# Multiscale Spillovers, Connectedness, and Portfolio Management among Commodity Futures Markets: Linkages among Precious and Industrial Metals, Energy, Agriculture, and Livestock

**Walid Mensi[a,b], Xuan Vinh Vo[c], Sang Hoon Kang[d,*]**

[a] Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman.

[b]Institute of Business Research, University of Economics Ho Chi Minh City; Vietnam

E-mail: walid.mensi@fsegt.rnu.tn

[c]Institute of Business REsearch and CFVG; University of Economics Ho Chi Minh City; Vietnam E-mail: vxvinh@yahoo.com

[d] Department of Business Administration, Pusan National University. E-mail: sanghoon-kang@pusan.ac.kr

**Abstract.** This study examines the connectedness among 28 commodity futures markets comprising energy, precious metals, industrial metals, agriculture, and livestock. We use the frequency-domain spillover method of Barunik and Krehlik (2018) and wavelet approach to account for investment horizons. The results show evidence of time-varying spillovers, which is intensified by economic and political events. The total spillover is higher in the short term than in the long term. Livestock markets is the least contributor/receiver of risk to/from other markets. A portfolio risk analysis reveals that a combined portfolio composed of WTI crude oil and other commodity assets offers better downside risk reduction. The latter is more important in the short term than in the long term. These results are important for investors and policymakers.

**JEL classification**: G14

**Keywords**: commodity futures prices, connectedness, frequency, spillover index

**Corresponding Author:** Department of Business Administration, Pusan National University, Jangjeon2-Dong, Ge-umjeong-Gu, Busan 609-735, Republic of Korea. Tel.: +82 515102558; Fax: +82 515813144. E-mail: sanghoonkang@pusan.ac.kr; kang.sanghoon@gmail.com

## Highlights

- We investigate the connectedness among metals, energy, agriculture, and livestock futures.
- The frequency-domain spillover method of Barunik and Krehlik (2018) and wavelet approach are applied.
- Economic and political events intensify total spillovers among commodity futures.
- Total spillover is higher in the short term than in long term.
- Livestock markets is the least contributor/receiver of risk to/from other markets.
- A mixed portfolio offers better diversification benefits and downside risk reduction especially in the short term.

## 1. Introduction

This study analyzes the short-term and long-term spillovers, directional spillovers, and net pairwise network connectedness among main commodity futures contracts (six energy futures, four precious metals futures, six industrial metals futures, nine agriculture futures, and three livestock futures). Empirically, we use the time-frequency spillover method of Barunik and Krehlik (2018) to assess the cross-market network spillover connectedness in different investment horizons (short-term and long-term). It is useful for investors and policymakers to identify the extent and direction of spillovers from one market to another, which is crucial for financial risk management. Considering a multiscale analysis to account for the time horizon is important. We note that shorter time horizons require more caution than longer ones. In addition, longer-term results are more predictable than shorter-term.

Commodity markets have experienced a rapid growth in liquidity over the last two decades. Commodity markets have significant instability when prices exhibit a simultaneous upside and downside trend. Mensi et al. (2014) document that the price instability of agricultural commodities can be explained by three factors. First, biofuels are derived from agricultural commodities. Higher price of energy markets pushes agricultural prices up as the cost of production of agricultural products increases. Second, the increasing and more prosperous world population and third, the adverse effects of global warming on climate change.

The role of commodities in portfolio allocation has increased, given the volatile times (Creti et al., 2013). Policymakers pay special attention to commodity market instability given its influence over inflation pressure. Connectedness among commodity futures prices is a strategic issue for all economies. With the financialization of commodities, traders and investors now consider them as a potential diversifier of portfolio risk exposure (Choi and Hammoudeh, 2010; Vivian and Wohar, 2012).

Very few empirical studies have examined the relationship among energy, metals, agriculture, and livestock commodities. Nazlioglu (2011) explored the nonlinear causalities between oil and agricultural commodity prices. Vivian and Wohar (2012) examined the volatility transmission among energy, animal products, grains, industrial metals, manufacturing inputs, and precious metals. Mensi et al. (2014) used dynamic conditional correlations in a generalized autoregressive conditional heteroskedasticity (GARCH) model to examine the impact of OPEC news releases on the dynamic spillovers in returns and volatility between energy and cereal commodity markets. Gorzgor et al. (2016) analyzed the driver variables of commodity markets volatility by accounting for uncertainty indexes (volatility index and equity market uncertainty index). Barbaglia et al. (2020) analyzed volatility spillovers among energy, agriculture, and biofuel commodity markets.

Our results show that total spillovers are 51.2% for the raw return series. Tin is the highest contributor of shocks to the other markets. West Texas Intermediate (WTI) and Brent crude oil markets are also high contributors of shocks to other markets. Energy futures prices act as price discovery tools for metals, agricultural, and livestock markets. Lean hogs and lumber contribute the least risk to other markets. Livestock futures have no risk contribution to energy, metals or agricultural futures markets. We also show that the magnitude of risk received from other markets is different for the four commodity classes. The risk spillover is dynamic and influenced by economic and geopolitical events. Total spillovers have intensified during the economic crises in the US and China, and the 2005 commodity crisis. After accounting for the time horizon, we find that WTI crude oil contributes 15% and 2% on the forecasting variance for Brent oil in the short term and long term, respectively. Energy, metals, and agricultural markets have low (no) contribution on the forecasting variance for livestock futures in the short term (long term). Livestock futures market is the least contributor/receiver of risk to/from other markets regardless of the time horizon. Risk spillovers among commodity futures show a significant upward trend during 2008–2009 for the short- and long-term due to economic and geopolitical events. We find that the magnitude of spillovers is more evident in the short term than in the long term.

The analysis of portfolio risk reveals that adding commodity futures to an individual WTI oil portfolio leads to significant risk reduction for short- and long-term. The magnitude of risk reduction is more pronounced for short-term than for long-term in many cases. Interestingly, WTI-Tin (WTI-Natural gas) portfolio offers the highest risk reduction in the short-term (long-term). In the long-term, Portfolio IV offers the highest risk reduction in 17 cases (particularly for metals and livestock markets), whereas Portfolio III (Portfolio II) provides the highest risk reduction in 8 cases (2 cases: natural gas and gasoline). In the short-term, we find that Portfolio IV, Portfolio III, and Portfolio II offer the highest risk reduction in 12, 13, and 2 cases, respectively. Portfolio IV offers the best downside risk reduction regardless of the time horizon.

The literature on spillovers studies spillover returns and volatility across assets (Baele, 2005). This study contributes to the literature in several ways. First, we identify the magnitude of risk spillovers among commodity futures markets. Second, we determine directional spillovers (net receiver and net transmitter of risk). Investors are interested in the pathway of spillovers and extent of net spillover contribution by different commodities in their portfolio. Third, to optimize investment decisions, we re-estimate risk spillover by accounting for time horizon. We use the wavelet approach to consider whether the directional spillovers and net spillovers are stable across heterogeneous scales. We consider a short-term horizon (2–8 days) and long-term horizon (8–256 days) to get more accurate information for investors as their risk appetite, behaviors, and beliefs differ for different time horizons. Short-term investors like traders and speculators are more concerned with short-term price movement whereas institutional investors are interested in long-term movement (Rua and Nunez, 2009). Finally, we use our results to study their implications in terms of risk reduction in general and downside risk reduction in particular for an investor holding an individual WTI oil portfolio. We consider different risk measures and a benchmark portfolio composed only of WTI oil for comparison with three other mixed portfolios (e.g., a risk-minimizing WTI-commodity portfolio, equal weights portfolio, and a portfolio whose weights are determined according to a variance minimization hedging strategy). The portfolio risk evaluation is examined for the short- and long-term. From a practical perspective, our findings are informative of commodity price discovery and network connectedness across commodity futures markets and are important to portfolio and fund managers.

The remainder of this paper is organized as follows. Section 2 discusses the methodology. Section 3 presents the data and descriptive statistics. Section 4 reports and discusses the empirical results. Section 5 discusses the relevant risk management implications and concludes.

## 2. Methodology

### *2.1. Time-frequency connectedness method*

We first discuss the methodology of Diebold and Yilmaz (2012) (DY method hereafter) and then elaborate on the Barunik and Krehlik (2018) frequency-domain spillover index. The DY spillover index is based on a generalized vector autoregressive process in which a forecast error variance decomposition (FEVD) is utilized to estimate connectedness and magnitude in the time domain. Let us describe the $n$-variate process $x_t = (x_{t,1}, \dots, x_{t,n})$ by the structural VAR$(p)$ at $\mathrm{t} = 1, \dots, T$ as:

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

where $\varepsilon \sim (0, \Sigma)$ is a vector of i.i.d. disturbances. Assuming stationary covariance, a moving average representation can be written as:

$$x_t = \sum_{i=0}^{\infty} \mathrm{Z}_i \varepsilon_{t-i}, \tag{2}$$

where $\sum_{i=0}^{\infty} \mathrm{Z}_i = \mathrm{Z}(L)$ is an $\mathrm{n} \times \mathrm{n}$ infinite-lag polynomial matrix of coefficients. Following Diebold and Yilmaz (2012), the generalized FEVD can be written as follows:

$$\Theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H} \left( (\mathrm{Z}_h \Sigma)_{ij} \right)^2}{\sum_{h=0}^{H} \left( \mathrm{Z}_h \Sigma \mathrm{Z}_h' \right)_{ii}}, \tag{3}$$

where $\mathrm{Z}_h$ is an $\mathrm{n} \times \mathrm{n}$ matrix of coefficients corresponding to lag $\mathrm{h}$ and $\sigma_{jj} = (\Sigma)_{jj}$. The term $\Theta_{ij}(H)$ denotes the contribution of the j-th variable of the system to the variance of the forecast error of the $i$th variable at forecast horizon $H$. As the contributions by own- and cross-variable variance do not sum to 1 under the generalized decomposition, the sum of the rows is used to normalize each element of the variance decomposition matrix:

$$\widetilde{\Theta}_{ij}(H) = \frac{\Theta_{ij}(H)}{\sum_{j=1}^{N} \Theta_{ij}(H)}, \tag{4}$$

with $\sum_{j=1}^{N} \Theta_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \Theta_{ij}(H) = N$ by construction. $\widetilde{\Theta}_{ij}$ provides the estimates of the pairwise connectedness from the j-th variable to the i th variable at horizon $H$.

Following Barunik and Krehlik (2018), we now discuss the method for measuring connectedness in the frequency domain considering the spectral representation of variance decompositions based on frequency responses to shocks. A frequency response function can be obtained from the Fourier transformation of the moving-average coefficients $\Psi_h$ with $\mathrm{i} = \sqrt{-1}$ and expressed as:

$$\Psi\left(e^{-i\omega}\right) = \sum_h e^{-i\omega h} \Psi_h, \tag{5}$$

where ω implies frequency. The power spectrum $S_X(\omega)$ of $x_t$ at frequency ω can be expressed as:

$$S_X(\omega) = \sum_{h=-\infty}^{\infty} E\left(x_t x_{t-1}^{'}\right) e^{-i\omega h} = \Psi\left(e^{-i\omega}\right) \sum \Psi^{'}\left(e^{+i\omega}\right), \tag{6}$$

The generalized causation spectrum over frequencies $\omega \in (-\pi, \pi)$ is specified as

$$\left(f(\omega)\right)_{ij} = \frac{\sigma_{jj}^{-1}\left(\Psi\left(e^{-ih\omega}\right)\Sigma\right)_{ij}^{2}}{\left(\Psi\left(e^{-ih\omega}\right)\Sigma\Psi\left(e^{-ih\omega}\right)\right)_{ii}}, \tag{7}$$

where $\left(f(\omega)\right)_{ij}$ is the portion of the spectrum of the i-th variable at frequency ω due to shocks to the j-th variable. Thus, we can interpret the quantity as a within-frequency causation, as the denominator holds the spectrum of the j-th variable. That is, the on-diagonal elements of the cross-spectral density of $x_t$, at a given frequency ω. To obtain a natural decomposition of the original generalized FEVD into frequencies, we can simply weight $\left(f(\omega)\right)_{ij}$ by the frequency share of the variance of the i-th variable. The weighting function is expressed as:

$$\Gamma_i(\omega) = \frac{\left(\Psi\left(e^{-ih\omega}\right)\Sigma\Psi'\left(e^{+ih\omega}\right)\right)_{ii}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi\left(e^{-ih\lambda}\right)\Sigma\Psi'\left(e^{+i\lambda}\right)\right)_{ii} d\lambda}, \tag{8}$$

where the power of the $i$-th variable at a given frequency, which sums through frequencies to a constant value of $2\pi$. The generalized FEVD on a frequency band $d$ can be defined as:

$$(\Theta_d)_{ij} = \frac{1}{2\pi}\int_d \Gamma_i(\omega)\left(f(\omega)\right)_{ij} d\omega, \tag{9}$$

The frequency connectedness $C_d^F$ and within connectedness $C_d^W$ on frequency band $\mathrm{d} = (a, b): a, b \in (-\pi, \pi),\ \ a < b$ can be respectively obtained by:

$$C_d^F = 100\left(\frac{\sum_{i\neq j}(\widetilde{\Theta}_d)_{ij}}{\Sigma(\widetilde{\Theta}_\infty)_{ij}} - \frac{Tr\{\widetilde{\Theta}_d\}}{\Sigma(\widetilde{\Theta}_\infty)_{ij}}\right). \quad (10)$$

$$C_d^W = 100\left(1 - \frac{Tr\{\widetilde{\Theta}_d\}}{\Sigma(\widetilde{\Theta}_\infty)_{ij}}\right), \quad (11)$$

where $\mathrm{Tr}\{\cdot\}$ is the trace operator and $(\widetilde{\Theta}_d)_{ij} = (\widetilde{\Theta}_d)_{ij} \Big/ \sum_j \left(\widetilde{\Theta}_\infty\right)_{ij}$.

Note that the within connectedness value provides the connectedness effect that occurs within the frequency band and is weighted by the power of the series on the given frequency band exclusively. Conversely, the frequency connectedness decomposes the original connectedness into separate parts that, when summed, provide the original connectedness measure.

