A_i includes infinite lags, it should be approximated with the moving average coefficients A_h computed at $h = 1, \dots, H$ horizons. By using the generalized variance decomposition introduced by Koop et al. (1996) and Pesaran and Shin (1998), Diebold and Yilmaz (2012, 2014) define a total connectedness measure, SI_{DY}^{G}, which indicate the average overall interdependence among variables, as

$$SI_{DY}^{G}(H) = \frac{\sum_{\substack{q,j=1 \\ q \neq j}}^{N} \tilde{\theta}_{ij}^{G}(H)}{N} \cdot 100 \quad \text{with } \tilde{\theta}_{qj}^{G}(H) = \frac{\theta_{qj}^{G}(H)}{\sum_{j=1}^{N} \theta_{qj}^{G}(H)} \tag{1}$$

[1] The concept of spillovers, which refers to the interdependence between different markets, was first introduced by Diebold and Yilmaz (2009). These authors used the term "connectedness" in their subsequent work (Diebold and Yilmaz, 2014).

[2] The generalized connectedness index of Diebold and Yilmaz (2012; 2014) allows to overcome the inadequacies of potentially order-dependent outcomes due to the Cholesky factorization in the original work by Diebold and Yilmaz (2009).

where $\theta_{qj}^{G}(H)$ is the H-step-ahead forecast error variance decompositions[1] and $\tilde{\theta}_{qj}^{G}(H)$ is the directional pairwise connectedness from variable j to variable q[2] at horizon H. The total connectedness index, SI_{DY}^{G}, measures the contribution of spillovers of volatility shocks to variable $j = 1, \dots, N$ to the total forecast error variance of variable $q = 1, \dots, N$, with $q \neq j$. The Diebold and Yilmaz's (2014) approach allows to extract the total directional volatility spillovers to variable q received from all remaining variables, $SI_{q \leftarrow j}^{G}$, which is given by

$$SI_{q\leftarrow\bullet}^{G}(H) = \frac{\sum_{j=1, j\neq q}^{N} \tilde{\theta}_{qj}^{G}(H)}{N} \cdot 100 \tag{2}$$

and, similarly, the total directional volatility spillovers transmitted from variable q to all remaining variables is given by

$$SI_{q\rightarrow\bullet}^{G}(H) = \frac{\sum_{j=1, j\neq q}^{N} \tilde{\theta}_{jq}^{G}(H)}{N} \cdot 100 \tag{3}$$

The difference between total contribution from variable q to all other variables and the contribution from all other variables toward variable q is called net volatility spillovers (or net connectedness).[3] Thus, the net volatility spillovers from variable q to all other variables j, NVS_{q}^{G}, can be obtained from equations (2) and (3) as follows

$$NVS_{q}^{G}(H) = SI_{q\rightarrow\bullet}^{G}(H) - SI_{q\leftarrow\bullet}^{G}(H) \tag{4}$$

which indicates whether a variable q is a net receiver or a net transmitter of volatility shocks.

While the Diebold and Yilmaz's (2014) framework enables to measure the connectedness in the time domain, it ignores heterogenous frequency responses to shocks. The frequency domain is a suitable, even a natural, place to measure the connectedness among markets, as it enables to measure the portion of forecast error variance at a given frequency band that is attributed to shocks in another variable (Dew-Becker and Giglio, 2016; Barunik and Krehlik, 2018). Indeed, to better understand the connectedness between different markets or assets, it is essential to understand the frequency dynamics of this connectedness, as shocks to one market may impact other markets at different frequency bands with different magnitudes. As in financial and economic applications it is more interesting to assess the connectedness at short-, medium-, and long-term cycles rather than at an aggregated single frequency to better understand the sources of connectedness, it is more convenient to disaggregate the total connectedness measure, defined in the time domain, into different frequency bands. For this reason, we also use, in a second step, the time-frequency connectedness measure of Barunik and Krehlik (2018), which will allow us to clearly observe and identify the connectedness among the considered set of variables over time and across different bands of frequencies. Barunik and Krehlik (2018) develop a new framework based on the general spectral representation of generalized forecast error variance decomposition (GFEVD) to estimate connectedness among financial variables in short-, medium-, and long-term financial cycles.

The power spectral density of x_t at frequency ω, $P_x(\omega)$, which describes how the variance of x_t is distributed over the frequency components ω, is given by

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[1] The H-step-ahead generalized forecast error variance decomposition, $\theta_{qj}^{G}(H)$, which measures how much of the variance forecast error of variable j, at horizon h, is due to shocks in variable q, is given by $\theta_{qj}^{G}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_q' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_q' A_h \Sigma A_h' e_q)}$ where A_h is a $(N \times N)$ matrix of moving average coefficients at lag h, Σ is the covariance matrix of ε, $\sigma_{jj} = (\Sigma)_{j,j}$ is the standard deviation of the error term for the j^{th} equation, and e_q is a $N \times 1$ selection vector with one as the q^{th} element and zeros otherwise.

[2] By construction, $\sum_{j=1}^{N} \tilde{\theta}_{qj}^{G}(H) = 1$ and $\sum_{q,j=1}^{N} \tilde{\theta}_{qj}^{G}(H) = N$.

[3] Alternatively, the net connectedness can be computed as the difference between the contribution of a commodity to other commodities including itself deducted by 100.

$$P_x(\omega) = A\left(e^{-i\omega}\right)\Sigma A'\left(e^{+i\omega}\right)$$

where the frequency response function, $A\left(e^{-i\omega}\right)$, is obtained as Fourier Transform of the coefficients A_h, such as $A\left(e^{-i\omega}\right) = \sum_{h=0}^{H} e^{-i\omega h} A_h$, with $i = \sqrt{-1}$.

Denoting the spectral representation of the generalized variance decomposition from variable q to variable j at frequency band $d = (a,b)$: $a, b \in (-\pi, \pi), a < b$, which gives us the strength of the relationship on given frequency d weighted by the power of the series on that frequency, by $\theta_{qj}(d)$, we have

$$\theta_{qj}(d) = \frac{1}{2\pi} \int_a^b \frac{\sigma_{jj}^{-1} \left| \left(A\left(e^{-i\omega}\right)\Sigma \right)_{qj} \right|^2}{\frac{1}{2\pi} \int_{-\pi}^{\pi} \left(A(e^{-i\lambda})\Sigma A'(e^{+i\lambda}) \right)_{qq} d\lambda} d\omega$$

The scaled generalized variance decomposition on frequency band $d = (a,b)$: $a, b \in (-\pi, \pi), a < b$ is given by

$$\tilde{\theta}_{qj}(d) = \frac{\theta_{qj}(d)}{\sum_{j=1}^{N} \theta_{qj}(\infty)} \quad \text{with } \theta_{qj}(\infty) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{\sigma_{jj}^{-1} \left| \left(A\left(e^{-i\omega}\right)\Sigma \right)_{qj} \right|^2}{\frac{1}{2\pi} \int_{-\pi}^{\pi} \left(A(e^{-i\lambda})\Sigma A'(e^{+i\lambda}) \right)_{qq} d\lambda} d\omega$$

By using the scaled generalized variance decomposition, $\tilde{\theta}_{qj}(d)$, the frequency connectedness on the frequency band d, denoted $SI_{BK}^{\mathcal{F}}(d)$, can then be conveniently defined as

$$SI_{BK}^{\mathcal{F}}(d) = \frac{\sum_{\substack{q,j=1 \\ q \neq j}}^{N} \tilde{\theta}_{qj}(d)}{\sum_{q,j=1}^{N} \tilde{\theta}_{qj}(\infty)} \cdot 100$$

which decompose the Diebold and Yilmaz's (2014) total time-domain-defined connectedness Index into separate parts that, when aggregated, give the original connectedness index SI_{DY}^{G}.

2.2. Data

Our underlying datasets are daily observations of commodity futures prices (WTI crude oil [**OIL**], natural gas [**GAS**], heating oil [**HOI**], wheat [**WHT**], corn [**CRN**], soybean [**SOY**], soybean oil [**SOI**], and gold [**GLD**]) for different maturities. The nominated commodities are traded on the New York Mercantile Exchange (NYMEX) and Chicago Board of Trade (CBOT)[1]. The data are collected from Bloomberg and cover the period running from January 3rd, 1995 to December 11th, 2020, providing a sample of 6768 trading days (approximately 26 years). This period is informative in terms of market development as it includes both calm and turbulent times in which shocks may transmit among commodities with different magnitudes. Indeed, during the sample period studied there were three recessions in the United States (2001Q1-2001Q4; 2007Q4-2009Q2; 2020Q1-…)[2] and in the Euro area (2008Q1-2009Q2; 2011Q3-2013Q1; 2020Q1-…)[3]. Furthermore, it includes several well-known episodes of increased uncertainty, such as, the Asian financial crisis (October 1997), the Russian debt crisis (August, 1998), the tech bubble (March, 2000), the September 11 attacks, the Middle East geopolitical tensions after the Iraq war (March, 2003), the bankruptcy of Lehman Brothers (September, 2008), the Arab Spring (early 2010), the Chinese stock market turbulence (June, 2015), and different phases of stability, rise and fall in oil prices.

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[1] Gold is traded on Commodity Exchange (COMEX), which is a division for trading futures and options in NYMEX.
[2] See: http://www.nber.org/cycles.html
[3] See: https://cepr.org/content/euro-area-business-cycle-dating-committee

For each commodity, there are several delivery dates for the futures contracts per year, e.g., monthly delivery for energy futures, 5 times per year for wheat and corn, 6, 7, and 8 times for gold, soybean, and soybean oil respectively (see Table 1.a.). We thus construct 12 maturities for each of WTI, natural gas, and heating oil; 8 maturities for soybean oil; 7 maturities for soybean; 6 maturities for gold; 5 maturities for each of wheat and corn. For a chosen day, the first price represents the futures price of the contract that is the closest to delivery, while the second price represents the futures price of the contract that is the second closest to delivery, etc. All series are expressed in U.S. dollars.

Following Forsberg and Ghysels (2007), Wang et al. (2016) and Antonakakis et al. (2018), the volatility of commodity c is computed as the daily absolute return, *i.e.* $\sigma_{t,T}^{c} = \left|\ln\left(F_{t,T}^{c}\right) - \ln\left(F_{t-1,T}^{c}\right)\right|$, where $F_{t,T}^{c}$ is the daily close price of commodity c on day t for maturity T[1]. Based on the available data, volatility spillovers are estimated for two different baskets of commodities, namely Basket 1 and Basket 2. Each basket covers different nearest-to-maturities, *i.e.*, we select commodities sharing the same delivery months. Basket 1 (energy-gold) includes four commodities (**OIL**, **GAS**, **HOI,** and **GLD**) and covers six nearest-to-maturities (2nd, 4th, 6th, 8th, 10th, and 12th nearest-to-maturities for energy, and 1st, 2nd, 3rd, 4th, 5th, and 6th nearest-to-maturities for **GLD**), and basket 2 (energy-agricultural) includes seven commodities (**OIL**, **GAS**, **HOI**, **WHT**, **CRN**, **SOY,** and **SOI**) and covers five nearest-to-maturities (3rd, 5th, 7th, 9th, and 12th nearest-to-maturities for energies, 1st, 2nd, 3rd, 4th and 5th nearest-to-maturities for **WHT** and **CRN**, 2nd, 3rd, 4th, 6th , and 7th for **SOY**, and 2nd, 3rd, 4th, 6th , and 8th for **SOI**). Tables 1.b. summarizes the maturities covered by each of the two baskets.

Table 1.a. Summary of commodity futures markets

Commodity	Exchange	Contract size		Prices quotation		Delivery											
						Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
Crude Oil (WTI)	NYMEX	1000	barrels	U.S.$	per barrel	1	2	3	4	5	6	7	8	9	10	11	12
Natural gas	NYMEX	10000	mmBtu	U.S.$	per mmBtu	1	2	3	4	5	6	7	8	9	10	11	12
Heating oil	NYMEX	42000	gallons	U.S.$	per gallon	1	2	3	4	5	6	7	8	9	10	11	12
Wheat	CBOT	5000	bushels	U.S.$	per bushel			1		2		3		4			5
Corn	CBOT	5000	bushels	U.S.$	per bushel			1		2		3		4			5
Soybean	CBOT	5000	bushels	U.S.$	per bushel	1		2		3		4	5	6		7	
Soybean oil	CBOT	60000	pounds	U.S.$	per pound	1		2		3		4	5	6	7		8
Gold	COMEX	100	ounces	U.S.$	per ounce		1		2		3		4		5		6

Table 1.b. Maturities covered by baskets 1 & 2

Commodity	Nearby month										
	Feb [2MTHS]	Mar [3MTHS]	Apr [4MTHS]	May [5MTHS]	Jun [6MTHS]	Jul [7MTHS]	Aug [8MTHS]	Sep [9MTHS]	Oct [10MTHS]	Dec [12MTHS]	
Crude Oil (WTI)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Natural gas	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Heating oil	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wheat		✓		✓		✓		✓		✓	
Corn		✓		✓		✓		✓		✓	
Soybean		✓		✓		✓	✓	✓		✓*	
Soybean oil		✓		✓		✓	✓	✓	✓	✓	
Gold	✓		✓		✓		✓		✓		✓

Basket 1: Crude Oil; Natural Gas; Heating Oil; Gold
Basket 2: Crude Oil; Natural Gas; Heating Oil; Wheat; Corn; Soybean; Soybean Oil

Notes: Note: Table 1.a. shows the summary of the commodity futures contracts. It expresses the exchanges where the commodity futures traded, the contract size, the price quotation, and the delivery months. Abbreviations: NYMEX, the New York Mercantile Exchange; CBOT, Chicago Board of Trade; mmBtu, million British thermal unit.
"Nearby month", sometimes referred to as "front month", is the month closest to maturity. * the fifth nearest-to-maturity for soybean is November's maturity and not December: Indeed, due to the absence of a 12-month maturity for soybean, the 11-month maturity was used.

For each of the baskets and maturities considered, the spillovers are estimated, in a first step, over the full sample period (i.e., from January 3rd, 1995 to December 11th, 2020), then, over U.S. recessions (henceforth crisis periods) and recoveries (henceforth tranquil periods) sub-periods. We relied on NBER's Business Cycle Dating Committee to determine the start and end dates of the U.S. recession

[1] Data as well as descriptive statistics are available upon request.

and recovery sub-periods[1]. In all the graphical results presented in this article, U.S. recession periods are shaded.

3. Results

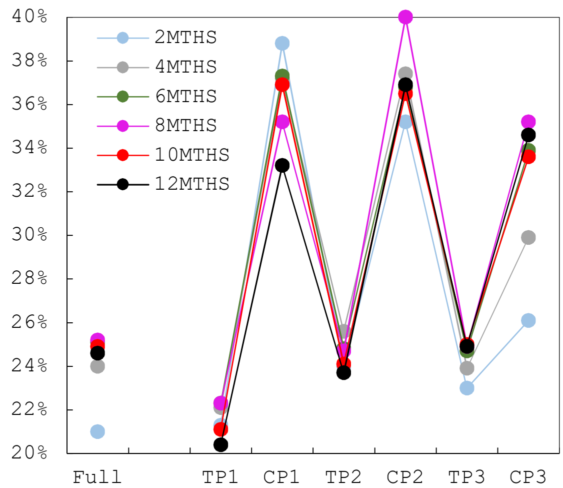
In this section, we assess the connectedness among the volatilities of the considered commodities over various maturities by investigating their spillover effects in the time and time-frequency domains. We start with an aggregated investigation of the interaction among commodities for different maturities. Then we disaggregate the total connectedness between commodities into different frequency bands, which enables us to deeply analyze the short-, medium- and long-term interdependence among commodities. We thus analyze our results into several steps: first, the connectedness between commodities in each basket over the full sample periods and for different maturities; second, the connectedness between commodities in each basket for different sub-periods; third, the connectedness between commodities in each basket at different frequencies.

3.1. Connectedness in time domain

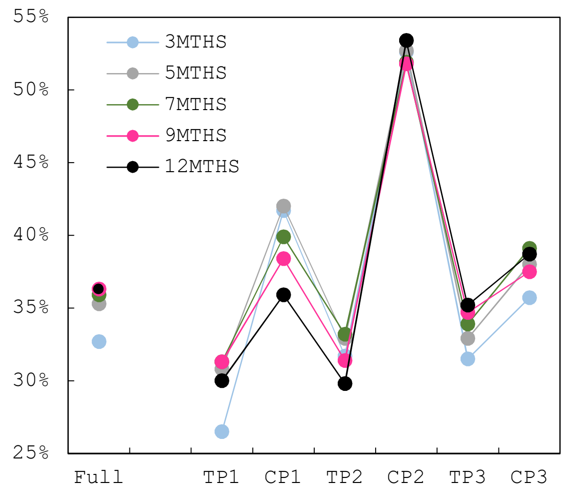
Tables 2 to 7 depict the total average connectedness indices (summarized in Figure 1.a) as well as their "input-output" decomposition for (**i**) the full sample period (summarized in Figure 2), (**ii**) the tranquil periods, and (**iii**) the crisis periods over different nearest-to-maturities for basket 1. In the same line, tables 8 to 12 depict the total connectedness indices (summarized in Figure 1.b) as well as their "input-output" decomposition (summarized in Figure 3) for basket 2.[2] Their (q,j)-th entries are the estimated contributions to the forecast error variance components of commodity q coming from innovations in commodity j. The total connectedness index for volatilities (**S.I**), reported in the south-east corner of each table, is the off-diagonal column sums (i.e., *contribution to others*) relative to the column sums including diagonals (i.e., *contribution to others including own*) expressed as a percentage. Volatility spillovers from all other commodities to a given commodity are shown in the last column.

