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Volatility Transmission and Market Connectivity of Metals and Energy Commodities: Insights from the Spillover Index

Mathias Tessmann[1]*, Carlos Carrasco-Gutierrez[2], Omar Khodr[3], Luiz Augusto Magalhães[4], Marcelo Passos[5]

[1]Brazilian Institute of Education, Development and Research – IDP, Brazil, [2]Catholic University of Brasília, Brazil, [3]University of Essex, United Kingdom, [4]Brazilian Institute of Education, Development and Research - IDP, Brazil, [5]Federal University of Pelotas, Brazil. *Email: mathias.tessmann@idp.edu.br

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ABSTRACT

This paper explores the interconnections between metal and energy commodities by assessing the transmission of volatility within their futures markets. Achieved through the spillover index, the analysis reveals the impact of shocks on asset pairs—highlighting which assets absorb and transmit volatility, thereby explaining market connectivity. The dataset covers a period of 20 years of daily closing prices from the London Metals Exchange for a range of commodities. The Diebold and Yilmaz (2012) index, enriched by Baruník and Krehlík (2018) was used to reflect the changes in trends. The results obtained provide insights into market connectivity and the propagation of volatility during periods of economic distress. In this context, following the 2008 crisis, precious metals exhibited significant interconnectivity, with the emergence of Silver's vulnerability along with Gold's volatility tied to pre-crisis returns. Furthermore, copper's volatility reflects conditional correlations with market stock prices and other commodities particularly during economic downturns.

Keywords: Volatility Transmission, Spillover Index, Metal and Energy Commodities, London Metals Exchange
JEL Classifications: G15, Q31, Q37, Q41

1. INTRODUCTION

The commodity market holds substantial interest for researchers due to its integral role in investment portfolios and close ties to industrial production and inflation signals (Zhu et al., 2015). Price fluctuations prompt investors to adjust portfolios for safety and diversify across asset classes. These fluctuations arise from supply-demand imbalances, information disparities, and shifts in transaction costs, necessitating models to comprehend information cascades, where one market's changes ripple across others (Cevik and Sedik, 2014; Zhang et al., 2018).

In this context, the metals market's impact extends to economic activities, national mineral resource concerns, and economic security. Furthermore, the increase in financialization since 2004 sparked interest in metal price fluctuations, linking them to real demand and financial factors like exchange rates, speculative capital, and oil prices (Chen et al., 2019).

This study investigates the interrelations between metallic and energy commodities. It gauges volatility transmission in these futures markets using a spillover index, easily interpreted on a scale of zero to one hundred. This approach reveals how shocks affect asset pairs: Which absorb and transmit volatility, indicating market connectivity.

Data spanning October 16, 1998, to September 1, 2018, includes daily closing prices from the London Metals Exchange for aluminum, copper, lead, nickel, tin, zinc, platinum, palladium, silver, and gold, and from the London Exchange for natural gas and oil futures. The Diebold and Yilmaz (2012) index, refined by Baruník and Krehlík (2015) into short, medium, and long-term bands, facilitates the analysis.

Our results offer unique insights into market connectivity and volatility transfers, benefiting investors, risk managers, public agents, and hedging strategies. Copper, Gold, Silver, and Zinc exhibit notable interconnectivity. The financial and economic theory suggests that after the 2008 crisis, Silver's vulnerability emerged, and in a similar context, Gold's volatility was tied to prior returns affected by this period of crisis. Copper's volatility relates to conditional correlations (CCs) with market stock prices, oil, and wheat, particularly during economic crises.

The 2008-2009 period significantly impacted copper prices, echoed in this study (Creti et al., 2013; Mollick and Assefa, 2013; Sadorsky, 2014; Bouei et al., 2016; Vardar et al., 2018; Dadzie et al., 2023). Additionally, a most recent study by Umar et al. (2021) underscores demand and risk shocks as key metal return transmission factors. Zinc experiences volatility inflow from net transmitters like Tin, Gold, Nickel, Lead, and Aluminum, highlighted through Diebold and Yilmaz's tables.