*2.2. Wavelet-based approach*

We calculate the wavelets of the time series of returns in frequency domain using the maximal overlap discrete wavelet transform (MODWT).[1] The MODWT wavelet and scaling coefficient $\widetilde{w}_{j,t}$ and $\tilde{v}_{j,t}$ for a return series $r(t)$ are defined as:

$$\widetilde{w}_{j,t} = \frac{1}{2^{j/2}}\sum_{l=0}^{L-1}\tilde{h}_{j,l} r_{t-j}, \text{ and } \tilde{v}_{j,t} = \frac{1}{2^{j/2}}\sum_{l=0}^{L-1}\tilde{g}_{j,t}\, r_{t-j}, \quad (12)$$

where $L$ is the length of the filter. Using the least asymmetric wavelet method of Daubechies (1988, 1992), we generate multiscale decomposition of the return series with a filter length of $L = 8$. The decomposed signals of the multi resolution analysis in the MODWT are obtained as follows:

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[1] In comparison with the discrete wavelet transform (DWT), MODWT can handle any sample size, such as a non-dyadic length sample size (Maghyereh, et al., 2019). Furthermore, MODWT does not introduce phase-shifts, which would change the location of events in time, and it is translation-invariant as a shift in signal does not change the pattern of wavelet transform coefficients (Khalfaoui et al., 2015; Boubaker and Raza, 2017). Thus, MODWT yields more asymptotically efficient wavelet variance than DWT (Lien and Shrestha, 2007).

$$r(t) = S_J(t) + \sum_{j=1}^{J} D_j(t), \quad (13)$$

where $S_J(t) = \sum_{l=-\infty}^{+\infty} h(l)\, S_{J-1}\left(t + 2^{j-1} \times l\right)$ denotes the smoothed version of series $r(t)$ at scale $J$, and $D_j(t) = \sum_{l=-\infty}^{+\infty} g(l) S_{j-1}\left(t + 2^{j-1} \times l\right)$ is called the wavelet scales, which represent local fluctuation over the period of returns as the each scale j $\{j = 1, \dots, J\}$.

We decompose our return series into four wavelet scales $(D_1, \dots, D_8)$, corresponding to: $D_1([2\text{–}4]days)$, $D_2([4\text{–}8]days)$, $D_3([8\text{–}16]days)$, $D_4([16\text{–}32]days)$, $D_5([32\text{–}64]days)$, $D_6([64\text{–}128]days)$, $D_7([128\text{–}256]days)$, and $D_8([256\text{–}512]days)$.

We construct the short-term and long-term horizon wavelet series as follows: the short-term horizon is defined as the sum of $D_1$ and $D_2$ series, corresponding to the periods 2 and 8 days whereas the long-term horizon is defined as the sum of $D_3$, $D_4$, $D_5$, $D_6$, and $D_7$, corresponding to the periods 8 and 256 days.

### *2.3. Portfolio evaluation*

We analyze the dynamic conditional correlations (DCCs) between different short-term and long-term horizon wavelet series using the DCC-GARCH model of Engle (2002).[2] Using estimate DCCs, we rebalance and manage portfolio risk by maintaining optimal portfolio weights. To minimize risk without a loss in expected returns, we calculate the optimal weights $(w_T^C)$ of the portfolio consisting of WTI and other commodity futures by following Kroner and Ng (1998). We also follow Kroner and Sultan's (1993) methodology to quantify the beta hedge to minimize the risk of this portfolio.

Following Reboredo and Rivera-Castro (2014), we assess the risk reduction measures in different investment horizons (short-term and long-term). The risk reduction $RE_{var}$ of each

[2] See Appendix.

of these portfolios is computed by comparing the conditional variances of portfolio $(P_j)$ and a benchmark portfolio $(P_I)$ as:

$$RE_{Var} = 1 - \frac{Var(P_j)}{Var(P_I)} \ , \tag{14}$$

where $j = II, III, IV$, and $\mathrm{Var}(P_j)$and $\mathrm{Var}(P_I)$ are the conditional variances of Portfolio $j$ and Portfolio $I$, respectively. Note that higher values of $RE_{var}$ indicate a greater risk reduction in these portfolios.

Variance at risk (VaR) is the loss associated with the α-th percentile of the portfolio returns distribution, which measures the maximum loss in portfolio value at a specific confidence level for a given time period. The VaR for a portfolio $(P_j)$ with a confidence level $(1-\alpha)$ is given by:

$$Pr(r_j \leq VaR_t | \psi_{t-1}) = \alpha \tag{15}$$

where $r_j$ is the portfolio return and $\psi_{t-1}$ is the information set at $\mathrm{t}-1$.

The semivariance (SV) measure accounts for the downside risk by measuring return variability below a threshold return. SV is defined as:

$$\mathrm{SV} = \mathrm{E}\left[\min\{0, r_j - E(r_t)\}\right]^2. \tag{16}$$

An alternative downside risk measure $(\mathrm{Re})$ considers the expected value of returns provided they are below zero:

$$\mathrm{Re} = -\mathrm{E}[\min\{0, r_t\}]. \tag{17}$$

## 3. Data and preliminary analysis

We use the daily price data for 28 commodity futures in five commodity categories; (i) energy (WTI crude oil (CL1), Brent crude oil (CO1), natural gas (NG1), gasoline (XBW1), heating oil (HO1), and gas oil (QS1)); (ii) precious metals (gold (GC1), silver (SI1), platinum (PL1), and palladium (PA1)); (iii) industrial metals (aluminum (LA1), copper (LP1), zinc (LX1), tin (LT1), lead (LL1), and nickel (LN1)); (iv) agriculture (wheat (W_1), corn (C_1), soybeans (S_1), coffee (KC1), sugar cane (SB1), sugar beets (QW1), cocoa (CC1), cotton (CT1), and lumber (LB1)); (v) livestock (lean hogs (LH1), feeder cattle (FC1), and live cattle (LC1).[3] The sample period is from July 23, 1997 through February 28, 2018, which covers several turbulent periods and includes all the sharp fluctuations in the commodity futures markets and major global events, such as the 1998 Asian crisis, 2007 US subprime mortgage crisis, 2008–2009 global financial crisis (GFC), 2007–2008 global food crisis, 2009–2012 European debt crisis (EDC), and oil price shocks (summer 2008 and June 2014).

Fig. 1 illustrates the annual trading volumes and open interests between 2008 and 2017. This figure shows that the trading volume experienced an upside trend from 2008 till 2016 followed by a decrease in 2014. Moreover, the trading volume of agricultural futures is the highest followed by industrial metals, precious metals, and energy futures. Conversely, the open interest for the four categories of markets is constant from 2015 till 2017. The open interest is significant for agriculture and livestock futures as compared to metals and energy futures.

All series were extracted from the DataStream database. We calculate the continuously compounded daily returns by taking the difference in the log values of two consecutive prices. Fig. 2 shows the dynamics of commodity returns and shows evidence of volatility clustering in all return series, indicating nonlinearity. There is a low correlation between metals and agricultural and livestock markets.

[3] The details of the sample data are given in Appendix.

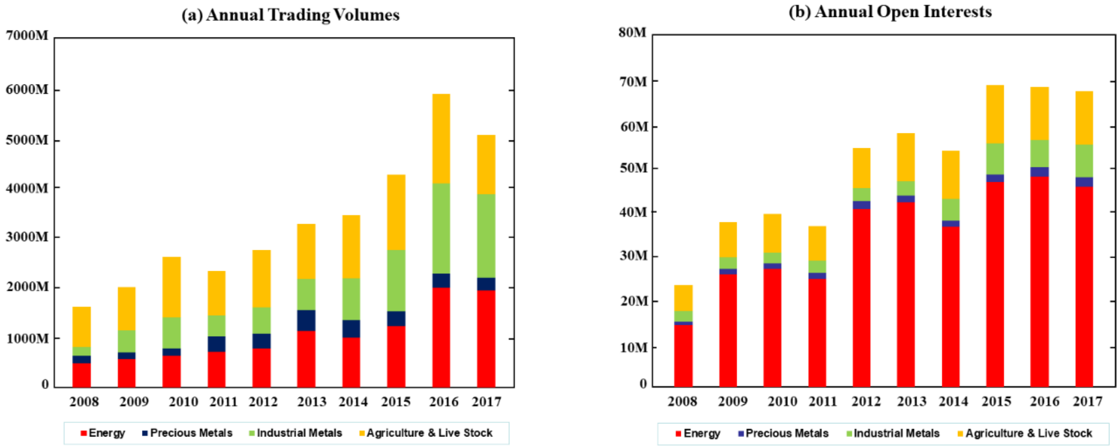



**Fig. 1.** Annual trading volumes and open interests (2008–2017).
Source: FIA database (www.fia.org).

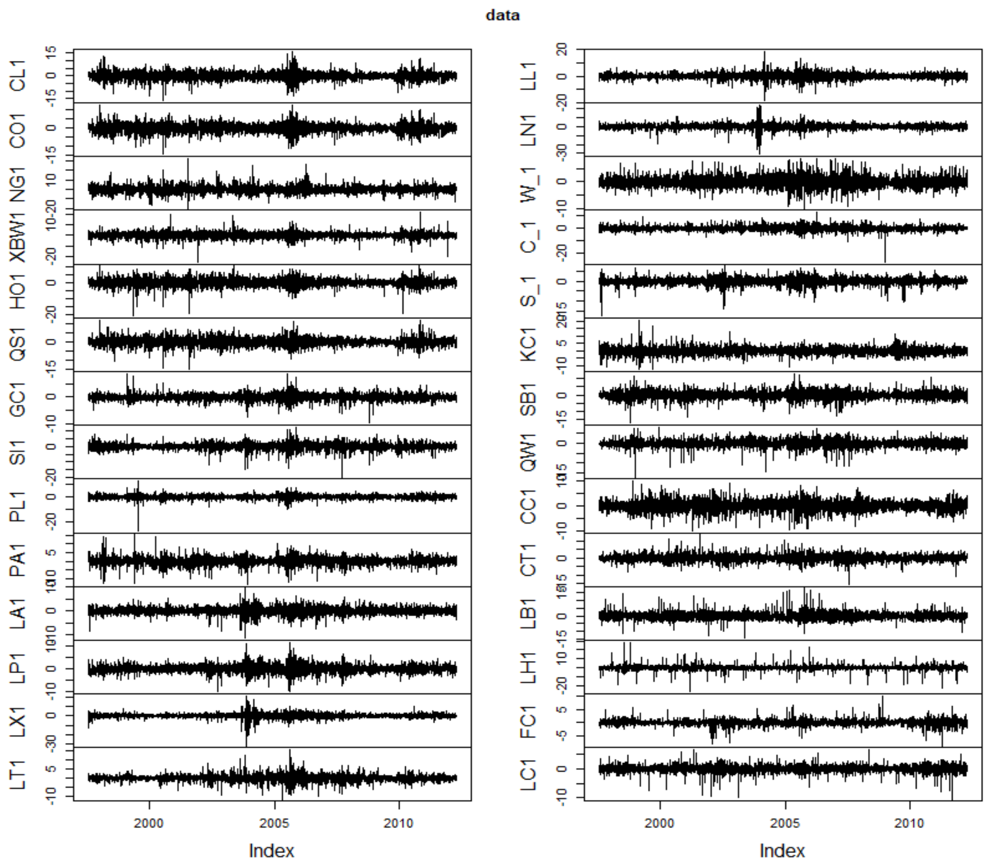



**Fig. 2**. Dynamics of commodity futures price returns

Table 1 summarizes the descriptive statistics for all return series. The average return series is positive for all series, except coffee and lean hogs price returns. We note that the average returns for all series is close to zero. Palladium has the highest average returns. Looking at the standard deviations, natural gas futures is the most volatile market and feeder cattle is the least volatile. All returns series are asymmetric and leptokurtic according to skewness and kurtosis values. Further, the Jarque-Bera test rejects normal distribution. The unit root and stationary tests of ADF and KPSS show evidence of stationarity for all 28 series.

Fig. 3 presents the heat map of the unconditional correlations in the commodity markets. The map shows a negative correlation between corn (C_1) and feeder cattle (FC1). This indicates a possibility of diversification benefits. A high correlation is observed among industrial metals as well as precious metals (gold, silver, platinum, and palladium) and energy markets. WTI crude oil (CL1) is highly correlated with Brent oil (CO1), natural gas (NG1), gasoline (XBW1), and gas oil (QA1). Natural gas (NG1) exhibits low correlations with all markets. This also shows the importance of this asset for hedging against risk exposure. We also observe a low correlation between energy markets and precious metals, industrial metals, agricultural, and livestock markets.

**Table 1.** Summary descriptive statistics and unit root tests

| | Mean (%) | Max | Min. | Std. Dev. | Skew. | Kurt. | J-B stat | ADF | KPSS |
|---|---|---|---|---|---|---|---|---|---|
| CL1 | 0.0212 | 16.41 | -16.54 | 2.357 | -0.0609 | 4.309 | 4163.*** | -42.86*** | 0.1042 |
| CO1 | 0.0237 | 12.89 | -14.43 | 2.177 | -0.0685 | 2.971 | 1982.*** | -42.25*** | 0.1355 |
| NG1 | 0.0040 | 32.43 | -19.89 | 3.340 | 0.5026 | 5.377 | 6704.*** | -43.50*** | 0.0876 |
| XBW1 | 0.0196 | 21.65 | -25.45 | 2.532 | -0.2336 | 7.048 | 11177.*** | -42.89*** | 0.0764 |
| HO1 | 0.0237 | 10.40 | -20.97 | 2.226 | -0.5062 | 5.988 | 8261.*** | -43.04*** | 0.1145 |
| QS1 | 0.0232 | 12.09 | -15.06 | 2.000 | -0.0664 | 3.519 | 2778.*** | -41.26*** | 0.1391 |
| GC1 | 0.0261 | 8.887 | -9.820 | 1.092 | -0.1060 | 6.614 | 9810.*** | -42.13*** | 0.1655 |
| SI1 | 0.0249 | 12.19 | -19.54 | 1.900 | -0.8286 | 7.687 | 13853.*** | -42.16*** | 0.1261 |
| PL1 | 0.0159 | 12.71 | -27.19 | 1.472 | -1.4302 | 25.50 | 1.47e+005*** | -44.41*** | 0.2137 |
| PA1 | 0.0328 | 15.25 | -13.38 | 2.092 | -0.2284 | 5.139 | 5964.*** | -43.33*** | 0.0805 |
| LA1 | 0.0048 | 9.306 | -11.40 | 1.349 | -0.3063 | 4.403 | 4427.*** | -44.33*** | 0.0500 |
| LP1 | 0.0202 | 11.92 | -10.32 | 1.614 | -0.0895 | 4.574 | 4694.*** | -44.72*** | 0.1502 |
| LX1 | 0.0146 | 20.99 | -31.68 | 2.034 | -1.0181 | 23.81 | 1.27e+005*** | -46.90*** | 0.1376 |
| LT1 | 0.0257 | 15.48 | -11.45 | 1.613 | 0.0045 | 7.612 | 12982.*** | -43.88*** | 0.0826 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| LL1 | 0.0251 | 18.69 | -18.53 | 2.005 | -0.1698 | 6.609 | 9811. *** | -44.09*** | 0.0719 |
| LN1 | 0.0133 | 24.17 | -31.31 | 2.456 | -0.5133 | 16.90 | 64220. *** | -45.87*** | 0.1061 |
| W_1 | 0.0056 | 8.794 | -9.972 | 1.908 | 0.1737 | 2.097 | 1012. *** | -43.19*** | 0.0559 |
| C_1 | 0.0077 | 12.75 | -26.86 | 1.762 | -0.5318 | 12.54 | 35524. *** | -42.17*** | 0.0688 |
| S_1 | 0.0064 | 7.629 | -17.42 | 1.595 | -1.0517 | 8.228 | 16157. *** | -41.50*** | 0.0749 |
| KC1 | -0.0075 | 21.2 | -12.84 | 2.204 | 0.2525 | 5.209 | 6135. *** | -41.92*** | 0.1177 |
| SB1 | 0.0029 | 13.06 | -17.11 | 2.146 | -0.2109 | 3.629 | 2990.3*** | -42.28*** | 0.0781 |
| QW1 | 0.0017 | 8.229 | -17.04 | 1.651 | -0.8652 | 8.052 | 15194. *** | -42.74*** | 0.1036 |
| CC1 | 0.0074 | 9.962 | -10.00 | 1.882 | -0.1212 | 2.475 | 1385.9*** | -41.43*** | 0.0535 |
| CT1 | 0.0016 | 13.62 | -15.55 | 1.826 | 0.0015 | 4.540 | 4618.5*** | -42.37*** | 0.0623 |
| LB1 | 0.0078 | 17.92 | -14.53 | 2.097 | 0.8412 | 7.587 | 13529. *** | -43.68*** | 0.0838 |
| LH1 | -0.0032 | 28.56 | -27.15 | 2.222 | -0.3089 | 34.25 | 2.62e+005*** | -40.57*** | 0.0298 |
| FC1 | 0.0104 | 10.00 | -8.611 | 0.933 | -0.1802 | 12.20 | 33421. *** | -40.77*** | 0.0617 |
| LC1 | 0.0120 | 6.635 | -10.59 | 1.097 | -1.0183 | 9.889 | 22836. *** | -41.41*** | 0.0221 |