Fig. 1 Total average spillovers over the full sample period and each of the sub-periods

a. Basket 1



b. Basket 2



Note: Each point is an average for the corresponding maturity (see the legend) over the corresponding period (see the x-axis). TP and CP stand for tranquil period and crisis period, respectively.

[1] See: https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions

[2] Directional spillovers network graphs for the tranquil and crisis subperiods are available upon request.

Figures 1.a&b show that, for the full sample period, the total connectedness indices for the nearest-to-maturities selected vary between 21 and 25.2% for Basket 1 (energy-gold), and between 32.7 and 36.3% for Basket 2 (energy-agricultural), which suggests a relatively higher interdependency among the commodities in Basket 2, *i.e.*, energy-agricultural, on average and across the entire sample for each of the considered nearest-to-maturities. Moreover, our results suggest that commodity markets tend to be clustered. Indeed, the magnitude of directional volatility spillovers to others (q) from each of the considered commodities (j) is different depending on the type of the commodity within each basket, *i.e.,* that they tend to be grouped according to the main category to which each commodity belongs (energy, precious metal or agricultural). Interestingly, for the full sample period estimations, the directional volatility spillovers to others (q) from each of the considered commodities (j) within each basket tend to be homogenous whatever the maturity. For instance, while energy commodities, particularly OIL and HOI, influence each other strongly, they seem to be largely insensitive to shocks on other agricultural and precious metal commodities (and vice versa). Similarly, agricultural commodities are influenced more by other agricultural commodities, but they appear to be widely insensitive to shocks on energy commodities[1]. This result suggests that commodity markets tend to be segmented, which is in line with the result of Gardebroek et al. (2016). Indeed, we notice that GLD (Basket 1) is hardly influenced by what is happening in the energy market, and that spillovers to others from innovations to GLD volatilities are relatively low as well and not very different for all the considered maturities. Moreover, a diagonal reading of Tables 2 to 12 reveals that, with contribution to own volatility forecast error variance ranging between 92%, GLD market is, on average, much more closed than other commodity markets, which contribution to own volatility forecast error variance could be as low as 53%. These results support that commodity markets are potentially segmented, and that GLD is potentially a safe haven asset, which is in line with the results of Hammoudeh et al. (2010).

Net connectedness, which is the difference between '*contribution to others*' and '*from others*' directional connectedness, reflects whether a commodity is a net transmitter (positive values of net connectedness) or a net receiver (negative value of net connectedness) of volatility. We notice that, for Basket 1, OIL and HOI are, on average over the entire period, net volatility transmitters to all other commodities in the basket, and, mechanically, GAS and GLD are net volatility receivers. As for Basket 2, the results show that, on average over the full sample period, OIL, HOI, CRN and SOY are net volatility transmitters to all other commodities, and, at the opposite side, GAS, WHT and SOI are net volatility receivers. The net connectedness within each of the two baskets considered is largely stable for the full sample period estimations, whatever the maturity.

To sum up, while the static total connectedness, as well as the directional spillovers, over the full sample period are broadly insensitive to maturity (*i.e.*, largely stable across the maturities), we should emphasize that these spillovers are based on the full sample estimations. Since the sample period runs from January 3rd, 1995 to December 11th, 2020 (almost 26 years), and given all the developments that characterize this period, it appears that the static connectedness measure, which provides useful evidences on the average connectedness among commodities over the entire sample period, may not capture the effects of these developments. It is therefore interesting to examine how the connectedness among commodities evolved over time. To examine the impact of crisis on the connectedness among commodities, we first split the full sample period into sub-periods: three tranquil sub-periods [(**i**) Jan 4th, 1995 – Mar 1st, 2001; (**ii**) Dec 1st, 2001 – Nov 30th, 2007; (**iii**) Jul 1st, 2009 – Jan 31st, 2020] and three crisis sub-periods [(**i**) Mar 1st, 2001 – Nov 30th, 2001; (**ii**) Dec 1st, 2007 – Jun 30th, 2009; (**iii**) Feb 1st, 2020 – Dec 11th, 2020], then, and as in Diebold and Yilmaz (2014), we use a time-varying analysis instead of the static full-sample one.

Figure 1.a&b summarizes total connectedness based on the tranquil and crisis sub-periods average estimations, denoted by TP and CP, respectively. While connectedness clustering is obvious, as the total

[1] Heating oil is derived from crude oil. Thus, the changes in the prices of heating oil are mimicking the prices of crude oil. For agricultural commodities, agriculture corps are affected by each other since they substitute each other and compete for fertilizers, water, and land (Baumeister and Kilian, 2014; Bastianin et al. 2014).

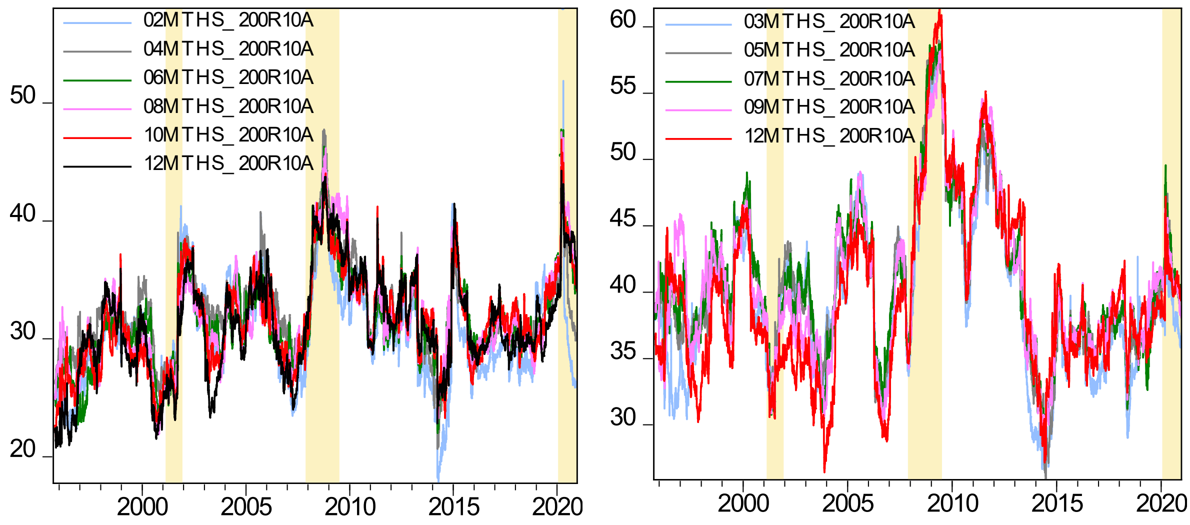
connectedness among commodities increases dramatically during the crisis sub-periods, which is consistent with the results of Silvennoinen and Thorp (2010) and Chevallier and Ielpo (2013), it remains however clearer for Basket 1. We notice that, for Basket 1 (respectively for Basket 2), the magnitude of the energy-gold (respectively energy-agricultural) connectedness during tranquil and crisis sub-periods does not evolve in the same way across all maturities. More precisely, the total connectedness indices tend to be relatively more concentrated in tranquil periods rather than in times of crisis, whereas for Basket 2, they are relatively more dispersed in tranquil periods and become relatively more concentrated in times of crisis. In other words, this result suggests that GLD seems to be a safe haven asset that, relative to agricultural commodities, helps to smooth volatility during the crisis sub-periods. Moreover, it is interesting to note that total as well as directional connectedness seem to be time-varying. Indeed, for Basket 1 (respectively for Basket 2), the total connectedness indices jumped to around 33-39%, 35-40% and 26-35% (respectively 36-42%, 52-53% and 36-39%) during the dot-com crisis (CP1), the subprime crisis (CP2), and the COVID-19 crisis (CP3), respectively, whereas low interdependencies are recorded during the tranquil sub-periods (TP1, TP2 and TP2). This result shows that the subprime crisis (CP2) witnessed a significant increase in the energy-agricultural connectedness compared to the other crises. Furthermore, in both baskets, there are some noticeable pairwise linkage: (**i**) in Basket 1, crude oil and heating oil are highly connected; (**ii**) in Basket 2, pairwise commodities such as OIL-HOI, CRN-WHT, CRN-SOY, SOY-SOI are comparatively highly linked; (**iii**) the directional spillovers' results for both baskets reveal an increase in the connectedness among the commodities making up each of the two baskets, supporting *shift contagion* among commodities during the crisis sub-periods. Moreover, net spillovers indices increased significantly, in absolute values, between tranquil and crisis sub-periods, with, for Basket 1, a clear dominance for (**i**) GLD and HOI during the dot-com crisis, (**ii**) OIL, GAS and GLD during the subprime crisis, and (**iii**) OIL, HOI and GLD during the COVID-19 crisis, and, for Basket 2, a clear dominance for (**i**) OIL, HOI and SOI during the dot-com crisis, (**ii**) OIL, GAS and WHT during the subprime crisis, and (**iii**) OIL and GAS during the COVID-19 crisis. This result suggests that, during crisis periods, a non-negligible part of the volatility spillovers in commodity markets is due to energies.

As we have shown, through the decomposition of the full sample into tranquil and crisis sub-periods, connectedness among commodities seems to be time-varying. However, and in spite of the interesting results presented in Tables 2 to 12 and in Figures 1 to 3, the static connectedness indices may not accurately track the evolution over time of the interdependence among commodities. To better understand how connectedness evolved over time as well as the effects of the financial and economic developments characterizing the period examined, we now estimate the total time-varying connectedness index, as in Diebold and Yilmaz (2014), using a 200-days rolling window and ten-days-ahead forecast horizon to check robustness.[1]

[1] We have also checked the robustness of our results based on alternative lengths of rolling windows (150 and 300-days) and forecast horizons (25, 50 and 100-days-ahead forecast horizon). We found that time-varying connectedness indices exhibit largely very similar time patterns whatever the length of the estimation rolling window and forecast horizon. We can make unreported results available upon request.

Fig. 4 Total time-varying connectedness

a. Basket 1 **b.** Basket 2



Note: U.S. recessions are shaded.

The Diebold and Yilmaz's (2014) total connectedness measure is a useful in revealing how systemic risk changed over time. Figures 4.a&b depict the evolution over time of the total connectedness for Baskets 1 and 2, respectively, as measured by time-domain variance decompositions. A first overall visual inspection from the connectedness plots shows that, for each of the two baskets, the connectedness indices of the different maturities exhibit different patterns over time[1] – which is quite expected because the studied period cover 26 years and includes both tranquil and stress times in which shocks spread across commodities with different magnitudes – and tend to evolve together. While the static total connectedness indices are estimated to be 21 to 25% on average and across the full-sample period for Basket 1 and 32 to 36% for Basket 2, it is interesting to notice that the connectedness indices range between 18 and 60% for Basket 1, and between 25 and 60% for Basket 2, with a substantial variation over the course of 26 years: The overall connectedness reached its highest level during the COVID-19 crisis for Basket 1, and during the subprime crisis for Basket 2. Indeed, and as expected, linkages among commodities within each of the two baskets become stronger in times of stress, when shocks to uncertainty were transmitting more among the studied commodities and maturities, thereby creating a more interconnected system (connectedness indices increase to relatively high levels), than in tranquil periods, when shocks created a small portion of future uncertainty and hence weak connectedness among commodities (overall connectedness drop to relatively low levels). More specifically, the total time-varying connectedness indices include six main peaks for each of the baskets. The first was between 1997 and 1998 when the index increased to almost 35% (respectively 50%) for Basket 1 (respectively Basket 2), which could be explained by the Asian financial and economic crisis. Indeed, the Asian financial crisis has been felt in many commodity markets (Caballero et al. 2008): From mid-1997 to mid-1998, commodity prices fell overall by about 10 to 15%. The second, reached in 2001, is concomitant with the WTC 9/11 attacks and the bursting of the dotcom bubble, pushing commodities into a bull market. Connectedness indices recorded an upward trend since mid-2003, coinciding with the war in Iraq, which put upward pressure on commodity prices, before reaching a third peak at the end of 2005. Moreover, from the mid-2006 the connectedness indices recorded an upward movement, concomitant with the further tightening of the U.S. monetary policy, before reaching a peak of over 45% for Basket 1 and 60% for Basket 2 in early 2009, which could be due to the global financial crisis. Indeed, the crisis, and the subsequent insecure economic situation, has increased uncertainty and caused stocks to plunge into a bear market and commodities into a bull market (Antonakakis et al., 2018;

[1] This result is consistent with the results of Diebold and Yilmaz (2012; 2014), Antonakakis et al. (2018), Tiwari et al. (2019) and Ben Amar et al. (2020).

Gamba-Santamaria et al., 2019). As a result, commodities were connected more strongly during the period following the subprime crisis. The connectedness plot also reveals another peak for Basket 2 towards the end of 2011. This spike is likely due to increased uncertainties (**i**) in the energy market that are, at least in part, induced by the Arab Spring and the resulting unrest in the MENA region, and (**ii**) in the euro area, when the European debt crisis peaked. After the "*whatever it takes*" speech by Mario Draghi, president of the European Central Bank, at the Global Investment Conference on July 26th, 2012, uncertainty and, consequently, overall connectedness among commodities decreased.[1] Furthermore, the time-varying connectedness indices capture a high level of interdependence among the volatilities of Basket 1 commodities towards the end of 2015, along with the oil price collapse from about \$106 in June 2014 to about \$37 in December 2015. More recently, and in the wake of the COVID-19 medical shock, the total connectedness increased to about 50% for both baskets by the end of January 2020.[2]

The time-varying net connectedness from commodity q to all other commodities j, which indicates whether a commodity q is a net receiver (negative value of net connectedness) or a net transmitter (positive values of net connectedness) of volatility shocks at time t, are depicted in Figures 5 and 7, and Table 14 presents the correlations between net time-varying spillovers for the different maturities for baskets 1 and 2. The correlation table shows that the net connectedness of OIL and HOI are strongly positively correlated for the two baskets and all maturities, suggesting that OIL and HOI affect the other commodities and are affected by the other commodities to the same extent and in the same direction. It also reveals that the net connectedness of OIL and GAS and, to a lesser extent, HOI and GAS are negatively correlated. This result suggests that the energy market appears to be segmented. We also find that, for Basket 1 and all maturities, the net connectedness of OIL and HOI are strongly negatively correlated with the net connectedness of GLD. On the other hand, the correlation between the net connectedness of GAS and GLD is too weak. For Basket 2, the net positions of energy commodities are negatively correlated with all the other agricultural commodities' net connectedness, except for (**i**) the correlation between OIL and SOI for the 5-months maturity and (**ii**) the correlation between GAS and CRN and that between GAS and SOY for the 5-, 7- and 12-months maturities which are slightly positive. The market for agricultural raw materials seems segmented as well. Indeed, while the net positions of WHT and CRN and, to a greater extent, of SOY and SOI are positively correlated, the other agricultural commodities' net positions are negatively correlated with each other.

Let's now focus on the net connectedness plot reported in Figures 5 and 7. Each point in these figures corresponds to $NVS_q^G(H)$ (Eq. 4) for Baskets 1 and 2, respectively. Except for CRN and SOI, whose rolling net spillovers are not stable[3], the patterns of the net positions of each of the other commodities belonging to Baskets 1 and 2 are largely stable throughout the entire sample period.[4] Assets that are almost always net volatility transmitters are OIL, HOI and SOY, while GAS, GLD and WHT are almost always net volatility receivers (Figures 6 and 8 depict frequency distributions for net volatilities).[5] This result does not mean that net volatility transmitters (respectively net volatility receivers) commodities do not receive (respectively do not transmit) volatility from (respectively to) the other commodities. In fact, they receive (respectively transmit) volatility spillovers from (respectively to) the other

[1] During the conference held on July 26, 2012 in London, Draghi said: "*Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough*". Interested readers can find a verbatim of the remarks made by Mario Draghi on the ECB website: https://www.ecb.europa.eu/press/key/date/2012/html/sp120726.en.html

[2] Although the Chinese authorities reported the first COVID-19 confirmed case on December 31st, investors did not take the epidemic risk too seriously initially. As a result, connectedness did not peak until late January 2020 (Ramelli and Wagner, 2020 a&b; Ozili and Arun, 2020; Ben Amar el al. 2020). However, once the Chinese authorities indicated on January 20 that the SARS-CoV-2, which is the virus that causes the COVID-19, could be transmitted between humans, attention to this new virus increased spectacularly.

[3] CRN and SOI are sometimes net volatility transmitters and sometimes net receivers.

[4] We should note that our findings emphasize that net connectedness for most of the commodities amplify during the periods of tensions compared to the normal periods.