2. LITERATURE REVIEW

Risk management is crucial to optimal portfolio management. One of the fastest-growing areas in empirical finance is the expansion of financial derivatives. While some of the main issues underlying risk and portfolio management are reasonably well understood, many of the technical and empirical aspects of issues underlying the creation and movements of financial derivatives are far less understood (Hammoudeh and McAleer, 2012).

Volatility provides a proxy for information flow, and by focusing on volatility structure rather than return, it provides additional and valuable insights into asset price dynamics and individual portfolios (Ross, 1989). As volatility comprises a measure of risk, volatility spillovers - which measure co-movements - in markets can have a large impact on risk-averse investors, and identifying them contributes to trading strategies, hedging, asset allocation, and forecasting prices (Cevik and Sedik, 2011).

Average trade size is of lesser relevance to the realized volatility of London Metals Exchange industrial metals futures and trading volume and trading frequency are important factors in the relative volume of volatility, and it is important to consider this relationship to understand how market participants market strive to incorporate useful information inherent in the series of trading activity to form forecasts of future returns and volatility (Todorova and Clements, 2018).

Investors looking to diversify their investments were encouraged to include commodities as part of their portfolio - as the returns on commodity investments have low correlations with investments in stocks and bonds, but until the creation of commodity Exchange Traded Funds, it was difficult for individual investors to invest in commodities because of exposure to price movements of futures contracts (Guedj et al., 2011).

They also turn to precious metals, for example, to resist inflation, and exchange rate risk and are considered as a reserve currency that could stimulate the production and consumption of the metals themselves, with their prices having positive effects on the price of oil and negative effects on the price of oil interest rate (Zhu et al., 2015).

Investors focus on the futures market rather than the spot market because futures contracts are widespread vehicles for speculation and the link between futures markets and different forms of speculation is more direct, with links existing between the activities of trading by speculators and price volatility of futures prices (Algieri and Leccadito, 2019) but the futures market can also increase market effectiveness and the price in efficient market will not change drastically when facing external shocks (Zhang et al., 2018).

In addition to investment strategies, for Sow (1996) the use or demand for metals is determined by their physical attributes and qualities, such as strength, ductility, heat and electrical conductivity, and corrosion resistance, and also depends on the demand for final goods that are used to produce, so their demand is called derived demand. Given the diversity of attributes and qualities, they replace each other for a given purpose and replace other materials in other sectors. This substitution effect, and its magnitude, plays an important role in shaping the prices of their prices.

The supply of these metals seems to depend on their prices, technological progress in mining and ore treatment, market structure, social events such as strikes and wars, and government activities. Market structure and industry concentration seem to be important factors affecting the supply of commodities in this group, the high concentration of producers suggests that, on a general basis, the prices of light metals have not been equal to their long-term marginal costs (Sow, 1996).

Global economic activity can increase prices and demand for these commodities, demand shocks cause prices to be highly correlated, and with the development of global economic integration and financialization, the transmission of information across markets has been enhanced, making the co-movement between commodity prices more complex (An et al., 2020). In 2000, there was a strong wave of financialization and speculation in the commodity markets in which the number of contracts traded in the futures markets increased significantly and the growth of long positions by index funds for various commodities in this period coincided with a phase of high volatility of prices (Algieri and Leccadito, 2018).

In Ahmadi et al. (2016) it is exposed that the responses of all commodities to an oil price shock are different depending on the underlying cause of the shock, they are also different. pre- and post-crisis periods and become stronger after the crisis. Metallic commodities - in this case, gold, silver, and copper - when the increase in oil prices is due to a positive global demand shock, the demand for metals increases, as they are production inputs for the entire economy, and consequently their prices increase. However, this shock affected price volatility in different directions before and after the 2008 crisis. One of the reasons may be the low attractiveness of stocks and bonds in the period 2000 to 2008, which led to an increase in demand for commodities, both physical and financial, increasing the volatility of these assets.