**Note**: *** stands for significance at 1% level.

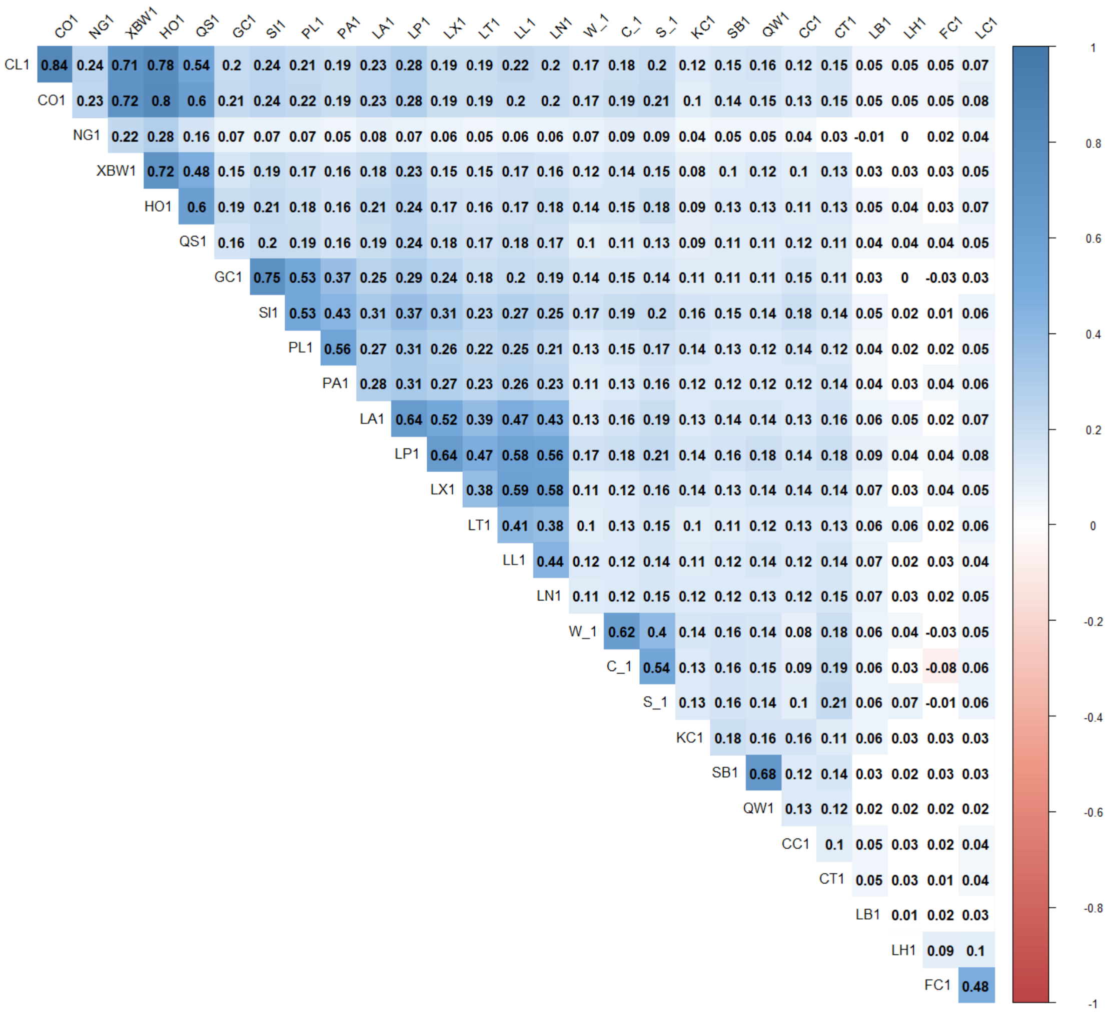



**Fig. 3.** Heat map of the correlations

**Note**: This figure shows a visual correlation matrix across different assets. The color intensity of the shaded boxes indicates the magnitude of correlation. Blue indicates a positive correlation, while red indicates a negative correlation.

## 4. Empirical results

### *4.1. The results of DY spillover for raw return series*

Table 2 reports the matrix of total spillovers for 28 commodities (energy, precious metals, industrial metals, agriculture, and livestock) futures prices. It shows that total spillovers are 51.2%. Regarding directional spillovers transmitted to other markets (TO), tin (LT1) is the highest contributor of shocks to the other markets. Further, WTI and Brent crude oil markets (CL1 and CO1) are high contributors of shocks to the other markets, accounting for 94% and 99%, respectively. Energy futures prices act as price discovery tools for metals, agricultural, and livestock markets. In contrast, lean hogs (LH1) and lumber (LB1) are the least contributors of risk to the other markets with 3.7% and 3.9%, respectively. In addition, gasoline (XBW1), cocoa (CC1), coffee (KC1), cotton (CT1), feeder cattle (FC1) and live cattle (LC1) have a low contribution of risk to the other markets with 12%, 14%, 16%, 19%, 20%, 23%, respectively. For the other markets, the degree of contribution ranges between 41% for sugar beets (QW1) and 78% for zinc (LX1).

Livestock futures have no risk contribution to energy, metals and agricultural futures markets. This has important implications for risk management. In fact, investors in energy, agricultural, and metals markets can hedge their position against risk exposure by adding livestock futures in their portfolios.

Regarding directional spillovers received from other markets (FROM), we observe that the magnitude of receiving risk from the other markets are different among the commodity classes (energy, precious metals, industrial metals, agricultural, and livestock) indicating heterogeneity of the markets. These markets do not belong to the same commodity class. Moreover, the degree of the receiving risk from the other markets ranges from 5.2% for lean hogs (LH1) to 75.5% for Brent futures (CO1). Crude oil markets (Brent and WTI) are the two highest receivers of shocks from the other markets. In energy futures markets, gasoline receives less risk from other markets. We find that precious metals futures markets receive approximatively the same risk from the other markets despite Palladium (PA1) receiving the least risk among them. Among the five commodity groups, livestock futures markets receive the least risk from the other markets. This confirms the importance of these markets for investors in futures commodities.

In sum, livestock futures markets have little or no contribution of risk to the other markets. It also receives less risk from the other markets. This indicates that this market is immune to the instability of the other markets. Lumber (LB1) is isolated from the other commodities as the degree of received risk is about 8.5%.

**Table 2**. DY' Total spillovers index across commodity futures markets

| | CL1 | CO1 | NG1 | XBW1 | HO1 | QS1 | GC1 | SI1 | PL1 | PA1 | LA1 | LP1 | LX1 | LT1 | LL1 | LN1 | W_1 | C_1 | S_1 | KC1 | SB1 | QW1 | CC1 | CT1 | LB1 | LH1 | FC1 | LC1 | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CL1 | 25. | 18. | 1.4 | 12. | 15. | 8.9 | 1.0 | 1.5 | 1.2 | 0.9 | 1.4 | 2.1 | 0.9 | 1 | 1.2 | 1.1 | 0.6 | 0.8 | 0.9 | 0.3 | 0.5 | 0.6 | 0.3 | 0.5 | 0.0 | 0.0 | 0.0 | 0.1 | 74.6 |
| CO1 | 17. | 24. | 1.2 | 12. | 15. | 10. | 1.0 | 1.4 | 1.1 | 0.9 | 1.3 | 2.0 | 0.9 | 0.9 | 1.0 | 1.0 | 0.7 | 0.8 | 1.0 | 0.2 | 0.4 | 0.5 | 0.4 | 0.5 | 0.0 | 0.0 | 0.0 | 0.1 | 75.5 |
| NG1 | 4.3 | 3.8 | 72. | 3.6 | 6.0 | 2.8 | 0.3 | 0.4 | 0.4 | 0.2 | 0.5 | 0.4 | 0.3 | 0.1 | 0.2 | 0.2 | 0.3 | 0.5 | 0.6 | 0.2 | 0.2 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.1 | 27 |
| XBW1 | 15. | 15. | 1.4 | 30. | 15. | 8.4 | 0.7 | 1.0 | 0.8 | 0.8 | 1.0 | 1.6 | 0.7 | 0.7 | 0.9 | 0.8 | 0.4 | 0.5 | 0.6 | 0.1 | 0.3 | 0.4 | 0.3 | 0.4 | 0.0 | 0.0 | 0.0 | 0.0 | 69.8 |
| HO1 | 15. | 16. | 2.1 | 13. | 26. | 11. | 0.9 | 1.2 | 0.9 | 0.7 | 1.1 | 1.6 | 0.8 | 0.7 | 0.8 | 0.8 | 0.5 | 0.6 | 0.8 | 0.2 | 0.4 | 0.4 | 0.3 | 0.4 | 0.0 | 0.0 | 0.0 | 0.1 | 73.9 |
| QS1 | 12. | 15. | 1.5 | 10. | 16. | 29. | 0.9 | 1.2 | 1.0 | 0.7 | 1.1 | 1.8 | 1.0 | 0.9 | 1.0 | 1 | 0.5 | 0.6 | 0.7 | 0.2 | 0.4 | 0.3 | 0.4 | 0.3 | 0.1 | 0.0 | 0.0 | 0.1 | 70.6 |
| GC1 | 1.5 | 1.6 | 0.2 | 0.9 | 1.4 | 1.0 | 37. | 21. | 10. | 5.2 | 2.3 | 3.3 | 2.4 | 1.4 | 1.6 | 1.4 | 0.7 | 0.8 | 0.7 | 0.5 | 0.4 | 0.4 | 0.9 | 0.4 | 0.1 | 0.0 | 0.0 | 0.0 | 62.2 |
| SI1 | 1.9 | 2 | 0.1 | 1.1 | 1.5 | 1.3 | 18. | 32. | 9.0 | 6.0 | 3.3 | 4.6 | 3.2 | 1.8 | 2.4 | 2.2 | 0.9 | 1.2 | 1.2 | 0.8 | 0.7 | 0.6 | 1.0 | 0.6 | 0.1 | 0.0 | 0.0 | 0.1 | 67.4 |
| PL1 | 1.9 | 2 | 0.2 | 1.1 | 1.4 | 1.3 | 10. | 10. | 37. | 11. | 2.9 | 3.7 | 2.7 | 1.9 | 2.5 | 1.9 | 0.7 | 0.9 | 1.1 | 0.7 | 0.6 | 0.6 | 0.7 | 0.6 | 0.0 | 0.0 | 0.0 | 0.1 | 62.8 |
| PA1 | 1.5 | 1.6 | 0.1 | 1.1 | 1.2 | 1.0 | 5.8 | 7.7 | 13. | 41. | 3.4 | 4.3 | 3.2 | 2.2 | 2.8 | 2.4 | 0.6 | 0.7 | 1.1 | 0.6 | 0.6 | 0.6 | 0.6 | 0.8 | 0.1 | 0.0 | 0.1 | 0.1 | 58.5 |
| LA1 | 1.9 | 1.8 | 0.3 | 1.1 | 1.4 | 1.2 | 2.1 | 3.3 | 2.6 | 2.7 | 33. | 13. | 9.0 | 4.9 | 7.2 | 6.3 | 0.6 | 0.9 | 1.2 | 0.5 | 0.6 | 0.6 | 0.6 | 0.7 | 0.1 | 0.0 | 0.0 | 0.1 | 66.8 |
| LP1 | 2.1 | 2.1 | 0.1 | 1.4 | 1.5 | 1.6 | 2.3 | 3.8 | 2.6 | 2.7 | 11. | 26. | 11. | 6.0 | 9.0 | 8.4 | 0.7 | 0.8 | 1.2 | 0.5 | 0.6 | 0.8 | 0.5 | 0.8 | 0.2 | 0.0 | 0.0 | 0.1 | 73.3 |
| LX1 | 1.1 | 1.2 | 0.1 | 0.7 | 0.9 | 1.1 | 1.9 | 3.1 | 2.2 | 2.4 | 8.5 | 12. | 31. | 4.9 | 10. | 10. | 0.4 | 0.4 | 0.8 | 0.5 | 0.5 | 0.6 | 0.6 | 0.6 | 0.2 | 0.0 | 0.1 | 0.1 | 68.4 |
| LT1 | 1.7 | 1.6 | 0.1 | 1.0 | 1.1 | 1.3 | 1.5 | 2.4 | 2.1 | 2.3 | 6.2 | 9.5 | 6.7 | 42. | 7.2 | 6.4 | 0.5 | 0.7 | 1.0 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.1 | 0.1 | 0.0 | 0.1 | 57.7 |
| LL1 | 1.7 | 1.5 | 0.1 | 1.1 | 1.1 | 1.1 | 1.5 | 2.6 | 2.3 | 2.4 | 7.7 | 11. | 12. | 5.9 | 34. | 6.6 | 0.5 | 0.4 | 0.7 | 0.4 | 0.5 | 0.6 | 0.5 | 0.7 | 0.1 | 0.0 | 0.0 | 0.1 | 65.1 |
| LN1 | 1.6 | 1.5 | 0.1 | 1.1 | 1.1 | 1.1 | 1.3 | 2.4 | 1.7 | 2.1 | 6.9 | 11. | 12. | 5.5 | 7.0 | 36. | 0.4 | 0.5 | 0.9 | 0.4 | 0.5 | 0.6 | 0.5 | 0.8 | 0.2 | 0.0 | 0.0 | 0.1 | 63.3 |
| W_1 | 1.4 | 1.5 | 0.2 | 0.7 | 1.1 | 0.7 | 0.9 | 1.4 | 0.9 | 0.7 | 0.9 | 1.5 | 0.7 | 0.7 | 0.8 | 0.6 | 50. | 19. | 8.1 | 1.0 | 1.2 | 1 | 0.3 | 1.8 | 0.2 | 0.1 | 0.0 | 0.2 | 49.2 |
| C_1 | 1.6 | 1.6 | 0.3 | 0.8 | 1.1 | 0.7 | 1.0 | 1.7 | 1.0 | 0.7 | 1.2 | 1.4 | 0.7 | 0.7 | 0.7 | 0.7 | 17. | 46. | 13. | 0.7 | 1.0 | 0.9 | 0.3 | 1.5 | 0.1 | 0.0 | 0.3 | 0.2 | 54 |
| S_1 | 1.9 | 2.1 | 0.4 | 1.1 | 1.6 | 1.0 | 1.0 | 1.9 | 1.3 | 1.2 | 1.7 | 2.2 | 1.2 | 1.2 | 0.9 | 1.2 | 7.8 | 14. | 48. | 0.8 | 1.2 | 0.9 | 0.4 | 2.1 | 0.2 | 0.2 | 0.0 | 0.2 | 51.3 |
| KC1 | 0.9 | 0.8 | 0.2 | 0.4 | 0.6 | 0.5 | 0.9 | 1.8 | 1.4 | 1.0 | 1.2 | 1.4 | 1.2 | 0.7 | 0.9 | 0.9 | 1.6 | 1.2 | 1.2 | 72. | 2.6 | 1.9 | 1.8 | 0.9 | 0.2 | 0.2 | 0.0 | 0.1 | 27.9 |
| SB1 | 1.1 | 1.0 | 0.2 | 0.5 | 0.8 | 0.6 | 0.6 | 1.1 | 0.8 | 0.8 | 1.0 | 1.3 | 0.9 | 0.7 | 0.7 | 0.7 | 1.3 | 1.2 | 1.4 | 1.9 | 53. | 24. | 0.8 | 1.0 | 0.1 | 0.0 | 0.0 | 0.0 | 46.6 |
| QW1 | 1.3 | 1.0 | 0.1 | 0.7 | 0.8 | 0.6 | 0.6 | 0.9 | 0.7 | 0.7 | 1.0 | 1.6 | 1.1 | 0.8 | 0.9 | 0.9 | 1.1 | 1.2 | 1.2 | 1.4 | 25. | 53. | 0.8 | 0.7 | 0.1 | 0.0 | 0.0 | 0.0 | 46.6 |
| CC1 | 1.1 | 1.2 | 0.2 | 0.8 | 0.9 | 1.1 | 1.7 | 2.3 | 1.4 | 1.0 | 1.3 | 1.5 | 1.4 | 1.2 | 1.0 | 1.0 | 0.4 | 0.7 | 0.7 | 1.8 | 1.1 | 1.2 | 72. | 0.8 | 0.1 | 0.0 | 0.0 | 0.2 | 27.5 |
| CT1 | 1.6 | 1.6 | 0.1 | 1.1 | 1.1 | 0.8 | 0.7 | 1.2 | 0.9 | 1.2 | 1.6 | 2.1 | 1.4 | 1.3 | 1.4 | 1.5 | 2.2 | 2.3 | 2.9 | 0.8 | 1.2 | 0.9 | 0.6 | 67. | 0.2 | 0.1 | 0.0 | 0.1 | 32.2 |
| LB1 | 0.2 | 0.4 | 0.0 | 0.1 | 0.2 | 0.5 | 0.0 | 0.3 | 0.2 | 0.2 | 0.4 | 0.8 | 0.5 | 0.4 | 0.4 | 0.5 | 0.3 | 0.3 | 0.3 | 0.3 | 0.1 | 0.1 | 0.2 | 0.2 | 91. | 0.0 | 0.0 | 0.2 | 8.5 |
| LH1 | 0.2 | 0.2 | 0.0 | 0.1 | 0.2 | 0.1 | 0.0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.2 | 0.1 | 0.3 | 0.0 | 0.1 | 0.1 | 0.1 | 0.5 | 0.0 | 0.1 | 0.0 | 0.0 | 0.2 | 0.1 | 93. | 0.7 | 1.0 | 6.2 |
| FC1 | 0.3 | 0.3 | 0.0 | 0.1 | 0.2 | 0.1 | 0.1 | 0.0 | 0.1 | 0.2 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 0.5 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.6 | 77. | 18. | 22.5 |
| LC1 | 0.3 | 0.4 | 0.2 | 0.2 | 0.3 | 0.2 | 0.1 | 0.3 | 0.3 | 0.3 | 0.4 | 0.5 | 0.3 | 0.3 | 0.2 | 0.2 | 0.2 | 0.3 | 0.2 | 0.1 | 0.1 | 0.0 | 0.1 | 0.2 | 0.1 | 0.8 | 17. | 74. | 25.1 |
| TO | 94. | 99. | 12. | 71. | 91. | 62. | 58. | 77. | 62 | 50. | 71 | 100 | 78. | 48. | 64. | 60. | 43. | 54. | 46 | 16. | 42. | 41. | 14. | 19. | 3.9 | 3.7 | 20. | 23. | 1434. |
| ALL | 120 | 124 | 85. | 101 | 117 | 92. | 96. | 110 | 99. | 92. | 104 | 127 | 110 | 90. | 99. | 97. | 94 | 100 | 94. | 88. | 96. | 94. | 87. | 87. | 95. | 97. | 97. | 97. | 51.20 |