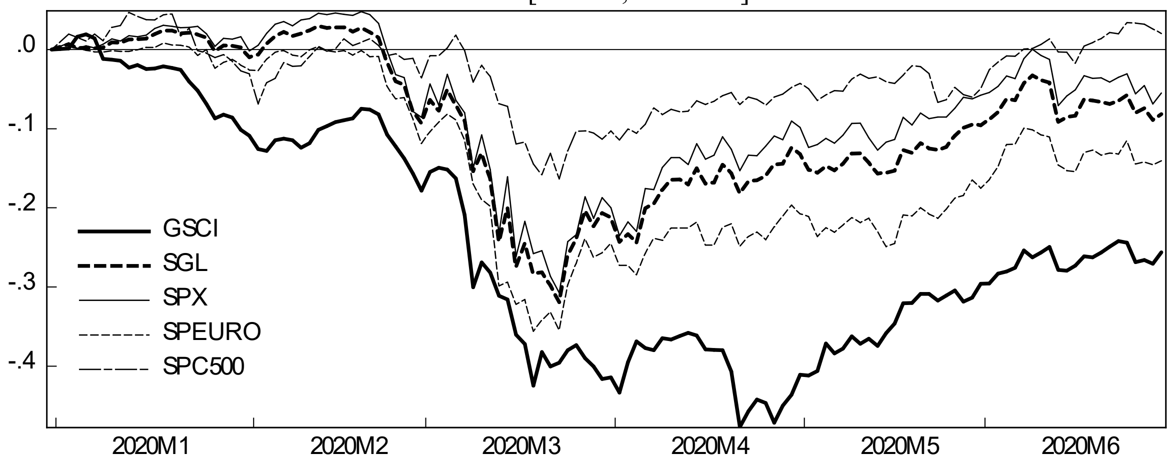
[5] It should be noted that OIL, HOI and SOY (respectively GAS, GLD and WHT) are broadly net volatility transmitters to (respectively net volatility receivers from) all other commodities, except for very short time periods in which they become net volatility receivers (respectively net volatility transmitters).

commodities all of the time, but the magnitude of volatility transmission (respectively volatility reception) is higher than that of reception (respectively transmission) most of the time. Note that, for Basket 1 (respectively Basket 2), net volatility-spillover effects are stronger from OIL (respectively from SOY) to other commodities, and GLD (respectively WHT) is the most affected from other commodities. Moreover, following the sharp rise in agricultural commodity prices in 2007-2008 (Balcombe, 2010; Hassouneh et al., 2016; Ceballos et al., 2017), it appears that the agricultural commodity market did not react homogeneously. Indeed, while SOY and SOI became net volatility transmitters between the end of 2008 and the end of 2009, WHT and CRN became net receivers over the same period. The results also show that, by the end of 2014, and following the collapse of oil prices, OIL and HOI have become high net transmitters of volatility, while all other variables have become strong net receivers of volatility. Indeed, towards the end of 2014, when the U.S. Federal Reserve was about to complete its Quantitative Easing (QE) program, the European Central Bank announced (on June 5, 2014) that it would launch its own. The consequence was a sharp appreciation of the dollar and, subsequently, a substantial fall in the oil price (Ben Amar et al. 2020). Besides monetary policy, this decline in oil prices also reflects imbalances in the oil market due mainly to global overproduction and the slowdown in global demand. More recently, high levels of net volatility spillovers were observed as early as the end of January 2020, following the announcement by the Chinese authorities that the SARS-CoV-2 is transmissible between humans. More precisely, with the onset of the COVID-19 crisis, OIL and HOI was the main volatility emitters during this period of high uncertainty, while GLD, WHT and SOI were the main volatility receivers for all maturities considered. However, as for GAS, CRN and SOY, the dynamics as well as the sign of their respective net positions during the COVID-19 crisis period varied according to the maturities. For Basket 1, GAS is a net volatility transmitter for the 10-months maturity, but a net receiver for all other maturities. As for Basket 2, (**i**) GAS and SOY are broadly net volatility receivers from all other commodities, except for very short time periods and specific maturities (5- and 9-months for GAS, and 12-months for SOY) in which they become net volatility transmitters, and (**ii**) SOI has a largely neutral position for 5-, 7- and 9-months maturities, a slightly negative then positive net position for the 3-months maturity, and a slightly positive then negative net position for the 12-months maturity. Thus, net volatility spillovers seem to indicate that both the energy commodities market and the agricultural commodities market are segmented, and that the transmission of shocks, in terms of direction and magnitude, could vary substantially from one maturity to another.

3.2. Connectedness in the time-frequency domain

As shocks may impact commodity markets at various frequencies with various strengths, the frequency domain is a natural place for measuring the connectedness. While Figure 1.a&b and Figure 4.a&b show that the total connectedness bottoms during the tranquil periods and peaks during the stress times, they don't reveal whether shocks that involve high uncertainty impact the considered baskets in the short-term or in the long-term. Thus, we now use the time-frequency connectedness measure of Barunik and Krehlik (2018) to clearly understand the sources of connectedness among commodities and to explore how the connectedness among them has evolved over time and on different frequencies. Figures 9 and 10 display the decomposition of the total connectedness into frequency bands up to 4 days, 4 days to 3 months, and 3 months to 9 months, computed as $SI_{BK}^{\mathcal{F}}(d_s)$ on the bands corresponding to short-term ($d_1 \in [1, 4]$ days), medium-term ($d_2 \in (4, 64]$ days), and long-term ($d_3 \in (64, 200]$ days) cycles. For each frequency band, time appear on the x-axis, while total connectedness on the y-axis. Periods in which connectedness comes from low frequencies are periods when markets appear to be inefficient (*i.e.*, market participants do not process information quickly), and shocks in the system (*i.e.*, Basket 1 and Basket 2) mainly affect long-term cyclical behavior, with responses at low frequencies. However, if the connectedness comes from high frequencies, it suggests that market participants appear to process information quickly, and shocks mainly affect short-term cyclical behavior, with responses mostly at high frequencies. A first visual assessment of the plots representing the frequency decomposition of the total connectedness allows detection of time and frequency varying dependencies between commodity markets volatilities, *i.e.*, that the connectedness among commodities is not stable over time and across frequency bands. Moreover, the frequency decomposition reveals that most of periods of high total connectedness are driven mostly by high frequency components ($d_1 \in [1,4]$ days movements), which may indicate that commodity markets process information rapidly, except for the COVID-19 crisis period where total connectedness has been driven by lower frequency components ($d_2 \in (4,64]$ days movements). Indeed, during the dotcom (2001-2002) and the subprime (2007-2009) crisis periods, as well as the unrest in the MENA region (2011-2012), it seems that the connectedness is driven by shocks creating uncertainty at high frequencies band (d_1). But how can we explain the fact that, during the COVID-19 crisis, the connectedness among commodities is rather driven by shocks creating uncertainty at lower frequencies? Before answering this question, it is useful to examine how the main stock markets evolved during the COVID-19 crisis period. Figure 11 plots the evolution of the U.S., European and Chinese stock markets indices as well as the S&P GSCI index over the COVID-19 crisis period (from December 31, 2019 to June 30, 2020). Interestingly, the most visible effect of the COVID-19 crisis on financial markets was the effect on the commodity markets (GSCI) and the European market (SPEUR), which fell by 45% and 35%, respectively, while the least visible effect of this shock was the effect on the Chinese market (SPC500), which fell by 15% only. This result suggests that the fall in the European stock market could have had a major effect on market sentiment.[1]

Fig. 11 Evolution of the U.S., European and Chinese stock market indices during the first two quarters of 2020 [Dec 31, 2019 = 0]



Note: GSCI, SGL, SPX, SPEURO, and SPC500 stand for S&P GSCI, S&P Global 1200, S&P 500, S&P Europe 350, and S&P China 500, respectively.

Indeed, according to Ramelli and Wagner (2020), Ben Amar et al. (2020) and Ozili and Arun (2020), until mid-January 2020, market participants did not attach too much importance to the coronavirus and its potential economic implications. Initially, it was perceived that the novel coronavirus outbreak would be contained within China only: the risk of leakage of this virus outside China was considered unlikely. However, attention to this new disease increased considerably when Chinese health authorities alerted, on January 20, 2020, that this new strain of coronavirus is a highly infectious between humans – with each infected person could contaminate two or three others on average – but not particularly deadly disease. Thus, the movement of people as well as social interactions accelerated the spread of the virus, which quickly hits almost all the countries of the world at the same time. It should be noted that even the intensity of Google's search for coronavirus significantly increased after the World Health Organization published its first situation report concerning the novel coronavirus outbreak on January 20, and reached a peak when Italy decided, on February 23, to put tens of thousands of people in Lombardy under quarantine, after registering its first deaths due to the COVID-19. The speed and magnitude of the spread of the COVID-19 in Europe shifted the attention of market participants and appears to have affected their sentiment about the resilience of the global economy as well as their

[1] Ozili and Arun (2020) state that "*although the oil price war, in which Russia and Saudi Arabia were driving down oil price by increasing oil production, played a role in the fall in stock markets indices, the subsequent fall in stock market indices in March was mainly due to investors' flight to safety during the coronavirus pandemic*".

perception of future economic conditions, triggering, therefore, the propagation of “bad news” to all financial markets across the world by a domino effect. Thus, the fact that market participants did not processed information quickly during the early stages of the COVID-19 crisis may explain that the connectedness among commodities is rather driven by shocks creating uncertainty at low frequencies. Beyond the initial impact of the COVID-19 shock on financial markets (*i.e.*, during the first quarter 2020), policy interventions helped to reassure market participants that the further spread of financial stress would be mitigated, which may explain, at least in part, the decrease in uncertainty and, therefore, in the total connectedness among commodities for all maturities and at all frequencies since the second quarter of 2020 (See Figures 9 and 10). Indeed, one of the goals of the fiscal, financial, and monetary measures adopted by governments and central banks all over the world is to reassure market participants and offset their response to the COVID-19 shock. These measures seem to have brought back a positive sentiment among market participants, allowing financial markets to converge to their pre-crisis level and dynamics, and thus explain the shift in the systemic risk to a relatively low level since the second quarter of 2020.

4. Concluding remarks

In this article, we seek to clarify the connectedness among different commodity markets for different maturities. The study introduces empirical contributions to the ongoing debate about the cross-commodity markets connectedness. Furthermore, we extend the discussion to study integration between commodity futures markets for different maturities, which is against most of the literature. Selecting different nearest-to-maturities is motivated by Buyuksahin and Robe (2014) and Isleimeyyeh (2020). We thus use a set of time and time-frequency tools to estimate the connectedness among various commodity markets: energy, agricultural, and precious metals. Since the commodities selected are restricted to different deliveries per year, we construct two baskets based on common nearest-to-maturities: energy-gold and energy-agricultural. We select datasets cover critical period between 1995 and 2020, which witnessed several uneven recessions; global, political, and financial concerns; and more importantly, the financialization of commodities. For obtaining robust and reliable results, we implement our estimations in different dimensions: the static connectedness over the full sample selected, the static connectedness over several subperiods that highlight certain episodes in the global economic and financial system, the time-varying connectedness, the connectedness between commodities in each basket using different time-frequency domains, and the connectedness across different maturities in each step.

Regarding results, we provide a set of stylized facts on the extent to which commodity markets are integrated or segmented. First, our results show several noticeable and comparatively high pairwise linkages between commodities in both selected baskets such as oil and heating oil, wheat and corn, corn and soybean, and soybean and soybean oil. Second, the static total average connectedness over the full sample period is broadly insensitive to maturity. However, after 2008 financial crisis, the connectedness between commodity futures prices increases when the maturity increases. This could be attributed to the role of financial investors in commodity futures markets who operate in short-term and long-term maturities, while the hedgers activities decrease when the maturity increases. Thus, financial investors activities overwhelm hedgers ones in long-term maturities. Therefore, financial investors effect increases as a consequence to the financialization of commodities (e.g., Isleimeyyeh, 2020). Since financial investors overwhelmingly operate in a basket of commodities, the increase of financial investors causes a greater information transmission between commodity markets, and thus higher connectedness. Third, the overall connectedness amplifies during crises periods compared to calm periods. The connectedness between energy and agricultural commodities during the 2008 financial crisis 2008 witnessed a significant jump in which it recorded a peak higher than other crises. Fourth, the results from net connectedness suggest that both the energy and the agricultural commodity markets are segmented, and that the transmission of shocks, in terms of direction and magnitude, could vary substantially from one maturity to another. Indeed, the results demonstrate that crude oil and heating oil are net transmitters in all circumstances (*i.e.*, all the time and across maturities). Inversely, natural gas, gold, and wheat are net receivers all the time and across maturities. For all sub-periods and maturities, soybean is net transmitter, except for the 2001 and 2020 crisis sub-periods in which it was converted to net receiver. Regarding soybean oil, it is net receiver for all sub-periods and maturities, except for the 2008 financial crisis period in which it was converted to net transmitter. Corn is an example of non-stable commodity: the net connectedness of corn keeps changing over time and across maturities, which is a motivation for future study to clarify the outcome of this market. Furthermore, the results show that the net volatility spillovers amplified during tension periods. Fifth, the results from the time-frequency estimation show that the connectedness among commodities is not stable over time and across frequency bands. Moreover, the frequency decomposition reveals that most of periods of high total connectedness are driven mostly by high frequency components, which may indicate that commodity markets process information rapidly, except for the COVID-19 crisis period where total connectedness has been driven by lower frequency components. Finally, this paper contributes to the literature discussing the connectedness across commodity futures markets such as Le Pen and Sevi (2018) and Gardebroek et al. (2016). It also shed light on several research questions to be studied in future.

Table 2: Volatility spillovers from asset (*j*) to asset (*q*) – Basket 1 [2MTHS]

a. 2MTHS - Full Sample Period

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	64.4	1.1	32.3	2.3	35.6
GAS	1.7	95.1	2.7	0.6	4.9
HOI	33.4	1.9	62.7	1.9	37.3
GLD	2.9	0.8	2.5	93.8	6.2
X	38.1	3.7	37.4	4.8	**S.I**
Y	102.4	98.9	100.2	98.6	21.00%
Z	2.5	-1.2	0.1	-1.4	

b. 2MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	61.6	1.1	36	1.2	38.4
GAS	1.7	95.2	2.3	0.8	4.8
HOI	36	1.5	61.4	1.1	38.6
GLD	1.2	1.1	1.2	96.5	3.5
X	38.9	3.7	39.6	3.2	**S.I**
Y	100.5	98.9	100.9	99.7	21.30%
Z	0.5	-1.1	1	-0.3	

c. 2MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	59.7	2.1	36.9	1.3	40.3
GAS	3.6	90.9	5	0.5	9.1
HOI	36.9	3.1	58.9	1.1	41.1
GLD	2.3	1.1	2.2	94.4	5.6
X	42.8	6.3	44.1	2.9	**S.I**
Y	102.5	97.2	103	97.4	24.00%
Z	2.5	-2.8	3	-2.7	

d. 2MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	58.8	0.8	38.3	2	41.2
GAS	1.2	97	1.1	0.7	3
HOI	39.5	0.7	58.5	1.3	41.5
GLD	3.5	0.6	2.1	93.8	6.2
X	44.3	2.1	41.5	4	**S.I**
Y	103.1	99.1	100	97.8	23.00%
Z	3.1	-0.9	0	-2.2	

e. 2MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	48	4.2	39.6	8.2	52
GAS	10.4	74.3	10.8	4.5	25.7
HOI	37.6	4	49.1	9.3	50.9
GLD	11.1	5.9	9.7	73.3	26.7
X	59	14.1	60.1	22	**S.I**
Y	107	88.4	109.3	95.3	38.80%
Z	7	-11.6	9.2	-4.7	

f. 2MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	52	4.9	35.8	7.3	48
GAS	7.6	78.8	9.6	4	21.2
HOI	37.2	5.7	51.1	6.1	48.9
GLD	10.3	4.5	7.9	77.3	22.7
X	55.1	15.1	53.4	17.4	**S.I**
Y	107.1	93.8	104.5	94.6	35.20%
Z	7.1	-6.1	4.5	-5.3	

g. 2MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	60.9	3.4	33	2.6	39.1
GAS	5.2	86.6	5.6	2.6	13.4
HOI	31.8	2.3	64.4	1.5	35.6
GLD	3.2	5.2	7.7	83.9	16.1
X	40.2	10.9	46.4	6.8	**S.I**
Y	101.1	97.5	110.8	90.6	26.10%
Z	1.1	-2.5	10.8	-9.3	

Notes: A VAR of order 8 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (*q,j*)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset *q* coming from innovations to asset *j*. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI** and **GLD** are acronyms for crude oil (WTI), natural gas, heating oil and gold, respectively.