The volatility of metal commodity prices decreased in the post-2008 period, which can be explained by the slow development of mining capacity and rising energy costs. However, the presence of inventories and the gradual increase in demand after the crisis reduced the gap between supply and demand, thus reducing volatility in metal markets (Ahmadi et al., 2016).

As this interaction between metallic commodities and energy commodities occurs, it is necessary to emphasize that oil market professionals - investors and regulators - need to be aware that the use of models assuming that energy markets are perfect markets becomes inconsistent with the data, as such an assumption excludes any non-linear structure of stochastic solutions for the models. Furthermore, the existence of this non-linear structure implies the possibility of exploitable profit opportunities for speculators who can model and use such a time series structure (Aghababa and Barnett, 2016).

Metallic commodities, including raw materials or partially processed materials that will be transformed into finished products, are often the most significant source of export earnings for many developing countries or even developed countries around the world, their exports are highly concentrated in commodities, this implies that the variation in their terms of trade, foreign exchange reserves and public expenditures correlate with their price fluctuations (Chen, 2010) and given the importance of these metals to the economy, government interventions are quite frequent in times of social and economic disturbances, with price controls always being used to contain inflation and to satisfy urgent needs (Sow, 1996).

Per capita consumption is more elastic concerning income than price itself, and this income elasticity can vary considerably across metals and countries, metal consumption is, in general, more sensitive to income than to prices (Fernandez, 2018). In the early 2000s, rapid global economic growth boosted demand for commodities, boosting the prices of metals and minerals that are used as inputs for manufacturing. As a result, the world witnessed the biggest commodity boom in half a century accompanied by tremendous price volatility and there is strong evidence that the world's metal product prices are associated with substantial volatility (Chen, 2010).

It is with this scientific literature that the present work dialogues and contributes by offering - in addition to the direct risks presented by traditional risk management instruments - indirect risks and presenting empirical evidence about the existing connectivity in the metallic and energy commodities markets, in addition to the interactions for each pair of assets that compose it.

3. METHODOLOGY

3.1. Data

The data used are daily closing prices in US dollars of the futures market with a continuous contract for natural gas and oil - from the London Exchange forward index - aluminum, copper, lead, nickel, tin, zinc, platinum, and palladium - traded on the London Metals Exchange - silver and gold - from the Handy and Harman index.

The period covered is from October 16, 1998, to September 1, 2018, totaling 4665 price observations for each commodity. We used these commodities because they are traded daily in the futures market and their closing prices are available for the period we seek to analyze.

We separate metallic commodities into two types, precious metals, and base metals. The assets that makes up the class of precious metals are gold - which is the main precious metal used by speculators as an investment vehicle, and even with the industry using the metal in some electronic parts, the vast majority of demand for gold derives from manufacturers, jewelry dealers and many consumers who see gold jewelry as a form of investment -, silver which is primarily used by electronics manufacturers, jewelry and traders who collect the metal in the form of coins or bars, platinum - is used to make jewelry and catalytic converters for cars and investors buy platinum for many of the same reasons they buy gold and silver - and palladium which is also used to make catalytic converters, dental equipment, electronic parts and is also in demand from traders. Prices for these precious metals are expressed in US dollars per troy ounce.

The class of base metals is made up of aluminum - which is mainly used in aerospace production, cans, automobiles, construction, electrical wiring, household appliances, sheets and packaging -, copper - manufacture of electrical wiring, plumbing, transport equipment, equipment electrical, electronics, consumer products, and industrial equipment, lead - manufacture of batteries, protective shielding, ammunition and industrial plates, nickel - used mainly in the manufacture of stainless steel, in addition to electronics, plating, catalysts, and rechargeable batteries, tin - used as a coating metal and as an alloy to strengthen other metals - and zinc - which is mainly used to galvanize steel and as an alloy to strengthen other metals.