Note: This total spillover table is estimated by the Diebold and Yilmaz (2012) methodology.

To observe the dynamics of spillovers among the 28 commodity futures during the sample period, we plot the trajectory of total spillovers in Fig. 4. The graph shows time-varying spillovers, with phases of rises and falls. We note that total volatility spillovers are 40% for some periods and less than 20% for others. This fluctuation in spillovers are influenced by bad and good market news and market data releases of heavily traded events in the commodity markets. External macro shocks including China's economic slowdown of 2015, OPEC announcements, and the US Fed interest rates influence total risk spillovers. Investors plan their strategies in advance and deploy them immediately following the release of information depending on whether the news or data is in line with their expectations. Total spillovers are intensified by economic and political crises as they increase significantly during those periods. We find that a decrease in total spillovers is a signal of potential diversification opportunities while an increase in volatility spillovers reduces the possibility of spillovers and indicates an increase in integration among commodity futures markets.

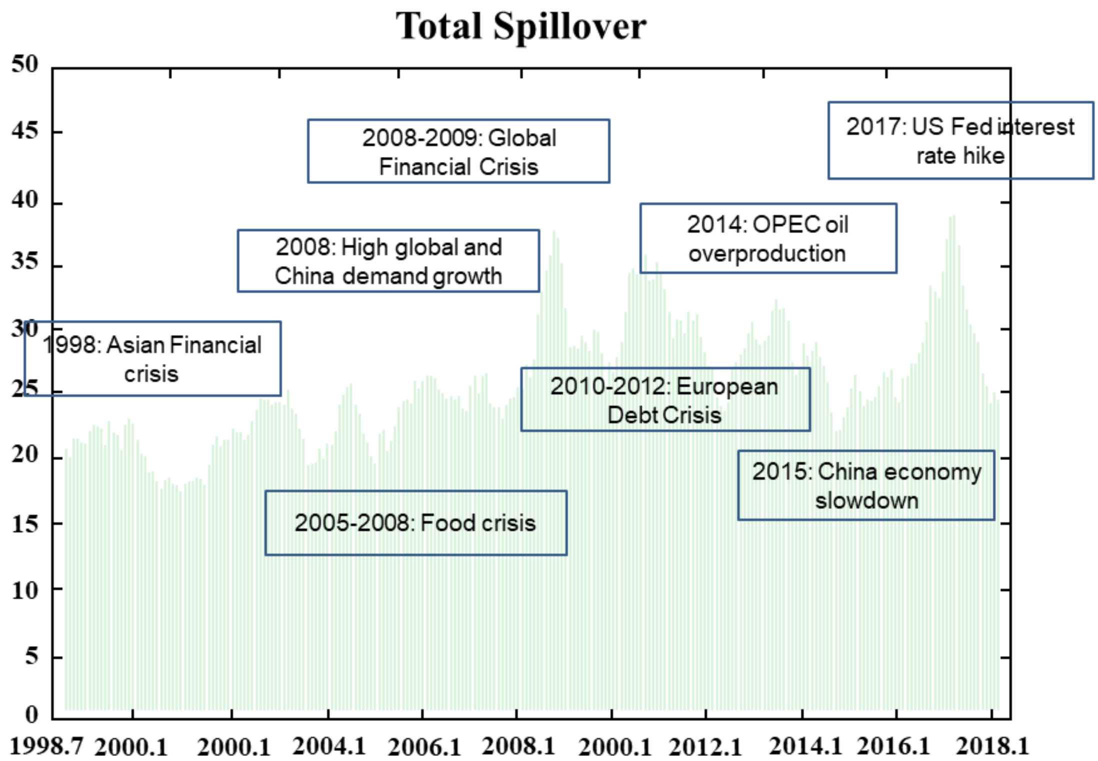



**Fig. 4.** Time-varying total spillover index based on the Diebold and Yilmaz (2012) framework

Note: This figure displays the time-varying behavior of the total return spillover index of the seven renewable energy stocks under examination computed using Diebold and Yilmaz (2012) approach. The dynamic total spillover index is calculated from the forecast error variance decompositions using a rolling window size of 250 days and forecast horizon of H=100 days.

*4.2. The results of DY spillover for multiscale return series*

Time investment horizon is a key factor for evaluating market risk and investors' decisions. Moreover, the reaction and expectations of market participants differ from short- to long-term. Some investors set a long investment horizon because they feel more comfortable taking riskier investment decisions and capitalize on the market volatility whereas speculators focus only on a few days (short-term horizon). In the short term, investors tend to have low risk tolerance and prefer secure investments. Hence, there is a possibility of asymmetric spillovers because the time horizon is different.

Tables 3 and 4 summarize the total spillovers at the short-term investment horizons (2–

8 days) and long-term horizon (8–256 days), respectively. The value of total spillovers is high for long-term horizon (51%) than for short-term (50.7%).

Conversely, the spillovers of risk from one commodity futures to another is important for investors and policymakers when short-term rather than long-term investment horizons are considered. WTI crude oil contributes 15% and 2% on the forecasting variance for Brent oil in the short- and long-term, respectively. Xiao and Wang (2020) showed that the WTI and Brent crude oil prices do not play identical roles in their interactions with multiple stock markets either statically or dynamically. Additionally, WTI oil contributes 0.2% on the forecasting variance for three livestock futures in the short term (from 2 to 8 days) but the results show an absence of risk transmission to the livestock markets in the long term (above 8 days). The other energy, metals, and agriculture futures have a low contribution of risk to livestock futures price returns over both time horizons. The livestock futures market is the least contributor of risk to the other markets. It is also the least receiver of risk from the other markets. This result persists for different time horizons and is in line with previous study results. Livestock assets are a good hedge tool for short-term and long-term investors to optimize the risk of their portfolio. The contribution of risk is important within each class of commodity. Taking energy as an example, the contribution to other markets (TO_ABS) ranges between 0.3 to 2.9 % in the short term and between 0 to 0.4% in the long term. The interpretations for the other markets are similar. Livestock futures markets receive less risk from the other markets in the short term than in the long term. In contrast, energy, industrial metals, precious metals, and agriculture futures markets receive less risk in the long-term than in the short-term.

Overall, the decomposition of the raw return series into short- and long-term enhances our understanding for market risk evaluation, risk management, and diversification opportunities.