Table 3: Volatility spillovers from asset (j) to asset (q) – Basket 1 [4MTHS]

a. 4MTHS - Full Sample Period

To (q)	OIL	GAS	HOI	GLD	From Others
	From (j)				
OIL	57.9	1.4	38.5	2.2	42.1
GAS	2.1	95	2.4	0.5	5
HOI	39.2	1.7	57.4	1.7	42.6
GLD	3.3	0.6	2.4	93.7	6.3
X	44.6	3.6	43.3	4.4	**S.I**
Y	102.5	98.7	100.7	98.1	24.00%
Z	2.5	-1.4	0.7	-1.9	

b. 4MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	OIL	GAS	HOI	GLD	From Others
	From (j)				
OIL	60.1	1.2	37.9	0.8	39.9
GAS	2.1	94.7	1.9	1.3	5.3
HOI	38	1.4	59.9	0.8	40.1
GLD	1.1	0.8	1.1	97	3
X	41.2	3.4	40.9	2.9	**S.I**
Y	101.3	98.1	100.8	99.8	22.10%
Z	1.3	-1.9	0.8	-0.1	

e. 4MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	OIL	GAS	HOI	GLD	From Others
	From (j)				
OIL	49.2	4.6	40.4	5.8	50.8
GAS	8.6	78.2	9.2	3.9	21.8
HOI	39	3.2	51.7	6.1	48.3
GLD	11.5	7.4	9.1	72	28
X	59.2	15.2	58.7	15.8	**S.I**
Y	108.3	93.4	110.4	87.8	37.20%
Z	8.4	-6.6	10.4	-12.2	

c. 4MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	OIL	GAS	HOI	GLD	From Others
	From (j)				
OIL	57.3	2.8	38.6	1.3	42.7
GAS	4.7	88.6	5.5	1.2	11.4
HOI	39	3.3	56.8	0.9	43.2
GLD	2.3	1.1	1.9	94.7	5.3
X	46	7.1	46.1	3.4	**S.I**
Y	103.3	95.7	102.9	98.1	25.60%
Z	3.3	-4.3	2.9	-1.9	

f. 4MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	OIL	GAS	HOI	GLD	From Others
	From (j)				
OIL	48.4	5.6	38.7	7.3	51.6
GAS	8.7	78	9.4	3.9	22
HOI	40.1	5.5	48.6	5.8	51.4
GLD	11.8	4.2	8.6	75.3	24.7
X	60.6	15.3	56.7	17.1	**S.I**
Y	109	93.3	105.3	92.4	37.40%
Z	9	-6.7	5.3	-7.6	

d. 4MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	OIL	GAS	HOI	GLD	From Others
	From (j)				
OIL	56.2	0.8	41.1	2	43.8
GAS	0.9	98	0.7	0.3	2
HOI	41.8	0.6	56.3	1.3	43.7
GLD	3.4	0.3	2.2	94.1	5.9
X	46.1	1.7	44	3.6	**S.I**
Y	102.3	99.7	100.3	97.7	23.90%
Z	2.3	-0.3	0.3	-2.3	

g. 4MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	OIL	GAS	HOI	GLD	From Others
	From (j)				
OIL	56.4	1.6	39.7	2.2	43.6
GAS	5.4	88.2	4.6	1.7	11.8
HOI	39.9	1.3	56.7	2.1	43.3
GLD	9.4	2.8	8.8	79	21
X	54.7	5.7	53.1	6	**S.I**
Y	111.2	93.9	109.9	85.1	29.90%
Z	11.1	-6.1	9.8	-15	

Notes: A VAR of order 10 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (q,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset q coming from innovations to asset j. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI** and **GLD** are acronyms for crude oil (WTI), natural gas, heating oil and gold, respectively.

Table 4: Volatility spillovers from asset (j) to asset (q) – Basket 1 [6MTHS]

a. 6MTHS - Full Sample Period

To (q)	From (j) OIL	GAS	HOI	GLD	From Others
OIL	56.8	1.5	39.3	2.4	43.2
GAS	2.4	94	2.7	0.9	6
HOI	40.1	1.9	56.2	1.8	43.8
GLD	3.7	1	2.6	92.7	7.3
X	46.1	4.4	44.7	5.1	**S.I**
Y	102.9	98.4	100.9	97.8	25.10%
Z	2.9	-1.6	0.9	-2.2	

b. 6MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	From (j) OIL	GAS	HOI	GLD	From Others
OIL	60.5	1.7	36.7	1.1	39.5
GAS	2.9	92.9	2.9	1.2	7.1
HOI	36.4	2.4	60.4	0.8	39.6
GLD	1.3	0.9	0.9	96.9	3.1
X	40.6	5	40.6	3.1	**S.I**
Y	101.1	98	100.9	100	22.30%
Z	1.1	-2.1	1	0	

e. 6MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	From (j) OIL	GAS	HOI	GLD	From Others
OIL	48.9	5.2	37.9	8	51.1
GAS	7.8	79.5	5.6	7	20.5
HOI	37.8	2.9	51.8	7.5	48.2
GLD	9.8	10.1	9.5	70.6	29.4
X	55.3	18.3	53	22.5	**S.I**
Y	104.3	97.8	104.8	93.1	37.30%
Z	4.2	-2.2	4.8	-6.9	

c. 6MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	From (j) OIL	GAS	HOI	GLD	From Others
OIL	57.4	2.3	39.1	1.2	42.6
GAS	4.2	90.8	4.5	0.5	9.2
HOI	39.6	2.6	57	0.8	43
GLD	2.2	0.7	1.6	95.5	4.5
X	46	5.5	45.3	2.5	**S.I**
Y	103.4	96.4	102.3	98	24.80%
Z	3.4	-3.7	2.3	-2	

f. 6MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	From (j) OIL	GAS	HOI	GLD	From Others
OIL	47.8	4.8	39.8	7.6	52.2
GAS	7.9	80.3	8.2	3.6	19.7
HOI	40.5	5.4	47.9	6.2	52.1
GLD	11.1	3.3	8.6	76.9	23.1
X	59.5	13.5	56.6	17.4	**S.I**
Y	107.2	93.8	104.5	94.4	36.80%
Z	7.3	-6.2	4.5	-5.7	

d. 6MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	From (j) OIL	GAS	HOI	GLD	From Others
OIL	55.4	0.5	42.2	1.9	44.6
GAS	0.9	97.3	0.8	0.9	2.7
HOI	43.1	0.5	55	1.4	45
GLD	3.4	0.6	2.4	93.6	6.4
X	47.5	1.6	45.4	4.2	**S.I**
Y	102.8	99	100.4	97.8	24.70%
Z	2.9	-1.1	0.4	-2.2	

g. 6MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	From (j) OIL	GAS	HOI	GLD	From Others
OIL	54.1	5.5	39.1	1.3	45.9
GAS	9.4	77.1	10.1	3.4	22.9
HOI	39.3	5.8	53.9	1.1	46.1
GLD	8	4.6	7.9	79.5	20.5
X	56.7	15.9	57.1	5.8	**S.I**
Y	110.8	93	110.9	85.3	33.90%
Z	10.8	-7	11	-14.7	

Notes: A VAR of order 8 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (q,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset q coming from innovations to asset j. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI** and **GLD** are acronyms for crude oil (WTI), natural gas, heating oil and gold, respectively.

Table 5: Volatility spillovers from asset (j) to asset (q) – Basket 1 [8MTHS]

a. 8MTHS - Full Sample Period

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	56.4	1.3	40	2.4	43.6
GAS	2	94.4	2.6	1	5.6
HOI	40.6	1.8	55.7	1.9	44.3
GLD	3.6	0.9	2.9	92.6	7.4
X	46.2	4	45.5	5.3	**S.I**
Y	102.6	98.4	101.2	97.9	25.20%
Z	2.6	-1.6	1.2	-2.1	

b. 8MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	60.4	1.5	37	1.1	39.6
GAS	2.3	93.8	3.3	0.6	6.2
HOI	36.8	2.2	60	1	40
GLD	1.3	0.6	1.5	96.6	3.4
X	40.4	4.3	41.9	2.6	**S.I**
Y	100.8	98.1	101.9	99.3	22.30%
Z	0.8	-1.9	1.9	-0.8	

e. 8MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	54	4.4	36.7	4.9	46
GAS	5.7	81.3	7	6	18.7
HOI	35.6	4.4	51	9	49
GLD	6	10	10.9	73.1	26.9
X	47.3	18.8	54.6	19.9	**S.I**
Y	101.3	100.1	105.6	93	35.20%
Z	1.3	0.1	5.6	-7	

c. 8MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	57.2	2.7	38.8	1.2	42.8
GAS	4.4	90.6	4.2	0.7	9.4
HOI	39.3	2.6	57.4	0.6	42.6
GLD	2.2	0.7	1.4	95.7	4.3
X	45.9	6	44.5	2.5	**S.I**
Y	103.2	96.6	101.9	98.3	24.70%
Z	3.1	-3.4	1.9	-1.8	

f. 8MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	46.7	7	38.8	7.5	53.3
GAS	12.1	70.5	12.2	5.1	29.5
HOI	39.9	6.8	47.3	6	52.7
GLD	11	5.1	8.3	75.6	24.4
X	63	19	59.3	18.7	**S.I**
Y	109.7	89.5	106.6	94.3	40%
Z	9.7	-10.5	6.6	-5.7	

d. 8MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	54.8	0.4	42.9	1.9	45.2
GAS	0.6	97.7	0.7	1	2.3
HOI	43.7	0.5	54.4	1.4	45.6
GLD	3.3	0.8	2.4	93.6	6.4
X	47.7	1.7	46	4.2	**S.I**
Y	102.5	99.4	100.4	97.7	24.90%
Z	2.5	-0.6	0.4	-2.2	

g. 8MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	55.2	1.9	41.5	1.5	44.8
GAS	6.5	78	6.3	9.2	22
HOI	42.2	2.8	54	1.1	46
GLD	8.5	11.9	7.7	71.9	28.1
X	57.2	16.6	55.5	11.7	**S.I**
Y	112.3	94.6	109.5	83.6	35.20%
Z	12.4	-5.4	9.5	-16.4	

Notes: A VAR of order 8 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (q,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset q coming from innovations to asset j. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI** and **GLD** are acronyms for crude oil (WTI), natural gas, heating oil and gold, respectively.

Table 6: Volatility spillovers from asset (*j*) to asset (*q*) – Basket 1 [10MTHS]

a. 10MTHS - Full Sample Period

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	56.4	1.1	40	2.4	43.6
GAS	1.6	95.5	2	1	4.5
HOI	40.8	1.4	55.9	1.9	44.1
GLD	3.7	1	2.9	92.4	7.6
X	46.1	3.5	44.9	5.3	**S.I**
Y	102.5	99	100.8	97.7	24.90%
Z	2.5	-1	0.8	-2.3	

b. 10MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	61.4	1.5	36	1.1	38.6
GAS	1.6	95.8	2	0.6	4.2
HOI	36.1	1.5	61.6	0.9	38.4
GLD	1.1	0.7	1.5	96.7	3.3
X	38.7	3.7	39.5	2.6	**S.I**
Y	100.1	99.5	101.1	99.3	21.10%
Z	0.1	-0.5	1.1	-0.7	

e. 10MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	52	4.7	36.2	7	48
GAS	6.6	80	6	7.4	20
HOI	34.7	4.6	50.5	10.2	49.5
GLD	9.5	12	8.6	69.9	30.1
X	50.8	21.4	50.9	24.6	**S.I**
Y	102.8	101.3	101.4	94.5	36.90%
Z	2.8	1.4	1.4	-5.5	

c. 10MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	58.2	2.4	38.3	1.2	41.8
GAS	3.4	92	3.6	1	8
HOI	38.8	2.3	58.1	0.8	41.9
GLD	2	0.7	1.8	95.5	4.5
X	44.3	5.4	43.6	3	**S.I**
Y	102.4	97.3	101.7	98.5	24.10%
Z	2.5	-2.6	1.7	-1.5	

f. 10MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	48.2	4	39.8	8	51.8
GAS	7	81.5	7.6	3.8	18.5
HOI	40.6	4.2	48.5	6.7	51.5
GLD	11.2	3.9	9	75.9	24.1
X	58.8	12.1	56.4	18.5	**S.I**
Y	107	93.7	104.9	94.4	36.50%
Z	7	-6.4	4.9	-5.6	

d. 10MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	54.6	0.3	43.1	1.9	45.4
GAS	0.7	97.8	0.7	0.8	2.2
HOI	44	0.3	54.3	1.4	45.7
GLD	3.3	0.7	2.5	93.5	6.5
X	48.1	1.4	46.3	4.1	**S.I**
Y	102.7	99.2	100.5	97.6	25%
Z	2.7	-0.8	0.6	-2.4	

g. 10MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	52.3	7.8	38.3	1.6	47.7
GAS	6	83.7	6.4	3.9	16.3
HOI	39.5	8.1	51.2	1.2	48.8
GLD	8.8	3.9	9	78.3	21.7
X	54.4	19.8	53.7	6.6	**S.I**
Y	106.7	103.6	104.9	84.9	33.60%
Z	6.7	3.5	4.9	-15.1	

Notes: A VAR of order 8 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (q,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset q coming from innovations to asset j. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI** and **GLD** are acronyms for crude oil (WTI), natural gas, heating oil and gold, respectively.

Table 7: Volatility spillovers from asset (j) to asset (q) – Basket 1 [12MTHS]

a. 12MTHS - Full Sample Period

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	57	1	39.5	2.5	43
GAS	1.6	95.6	1.8	1	4.4
HOI	40.4	1.4	56.4	1.8	43.6
GLD	3.7	1	2.7	92.6	7.4
X	45.6	3.4	44.1	5.4	**S.I**
Y	102.6	99	100.4	98	24.60%
Z	2.6	-1	0.5	-2	

b. 12MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	63.1	1.7	34	1.1	36.9
GAS	1.9	95.4	1.6	1.2	4.6
HOI	34.3	1.7	63.1	0.9	36.9
GLD	1	1.1	1.1	96.8	3.2
X	37.1	4.5	36.7	3.2	**S.I**
Y	100.3	99.9	99.9	100	20.40%
Z	0.2	-0.1	-0.2	0	

e. 12MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	53.6	3.9	36.4	6.2	46.4
GAS	4.9	82.4	5.5	7.1	17.6
HOI	33.4	4.3	55.5	6.9	44.5
GLD	8.4	11.1	4.9	75.6	24.4
X	46.8	19.2	46.8	20.2	**S.I**
Y	100.3	101.7	102.2	95.8	33.20%
Z	0.4	1.6	2.3	-4.2	

c. 12MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	59.7	2.1	37.1	1.2	40.3
GAS	3.7	91.3	4.5	0.5	8.7
HOI	37.3	2.8	59	0.9	41
GLD	2	0.7	1.9	95.4	4.6
X	43	5.6	43.5	2.5	**S.I**
Y	102.6	96.9	102.5	97.9	23.70%
Z	2.7	-3.1	2.5	-2.1	

f. 12MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	48	4.8	39.3	8	52
GAS	7.5	79.6	7	5.9	20.4
HOI	40.6	4.4	48.5	6.6	51.5
GLD	10.9	3.9	8.7	76.4	23.6
X	59	13.1	55	20.5	**S.I**
Y	107	92.7	103.5	96.9	36.90%
Z	7	-7.3	3.5	-3.1	

d. 12MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	54.6	0.3	43.2	1.9	45.4
GAS	0.5	98.1	0.5	0.9	1.9
HOI	44.1	0.5	54.1	1.3	45.9
GLD	3.3	0.8	2.4	93.5	6.5
X	47.9	1.6	46	4.1	**S.I**
Y	102.5	99.7	100.1	97.6	24.90%
Z	2.5	-0.3	0.1	-2.4	

g. 12MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	*From (j)* OIL	GAS	HOI	GLD	From Others
OIL	52.9	4.4	41	1.6	47.1
GAS	4.9	81	4.4	9.7	19
HOI	42.7	3.9	52.4	1	47.6
GLD	9.5	5.7	9.6	75.3	24.7
X	57	13.9	55	12.4	**S.I**
Y	110	95	107.4	87.6	34.60%
Z	9.9	-5.1	7.4	-12.3	

Notes: A VAR of order 8 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (q,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset q coming from innovations to asset j. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI** and **GLD** are acronyms for crude oil (WTI), natural gas, heating oil and gold, respectively.