Base metals are priced in US dollars per metric ton, natural gas are expressed in US dollars per billion cubic meters, and oil in US dollars per barrel. Table 1 presents descriptive statistics with mean, standard deviation, minimum, and maximum closing prices and returns. The calculation of returns was made by the difference between the logarithm of the price on the day and the logarithm of the price on the previous day, $logP_t – logP_{t-1}$.

With the descriptive table, we can see that the assets with the highest standard deviation in their closing prices are nickel, tin, and copper, as well as those with the lowest standard deviations are silver, natural gas, and oil. Considering the returns, the assets with the highest standard deviations are zinc, palladium, and natural gas, while those with the lowest standard deviations are gold and aluminum. Figure 1 shows the trajectory of closing prices for each commodity analyzed from 1998 to 2018.

3.2. Diebold-Yilmaz Method

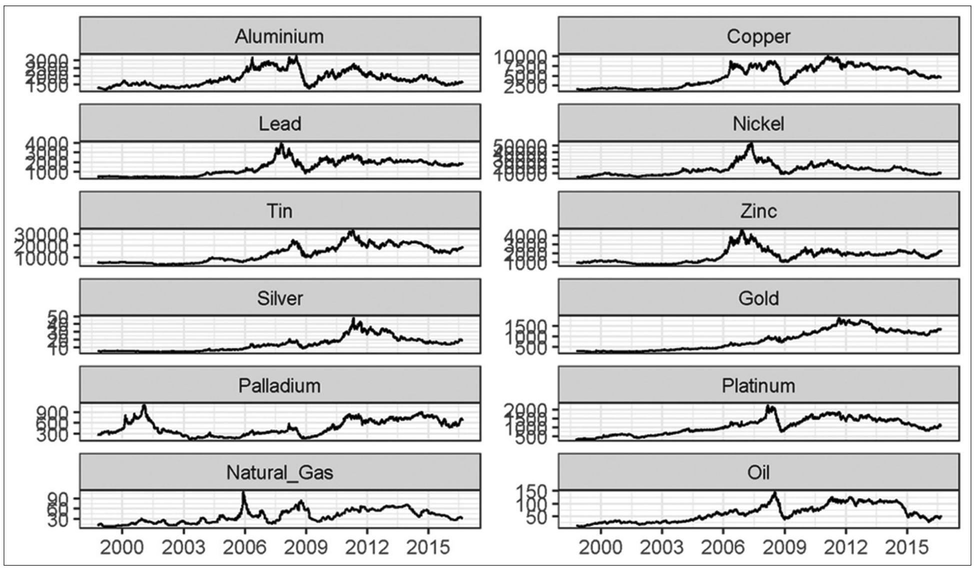
As presented in De Oliveira Passos et al. (2020), the Diebold and Yilmaz (2012) method uses a variance decomposition associated

Table 1: Statistics descriptives

	Closing prices				Returns			
Commodity	**Average**	**Std. Dev.**	**Min**	**Max**	**Average**	**Std. Dev.**	**Min**	**Max**
Aluminium	1874.270	461.186	1126.200	3271.250	0.00004	0.0135	−0.0826	0.0607
Copper	4942.937	2640.619	1318.250	10179.500	0.0002	0.0167	−0.1036	0.1173
Lead	1445.975	800.887	400.750	3989.000	0.0003	0.0202	−0.1320	0.1301
Nickel	15419.140	8597.959	3730	54050	0.0002	0.0233	−0.1836	0.1331
Tin	13171.330	7431.099	3601.000	33265.000	0.0003	0.0169	−0.1145	0.1539
Zinc	1732.454	777.861	722.750	4603.000	0.0002	0.0184	−0.1147	0.0995
Silver	14.007	9.300	4.050	48.550	0.0003	0.0188	−0.1300	0.1366
Gold	822.207	480.570	252.800	1895.000	0.0003	0.0112	−0.0960	0.0701
Palladium	476.857	218.492	150	1100	0.0002	0.0210	−0.1759	0.1811
Platinum	1073.237	447.187	334	2273	0.0002	0.0146	−0.1728	0.0843
Nat. Gas	37.721	18.952	8.440	108.430	0.0002	0.0267	−0.3526	0.3445
Oil	62.267	33.752	9.790	145.65	0.0003	0.0178	−0.1135	0.1041