**Table 3**. Total spillovers at the short-term investment horizon

| | CL1 | CO1 | NG1 | XBW1 | HO1 | QS1 | GC1 | SI1 | PL1 | PA1 | LA1 | LP1 | LX1 | LT1 | LL1 | LN1 | W_1 | C_1 | S_1 | KC1 | SB1 | QW1 | CC1 | CT1 | LB1 | LH1 | FC1 | LC1 | FROM _ABS | FROM _WTH |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CL1 | 22. | 16. | 1.2 | 11. | 13. | 7.7 | 0.9 | 1.3 | 1.0 | 0.8 | 1.2 | 1.8 | 0.8 | 0.8 | 1.1 | 0.9 | 0.6 | 0.7 | 0.8 | 0.3 | 0.5 | 0.5 | 0.3 | 0.5 | 0.0 | 0.0 | 0.0 | 0.1 | 2.3 | 2.68 |
| CO1 | 15. | 22. | 1.1 | 11. | 14. | 9.3 | 0.9 | 1.3 | 1.0 | 0.8 | 1.1 | 1.7 | 0.8 | 0.7 | 0.9 | 0.8 | 0.6 | 0.7 | 0.9 | 0.2 | 0.4 | 0.4 | 0.3 | 0.5 | 0.0 | 0.0 | 0.0 | 0.1 | 2.3 | 2.71 |
| NG1 | 3.9 | 3.5 | 65. | 3.2 | 5.4 | 2.5 | 0.3 | 0.3 | 0.3 | 0.2 | 0.4 | 0.3 | 0.2 | 0.1 | 0.2 | 0.2 | 0.3 | 0.5 | 0.5 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.8 | 0.97 |
| XBW1 | 13. | 14. | 1.2 | 26. | 14. | 7.2 | 0.7 | 0.9 | 0.7 | 0.7 | 0.8 | 1.4 | 0.6 | 0.6 | 0.8 | 0.7 | 0.3 | 0.5 | 0.6 | 0.1 | 0.2 | 0.3 | 0.2 | 0.4 | 0.0 | 0.0 | 0.0 | 0.0 | 2.2 | 2.51 |
| HO1 | 14. | 14. | 1.7 | 12. | 23. | 10. | 0.8 | 1.0 | 0.7 | 0.6 | 0.9 | 1.3 | 0.7 | 0.5 | 0.6 | 0.7 | 0.4 | 0.5 | 0.7 | 0.1 | 0.3 | 0.3 | 0.2 | 0.3 | 0.0 | 0.0 | 0.0 | 0.1 | 2.3 | 2.65 |
| QS1 | 10. | 12. | 1.1 | 8.2 | 13. | 26. | 0.6 | 1 | 0.9 | 0.6 | 0.9 | 1.6 | 0.9 | 0.8 | 0.9 | 0.8 | 0.4 | 0.5 | 0.6 | 0.2 | 0.3 | 0.3 | 0.3 | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 2.0 | 2.35 |
| GC1 | 1.3 | 1.4 | 0.1 | 0.8 | 1.2 | 0.8 | 33. | 19. | 9.3 | 4.7 | 2.0 | 2.8 | 2.0 | 1.1 | 1.3 | 1.2 | 0.6 | 0.7 | 0.6 | 0.4 | 0.3 | 0.3 | 0.7 | 0.3 | 0.0 | 0.0 | 0.0 | 0.0 | 1.9 | 2.21 |
| SI1 | 1.6 | 1.7 | 0.1 | 1 | 1.3 | 1.0 | 16. | 29. | 7.9 | 5.3 | 2.8 | 4.0 | 2.8 | 1.5 | 2.1 | 1.8 | 0.8 | 1.0 | 1.0 | 0.7 | 0.6 | 0.5 | 0.9 | 0.5 | 0.1 | 0.0 | 0.0 | 0.1 | 2.0 | 2.39 |
| PL1 | 1.5 | 1.6 | 0.1 | 0.9 | 1.1 | 1.0 | 9.0 | 8.9 | 32. | 10. | 2.4 | 3.1 | 2.2 | 1.5 | 2.1 | 1.5 | 0.6 | 0.8 | 0.9 | 0.6 | 0.5 | 0.4 | 0.6 | 0.5 | 0.0 | 0.0 | 0.0 | 0.0 | 1.9 | 2.17 |
| PA1 | 1.3 | 1.4 | 0.1 | 0.9 | 1.0 | 0.8 | 4.9 | 6.6 | 11. | 35. | 2.9 | 3.6 | 2.7 | 1.9 | 2.4 | 2.0 | 0.5 | 0.6 | 0.8 | 0.5 | 0.5 | 0.5 | 0.4 | 0.6 | 0.0 | 0.0 | 0.0 | 0.1 | 1.7 | 2.01 |
| LA1 | 1.6 | 1.5 | 0.2 | 0.9 | 1.2 | 1.0 | 1.7 | 2.9 | 2.1 | 2.4 | 30. | 12. | 8.2 | 4.5 | 6.5 | 5.7 | 0.4 | 0.7 | 1.0 | 0.4 | 0.5 | 0.5 | 0.5 | 0.6 | 0.1 | 0.0 | 0.0 | 0.1 | 2.1 | 2.39 |
| LP1 | 1.9 | 1.8 | 0.1 | 1.2 | 1.3 | 1.4 | 2.0 | 3.4 | 2.3 | 2.4 | 10. | 23. | 10. | 5.4 | 8.2 | 7.5 | 0.6 | 0.7 | 1.0 | 0.5 | 0.6 | 0.7 | 0.5 | 0.7 | 0.2 | 0.0 | 0.0 | 0.1 | 2.3 | 2.66 |
| LX1 | 1.0 | 1.0 | 0.1 | 0.6 | 0.8 | 0.9 | 1.7 | 2.7 | 1.9 | 2.1 | 7.4 | 11. | 28. | 4.4 | 9.7 | 9.6 | 0.3 | 0.4 | 0.6 | 0.5 | 0.4 | 0.5 | 0.5 | 0.5 | 0.1 | 0.0 | 0.0 | 0.0 | 2.1 | 2.47 |
| LT1 | 1.4 | 1.3 | 0.0 | 0.8 | 0.9 | 1.1 | 1.2 | 2.0 | 1.7 | 1.9 | 5.6 | 8.4 | 5.9 | 37. | 6.4 | 5.5 | 0.3 | 0.5 | 0.8 | 0.3 | 0.4 | 0.5 | 0.5 | 0.6 | 0.1 | 0.1 | 0.0 | 0.1 | 1.7 | 2.01 |
| LL1 | 1.5 | 1.3 | 0.1 | 0.9 | 0.9 | 1.0 | 1.2 | 2.2 | 1.9 | 2.0 | 6.7 | 10. | 10. | 5.2 | 30. | 5.9 | 0.4 | 0.4 | 0.5 | 0.3 | 0.4 | 0.5 | 0.4 | 0.6 | 0.1 | 0.0 | 0.0 | 0.0 | 2.0 | 2.32 |
| LN1 | 1.3 | 1.3 | 0.1 | 0.8 | 0.9 | 1 | 1.2 | 2.0 | 1.4 | 1.8 | 6.1 | 10. | 11. | 4.9 | 6.3 | 32. | 0.3 | 0.4 | 0.7 | 0.4 | 0.4 | 0.5 | 0.4 | 0.7 | 0.1 | 0.0 | 0.0 | 0.1 | 2 | 2.28 |
| W_1 | 1.3 | 1.5 | 0.2 | 0.6 | 1.0 | 0.6 | 0.8 | 1.3 | 0.8 | 0.6 | 0.8 | 1.4 | 0.6 | 0.5 | 0.7 | 0.5 | 44. | 17. | 7.2 | 0.9 | 1.0 | 0.8 | 0.2 | 1.4 | 0.1 | 0.1 | 0.0 | 0.1 | 1.5 | 1.78 |
| C_1 | 1.4 | 1.5 | 0.3 | 0.8 | 1.0 | 0.7 | 0.8 | 1.5 | 0.9 | 0.6 | 1.1 | 1.3 | 0.6 | 0.6 | 0.5 | 0.5 | 15. | 40. | 12. | 0.6 | 0.9 | 0.8 | 0.3 | 1.3 | 0.1 | 0.0 | 0.2 | 0.1 | 1.7 | 1.93 |
| S_1 | 1.7 | 1.9 | 0.3 | 1.0 | 1.5 | 0.9 | 0.8 | 1.7 | 1.2 | 1.0 | 1.5 | 2.0 | 1.1 | 1.0 | 0.8 | 1.0 | 7.0 | 12. | 42. | 0.7 | 1.0 | 0.8 | 0.4 | 1.7 | 0.1 | 0.2 | 0.0 | 0.1 | 1.6 | 1.85 |
| KC1 | 0.8 | 0.7 | 0.1 | 0.4 | 0.5 | 0.5 | 0.7 | 1.6 | 1.2 | 0.9 | 1.0 | 1.3 | 1.1 | 0.5 | 0.7 | 0.8 | 1.3 | 1.0 | 1.0 | 64. | 2.2 | 1.6 | 1.7 | 0.7 | 0.2 | 0.0 | 0.0 | 0.0 | 0.8 | 0.96 |
| SB1 | 1.1 | 1 | 0.1 | 0.5 | 0.8 | 0.6 | 0.5 | 1.1 | 0.8 | 0.7 | 0.9 | 1.1 | 0.8 | 0.6 | 0.6 | 0.7 | 1.1 | 1.1 | 1.1 | 1.6 | 47. | 22. | 0.7 | 0.9 | 0.0 | 0.0 | 0.0 | 0.0 | 1.4 | 1.68 |
| QW1 | 1.2 | 1.0 | 0.1 | 0.6 | 0.8 | 0.6 | 0.5 | 0.8 | 0.7 | 0.6 | 0.8 | 1.4 | 0.9 | 0.6 | 0.8 | 0.8 | 0.9 | 0.9 | 0.9 | 1.2 | 21. | 47. | 0.7 | 0.6 | 0.0 | 0.0 | 0.0 | 0.0 | 1.4 | 1.65 |
| CC1 | 0.9 | 1 | 0.1 | 0.6 | 0.7 | 0.8 | 1.4 | 2.0 | 1.2 | 0.8 | 1.1 | 1.3 | 1.2 | 0.9 | 0.9 | 0.8 | 0.3 | 0.5 | 0.6 | 1.6 | 0.9 | 0.9 | 64. | 0.6 | 0.2 | 0.0 | 0.0 | 0.1 | 0.8 | 0.91 |
| CT1 | 1.4 | 1.3 | 0.0 | 1.0 | 0.9 | 0.8 | 0.7 | 1.2 | 0.8 | 1.0 | 1.4 | 2 | 1.2 | 1.1 | 1.2 | 1.3 | 1.9 | 1.9 | 2.4 | 0.7 | 1.1 | 0.8 | 0.5 | 59. | 0.2 | 0.1 | 0.0 | 0.1 | 1.0 | 1.15 |
| LB1 | 0.2 | 0.2 | 0.0 | 0.1 | 0.1 | 0.3 | 0.0 | 0.2 | 0.1 | 0.1 | 0.3 | 0.6 | 0.3 | 0.2 | 0.3 | 0.3 | 0.2 | 0.3 | 0.2 | 0.2 | 0.0 | 0.0 | 0.2 | 0.2 | 80. | 0.0 | 0.0 | 0.1 | 0.2 | 0.25 |
| LH1 | 0.2 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.0 | 0.3 | 0.0 | 0.0 | 0.1 | 0.0 | 0.4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 82. | 0.6 | 0.9 | 0.1 | 0.18 |
| FC1 | 0.2 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.5 | 68. | 15. | 0.6 | 0.73 |
| LC1 | 0.3 | 0.3 | 0.1 | 0.1 | 0.3 | 0.2 | 0.0 | 0.3 | 0.2 | 0.3 | 0.4 | 0.5 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.0 | 0.7 | 15. | 65. | 0.7 | 0.87 |
| TO_ABS | 2.9 | 3.1 | 0.3 | 2.2 | 2.8 | 1.9 | 1.8 | 2.4 | 1.9 | 1.5 | 2.2 | 3.1 | 2.4 | 1.4 | 2.0 | 1.8 | 1.3 | 1.6 | 1.4 | 0.5 | 1.3 | 1.2 | 0.4 | 0.5 | 0.1 | 0.1 | 0.6 | 0.6 | 44. | |
| TO_WTH | 3.3 | 3.5 | 0.3 | 2.5 | 3.2 | 2.2 | 2.0 | 2.7 | 2.1 | 1.8 | 2.5 | 3.6 | 2.8 | 1.7 | 2.3 | 2.1 | 1.5 | 1.9 | 1.6 | 0.5 | 1.5 | 1.4 | 0.5 | 0.6 | 0.1 | 0.1 | 0.6 | 0.7 | | 50.7 |

Notes: This table displays the total spillover index of Barunik and Krehlik (2018) at the short-term horizon (overall spillovers on band: 3.14 to 0.39). ABS and WTH refer to absolute and within the estimated system.

**Table 4**. Total spillovers at the long-term investment horizon

| | CL1 | CO1 | NG1 | XBW1 | HO1 | QS1 | GC1 | SI1 | PL1 | PA1 | LA1 | LP1 | LX1 | LT1 | LL1 | LN1 | W_1 | C_1 | S_1 | KC1 | SB1 | QW1 | CC1 | CT1 | LB1 | LH1 | FC1 | LC1 | FROM _ABS | FROM _WTH |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CL1 | 2.9 | 2.1 | 0.1 | 1.4 | 1.7 | 1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.1 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.3 | 2.48 |
| CO1 | 2.0 | 2.6 | 0.1 | 1.5 | 1.7 | 1.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.3 | 2.51 |
| NG1 | 0.3 | 0.3 | 8 | 0.2 | 0.4 | 0.2 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0 | 0 | 0.0 | 0.0 | 0.0 | 0.7 |
| XBW1 | 1.7 | 1.8 | 0.1 | 3.6 | 1.7 | 0.9 | 0.0 | 0.0 | 0.1 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0.0 | 0.2 | 2.3 |
| HO1 | 1.8 | 1.9 | 0.2 | 1.5 | 2.9 | 1.3 | 0.1 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0.3 | 2.51 |
| QS1 | 2.1 | 2.5 | 0.2 | 1.8 | 2.7 | 3.9 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 3.5 |
| GC1 | 0.2 | 0.2 | 0.0 | 0.1 | 0.1 | 0.1 | 4.5 | 2.5 | 1.2 | 0.5 | 0.2 | 0.3 | 0.2 | 0.1 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0 | 0 | 0 | 0 | 0.2 | 2.16 |
| SI1 | 0.2 | 0.2 | 0.0 | 0.1 | 0.2 | 0.1 | 2.1 | 3.8 | 1.0 | 0.7 | 0.3 | 0.5 | 0.3 | 0.2 | 0.3 | 0.3 | 0.1 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0 | 0 | 0 | 0.0 | 0.3 | 2.47 |
| PL1 | 0.3 | 0.3 | 0.0 | 0.2 | 0.2 | 0.2 | 1.3 | 1.3 | 4.7 | 1.5 | 0.4 | 0.5 | 0.3 | 0.2 | 0.4 | 0.2 | 0.1 | 0.1 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.3 | 2.68 |
| PA1 | 0.2 | 0.2 | 0.0 | 0.2 | 0.2 | 0.1 | 0.7 | 1.1 | 1.9 | 5.8 | 0.5 | 0.6 | 0.4 | 0.2 | 0.4 | 0.3 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.3 | 2.56 |
| LA1 | 0.2 | 0.2 | 0.0 | 0.1 | 0.2 | 0.1 | 0.2 | 0.3 | 0.3 | 0.3 | 3.6 | 1.4 | 0.9 | 0.5 | 0.8 | 0.6 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0 | 0 | 0.0 | 0.2 | 2.2 |
| LP1 | 0.2 | 0.2 | 0.0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0.2 | 0.3 | 1.1 | 2.8 | 1.1 | 0.6 | 0.9 | 0.8 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.2 | 2.25 |
| LX1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 0.2 | 0.3 | 0.2 | 0.3 | 1.0 | 1.4 | 3.0 | 0.5 | 1.2 | 0.9 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.2 | 2.19 |
| LT1 | 0.2 | 0.2 | 0.0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0.2 | 0.3 | 0.7 | 1.1 | 0.8 | 5.4 | 0.8 | 1 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0 | 0.0 | 0.2 | 2.22 |
| LL1 | 0.2 | 0.1 | 0.0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0.2 | 0.3 | 0.9 | 1.4 | 1.4 | 0.7 | 4.2 | 0.7 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0.2 | 2.3 |
| LN1 | 0.2 | 0.2 | 0.0 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.2 | 0.2 | 0.8 | 1.2 | 1.1 | 0.5 | 0.7 | 3.9 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0 | 0.0 | 0.2 | 2.05 |
| W_1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 6.1 | 2.3 | 0.8 | 0.1 | 0.1 | 0.1 | 0.0 | 0.2 | 0.0 | 0.0 | 0 | 0.0 | 0.1 | 1.5 |
| C_1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.1 | 2.1 | 5.8 | 1.6 | 0.1 | 0.1 | 0.1 | 0.0 | 0.2 | 0.0 | 0 | 0.0 | 0.0 | 0.2 | 1.79 |
| S_1 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.1 | 0.0 | 0.1 | 0.1 | 0.7 | 1.6 | 6.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.3 | 0.0 | 0.0 | 0 | 0.0 | 0.2 | 1.6 |
| KC1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.2 | 0.2 | 0.1 | 0.2 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.2 | 0.2 | 0.2 | 8.3 | 0.3 | 0.2 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 1.12 |
| SB1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.2 | 6.2 | 2.9 | 0.0 | 0.1 | 0.0 | 0 | 0 | 0 | 0.1 | 1.58 |
| QW1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.2 | 0.2 | 3.4 | 6.4 | 0.0 | 0.1 | 0.0 | 0 | 0 | 0 | 0.2 | 1.69 |
| CC1 | 0.2 | 0.1 | 0.0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0.2 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.3 | 0.2 | 0.1 | 8.8 | 0.2 | 0.0 | 0.0 | 0 | 0.0 | 0.1 | 1.25 |
| CT1 | 0.2 | 0.1 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.1 | 0.0 | 0.1 | 0.2 | 0.2 | 0.3 | 0.3 | 0.1 | 0.1 | 0.1 | 0.0 | 9.1 | 0.0 | 0 | 0 | 0.0 | 0.1 | 1.06 |
| LB1 | 0.0 | 0.1 | 0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 12. | 0.0 | 0.0 | 0.0 | 0.0 | 0.41 |
| LH1 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0.0 | 0 | 0.0 | 0 | 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0.0 | 12. | 0.0 | 0.1 | 0.0 | 0.21 |
| FC1 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0.0 | 0 | 0 | 0 | 0.0 | 0 | 0.0 | 0 | 0.0 | 0 | 0 | 0 | 0.0 | 0 | 0 | 0.0 | 0 | 0 | 0 | 0.0 | 0.1 | 10. | 2.8 | 0.1 | 0.95 |
| LC1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0 | 0.0 | 0 | 0 | 0.0 | 0.0 | 0.0 | 2.5 | 9.7 | 0.1 | 0.88 |
| TO_ABS | 0.4 | 0.4 | 0.0 | 0.3 | 0.4 | 0.2 | 0.2 | 0.3 | 0.2 | 0.2 | 0.3 | 0.4 | 0.3 | 0.1 | 0.2 | 0.2 | 0.1 | 0.2 | 0.2 | 0.0 | 0.2 | 0.1 | 0.0 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 6.2 | |
| TO_WTH | 3.4 | 3.6 | 0.4 | 2.6 | 3.3 | 2.0 | 2.0 | 2.7 | 2.2 | 1.7 | 2.4 | 3.3 | 2.4 | 1.4 | 2.2 | 2.1 | 1.5 | 2.0 | 1.7 | 0.7 | 1.7 | 1.4 | 0.4 | 0.8 | 0.0 | 0.1 | 0.8 | 1.0 | | 51.0 |