Table 8: Volatility spillovers from asset (j) to asset (q) – Basket 2 [3MTHS]

a. 3MTHS - Full Sample Period

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	57.3	1.4	36.4	0.7	0.8	1	2.5	42.7
GAS	2.2	93.4	3	0.2	0.3	0.5	0.5	6.6
HOI	37.1	2	56.5	0.4	0.4	1	2.6	43.5
WHT	1	0.1	0.7	74.1	13.4	6.1	4.5	25.9
CRN	0.9	0.1	0.5	11.7	66.2	14.1	6.4	33.8
SOY	1.1	0.2	1.1	4.9	12.6	60.5	19.5	39.5
SOI	2.6	0.3	2.8	4	6.2	21	63.2	36.8
X	44.9	4.2	44.4	21.9	33.7	43.7	36.1	**S.I**
Y	102.2	97.6	100.9	96	99.9	104.2	99.2	32.70%
Z	2.2	-2.4	0.9	-4	-0.1	4.2	-0.7	

b. 3MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	60.3	0.9	37.3	0.3	0.5	0.4	0.4	39.7
GAS	1.7	94.7	2.1	0.2	0.5	0.4	0.3	5.3
HOI	37.1	1.4	60.4	0.1	0.1	0.4	0.4	39.6
WHT	0.5	0.4	0.2	85.6	6.6	4.4	2.3	14.4
CRN	0.6	0.3	0.4	5.5	73.6	13.5	6.2	26.4
SOY	0.4	0.1	0.5	3.5	12	67.3	16.2	32.7
SOI	0.5	0.6	0.5	1.9	5.9	18.3	72.3	27.7
X	41	3.6	40.9	11.5	25.6	37.3	25.8	**S.I**
Y	101.3	98.4	101.3	97.1	99.2	104.6	98.1	26.50%
Z	1.3	-1.7	1.3	-2.9	-0.8	4.6	-1.9	

e. 3MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
	50.2	3	42	0.8	0.4	2.2	1.3	49.8
	7.9	77.2	6.9	2.7	1.6	1.9	1.9	22.8
	40.3	2	52.6	1.3	0.7	1.9	1.2	47.4
	1.9	1.8	3.1	60.8	16	10.2	6.3	39.2
	1.5	1.8	2.3	12.4	58.6	14.8	8.6	41.4
	3.8	0.9	3.6	8.7	15.5	51.1	16.4	48.9
	6.8	2.9	4.3	3.4	7.3	17.4	57.9	42.1
X	62.1	12.4	62.2	29.3	41.5	48.3	35.7	**S.I**
Y	112.3	89.6	114.8	90.1	100.2	99.4	93.7	41.70%
Z	12.3	-10	14.8	-9.9	0.1	-0.6	-6.4	

c. 3MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	57.5	2.4	37.4	0.7	0.5	0.5	1	42.5
GAS	4	87.5	5.1	0.5	0.8	1	1.2	12.5
HOI	37.2	3.2	56.9	0.8	0.8	0.4	0.7	43.1
WHT	1.3	0.3	0.7	76.5	14.7	3.5	3	23.5
CRN	0.3	0.6	0.4	12.1	70.1	11	5.6	29.9
SOY	0.3	0.3	0.1	3	10.1	63.5	22.5	36.5
SOI	0.9	0.5	0.6	2.7	5.8	23.6	65.9	34.1
X	44	7.3	44.4	19.8	32.7	40	34	**S.I**
Y	101.5	94.8	101.3	96.2	102.7	103.5	100	31.70%
Z	1.5	-5.2	1.3	-3.7	2.8	3.5	-0.1	

f. 3MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	40	3.7	30.9	4.2	6.1	5.7	9.3	60
GAS	7.5	74.9	8.5	2.2	2.9	1.6	2.4	25.1
HOI	33.4	4.2	41.8	2.9	4.2	5.1	8.3	58.2
WHT	6	1.4	3.7	52.1	13.5	11	12.3	47.9
CRN	7.4	1.8	4.9	11.4	44.6	16.9	13	55.4
SOY	6.3	0.9	5.3	8.7	15	40.1	23.7	59.9
SOI	9.7	1.1	8.6	8.9	11.4	22.3	38	62
X	70.4	13.1	61.9	38.4	53.2	62.6	68.9	**S.I**
Y	110.4	88	103.7	90.5	97.7	102.7	107	52.60%
Z	10.4	-12	3.7	-9.5	-2.2	2.7	6.9	

d. 3MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	55.8	0.9	39	0.5	0.5	1	2.2	44.2
GAS	1.1	96.1	0.8	0.3	0.3	0.9	0.6	3.9
HOI	39.5	0.7	55.1	0.4	0.5	1.2	2.7	44.9
WHT	0.5	0.3	0.4	73.8	16.4	5.5	3.1	26.2
CRN	0.4	0.3	0.4	15.2	65.7	14.1	4	34.3
SOY	1.2	0.7	1.4	5.1	13.2	63.8	14.5	36.2
SOI	2.4	0.5	3.3	3.3	4.3	16.7	69.5	30.5
X	45	3.4	45.3	24.8	35.3	39.3	27.1	**S.I**
Y	100.9	99.5	100.4	98.6	101	103.1	96.5	31.50%
Z	0.8	-0.5	0.4	-1.4	1	3.1	-3.4	

g. 3MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	53.6	1.2	34.8	0.6	3.4	1	5.4	46.4
GAS	4.5	79.3	3.9	3.5	5.2	1.4	2.2	20.7
HOI	36.7	0.6	52.1	1.6	1.4	1.5	6.1	47.9
WHT	2.5	1.2	0.8	73.8	13.2	5	3.5	26.2
CRN	4.3	0.7	2.4	10.5	66.8	11.5	3.9	33.2
SOY	1.6	0.7	2.4	4.9	13.4	62.3	14.7	37.7
SOI	8.1	1.6	8	3.9	3.9	12.6	62	38
X	57.6	6.1	52.3	24.9	40.6	32.9	35.8	**S.I**
Y	111.2	85.3	104.4	98.7	107.4	95.2	97.8	35.70%
Z	11.2	-15	4.4	-1.3	7.4	-4.8	-2.2	

Notes: A VAR of order 5 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (q,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset q coming from innovations to asset j. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI**, **WHT**, **CRN**, **SOY** and **SOI** are acronyms for crude oil (WTI), natural gas, heating oil, wheat, corn, soybean and soybean oil, respectively.

Table 9: Volatility spillovers from asset (j) to asset (q) – Basket 2 [5MTHS]

a. 5MTHS - Full Sample Period²

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	54.8	1.7	37.8	0.9	0.8	1.2	2.8	45.2
GAS	2.7	92.5	3	0.3	0.4	0.4	0.6	7.5
HOI	38.4	2.1	54.3	0.7	0.6	1.3	2.7	45.7
WHT	1.3	0.2	0.9	69.3	16.1	7.3	4.9	30.7
CRN	0.9	0.3	0.6	14	62.9	14.4	6.8	37.1
SOY	1.3	0.3	1.3	6.1	13.3	58.1	19.6	41.9
SOI	2.9	0.5	2.9	4.4	7	21.4	61	39
X	47.5	5.1	46.5	26.4	38.2	46	37.4	**S.I**
Y	102.3	97.6	100.8	95.7	101.1	104.1	98.5	35.30%
Z	2.3	-2.4	0.8	-4.3	1.1	4.1	-1.6	

b. 5MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	59.8	1.2	37.4	0.4	0.5	0.3	0.4	40.2
GAS	2.8	91.7	3.1	0.8	0.9	0.2	0.4	8.3
HOI	36.8	1.7	59.9	0.2	0.4	0.4	0.6	40.1
WHT	0.4	0.3	0.3	75.6	13	6.7	3.6	24.4
CRN	0.8	0	0.8	10.1	65.7	15.8	6.8	34.3
SOY	0.5	0	0.6	4.8	14.9	62.6	16.6	37.4
SOI	0.5	0.3	0.6	2.5	7.3	19.6	69.1	30.9
X	41.8	3.5	42.8	18.7	37.2	43.2	28.4	**S.I**
Y	101.6	95.3	102.6	94.3	102.8	105.8	97.5	30.80%
Z	1.6	-4.8	2.7	-5.7	2.9	5.8	-2.5	

e. 5MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	51.8	3	41	1.8	0.4	1.2	0.9	48.2
GAS	4.4	81.6	4.3	4.9	2.1	1.4	1.3	18.4
HOI	40.4	1.8	53.6	1.9	0.6	1.1	0.7	46.4
WHT	2	3.7	2.6	58.3	16.8	10.7	5.8	41.7
CRN	2	3.5	3.3	13.9	55.9	14.7	6.8	44.1
SOY	3.9	3.4	4.3	9.9	14.6	47.3	16.5	52.7
SOI	6.8	1.8	4.5	4.9	6.6	18.1	57.3	42.7
X	59.5	17.1	60	37.2	41.1	47.2	32	**S.I**
Y	111.3	98.7	113.6	95.5	97	94.5	89.4	42%
Z	11.3	-1.3	13.6	-4.5	-3	-5.5	-10.7	

c. 5MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	56.1	2.5	38.3	0.8	0.5	0.6	1.2	43.9
GAS	4.1	89.3	4.4	0.6	0.5	0.7	0.4	10.7
HOI	38.5	2.8	56	0.9	0.7	0.4	0.7	44
WHT	1.3	0.2	0.9	72.8	16.3	5.2	3.2	27.2
CRN	0.4	0.4	0.6	13.8	69	10.3	5.5	31
SOY	0.6	0.1	0.3	4.5	9.4	61.9	23.1	38.1
SOI	1.1	0.4	0.7	3	5.7	24.6	64.6	35.4
X	46	6.5	45.2	23.6	33.1	41.8	34.1	**S.I**
Y	102.1	95.8	101.1	96.4	102.1	103.7	98.7	32.90%
Z	2.1	-4.2	1.2	-3.6	2.1	3.7	-1.3	

f. 5MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	38.7	3.5	31.9	4.3	6	6	9.5	61.3
GAS	7	76.9	7.2	1.9	2.6	2	2.4	23.1
HOI	34.5	3.9	40.7	3	4.4	5.3	8.2	59.3
WHT	6.5	1.4	4.2	51.9	13.1	11	11.9	48.1
CRN	7.2	1.5	4.9	11.3	45.3	16.9	13	54.7
SOY	6.7	0.9	5.6	8.9	14.7	39.8	23.4	60.2
SOI	10.2	1.1	8.6	8.8	11.2	22	38	62
X	72.2	12.4	62.3	38.2	52	63.1	68.5	**S.I**
Y	110.9	89.3	103	90.2	97.2	102.9	106.5	52.70%
Z	10.9	-11	3	-9.9	-2.7	2.9	6.5	

d. 5MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	54.3	0.8	40.7	0.5	0.4	1.1	2.2	45.7
GAS	1	95.7	0.8	0.6	0.4	0.7	0.8	4.3
HOI	40.9	0.7	53.5	0.4	0.5	1.2	2.7	46.5
WHT	0.7	0.4	0.6	71.7	17.9	5.7	3.1	28.3
CRN	0.3	0.6	0.3	16.1	63.7	14.5	4.5	36.3
SOY	1.3	0.7	1.4	5.4	13.8	62.5	14.9	37.5
SOI	2.4	0.5	3.4	3.4	5.1	17.2	67.9	32.1
X	46.6	3.7	47.2	26.6	38.1	40.4	28.1	**S.I**
Y	100.9	99.4	100.8	98.2	101.9	102.9	96	32.90%
Z	0.9	-0.6	0.7	-1.7	1.8	2.9	-4	

g. 5MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	51.9	2.1	35.7	0.6	2	1	6.6	48.1
GAS	6.7	78.6	4.2	2.2	3.4	0.9	3.9	21.4
HOI	38.7	1.4	50.9	1.3	0.7	0.8	6.2	49.1
WHT	3.2	1.1	2.1	72.4	9.9	7	4.3	27.6
CRN	3.1	6	1.8	7.6	63	14.7	3.8	37
SOY	1.5	2.5	1.8	5.5	14.7	58.8	15.2	41.2
SOI	10	1.3	7.8	5.1	4	13.4	58.4	41.6
X	63.3	14.4	53.5	22.3	34.7	37.8	39.9	**S.I**
Y	115.2	93	104.4	94.7	97.7	96.5	98.3	38%
Z	15.2	-7	4.4	-5.3	-2.3	-3.4	-1.7	

Notes: A VAR of order 5 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (q,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset q coming from innovations to asset j. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI**, **WHT**, **CRN**, **SOY** and **SOI** are acronyms for crude oil (WTI), natural gas, heating oil, wheat, corn, soybean and soybean oil, respectively.

Table 10: Volatility spillovers from asset (*j*) to asset (*q*) – Basket 2 [7MTHS]

a. 7MTHS - Full Sample Period

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	54	1.4	38.5	0.9	0.9	1.4	2.9	46
GAS	2.2	92.6	3	0.3	0.6	0.6	0.8	7.4
HOI	39.1	1.9	53.5	0.6	0.7	1.4	2.8	46.5
WHT	1.3	0.3	1	70	14.8	7.4	5.1	30
CRN	1	0.4	0.7	12.5	62	16	7.3	38
SOY	1.5	0.4	1.5	5.7	14.7	56.6	19.6	43.4
SOI	3	0.6	2.9	4.4	7.5	21.5	60	40
X	48.2	5	47.6	24.4	39.2	48.3	38.5	**S.I**
Y	102.2	97.5	101.2	94.4	101.2	105	98.5	35.90%
Z	2.2	-2.4	1.1	-5.6	1.2	4.9	-1.5	

b. 7MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	59.9	1.2	37.5	0.4	0.3	0.3	0.4	40.1
GAS	3.1	90.6	3.7	0.9	1	0.3	0.5	9.4
HOI	37	1.8	60.1	0.1	0.3	0.3	0.5	39.9
WHT	0.4	0.5	0.3	76	10.8	7.6	4.5	24
CRN	0.5	0.1	0.6	8	66.6	16.6	7.6	33.4
SOY	0.5	0.1	0.5	5.2	15.7	60.7	17.4	39.3
SOI	0.6	0.1	0.6	3	8.1	20.6	67	33
X	42.1	3.8	43.2	17.5	36.2	45.6	30.8	**S.I**
Y	102	94.4	103.3	93.5	102.8	106.3	97.8	31.30%
Z	2	-5.6	3.3	-6.5	2.8	6.3	-2.2	

e. 7MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	52.2	4.4	39.6	0.7	0.4	1.6	1	47.8
GAS	4.2	81.1	4.5	5.3	1.9	1.6	1.3	18.9
HOI	39.3	2.6	53.9	0.6	0.6	1.5	1.4	46.1
WHT	1.3	3.4	2	61.6	18.6	7.9	5.2	38.4
CRN	1.4	3.9	2.3	14.7	59.2	12.2	6.2	40.8
SOY	4	2.3	4.8	7.8	11.9	53.3	15.9	46.7
SOI	7.1	1.6	5.2	4.7	5.3	16.9	59.2	40.8
X	57.4	18.2	58.4	33.8	38.8	41.9	31	**S.I**
Y	109.6	99.3	112.3	95.4	98	95.1	90.2	39.90%
Z	9.6	-0.7	12.3	-4.6	-2	-4.8	-9.8	

c. 7MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	56	2.1	38.4	0.9	0.6	0.8	1	44
GAS	3.3	88.7	4.3	0.8	0.7	1.1	1	11.3
HOI	38.5	2.8	55.9	0.9	0.7	0.6	0.6	44.1
WHT	1	0.2	0.8	74	15.3	5.5	3.2	26
CRN	0.5	0.4	0.6	13	67.8	12.2	5.5	32.2
SOY	0.8	0.3	0.7	4.5	11	60.3	22.3	39.7
SOI	1	0.5	0.7	2.9	5.8	24.3	64.7	35.3
X	45.1	6.4	45.6	23	34.2	44.5	33.6	**S.I**
Y	101.2	95.1	101.6	97	102	104.9	98.2	33.20%
Z	1.1	-4.9	1.5	-3	2	4.8	-1.7	

f. 7MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	38.6	4.3	31.9	2.6	5.8	7	9.8	61.4
GAS	8.8	70.8	9.3	1.1	3.5	3.6	2.9	29.2
HOI	34.6	4.7	40.7	1.7	4.2	5.7	8.4	59.3
WHT	5.2	1	3.4	61.4	11.4	7.7	9.9	38.6
CRN	7.1	2.2	4.6	8.1	46.2	18.1	13.7	53.8
SOY	7.5	2	6	5.1	15.5	40.6	23.4	59.4
SOI	10.8	1.7	9	6.3	11.5	22	38.8	61.2
X	74	15.9	64.2	24.8	51.9	64.1	68.1	**S.I**
Y	112.6	86.7	104.9	86.2	98	104.6	107	51.90%
Z	12.6	-13	4.9	-13.8	-1.9	4.7	6.9	

d. 7MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	53.6	0.4	41.6	0.6	0.6	1.2	2.1	46.4
GAS	0.5	96.8	0.4	0.7	0.4	0.6	0.7	3.2
HOI	41.8	0.4	52.7	0.5	0.6	1.3	2.7	47.3
WHT	0.8	0.6	0.7	71.1	17.3	6.2	3.3	28.9
CRN	0.4	0.7	0.4	15.3	61.9	16.1	5.1	38.1
SOY	1.3	0.5	1.4	5.7	15.7	60.1	15.3	39.9
SOI	2.3	0.4	3.4	3.6	5.9	17.9	66.5	33.5
X	47.1	2.9	47.9	26.4	40.5	43.3	29.2	**S.I**
Y	100.7	99.7	100.6	97.5	102.4	103.4	95.7	33.90%
Z	0.7	-0.3	0.6	-2.5	2.4	3.4	-4.3	

g. 7MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	51.3	2.5	35.5	1.2	1.5	0.8	7.2	48.7
GAS	8.4	78.4	5.5	2.3	2	0.6	2.9	21.6
HOI	38.3	3.5	48.1	1.5	1.1	0.9	6.6	51.9
WHT	3.9	1.4	3	72.4	9.7	5.5	4.1	27.6
CRN	2.2	1.1	1.6	7.9	62	20.3	5.1	38
SOY	1.4	0.6	2	4.1	19.4	58	14.6	42
SOI	10.7	1.1	9	4.2	5.1	13.3	56.5	43.5
X	64.9	10.2	56.6	21.1	38.8	41.4	40.4	**S.I**
Y	116.2	88.5	104.7	93.5	100.7	99.4	97	39.10%
Z	16.2	-11	4.7	-6.5	0.8	-0.6	-3.1	

Notes: A VAR of order 5 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (*q*,*j*)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset *q* coming from innovations to asset *j*. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI**, **WHT**, **CRN**, **SOY** and **SOI** are acronyms for crude oil (WTI), natural gas, heating oil, wheat, corn, soybean and soybean oil, respectively.