Source: Elaborated by authors

Figure 1: Closing prices trajectory



Source: Elaborated by authors

with autoregressive vectors, VAR, which were estimated using the Akaike criterion for lag selection. Considering a stationary covariance of n variables VAR (p), $x_t = \sum_{i=1}^{P} \varnothing_i x_{t-1} + \varepsilon_t$, where $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disorders. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1}$ where the coefficient matrices N × N A_i obey recursion $A_i = \varnothing_1 A_{i-1} + \varnothing_2 A_{i-2} + \cdots + \varnothing p A_{i-p}$, with A_0 being an identity matrix N × N and with $A_i = 0$ for $i < 0$.

Moving average coefficients (or transformations as impulse response or variance decomposition functions) are the key to understanding system dynamics. Variance decompositions allow you to analyze the prediction error variations of each variable in parts that are attributable to the various system shocks and also allow you to evaluate the fraction of the error variance H steps forward in the prediction x_i which is due to shocks to x_j, $\forall j \neq i$, for each i.

Since VARs are generally correlated contemporaneously, the authors circumvented this problem by exploring Koop, Pesaran and Potter's (1996) generalized VAR structure and ordering them, because shocks for each variable are not orthogonalized, the sum of the contributions to the variance of the VAR. prediction error (that is, the sum of the row elements of the variance decomposition table) is not necessarily equal to one.

In shared installment the parts of variance themselves are defined as the fractions of error variations H steps ahead in forecasting x_i that is due to shocks to x_i, for $i = 1,2,\ldots,N$, and cross-variance parts, or spillovers, such as the fractions of the error variations H steps ahead in the forecast x_i that is due to shocks to x_j for $i,j = 1,2,\ldots,N$, such that $i \neq j$.

Denoting the prediction error variation decompositions of H steps forward by $\theta_{ij}^{g}(H)$, para $H = 1,2,\ldots$, we have

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i^{'} A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i^{'} A_h \sum A_h^{'} e_i)} \# \qquad (1)$$

Where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the equation jth, and e_i is the selection vector, with one as the ith element and zeros otherwise. To use the information available on the decomposition matrix variance in calculating the spillover index, each entry of the variance decomposition matrix is normalized by the sum of the line as:

$$\vartheta_{ij}^{g}(H)=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)}\#\tag{2}$$

By construction, $\sum_{j=1}^{N}\vartheta_{ij}^{g}(H)=1$ and $\sum_{i,j=1}^{N}\vartheta_{ij}^{g}(H)=N$. For the total spillovers the volatility contributions of the decomposition of the variable are used, thus the total volatility reversal index can be constructed:

$$S^{g}(H)=\frac{\sum_{\substack{i,j=0\\ i\neq j}}^{N}\vartheta_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\vartheta_{ij}^{g}(H)}100=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\vartheta_{ij}^{g}(H)}{N}100\#\tag{3}$$

The total spillover index measures the contribution of volatility shock spillovers in four asset classes to the total forecast error variance. The same is sufficient to allow us to understand how much of the volatility shocks spread across major asset classes, the generalized VAR approach allows us to learn about the direction of volatility spillovers in large asset classes. As generalized impulse responses and variance decompositions are invariant for variable ordering, directional spillovers are calculated using the normalized elements of the generalized variance decomposition matrix. Measuring directional volatility spillovers received by the market i from all other markets j as:

$$S_{i.}^{g}(H)=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\vartheta_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\vartheta_{ij}^{g}(H)}100=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\vartheta_{ij}^{g}(H)}{N}100\#\tag{4}$$