Notes: This table displays the total spillover index of Barunik and Krehlik (2018) at the long-term horizon (overall spillovers on band: 0.39 to 0.01). ABS and WTH refer to absolute and within the estimated system.

Fig. 5 displays the time-varying total spillovers among 28 commodity futures markets in short-term and long-term. We observe a significant upward trend in spillovers during 2008–2009 for both short- and long-term. This shows that commodity futures markets were influenced by the global economic downturn. More interestingly, the magnitude of the spillovers is more evident in the short-term than the long-term, indicating that commodity markets react rapidly and absorb external shocks quickly. Investors in commodity futures markets react according to the external shocks. The increase in spillovers indicates that commodity futures markets are more vulnerable to major events and are more integrated. The intensity of the spillover is greater during 2007–2009 and 2011–2013, corresponding to the 2008 GFC and 2011 European debt crisis. After 2013, the total spillovers experience a gradual downside trend during the rest of the periods.

For the short-term, the total spillovers exceed 70% and the minimum is less than 30% whereas for the long-term, it ranges between 5% and 11%. This indicates the significant difference in the total spillovers between the short- and long-term horizons. It also shows the importance of considering time horizon in analyzing market risk. Overall, the dynamic analysis of spillovers is amplified by global economic and political events that are likely to have led to significant fluctuations in spillovers across markets: the 1998 Asian crisis, 2008 global financial crisis, 2012 European crisis, and the financialization of commodities.

The net directional connectedness of stocks and commodities at short-term and long-term are given in Figs. 6 and 7, respectively. The net directional connectedness is dynamic and more important in the short-term than in the long-term. The variation of net total directional connectedness is negative for some periods indicating that the market is a net receiver of risk whereas positive for other periods indicating that the market is net transmitter of risks. The plots of the net total directional connectedness are much smoother from 1997 to 2005 than for the rest of the sample period (2006–2018).

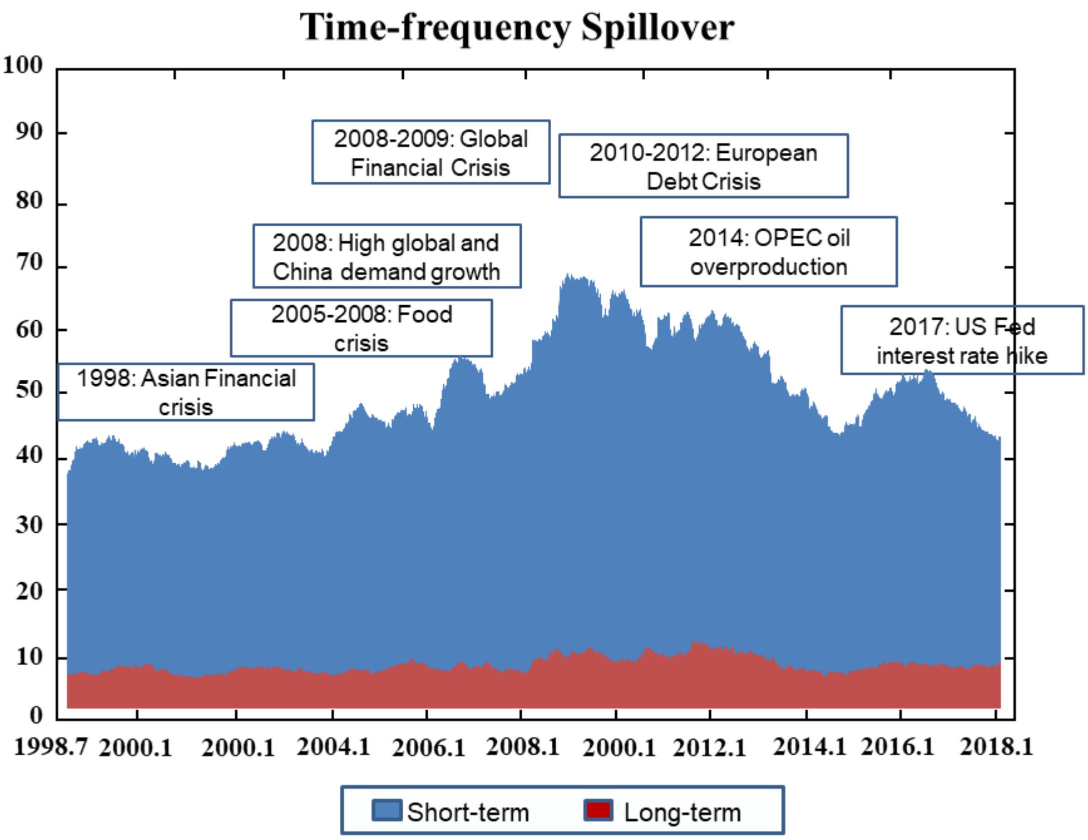



**Fig. 5.** Short- and long-term dynamic frequency connectedness between commodity futures

**Notes**: These figures represent frequency connectedness; short-term (overall spillovers on band: 3.14 to 0.39); long-term (overall spillovers on band: 0.39 to 0.01).

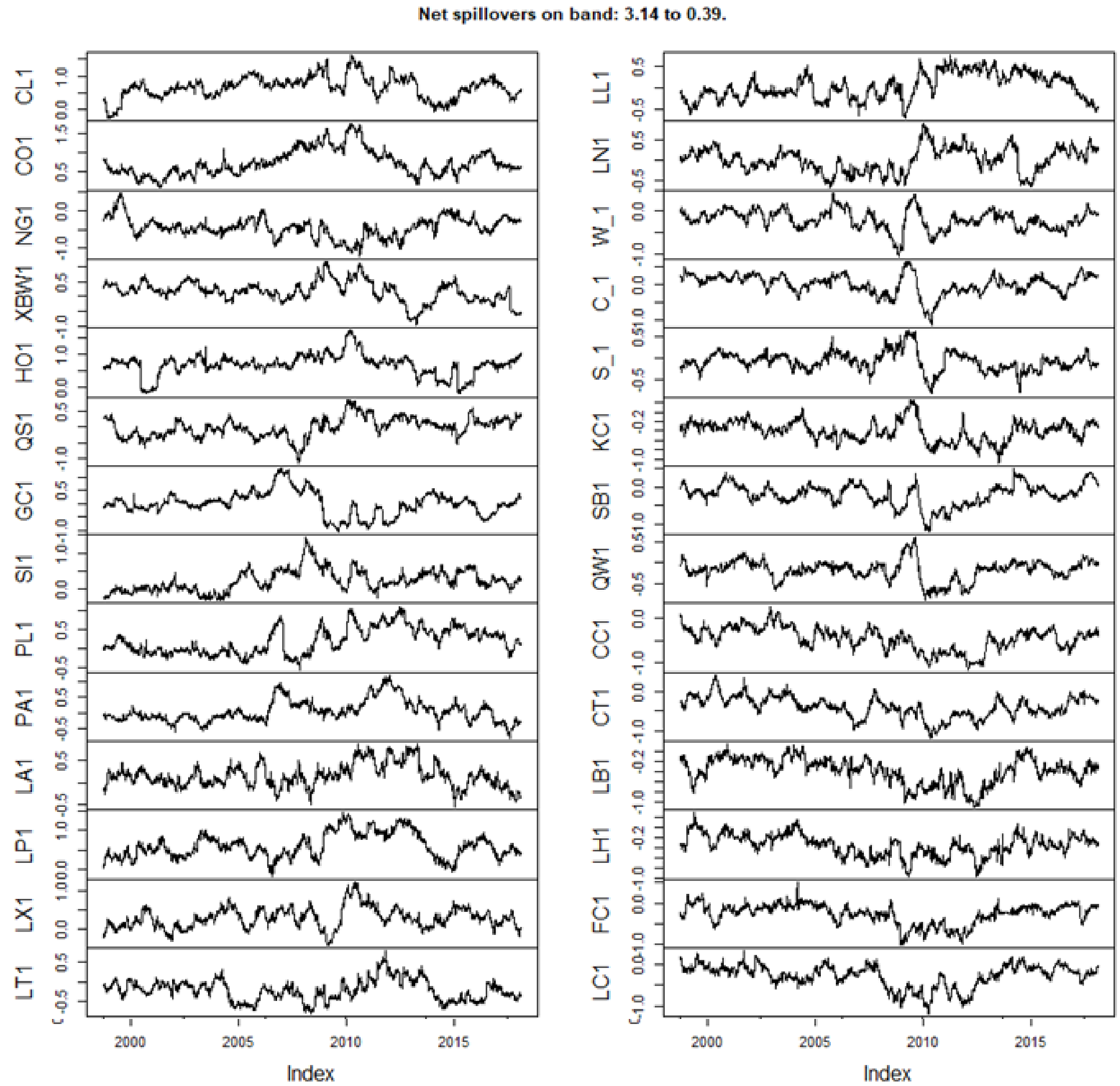



**Fig. 6.** Short-term net directional connectedness of commodity futures

**Notes**: The net total directional connectedness is the difference between total directional connectedness to others and total directional connectedness from others.