Table 11: Volatility spillovers from asset (*j*) to asset (*q*) – Basket 2 [9MTHS]

a. 9MTHS - Full Sample Period

To (q)	From (j) OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	53.7	1.1	38.6	1	0.9	1.7	3	46.3
GAS	2	93.4	2.4	0.5	0.3	0.5	0.8	6.6
HOI	39.3	1.5	53.3	0.8	0.7	1.6	2.9	46.7
WHT	1.4	0.5	1.2	68	15.5	7.7	5.8	32
CRN	1.1	0.4	0.8	13.4	61.5	15.2	7.6	38.5
SOY	1.7	0.4	1.6	6.1	14.4	56.3	19.4	43.7
SOI	3.1	0.6	3.1	5	7.8	21.1	59.4	40.6
X	48.6	4.4	47.6	26.8	39.8	47.8	39.4	**S.I**
Y	102.3	97.9	100.9	94.8	101.2	104.1	98.8	36.30%
Z	2.3	-2.2	0.9	-5.2	1.3	4.1	-1.2	

b. 9MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	From (j) OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	60.5	1	37	0.5	0.4	0.2	0.4	39.5
GAS	1.9	94	2.7	0.3	0.5	0.3	0.2	6
HOI	36.5	1.5	60.5	0.4	0.3	0.3	0.6	39.5
WHT	0.3	0.2	0.5	75.4	10.7	7.3	5.5	24.6
CRN	0.4	0.2	0.3	8.1	65.4	17.5	8.2	34.6
SOY	0.4	0	0.4	4.9	16.3	59.5	18.5	40.5
SOI	0.4	0.2	0.5	3.7	8.6	21.2	65.4	34.6
X	40	3.1	41.4	17.9	36.8	46.6	33.3	**S.I**
Y	100.6	97.1	101.9	93.4	102.2	106.2	98.7	31.30%
Z	0.5	-2.9	1.9	-6.7	2.2	6.1	-1.3	

c. 9MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	From (j) OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	56.6	2.4	37.9	0.6	0.5	0.9	1.1	43.4
GAS	3.9	89.9	3.9	0.2	0.4	0.6	1.2	10.1
HOI	38.2	2.3	56.8	0.7	0.7	0.5	0.7	43.2
WHT	0.6	0.2	1	76.8	14.3	3.9	3.1	23.2
CRN	0.4	0.2	0.6	11.8	69.8	11.9	5.2	30.2
SOY	1	0.3	0.7	3.4	11.3	63.2	20.1	36.8
SOI	1.2	0.5	0.9	2.8	5.6	21.5	67.4	32.6
X	45.4	5.8	45	19.6	32.8	39.4	31.5	**S.I**
Y	102	95.7	101.8	96.4	102.6	102.6	98.9	31.40%
Z	2	-4.3	1.8	-3.6	2.6	2.6	-1.1	

d. 9MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	From (j) OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	53.1	0.4	41.9	0.7	0.5	1.3	2.1	46.9
GAS	0.6	96.6	0.6	0.6	0.4	0.5	0.7	3.4
HOI	41.9	0.4	52.1	0.7	0.6	1.5	2.8	47.9
WHT	0.8	0.9	0.8	68.9	17.9	6.9	3.8	31.1
CRN	0.5	1	0.5	16	61.9	14.6	5.6	38.1
SOY	1.4	0.3	1.6	6.4	14.1	59.7	16.3	40.3
SOI	2.3	0.4	3.4	4.2	6.3	18.8	64.6	35.4
X	47.5	3.4	48.7	28.6	39.9	43.5	31.3	**S.I**
Y	100.6	100.1	100.8	97.5	101.8	103.3	95.9	34.70%
Z	0.6	0	0.8	-2.5	1.8	3.2	-4.1	

e. 9MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	From (j) OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	53	4	38	1.3	0.7	1.9	1.1	47
GAS	4.8	81.1	5.5	2.7	2.5	1.4	2	18.9
HOI	36.3	3.1	54.3	0.9	1.5	2.6	1.3	45.7
WHT	1.4	2.5	2.4	62.7	17.3	9	4.7	37.3
CRN	1.3	3.5	1.8	11.7	60.6	14.2	6.9	39.4
SOY	4.2	2.5	3.5	8.1	14.2	56.9	10.7	43.1
SOI	7.1	2.1	5.9	4.9	5.6	12	62.5	37.5
X	55.1	17.6	57	29.5	41.8	41.1	26.8	**S.I**
Y	108.1	98.8	111.3	92.1	102.4	98	89.3	38.40%
Z	8.1	-1.3	11.3	-7.8	2.4	-2	-10.7	

f. 9MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	From (j) OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	39	2.5	32.1	3.8	5.7	7.2	9.7	61
GAS	6.1	81	6.7	2.1	1.2	0.9	2	19
HOI	34.7	2.9	40.8	2.6	4.3	5.9	8.8	59.2
WHT	5.7	1.5	3.6	51.9	13.5	11.4	12.5	48.1
CRN	6.9	0.9	4.3	11.6	46.2	17.3	12.8	53.8
SOY	7.5	0.7	5.8	8.7	15.5	39.8	22	60.2
SOI	10.5	0.8	9.2	9	10.7	21.2	38.6	61.4
X	71.3	9.4	61.8	37.7	50.8	63.9	67.8	**S.I**
Y	110.3	90.4	102.6	89.7	97	103.7	106.3	51.80%
Z	10.3	-9.6	2.6	-10.4	-3	3.7	6.4	

g. 9MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	From (j) OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	51.9	1.9	36.7	0.8	1.2	0.5	7.1	48.1
GAS	4.9	82.3	3.5	4	2.8	0.4	2.2	17.7
HOI	39.6	1	49.9	0.9	1.1	0.5	7	50.1
WHT	4.4	0.7	2.8	72.9	9.8	5.5	4	27.1
CRN	1.6	5.1	2.1	8	60.8	17.3	5	39.2
SOY	1.8	2.6	2.8	4	17.8	59.5	11.5	40.5
SOI	10.5	1.1	9.5	3.1	5.2	10.7	59.9	40.1
X	62.8	12.4	57.4	20.8	37.7	34.9	36.7	**S.I**
Y	114.7	94.7	107.3	93.7	98.5	94.5	96.6	37.50%
Z	14.7	-5.3	7.3	-6.3	-1.5	-5.6	-3.4	

Notes: A VAR of order 5 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (q,j)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset q coming from innovations to asset j. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI**, **WHT**, **CRN**, **SOY** and **SOI** are acronyms for crude oil (WTI), natural gas, heating oil, wheat, corn, soybean and soybean oil, respectively.

Table 12: Volatility spillovers from asset (*j*) to asset (*q*) – Basket 2 [12MTHS]

a. 12MTHS - Full Sample Period

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	54	1	37.8	1.2	1.1	2	3	46
GAS	1.6	94.5	1.9	0.4	0.4	0.5	0.6	5.5
HOI	38.5	1.4	53.6	1	0.8	1.8	2.8	46.4
WHT	1.6	0.4	1.4	67.4	15.3	8	5.9	32.6
CRN	1.2	0.3	0.9	13	60.6	16.2	7.7	39.4
SOY	1.9	0.4	1.8	6.5	15.4	55.9	18.1	44.1
SOI	3.1	0.5	2.9	5.3	8.1	20.3	59.7	40.3
X	48.1	4	46.7	27.5	41.1	48.8	38.1	**S.I**
Y	102.1	98.5	100.3	94.9	101.7	104.7	97.9	36.30%
Z	2.1	-1.5	0.3	-5.1	1.7	4.7	-2.2	

b. 12MTHS – Tranquil Period 1 [Jan 4th, 1995 – Mar 1st, 2001]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	63.2	1.1	34.3	0.2	0.4	0.3	0.5	36.8
GAS	1.9	94.8	1.6	0.3	0.9	0.4	0.1	5.2
HOI	33.8	1.4	62.7	0.4	0.5	0.5	0.7	37.3
WHT	0.6	0.4	1.1	78.7	9.7	5.1	4.4	21.3
CRN	0.4	0.1	0.5	6.8	63.8	19.5	8.9	36.2
SOY	0.4	0.1	0.5	3.6	19	59.9	16.4	40.1
SOI	0.5	0.4	0.7	3.1	9.5	18.7	67.1	32.9
X	37.6	3.4	38.7	14.4	40	44.6	31.1	**S.I**
Y	100.7	98.2	101.4	93.1	103.8	104.6	98.2	30%
Z	0.8	-1.8	1.4	-6.9	3.8	4.5	-1.8	

e. 12MTHS – Crisis Period 1 [Mar 1st, 2001 – Nov 30th, 2001]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	52.9	3.8	36.1	3.1	1.2	1.8	1.1	47.1
GAS	3.2	83.7	4.5	2.8	2.2	1.4	2.1	16.3
HOI	34.6	3.1	57	2.4	1.5	1	0.5	43
WHT	1.5	4.5	2.4	65.7	14.7	6.4	4.9	34.3
CRN	1.1	2.4	1.1	8.2	67.9	14.4	5.1	32.1
SOY	4.1	2.4	3.4	6.1	14.3	57.6	12.2	42.4
SOI	5.7	1.8	4.4	4	6.1	14.1	63.8	36.2
X	50.2	17.9	51.9	26.7	39.9	39.1	25.8	**S.I**
Y	103.1	101.6	108.9	92.4	107.8	96.7	89.5	35.90%
Z	3.1	1.6	8.9	-7.6	7.8	-3.3	-10.4	

c. 12MTHS – Tranquil Period 2 [Dec 1st, 2001 – Nov 30th, 2007]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	58.3	2	36.5	0.7	0.5	0.9	1.1	41.7
GAS	3.3	89.4	4.1	0.7	0.9	1	0.5	10.6
HOI	36.8	2.6	58.2	0.7	0.7	0.3	0.7	41.8
WHT	0.9	0.1	0.8	76.3	13.6	5.5	2.8	23.7
CRN	0.4	0.2	0.6	11.6	70.8	12.3	4.1	29.2
SOY	0.9	0.2	0.5	4.7	11.5	66.2	16	33.8
SOI	1.4	0.1	0.9	2.9	4.6	17.9	72.2	27.8
X	43.7	5.2	43.4	21.3	31.8	37.8	25.2	**S.I**
Y	102.1	94.6	101.7	97.6	102.7	104	97.4	29.80%
Z	2	-5.4	1.6	-2.4	2.6	4	-2.6	

f. 12MTHS – Crisis Period 2 [Dec 1st, 2007 – Jun 30th, 2009]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	38.7	3.7	31.1	3.8	5.7	7.4	9.6	61.3
GAS	6.9	72.6	6.3	2.7	2.8	3.8	4.9	27.4
HOI	34.1	3.6	40.6	2.6	4.3	6.4	8.4	59.4
WHT	5.5	1.5	3.5	52.5	13	11.5	12.5	47.5
CRN	6.8	1.3	4.1	10.8	45.4	17.9	13.7	54.6
SOY	7.5	2.7	6.1	8.4	15.7	38.4	21.2	61.6
SOI	10.1	3.1	8.2	8.7	11.1	20.9	37.8	62.2
X	70.8	16	59.2	37	52.7	68	70.3	**S.I**
Y	109.5	88.5	99.9	89.5	98.1	106.4	108.1	53.40%
Z	9.5	-11.4	-0.2	-10.5	-1.9	6.4	8.1	

d. 12MTHS – Tranquil Period 3 [Jul 1st, 2009 – Jan 31st, 2020]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	52.9	0.3	42	0.8	0.6	1.3	2	47.1
GAS	0.4	97.6	0.4	0.6	0.3	0.3	0.4	2.4
HOI	42.1	0.4	52	0.8	0.6	1.5	2.6	48
WHT	0.9	0.4	1	68	18.8	6.7	4.1	32
CRN	0.5	0.7	0.5	16.2	60.5	15.8	5.7	39.5
SOY	1.4	0.3	1.6	6.1	15.6	58.6	16.3	41.4
SOI	2.1	0.3	3.2	4.4	7	19.1	63.8	36.2
X	47.5	2.5	48.8	29	42.9	44.7	31.2	**S.I**
Y	100.4	100.1	100.8	97	103.5	103.3	95	35.20%
Z	0.4	0.1	0.8	-3	3.4	3.3	-5	

g. 12MTHS – Crisis Period 3 [Feb 1st, 2020 – Dec 11th, 2020]

To (q)	*From (j)* OIL	GAS	HOI	WHT	CRN	SOY	SOI	From Others
OIL	51.2	2.4	37.2	0.8	1.1	1.6	5.6	48.8
GAS	5.9	78.9	5.1	5.7	1.8	1.8	0.9	21.1
HOI	39.9	1.8	48.7	1	1.3	1.4	5.8	51.3
WHT	4.7	0.9	3.3	75.1	6.5	4.9	4.6	24.9
CRN	1.6	3.2	1.3	6	61.3	21.5	5.1	38.7
SOY	5.4	2	5.5	2.4	19.3	53.4	11.9	46.6
SOI	8.2	1.1	8.2	2.4	6.4	13.5	60.2	39.8
X	65.7	11.5	60.5	18.4	36.3	44.7	34	**S.I**
Y	117	90.4	109.2	93.5	97.6	98.1	94.2	38.70%
Z	16.9	-9.6	9.2	-6.5	-2.4	-1.9	-5.8	

Notes: A VAR of order 5 was selected: the Bayesian Information Criterion was used to choose the lag order. Variance decompositions are based on 10-days-ahead forecasts, as in Diebold and Yilmaz (2012). The (*q*,*j*)-th value is the estimated contribution to the variance of the 10-days-ahead stock volatility forecast error of asset *q* coming from innovations to asset *j*. **X**, **W** and **Z** stand for "contribution to others", "contribution to others including own", and "net spillovers", respectively. **OIL**, **GAS**, **HOI**, **WHT**, **CRN**, **SOY** and **SOI** are acronyms for crude oil (WTI), natural gas, heating oil, wheat, corn, soybean and soybean oil, respectively.

Table 13: Correlation between net time-varying spillovers for the different maturities

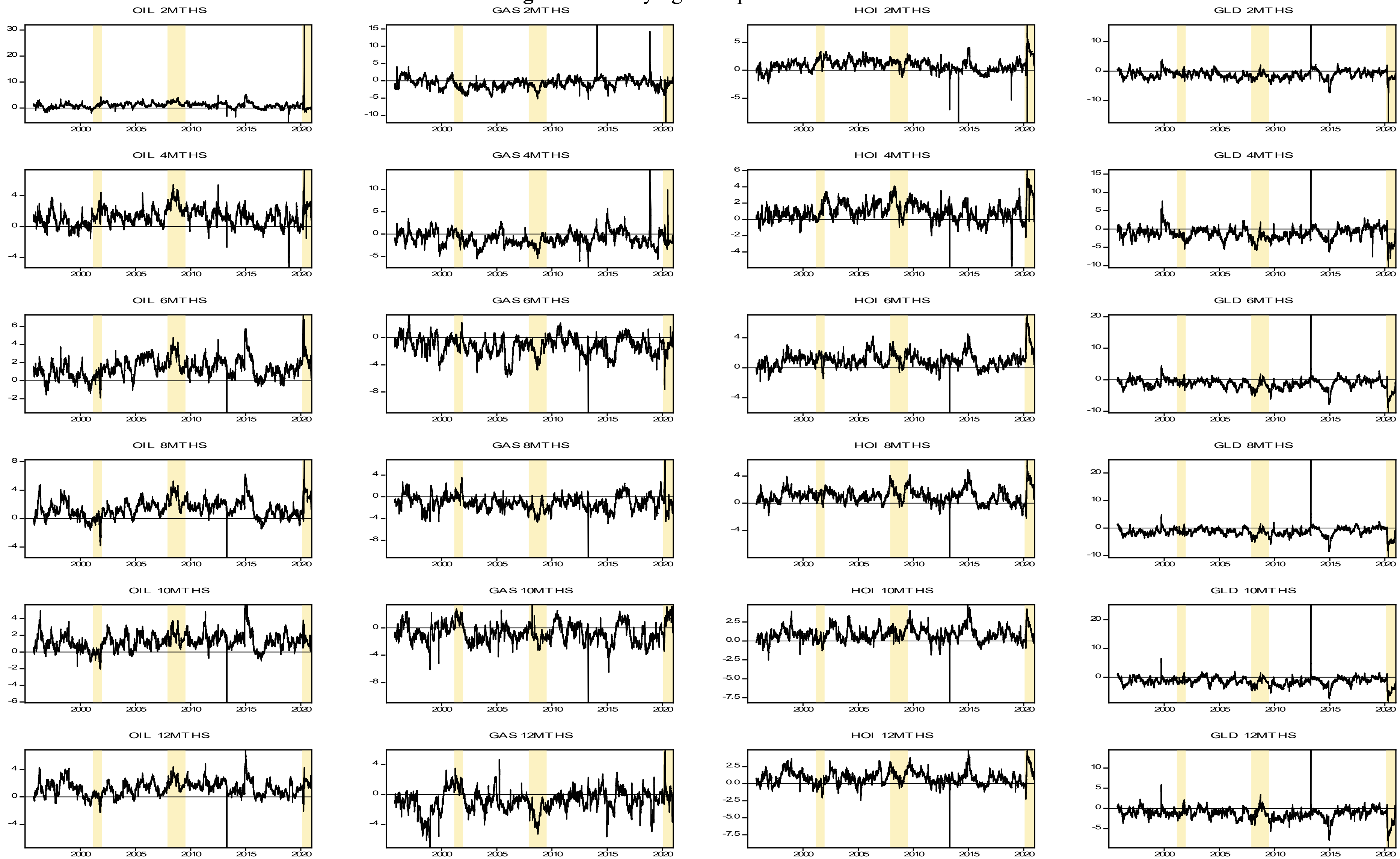
a. Basket 1

2MTHS				8MTHS			
	OIL	**GAS**	**HOI**		**OIL**	**GAS**	**HOI**
GAS	-0.526616			**GAS**	-0.663895		
HOI	0.303385	-0.536956		**HOI**	0.594025	-0.561774	
GLD	-0.521454	-0.186814	-0.472562	**GLD**	-0.664703	0.05825	-0.700436
4MTHS				10MTHS			
	OIL	**GAS**	**HOI**		**OIL**	**GAS**	**HOI**
GAS	-0.494571			**GAS**	-0.539008		
HOI	0.62922	-0.57778		**HOI**	0.539787	-0.452097	
GLD	-0.612193	-0.247077	-0.529897	**GLD**	-0.514824	-0.297451	-0.572503
6MTHS				12MTHS			
	OIL	**GAS**	**HOI**		**OIL**	**GAS**	**HOI**
GAS	-0.542736			GAS	-0.676886		
HOI	0.561095	-0.456121		HOI	0.573837	-0.534676	
GLD	-0.573818	-0.214204	-0.635766	GLD	-0.487417	-0.147692	-0.615003