Similarly, by measuring the directional volatility spillovers transmitted by the market i for all other markets j as:

$$S_{.i}^{g}(H)=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\vartheta_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\vartheta_{ij}^{g}(H)}100=\frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\vartheta_{ji}^{g}(H)}{N}100\#\tag{5}$$

3.3. Baruník-Krehlík Refinement

Following the construction of the commodities volatility spillover index, we divide it into overnight (1 day), very short term (1-4 days), short term (4-30 days), and medium/long term (more than 30 days) using the method developed by Baruník and Krehlík (2018). As presented commodities Tessmann et al. (2021), and Baruník and Krehlík (2018) proposed a general framework for measuring connectivity frequency dynamics in economic variables based on the spectral representation of variance decompositions.

Frequency dynamics are insightful when studying variable connectivity because shocks with heterogeneous frequency responses create frequency-dependent connections of different strength that remain hidden when time domain measurements are used, ie the main interest lies in the portion of the forecast error variance at a given frequency that is attributed to shocks in another variable.

These generalized prediction error variance decompositions are central to measuring connectivity, so to define frequency-dependent measures, you need to consider their spectral counterpart. The measure of connectivity is based on impulse response functions, defined in the time domain. It is considered a frequency response function $\Psi\left(e^{-iw}\right)=\sum_{h}e^{-i\omega h}\Psi_{h}$ which can simply be obtained from the Fourier transform of the coefficients Ψ, with $i=\sqrt{-1}$. A spectral density of x_t at frequency w can then be conveniently defined as a Fourier transform of MA (∞) filtered series as:

$$S_{x}(w)=\sum_{h=-\infty}^{\infty}E\left(x_{t}x_{t-h}^{'}\right)e^{-i\omega h}=\Psi(\mathrm{e}^{-i\omega})\sum\Psi^{'}\left(e^{+i\omega}\right)\#\tag{6}$$

The power spectrum S_x (ω) describes how the variation of x_t is distributed by the frequency components ω. Using the spectral representation for covariance, i.e., $E\left(x_{t}x_{t-h}^{'}\right)=\int_{-\pi}^{\pi}S_{x}(\omega)d\omega$, introduces the counterparts in the variance decomposition frequency domain.

Defining the generalized decompositions of staggered error variance in the frequency bands $d=(a,b)$: $a, b \in (-\pi, \pi)$ $a<b$ as:

$$\left(\theta_{\tilde{d}}\right)_{j,k}=\frac{\left(\theta_{d}\right)_{j,k}}{\sum_{k}\left(\theta_{\infty}\right)_{j,k}}\#\tag{7}$$

The frequency connection in frequency band d is then defined as:

$$C_{d}^{F}=100\left(\frac{\sum(\theta_{\tilde{d}})_{j,k}}{\sum(\theta_{\tilde{\infty}})_{j,k}}-\frac{T_{r}\{\theta_{\tilde{d}}\}}{\sum(\theta_{\tilde{\infty}})_{j,k}}\right)\#\tag{8}$$

The internal connection in frequency band d is then defined as:

$$C_{d}^{w}=100\left(1-\frac{T_{r}\{\theta_{\tilde{d}}\}}{\sum(\theta_{\tilde{d}})_{j,k}}\right)\#\tag{9}$$

The internal connection denotes the connection effect that occurs within the frequency range and is weighted exclusively by the power of the series in the given frequency band. On the other hand, the frequency connection breaks down the original connection into distinct parts which, in short, provide the original connection measurement C_∞.