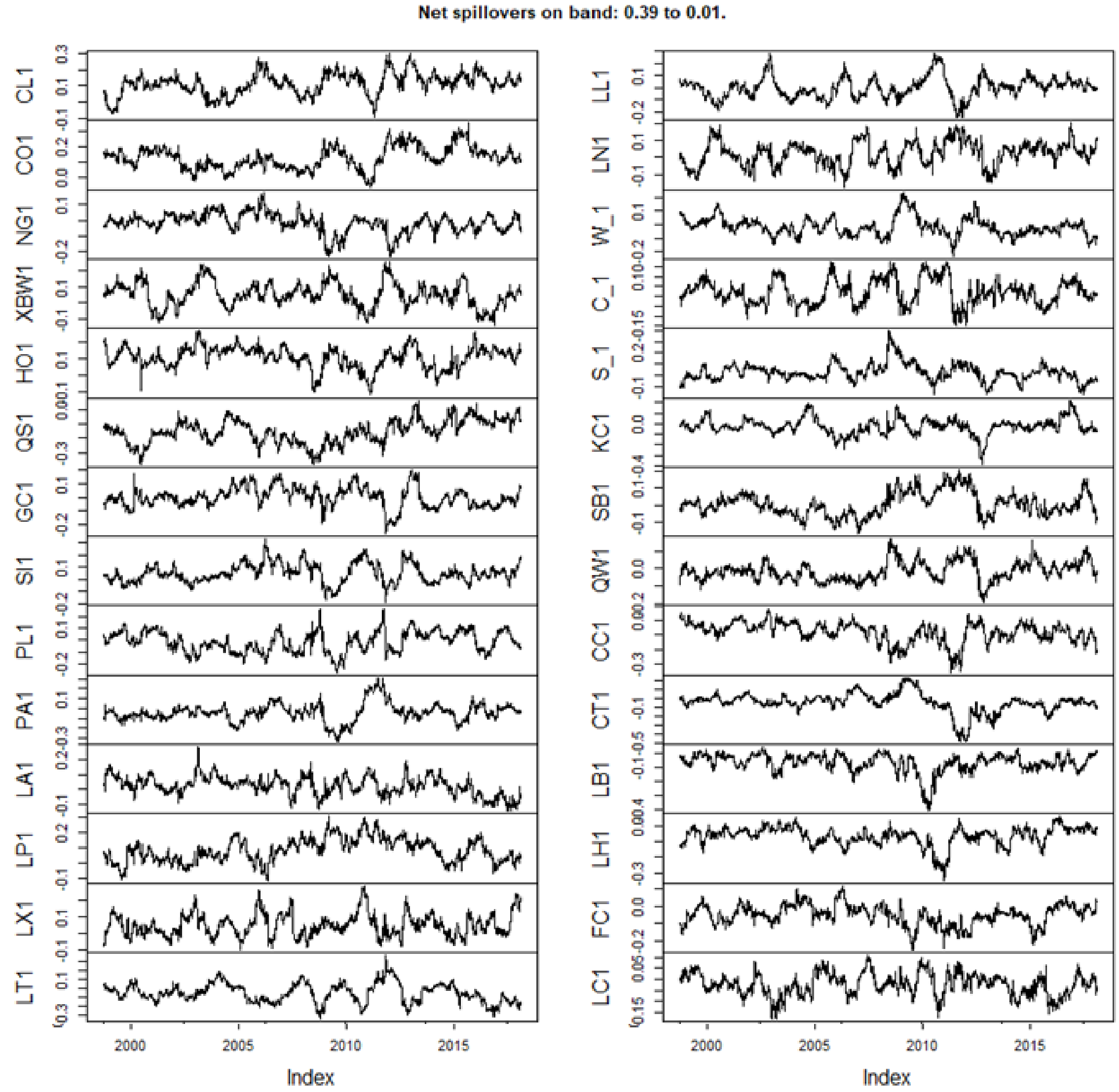
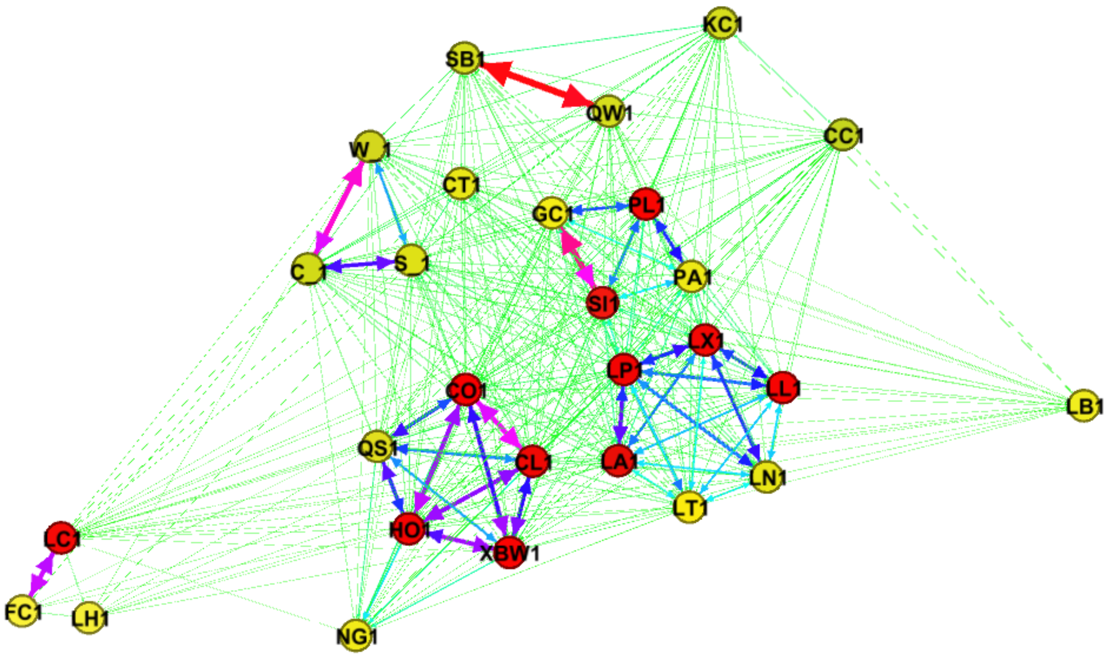



**Fig. 7.** Long-term net directional connectedness of commodity futures
**Notes**: See the notes of Fig. 6.

*4.3 Connectedness network results*

Fig. 8 illustrates the net pairwise directional connectedness among the commodity futures markets under short-term (panel a) and long-term (panel b). The analysis of connectedness provides rich information about the intensity and pathway of risk spillover from one commodity futures market to another. The width of the arrows denotes the magnitude of spillovers and node diameter denotes the size of net spillover. The figure shows the complexity of evaluating market risk and portfolio management. Panel (a) shows that PL1, LX1, LL1, LA1, LC1, CO1, CL1, XBW1, and HO1 are net transmitters of risk and the remaining markets are net receivers of risk. A bidirectional risk spillover is observed between agriculture futures (sugar cane (SB1) and sugar beets (QW1)), between energy futures (WTI (CO1) and Brent (CL1)) and precious metal futures (gold (GC1) and silver (SI1), gold (GC1) and platinum (PL1), platinum (PL1) and palladium (PA1)), industrial metal futures (aluminum (LP1) and copper (LA1)), and energy futures (WTI (CO1) and gas oil (QS1)). Livestock markets, coffee, cocoa, and lumber are weakly related to the other markets.

(a) Short-term (overall spillovers on band: 3.14 to 0.39)




(b) Long-term (overall spillovers on band: 0.39 to 0.01)

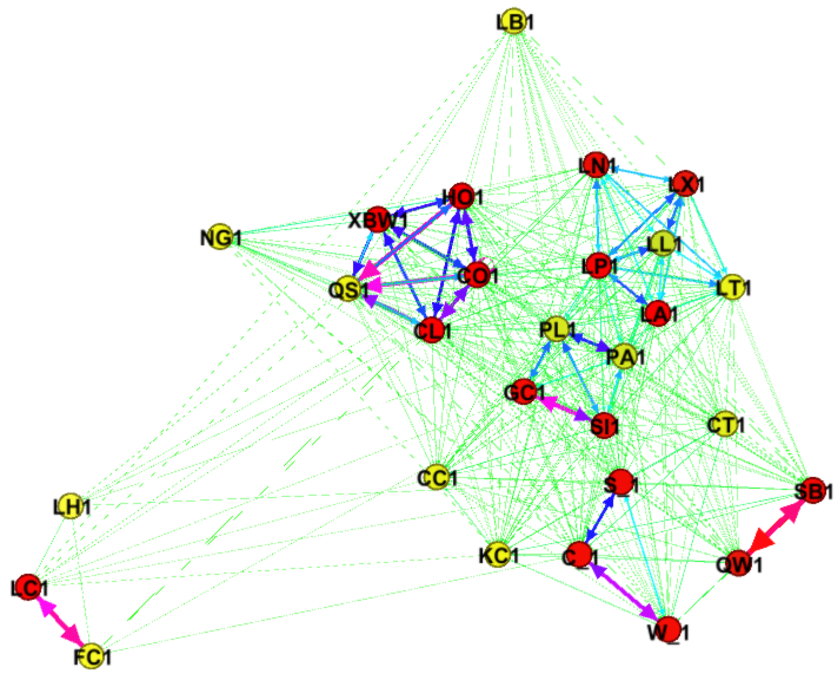



**Fig. 8.** Net pairwise directional connectedness at different frequency bands

**Notes**: These figures represent the frequency connectedness networks; (a) short-term (overall spillovers on band: 3.14 to 0.39); (b) long-term (overall spillovers on band: 0.39 to 0.01). A red (yellow) a node is the most significant transmitter (recipient) of spillover. The edge color ranks green (weak), light blue (medium), blue and red (strong).

*4.4 Portfolio risk analysis*

We assess the ability of WTI to provide risk reduction and downside risk protection to other commodity futures markets by quantifying risk reduction, value at risk, semivariance, and regret measures. Three different portfolios are considered in this analysis and compared with a benchmark portfolio composed only of WTI oil. Portfolio II is a risk-minimizing WTI-commodity portfolio, Portfolio III has equal weights, and Portfolio IV's weights are determined according to a variance minimization hedging strategy.

Tables 5 and 6 report the estimates of risk evaluation for different WTI-commodity futures portfolios in the short-term and long-term frequencies, respectively. The results show that non-WTI oil futures provide significant risk reduction for short- and long-term to a benchmark WTI portfolio. The magnitude of risk reduction is more pronounced for short-term than for long-term for 16 out of 27 cases (gas oil, gold, palladium, tin, lead, wheat, corn, coffee, sugar cane, sugar beets, cocoa, cotton, lumber, lean hogs, feeder cattle, and live cattle). WTI-tin (WTI-natural gas) portfolio offers the highest risk reduction in the short-term (long-term). Under the long-term, Portfolio IV offers the highest risk reduction for 17 cases (particularly for metals and livestock markets), whereas Portfolio III (Portfolio II) provides the highest risk reduction for 8 cases (2 cases: natural gas and gasoline). As for the short-term, we find that Portfolio IV, Portfolio III, and Portfolio II offers the highest risk reductions for 12, 13, and 2 cases, respectively. As regards downside risk reduction, the results show that Portfolio IV offers the best downside risk reduction regardless of the time horizon. The magnitude of downside risk reduction is higher in the short-term than in the long-term. In addition, the largest reduction in VaR is obtained for Brent-WTI crude oil and cotton-WTI portfolio for short-term and for natural gas-WTI portfolio for the long-term.

**Table 5.** Risk evaluations for different WTI-commodity portfolios in the short-term horizon

| | Portfolio | Brent | Natural Gas | Gasoline | Heating Oil | Gas Oil | Gold | Silver | Platinum | Palladium | Aluminum | Copper | Zinc | Tin | Lead |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RiskRed. | PII | 0.1250 | **0.5453** | 0.0544 | 0.0590 | 0.2720 | 0.1714 | 0.2049 | 0.2319 | 0.2400 | 0.2038 | 0.2389 | **0.0506** | 0.2362 | 0.2023 |
| | PIII | 0.1518 | 0.0724 | **0.0861** | **0.1556** | **0.3864** | 0.6523 | 0.4976 | 0.5944 | **0.4877** | 0.6029 | 0.5358 | 0.4713 | 0.5777 | **0.4829** |
| | PIV | **0.1564** | 0.3258 | 0.0034 | 0.1413 | 0.3660 | **0.8032** | **0.5125** | **0.6647** | 0.4206 | **0.7074** | **0.5922** | 0.4806 | **0.6338** | 0.4959 |
| VaRRed. | PII | 0.0517 | **0.0515** | **0.0507** | 0.0496 | **0.0518** | **0.0502** | **0.0513** | **0.0517** | **0.0515** | **0.0498** | **0.0500** | **0.0470** | **0.0530** | 0.0487 |
| | PIII | 0.0520 | 0.0515 | 0.0502 | 0.0515 | 0.0500 | 0.0496 | 0.0487 | 0.0513 | 0.0476 | 0.0494 | 0.0496 | 0.0463 | 0.0507 | **0.0494** |
| | PIV | **0.0543** | 0.0494 | 0.0489 | **0.0526** | 0.0509 | 0.0491 | 0.0509 | 0.0479 | 0.0472 | 0.0441 | 0.0470 | 0.0459 | 0.0453 | 0.0465 |
| SV Red. | PII | **1.9087** | **3.4018** | **2.3205** | **2.0141** | **1.5258** | **1.3137** | **1.6494** | **1.5417** | **1.5591** | **1.6392** | **1.5791** | **1.7432** | **1.5612** | **1.6215** |
| | PIII | 1.8603 | 2.1567 | 2.0647 | 1.8569 | 1.3193 | 0.8788 | 1.1043 | 0.8796 | 1.1376 | 0.8966 | 0.9788 | 1.0961 | 0.9266 | 1.1187 |
| | PIV | 1.8768 | 3.0619 | 2.2142 | 1.8778 | 1.4083 | 0.6559 | 1.0892 | 0.7027 | 1.2497 | 0.6577 | 0.8672 | 1.0697 | 0.7172 | 1.0931 |
| ReRed | PII | **1.3813** | **1.8449** | **1.5231** | **1.4190** | **1.2350** | **1.7265** | **1.2827** | **1.2414** | **1.2487** | **1.2801** | **1.2566** | **1.3201** | **1.2494** | **1.2734** |
| | PIII | 1.3639 | 1.4685 | 1.4369 | 1.3627 | 1.1486 | 0.7723 | 1.0508 | 0.9379 | 1.0666 | 0.9469 | 0.9893 | 1.0469 | 0.9626 | 1.0576 |
| | PIV | 1.3703 | 1.7497 | 1.4884 | 1.3702 | 1.1867 | 0.4304 | 1.0439 | 0.8381 | 1.1178 | 0.8109 | 0.9311 | 1.0341 | 0.8469 | 1.0455 |

| | Portfolio | Nickel | Wheat | Corn | Soybeans | Coffee | Sugar Cane | Sugar Beets | Cocoa | Cotton | Lumber | Lean Hogs | Feeder Cattle | Live Cattle |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RiskRed. | PII | 0.0084 | 0.2565 | 0.2266 | 0.2129 | 0.1931 | 0.2137 | 0.2241 | 0.3176 | 0.2727 | 0.2642 | 0.0045 | 0.1248 | 0.1649 |
| | PIII | **0.3727** | **0.5190** | 0.5454 | 0.5734 | **0.4814** | **0.4789** | 0.5737 | **0.5528** | **0.5537** | **0.5398** | **0.5024** | 0.7050 | 0.6847 |
| | PIV | 0.2197 | 0.4983 | **0.5731** | **0.6262** | 0.3270 | 0.3778 | **0.6135** | 0.4923 | 0.5465 | 0.4411 | 0.4611 | **0.8713** | **0.8228** |
| VaRRed. | PII | 0.0438 | **0.0506** | **0.0524** | **0.0519** | 0.0485 | **0.0492** | **0.0518** | **0.0528** | 0.0502 | 0.0455 | 0.0442 | **0.0541** | **0.0515** |
| | PIII | **0.0453** | 0.0485 | 0.0502 | 0.0489 | 0.0505 | 0.0489 | 0.0502 | 0.0524 | **0.0531** | **0.0478** | 0.0478 | 0.0522 | 0.0452 |
| | PIV | 0.0427 | 0.0450 | 0.0483 | 0.0505 | **0.0518** | 0.0478 | 0.0459 | 0.0481 | 0.0476 | 0.0448 | **0.0517** | 0.0489 | 0.0474 |
| SV Red. | PII | **1.7471** | **1.5203** | **1.5827** | **1.5944** | **1.6312** | **1.6089** | **1.5611** | **1.3992** | **1.4945** | **1.4488** | **1.7282** | **1.7797** | **1.7059** |
| | PIII | 1.2968 | 1.0917 | 1.0311 | 0.9549 | 1.1899 | 1.1872 | 0.9750 | 1.0212 | 1.0199 | 1.0375 | 0.9963 | 0.6362 | 0.6975 |
| | PIV | 1.6221 | 1.1616 | 0.9116 | 0.8219 | 1.5220 | 1.3902 | 0.8226 | 1.1741 | 1.0203 | 1.2613 | 0.9908 | 0.2479 | 0.3922 |
| ReRed | PII | **1.3218** | **1.2329** | **1.2581** | **1.2627** | **1.2772** | **1.2684** | **1.2494** | **1.1829** | **1.2225** | **1.2036** | **1.3146** | **1.3340** | **1.3061** |
| | PIII | 1.1388 | 1.0448 | 1.0154 | 0.9772 | 1.0908 | 1.0896 | 0.9874 | 1.0105 | 1.0099 | 1.0186 | 0.9982 | 0.7976 | 0.8351 |
| | PIV | 1.2736 | 1.0778 | 0.9548 | 0.9066 | 1.2337 | 1.1791 | 0.9070 | 1.0835 | 1.0101 | 1.1232 | 0.9954 | 0.4979 | 0.6262 |

Notes: This table reports the results of risk reduction and downside risk gain for portfolios composed of the WTI and commodity futures with respect to a reference portfolio composed exclusively of the WTI. Portfolio II is a risk-minimizing WTI-commodity portfolio, Portfolio III has equal weights, and Portfolio IV's weights are determined according to a variance minimization hedging strategy. VaR Red.is the reduction in the VaR portfolio with respect to Portfolio I (where positive values indicate a VaR reduction). SV Red and Re Red are, respectively, the semi variance and regret reduction. The bold values indicate the portfolio that has the best risk reduction among the three portfolios for each WTI-commodity pair.