b. Basket 2

3MTHS						
	OIL	**GAS**	**HOI**	**WHT**	**CRN**	**SOY**
GAS	-0.328274					
HOI	0.649961	-0.169839				
WHT	-0.310483	-0.065652	-0.396095			
CRN	-0.222628	-0.160127	-0.165754	-0.042484		
SOY	-0.440531	-0.248581	-0.423387	-0.172529	-0.049526	
SOI	-0.159726	-0.2131	-0.298904	-0.19752	-0.390196	0.34873
5MTHS						
	OIL	**GAS**	**HOI**	**WHT**	**CRN**	**SOY**
GAS	-0.32895					
HOI	0.61584	-0.173725				
WHT	-0.42716	0.193214	-0.362012			
CRN	-0.43419	0.064179	-0.235385	0.17031		
SOY	-0.245753	-0.440517	-0.415737	-0.242789	-0.213758	
SOI	0.086712	-0.438118	-0.129981	-0.419821	-0.507144	0.44004
7MTHS						
	OIL	**GAS**	**HOI**	**WHT**	**CRN**	**SOY**
GAS	-0.473981					
HOI	0.693712	-0.294251				
WHT	-0.345546	0.162076	-0.236708			
CRN	-0.431358	0.033755	-0.297101	0.274447		
SOY	-0.161682	-0.304383	-0.368154	-0.444097	-0.261878	
SOI	-0.097677	-0.2198	-0.278777	-0.513685	-0.379455	0.471304
9MTHS						
	OIL	**GAS**	**HOI**	**WHT**	**CRN**	**SOY**
GAS	-0.174411					
HOI	0.700022	-0.085818				
WHT	-0.396775	-0.064753	-0.335317			
CRN	-0.543024	-0.027546	-0.377564	0.224852		
SOY	-0.209129	-0.462515	-0.344122	-0.244142	-0.110209	
SOI	-0.080341	-0.387727	-0.278522	-0.352811	-0.317364	0.433651
12MTHS						
	OIL	**GAS**	**HOI**	**WHT**	**CRN**	**SOY**
GAS	-0.398662					
HOI	0.679574	-0.259496				
WHT	-0.368075	0.030077	-0.295776			
CRN	-0.448404	0.018404	-0.291158	0.162477		
SOY	-0.079539	-0.318293	-0.203007	-0.354358	-0.27266	
SOI	-0.197034	-0.156414	-0.415858	-0.264433	-0.308343	0.27009

Fig. 5 Time-varying Net Spillovers – Basket 1



Note: U.S. recessions are shaded.

Fig. 6 Net volatilities' frequency distributions – Basket 1

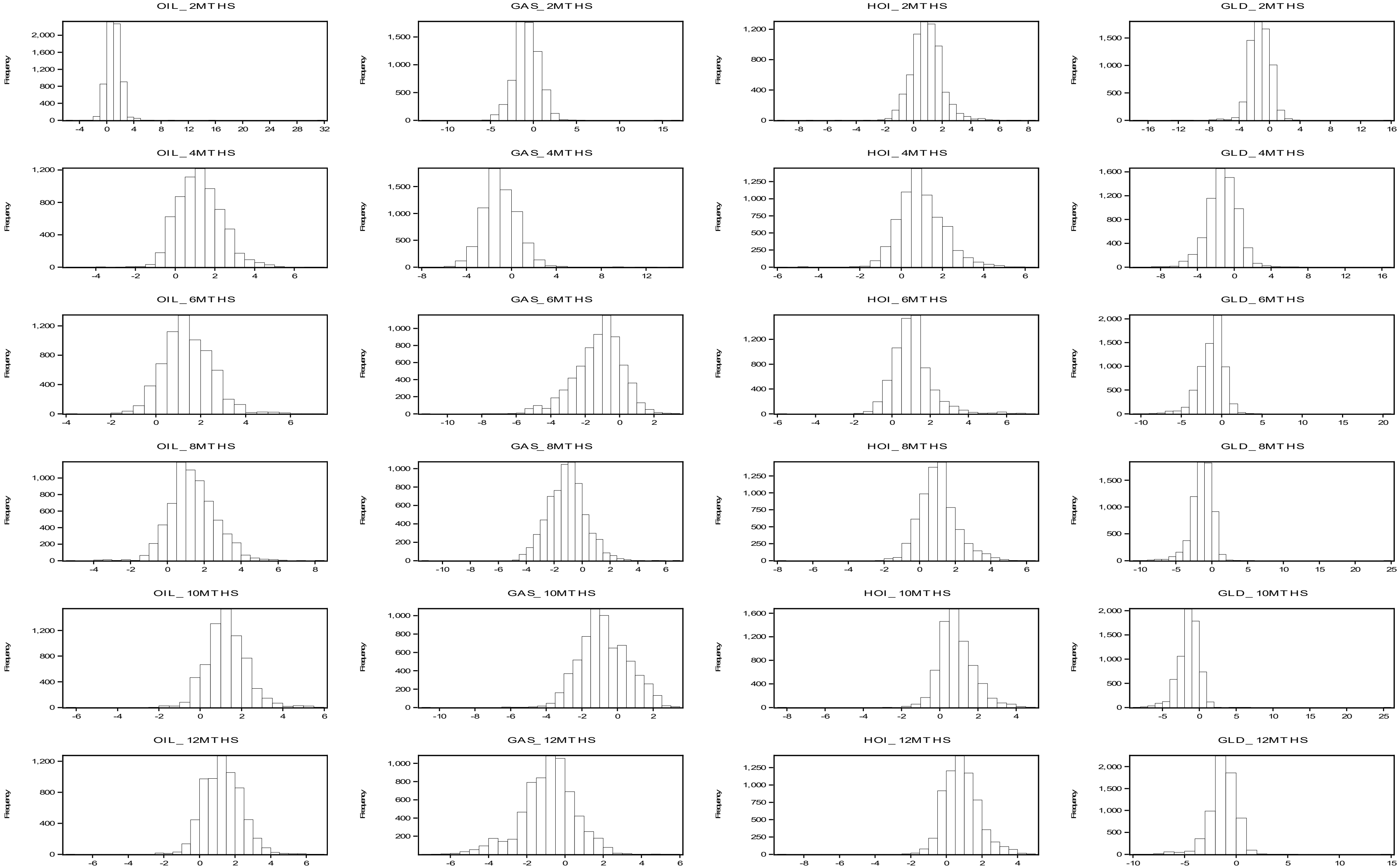
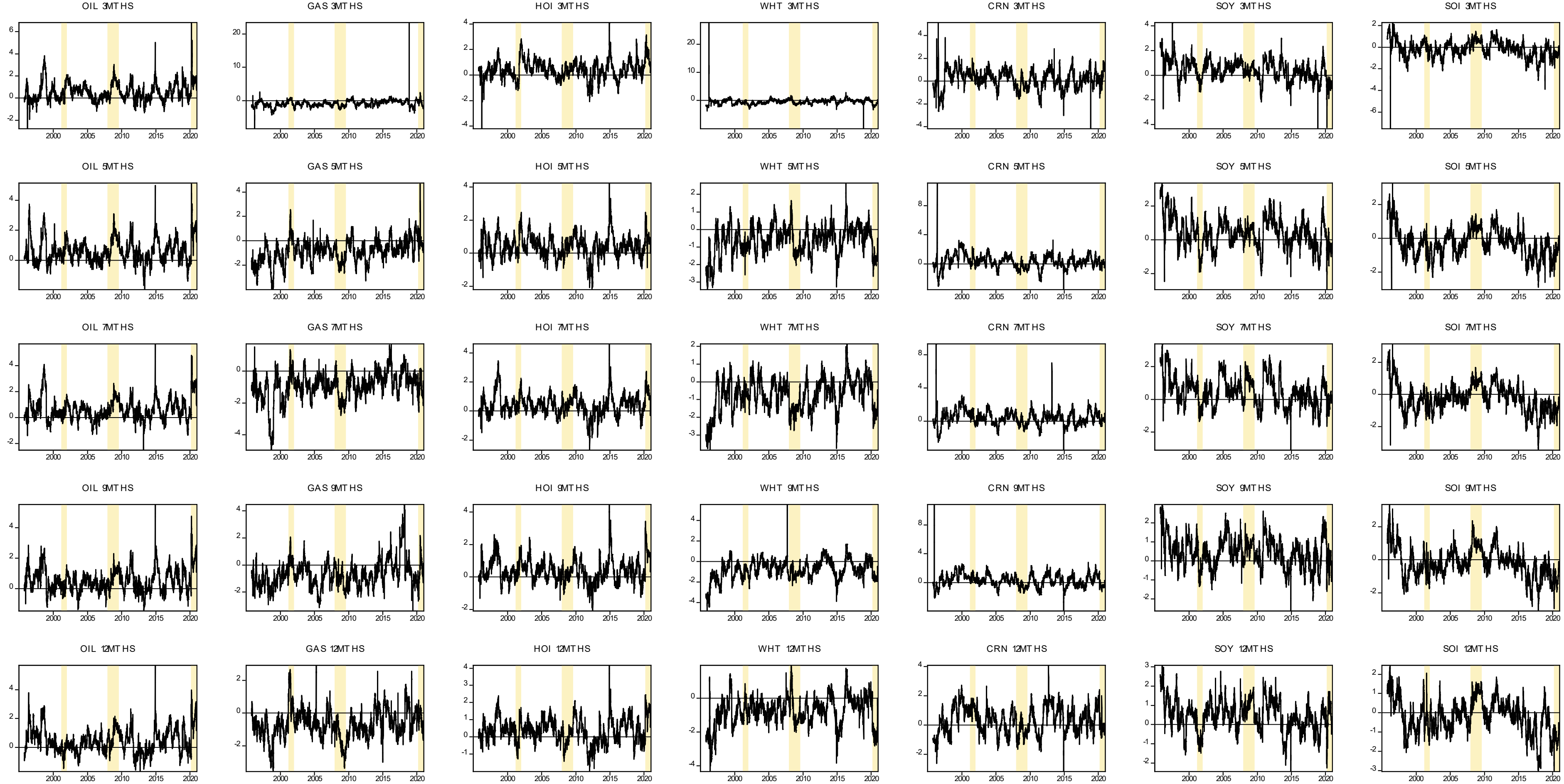


Fig. 7 Time-varying Net Spillovers – Basket 2



Note: U.S. recessions are shaded.