4. RESULTS

The spillover index allows us to scrutinize the intricate relationships that underlie each asset pair, unveiling the extent to which each asset conveys and absorbs the volatility inherent in the components of this market. Table 2 presents an overview of all interactions among these assets. As an illustration of interpreting the table, we observe that the cell at the intersection of the second column and the first row indicates that copper received a volatility spillover of 16.67 from aluminum. Similarly, in the cell at the crossroads of the first column and the second row, it is evident that copper transmitted a volatility spillover of 14.57 to aluminum.

Among the assets considered in this market composition, copper exhibits the highest degree of connectivity, receiving a market volatility transmission of 8.15 and transmitting 5.88, closely trailed by zinc, which receives 7.19 and transmits 5.73, and aluminum, recording 6.41 and 5.52, respectively. The most pronounced connection between commodity pairs lies between silver and gold, with copper and aluminum following closely.

In this context, the interconnectivity between assets displays a pronounced volatility quotient. Notably, Silver demonstrates a significant transmission level to Gold, registering at 16.24. Following closely is the interaction between platinum and palladium, showing a transmission level of 13.99. Finally, we observe Nickel's transmission to copper at 13.92, showcasing its influence in this dynamic landscape.

On the opposite end, assets such as natural gas, due to its exclusion from the extraction and preparation processes of other commodities, as well as other commodities associated with extraction and storage, exhibit minimal interactions. Oil, despite a lower degree of interaction, serves as an input in the extraction of metals, notably nickel, which contributes to the manufacture of oil storage barrels. Moreover, Table 2 discloses that the aggregate market connectivity stands at 53.01%, a level surpassing that of other markets such as stocks, foreign exchange, and government bonds (Diebold and Yilmaz, 2012).

By employing bootstrap resampling techniques, as demonstrated in Figures 2-4, we can validate the trajectory of the overall market connectivity throughout the analyzed period. Furthermore, we can discern the extent to which each asset contributed to both transmitting and receiving market volatility. The surge in volatility observed in 2005 can be attributed to the terrorist attacks in London that transpired in July of that year.

Figure 2: Overall market connectivity trajectory

Source: Elaborated by authors

Over the span of years, a discernible pattern emerged, characterized by a gradual decline in volatility until the pivotal year of 2008 marked by the global financial crisis and its subsequent aftermath. Notably, there is an incremental upswing that persists until 2013, followed by a subsequent downturn in volatility. This pattern can also be noticed in Figures 3 and 4, which respectively measure volatility transmission to the market and receiving market volatility.

Thus, Table 2 presents the general spillover index. Conducted through bootstrap, Figure 2 shows the trajectory of market connectivity over the period, while Figures 3 and 4 show how much each asset transmitted and received in market volatility, respectively.

Tables 3-6, respectively portray interactions spanning overnight (very short term), 1-4 days (short term), 4-30 days (medium term), and beyond 30 days (long term).

By partitioning it into frequency bands representing different periods, we discern that the dynamics of volatility transmissions between assets mirror the overarching spillover index pattern, with changes primarily in the magnitude of these transmissions. Moreover, as volatility transmission tends to wane as the time frame increases, the same cannot be said about the interconnectivity between assets.