**Table 6.** Risk evaluations for different WTI-commodity portfolios in the long-term horizon

| | Portfolio | Brent | Natural Gas | Gasoline | Heating Oil | Gas Oil | Gold | Silver | Platinum | Palladium | Aluminum | Copper | Zinc | Tin | Lead |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RiskRed. | PII | 0.0226 | **0.9181** | **0.2932** | 0.0469 | 0.0108 | 0.0848 | 0.0707 | 0.0890 | 0.0827 | 0.0896 | 0.0662 | 0.0247 | 0.0063 | 0.0968 |
| | PIII | 0.1371 | 0.1015 | 0.0620 | 0.1772 | 0.2138 | 0.6400 | 0.4674 | 0.5641 | **0.4349** | 0.6017 | 0.5409 | 0.5204 | 0.5391 | 0.4651 |
| | PIV | **1.7702** | 0.2096 | 0.0103 | **0.1930** | **0.2531** | **0.7945** | **0.5169** | **0.6592** | 0.3556 | **0.7332** | **0.6433** | **0.5835** | **0.6123** | **0.4781** |
| VaRRed. | PII | **0.0416** | **0.0720** | **0.0551** | **0.0427** | **0.0493** | **0.0373** | **0.0427** | **0.0373** | **0.0439** | **0.0369** | **0.0370** | **0.0416** | **0.0401** | **0.0321** |
| | PIII | 0.0375 | 0.0368 | 0.0408 | 0.0345 | 0.0337 | 0.0147 | 0.0223 | 0.0186 | 0.0250 | 0.0162 | 0.0194 | 0.0203 | 0.0185 | 0.0213 |
| | PIV | 0.0352 | 0.0460 | 0.0429 | 0.0330 | 0.0309 | 0.0084 | 0.0199 | 0.0145 | 0.0272 | 0.0098 | 0.0146 | 0.0174 | 0.0156 | 0.0209 |
| SV Red. | PII | **0.6629** | **1.1751** | **0.8526** | **0.6899** | **0.6710** | **0.5907** | 0.7192 | **0.5821** | **0.7229** | **0.5699** | **0.5931** | **0.6799** | **0.6536** | **0.7051** |
| | PIII | 0.5948 | 0.5969 | 0.6426 | 0.5671 | 0.5404 | 0.2442 | 0.3602 | 0.2980 | 0.3987 | 0.2754 | 0.3069 | 0.3429 | 0.3001 | 0.3590 |
| | PIV | 0.5622 | 0.7431 | 0.6902 | 0.5375 | 0.4965 | 0.1364 | **0.8622** | 0.2267 | 0.4268 | 0.1635 | 0.2245 | 0.2617 | 0.2179 | 0.3089 |
| ReRed | PII | **0.8149** | **1.0831** | **0.9231** | **0.8329** | **0.8199** | **0.7685** | **0.8510** | **0.7680** | **0.8524** | **0.7569** | **0.7749** | **0.8301** | **0.8161** | **0.8427** |
| | PIII | 0.7712 | 0.7731 | 0.8016 | 0.7531 | 0.7351 | 0.4942 | 0.6002 | 0.5459 | 0.6314 | 0.5248 | 0.5540 | 0.5856 | 0.5478 | 0.5991 |
| | PIV | 0.7509 | 0.8517 | 0.8318 | 0.7333 | 0.7046 | 0.3692 | 0.5533 | 0.4761 | 0.6531 | 0.4042 | 0.4734 | 0.5082 | 0.4669 | 0.5550 |
| | | **Nickel** | **Wheat** | **Corn** | **Soybeans** | **Coffee** | **Sugar Cane** | **Sugar Beets** | **Cocoa** | **Cotton** | **Lumber** | **Lean Hogs** | **Feeder Cattle** | **Live Cattle** | |
| RiskRed. | PII | 0.1451 | 0.0127 | 0.0166 | 0.0224 | 0.1490 | 0.1037 | 0.0157 | 0.0644 | 0.0598 | 0.0990 | 0.3623 | 0.0737 | 0.0874 | |
| | PIII | **0.3748** | **0.5164** | 0.0525 | 0.5595 | **0.4665** | **0.4617** | 0.5602 | **0.5150** | 0.5019 | **0.5042** | **0.4571** | 0.6881 | 0.6629 | |
| | PIV | 0.3315 | 0.4998 | **0.5541** | **0.6282** | 0.3899 | 0.4007 | **0.6090** | 0.4981 | **0.5152** | 0.2208 | 0.3754 | **0.8407** | **0.7846** | |
| VaRRed. | PII | **0.0443** | **0.0384** | **0.0399** | **0.0411** | **0.0452** | **0.0437** | **0.0418** | **0.0399** | **0.0397** | **0.0427** | **0.0555** | **0.0382** | **0.0373** | |
| | PIII | 0.0241 | 0.0194 | 0.0196 | 0.0184 | 0.0222 | 0.0226 | 0.0186 | 0.0185 | 0.0195 | 0.0202 | 0.0228 | 0.0134 | 0.0141 | |
| | PIV | 0.0262 | 0.0182 | 0.0179 | 0.0144 | 0.0238 | 0.0247 | 0.0363 | 0.0163 | 0.0193 | 0.0221 | 0.0241 | 0.0068 | 0.0090 | |
| SV Red. | PII | **0.7090** | **0.6036** | **0.6480** | **0.6848** | **0.7337** | **0.7221** | **0.6516** | **0.5644** | **0.6894** | **0.6725** | **0.8345** | **0.5959** | **0.5801** | |
| | PIII | 0.4025 | 0.3130 | 0.3225 | 0.3024 | 0.3623 | 0.3662 | 0.3092 | 0.3427 | 0.3429 | 0.3219 | 0.3567 | 0.2200 | 0.2385 | |
| | PIV | 0.4234 | 0.3135 | 0.2869 | 0.2455 | 0.4053 | 0.3921 | 0.2596 | 0.5911 | 0.3116 | 0.3817 | 0.3720 | 0.1049 | 0.1467 | |
| ReRed | PII | **0.8476** | **0.7757** | **0.8065** | **0.8319** | **0.8643** | **0.8497** | **0.8086** | **0.7583** | **0.8348** | **0.8166** | **0.9159** | **0.7751** | **0.7632** | |
| | PIII | 0.6344 | 0.5594 | 0.5679 | 0.5499 | 0.6019 | 0.6051 | 0.0009 | 0.5856 | 0.5856 | 0.5674 | 0.5973 | 0.4691 | 0.4883 | |
| | PIV | 0.6504 | 0.5587 | 0.5358 | 0.4931 | 0.6340 | 0.6256 | 0.5009 | 0.5911 | 0.5579 | 0.6255 | 0.6036 | 0.3167 | 0.3820 | |

Notes: See the notes of Table 5.

## 5. Conclusions

Over the last two decades, commodity prices have experienced significant instability (sharp falls and rises). Various stakeholders, including international investors, policymakers, and academicians have increased their interest in the financialization of commodities. This study analyzes the short- and long-term risk spillovers among 28 major commodity futures markets: energy, precious metals, industrial metals, agriculture, and livestock. Moreover, we analyze the risk reduction in general and downside risk reduction in particular by examining the effects of adding WTI crude oil to each of the other commodity markets. To achieve these objectives, we use the Diebold and Yilmaz methodology, wavelet approach, and three risk measures of value at risk, semivariance, and regret along with a risk reduction measure for three different portfolios.

The results show that, for the raw return series, total spillovers is 51.2%. Tin is the highest contributor of shocks to the other markets. WTI and Brent crude oil markets are also high contributors of shocks to the other markets. Energy futures prices act as price discovery tools for metals, agricultural, and livestock markets. Lean hogs and lumber are the least contributors of risk to the other markets. Livestock futures have no risk contribution to energy, metals, and agricultural futures markets. We also show that the magnitude of receiving risk from the other markets is different for the four commodity classes. The risk spillover is dynamic and influenced by economic and geopolitical events. Total spillovers had intensified during the economic crises in the US and China, and 2005 commodities crisis.

After accounting for time horizon, we find that WTI crude oil contributes 15%, and 2% on the forecasting variance for Brent oil in the short- and long-term. Energy, metals, and agriculture markets have low (no) contribution on the forecasting variance for livestock futures in the short-term (long-term). Livestock futures markets is the least contributor/ receiver of risk to/from the other markets regardless of the time horizon. The risk spillovers among commodity futures shows a significant upward trend during 2008–2009 for short- and long-term due to economic and geopolitical events. We find that the magnitude of spillovers is more evident in the short-term than in long-term.

The analysis of portfolio risk reveals that adding commodity futures to an individual WTI oil portfolio provides significant risk reduction for short- and long-term. The magnitude of risk reduction is more pronounced for short-term than for long-term in many cases. Interestingly, WTI-Tin (WTI-Natural gas) portfolio offers the highest risk reduction in the short-term (long-term). Under the long-term, Portfolio IV offers the highest risk reduction for 17 cases (particularly for metals and livestock markets), whereas Portfolio III (Portfolio II) provides the highest risk reduction for 8 cases (2 cases: natural gas and gasoline). As for the short-term, we find that Portfolio IV, Portfolio III, and Portfolio II offer the highest risk reduction for 12, 13, and 2 cases, respectively. Portfolio IV offers the best downside risk reduction regardless of the time horizon.

These findings are relevant for investors and policymakers. Investors should keep in mind that risk spillovers among main commodity futures is time-varying and strong during episodes of economic crisis. Holding a short or long position depends on the magnitude of risk spillovers. Investors should be cautious in the short term (one week) as spillover is important and decreases after one week. Investors can consider investment in livestock futures due to their independence from the other markets. Our results also reveal the importance of adding non-WTI energy, metals, agriculture, and livestock assets to WTI crude oil portfolio in terms of risk reduction and downside risk reduction. Investors earn more risk reduction and downside gains in the short term. For policymakers, they should consider the dynamic and large extent of connectedness among commodity futures to formulate effective commodity policies.

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## Appendix

**Table A1:** The description of commodity futures

| | Codes | Commodity futures contracts |
|---|---|---|
| Energy | CL1 | WTI Crude Oil |
| | CO1 | Brent Crude Oil |
| | NG1 | Natural Gas |
| | XBW1 | Gasoline |
| | HO1 | Heating Oil |
| | QS1 | Gas Oil |
| Precious metals | GC1 | Gold |
| | SI1 | Silver |
| | PL1 | Platinum |
| | PA1 | Palladium |
| Industrial metals | LA1 | Aluminum |
| | LP1 | Copper |
| | LX1 | Zinc |
| | LT1 | Tin |
| | LL1 | Lead |
| | LN1 | Nickel |
| Agriculture | W 1 | Wheat |
| | C 1 | Corn |
| | S 1 | Soybeans |
| | KC1 | Coffee |
| | SB1 | Sugar Cane |
| | QW1 | Sugar Beets |
| | CC1 | Cocoa |
| | CT1 | Cotton |
| | LB1 | Lumber |
| Live stock | LH1 | Lean Hogs |
| | FC1 | Feeder Cattle |
| | LC1 | Live Cattle |

**Multivariate DCC-GARCH model**

Let $D_j(t)$ be a vector of wavelet return series at time $\mathrm{t}$ and $\mathrm{j}$ scale. The AR(1) of return process is defined as follows:

$$D_j(t) = \mu_i + \psi_i(L)D_j(t) + \varepsilon_{i,t}, \tag{A1}$$

where $|\mu_i| \in [0, \infty)$, $|\psi_i| < 1$, and $\varepsilon_{i,t} = [\varepsilon_{i,t}, \dots, \varepsilon_{n,t}]$ is the vector of the residuals. The conditional volatilities $h_{i,t}$ from the univariate GARCH (1,1) processes are described by:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1}, \tag{A2}$$

where $\omega_i > 0$, $\alpha_i \geq 0$, and $\beta_i \geq 0$. To estimate the conditional correlation matrix across stock market returns, we obtain the dynamic correlations using the conditional variance-covariance matrix $H_t$, which can be written as:

$$H_t = \Gamma_t^{1/2} R_t \Gamma_t^{1/2}, \tag{A3}$$

where, $D_t = diag\left(\sqrt{h_{i,t}}, \cdots, \sqrt{h_{n,t}}\right)$ is a diagonal matrix of time-varying variances $H_t$ from the univariate GARCH process and $R_t$ is the $n \times n$ time-varying conditional correlation matrix of standardized residuals. The conditional correlation matrix $R_t$ is defined as:

$$R_t = \{Q_t^*\}^{-1/2} Q_t \{Q_t^*\}^{-1/2}, \tag{A4}$$

where an element of $R_t$ has the following form:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t} q_{jj,t}}}, \tag{A5}$$

where $Q_t^* = diag[Q_t]$ are the diagonal elements of the covariance matrix $Q_t$. The covariance matrix $Q_t$ of the DCC model evolves according to

$$Q_t \equiv [q_{i,j,t}] = (1 - a - b)S + a(z_{t-1} z_{t-1}') + bQ_{t-1}, \tag{A6}$$

where $z_t = [z_{1,t}, \cdots, z_{n,t}]'$ is the standardized residual (i.e., $z_{i,t} = \varepsilon_{i,t}/\sqrt{h_{i,t}}$), $S \equiv [s_{i,j}] = E[z_t z_t']$ is the $(n \times n)$ unconditional covariance matrix of $z_t$, and $a$ and $b$ are non-negative scalars satisfying $(a + b) < 1$. The parameters of the multivariate DCC-GARCH model are estimated by QMLE.