Fig. 8 Net volatilities' frequency distributions – Basket 2

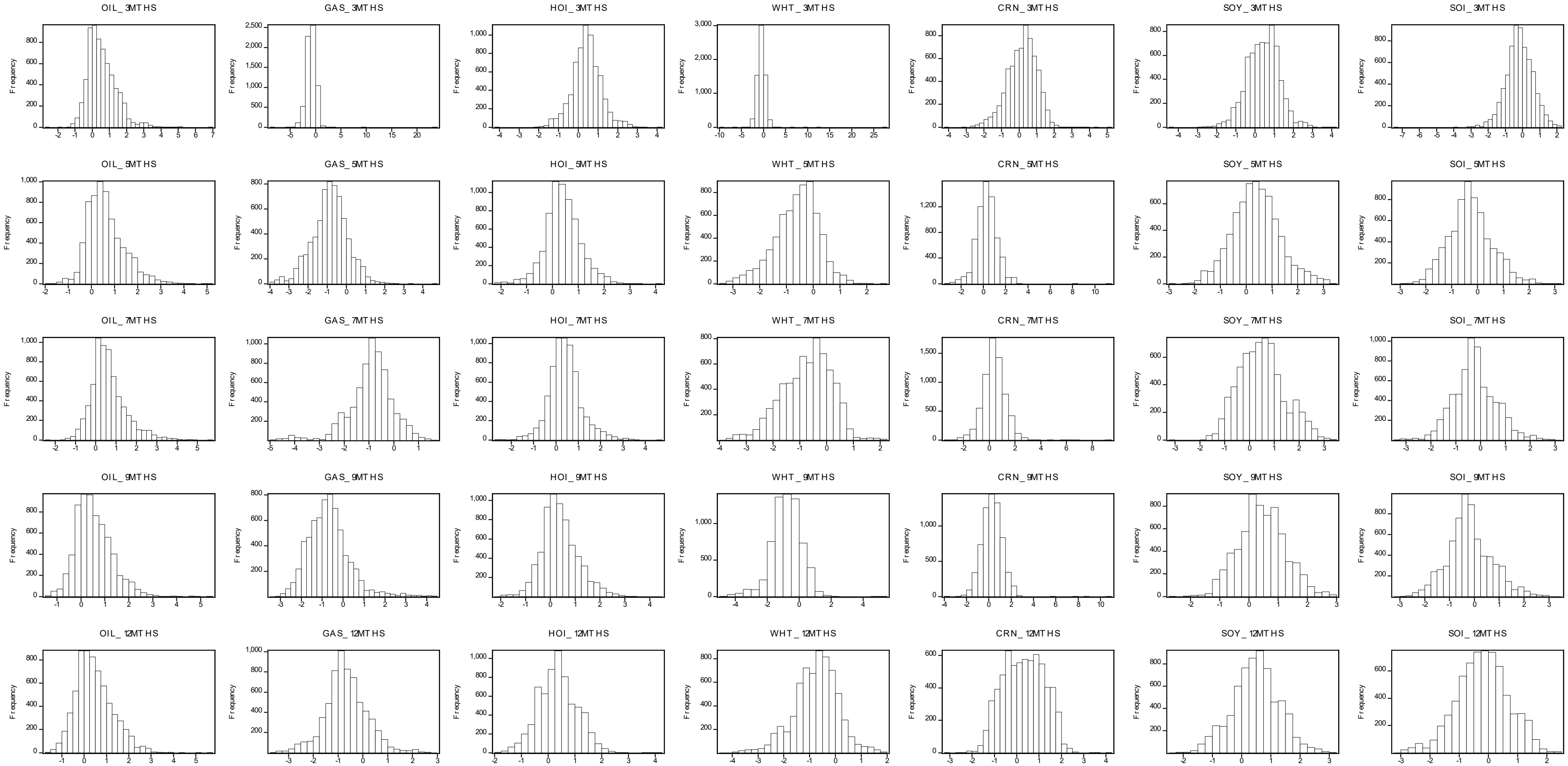
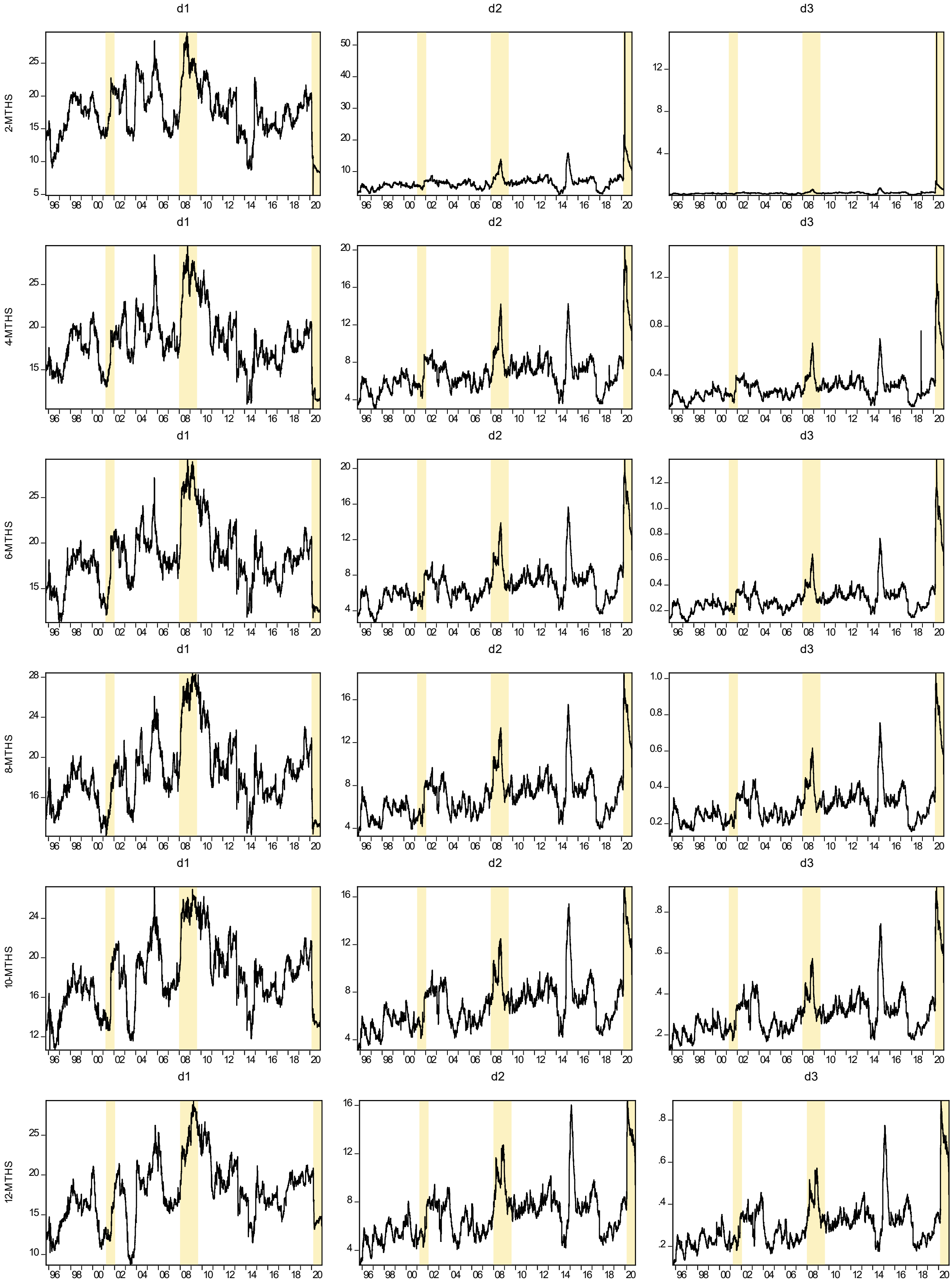
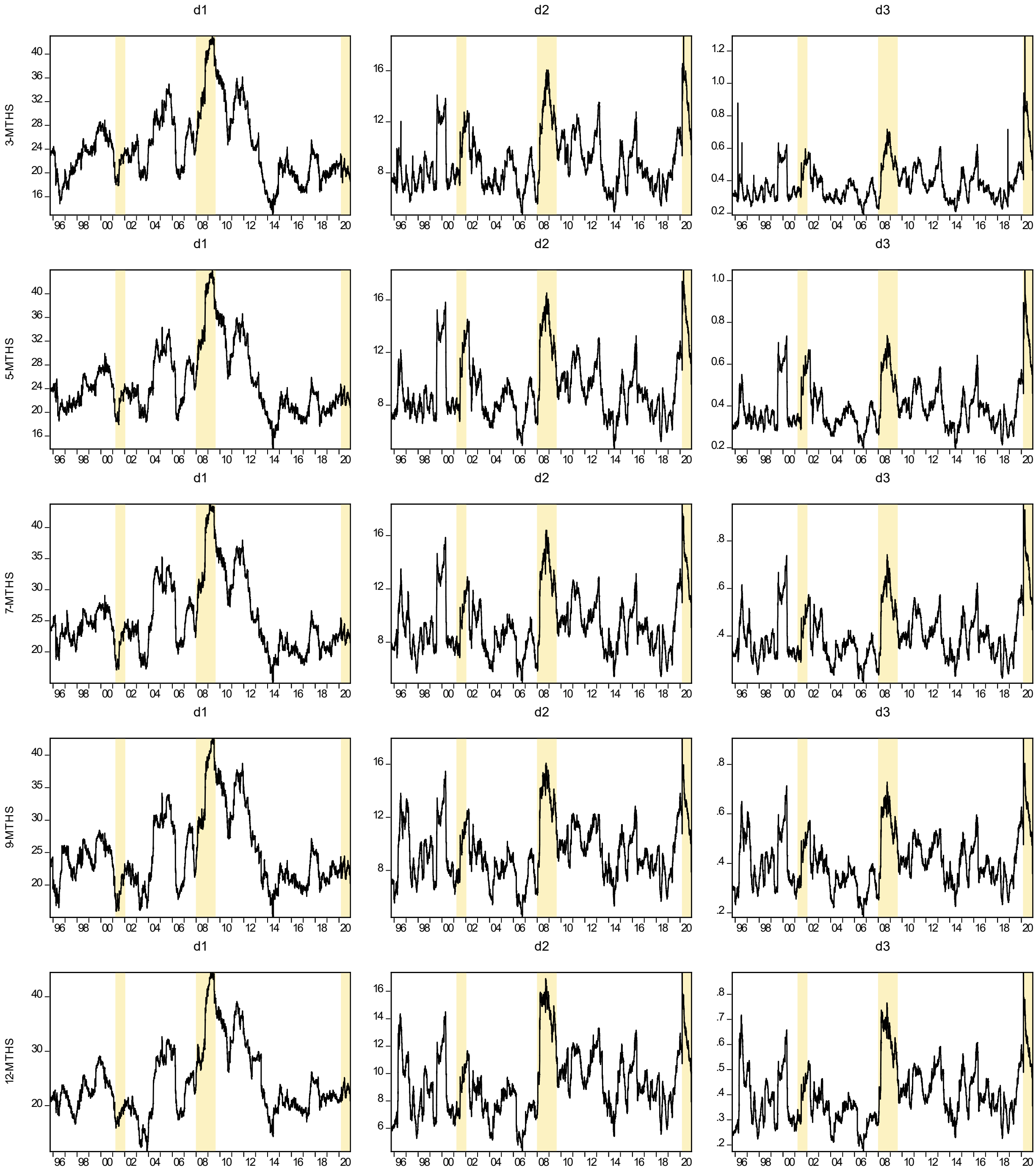


Fig. 9 Frequency decomposition of total connectedness – Basket 1



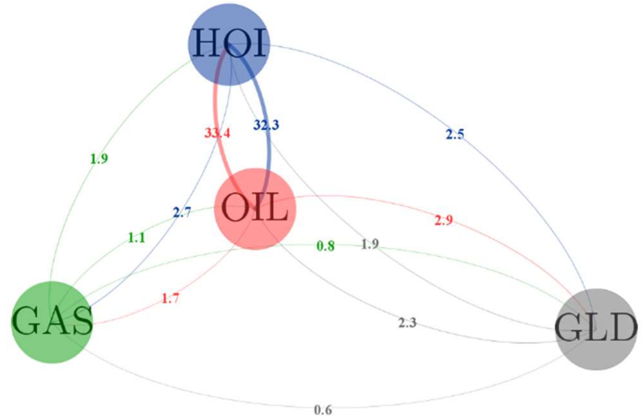
Note: U.S. recessions are shaded. $d_1 \in [1, 4]$ days, $d_2 \in (4, 64]$ days, and $d_3 \in (64, 200]$ days. Note that $\sum_{s=1}^{3} SI_{BK}^{\mathcal{F}}(d_s) = SI_{DY}^{G}$.

Fig. 10 Frequency decomposition of total connectedness – Basket 2

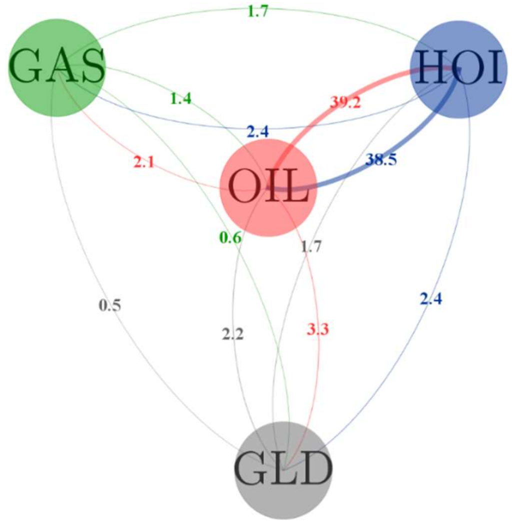


Note: U.S. recessions are shaded. $d_1 \in [1,4]$ days, $d_2 \in (4,64]$ days, and $d_3 \in (64,200]$ days. Note that $\sum_{s=1}^{3} SI_{BK}^{\mathcal{F}}(d_s) = SI_{DY}^{G}$.

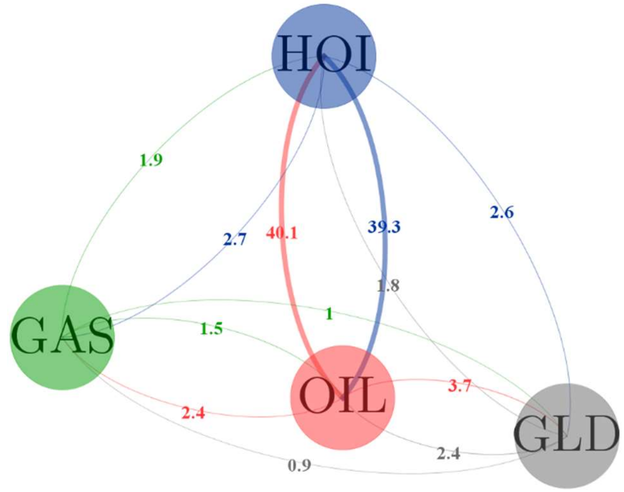
Fig. 2 Directional Spillovers network graph – Basket 1 [Full sample estimations]



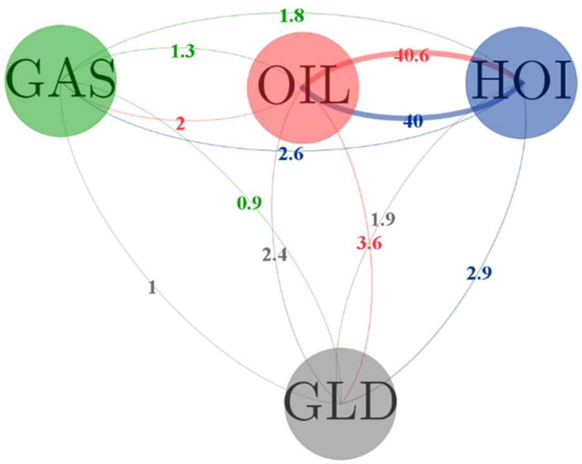
(a)



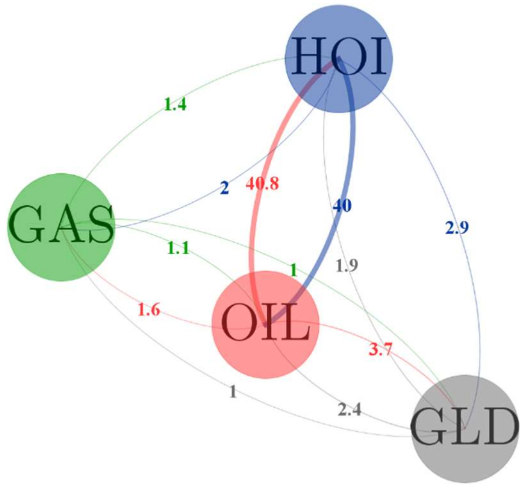
(b)



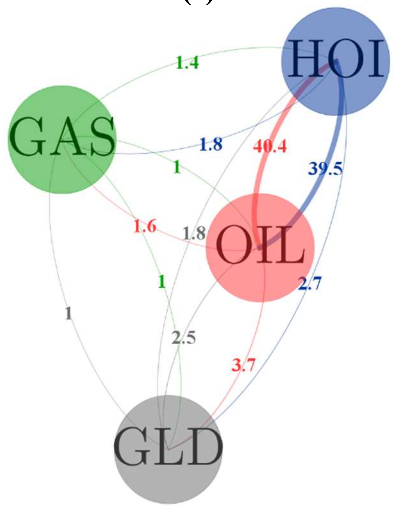
(c)



(d)



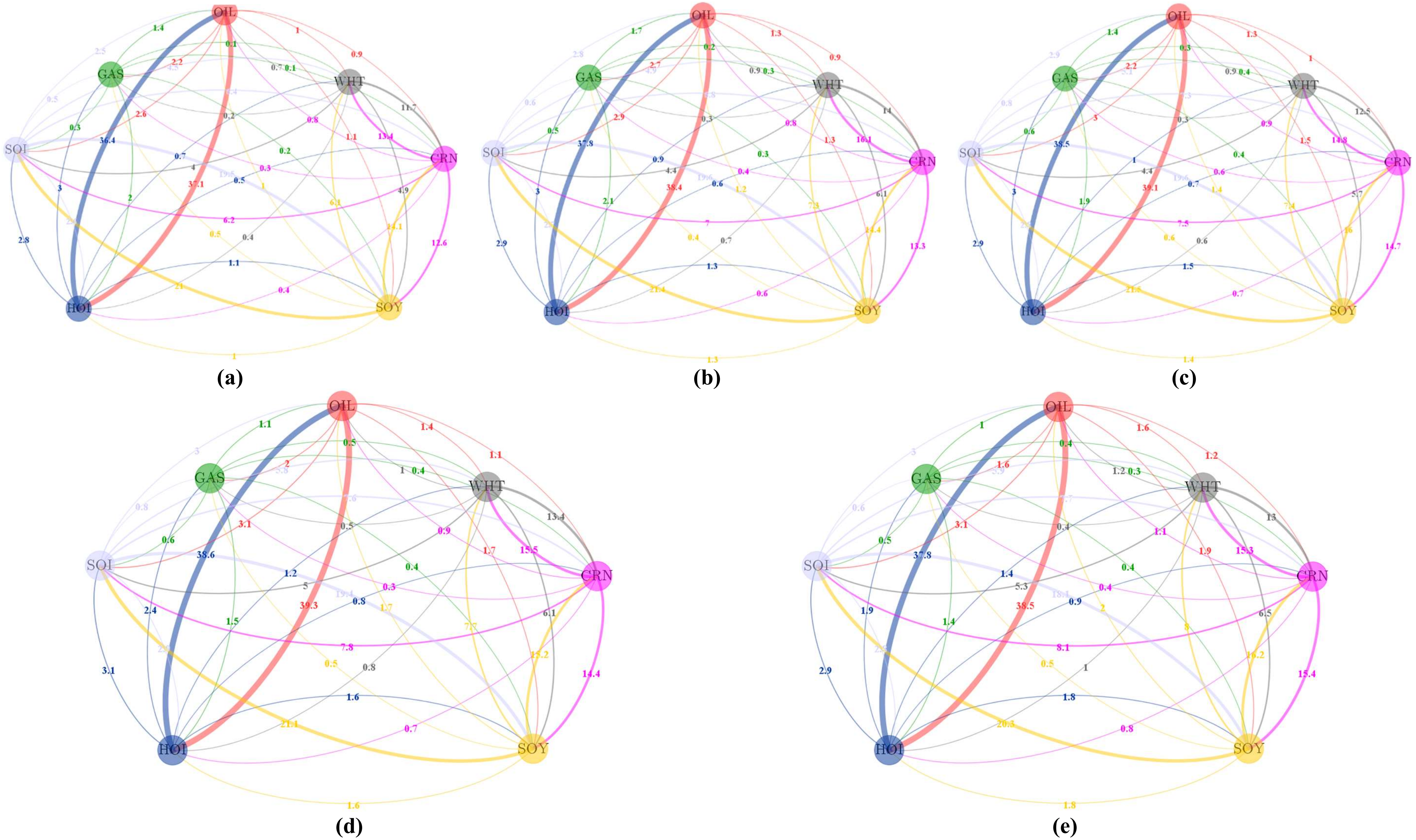
(e)



(f)

Note: **(a)** 2-months maturity; **(b)** 4-months maturity; **(c)** 6-months maturity; **(d)** 8-months maturity; **(e)** 10-months maturity; **(f)** 12-months maturity. **OIL**, **GAS**, **HOI** and **GLD** are acronyms for crude oil (WTI), natural gas, heating oil and gold, respectively. Directional spillovers network graphs for the tranquil and crisis subperiods are available upon request. Gephi, an open-source software, is used to create and visualize network graphs.

Fig. 3 Directional Spillovers network graph – Basket 2 [Full sample estimations]



Note: **(a)** 3-months maturity; **(b)** 5-months maturity; **(c)** 7-months maturity; **(d)** 9-months maturity; **(e)** 12-months maturity. **OIL**, **GAS**, **HOI**, **WHT**, **CRN**, **SOY** and **SOI** are acronyms for crude oil (WTI), natural gas, heating oil, wheat, corn, soybean, and soybean oil, respectively. Directional spillovers network graphs for the tranquil and crisis subperiods are available upon request. Gephi, an open-source software, is used to create and visualize network graphs.

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