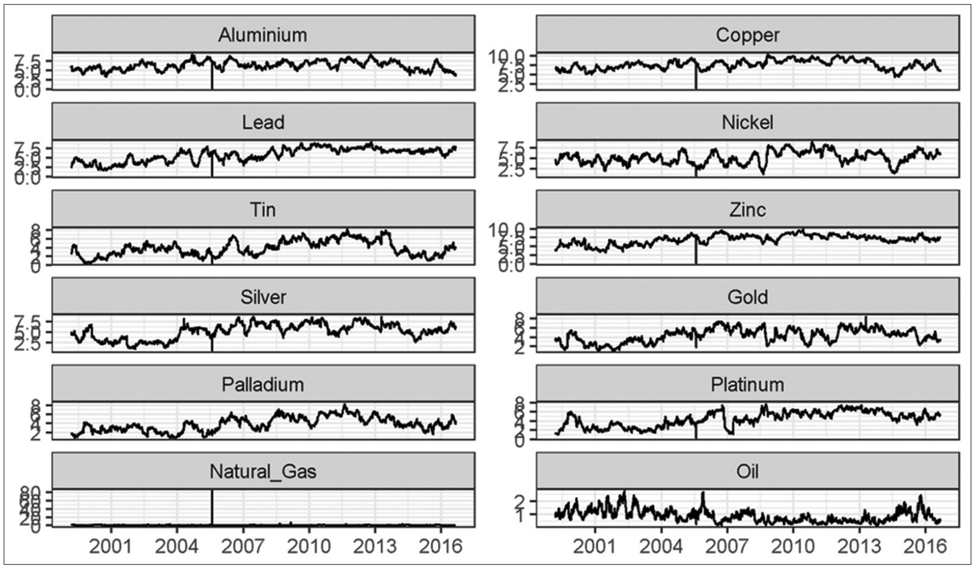
For instance, as highlighted in Table 3, Aluminum demonstrates a transmission coefficient of 6.32 to copper, while Zinc exhibits a transmission coefficient of 6.09 to copper. Furthermore, Silver showcases a transmission coefficient of 5.43 to Gold, underscoring the intricate web of relationships between these assets. Within this context, Table 4 reveals a sustained presence of noteworthy, interlinked volatility between Gold and Silver. Gold transmits a substantial 9.18 to Silver, reciprocated by Silver transmitting 6.79 to Gold. This consistent pattern also manifests in the volatility transfer between Zinc and Copper. Notably, Copper transmits 6.24 to Zinc, while Zinc reciprocates by transmitting 6.71 to copper. However, a significant shift in the pattern of interconnectivity between assets becomes evident in Tables 5 and 6, where the level of transmission undergoes a considerable decline.

Table 2: General spillovers index

Commodity	Aluminium	Copper	Lead	Nickel	Tin	Zinc	Silver	Gold	Palladium	Platinum	Nat.Gas	Oil	Transmitted
Aluminium	33.81	16.67	10.11	9.03	6.28	14.34	4.15	1.74	1.82	2.02	0.00	0.02	5.52
Copper	14.57	29.41	11.58	10.37	7.36	15.56	5.09	1.94	1.98	2.12	0.01	0.01	5.88
Lead	10.56	13.97	35.55	8.60	6.94	15.41	3.61	1.51	1.98	1.86	0.01	0.01	5.37
Nickel	10.58	13.92	9.59	39.37	7.29	12.04	3.18	1.03	1.55	1.42	0.01	0.03	5.05
Tin	8.32	11.29	8.83	8.48	45.20	9.43	3.08	1.52	1.91	1.93	0.00	0.02	4.57
Zinc	13.21	16.51	13.55	9.55	6.55	31.21	4.26	1.62	1.83	1.70	0.00	0.02	5.73
Silver	5.21	7.20	4.34	3.43	2.89	5.77	42.27	16.24	5.55	7.06	0.02	0.01	4.81
Gold	2.84	3.68	2.37	1.53	1.73	2.86	19.73	48.74	5.88	10.58	0.03	0.04	4.27
Palladium	3.64	4.51	3.79	2.77	2.64	3.85	7.72	6.11	50.27	14.68	0.01	0.01	4.14
Platinum	3.65	4.41	3.21	2.41	2.38	3.39	9.24	10.33	13.99	46.88	0.01	0.09	4.43
Nat. Gas	0.01	0.03	0.04	0.02	0.00	0.01	0.07	0.07	0.02	0.01	99.70	0.01	0.03
Oil	4.27	5.55	4.20	3.35	3.07	3.68	4.38	2.51	3.20	4.32	0.02	61.44	3.21
Received	6.41	8.15	5.97	4.96	3.93	7.19	5.38	3.72	3.31	3.98	0.01	0.02	53.01

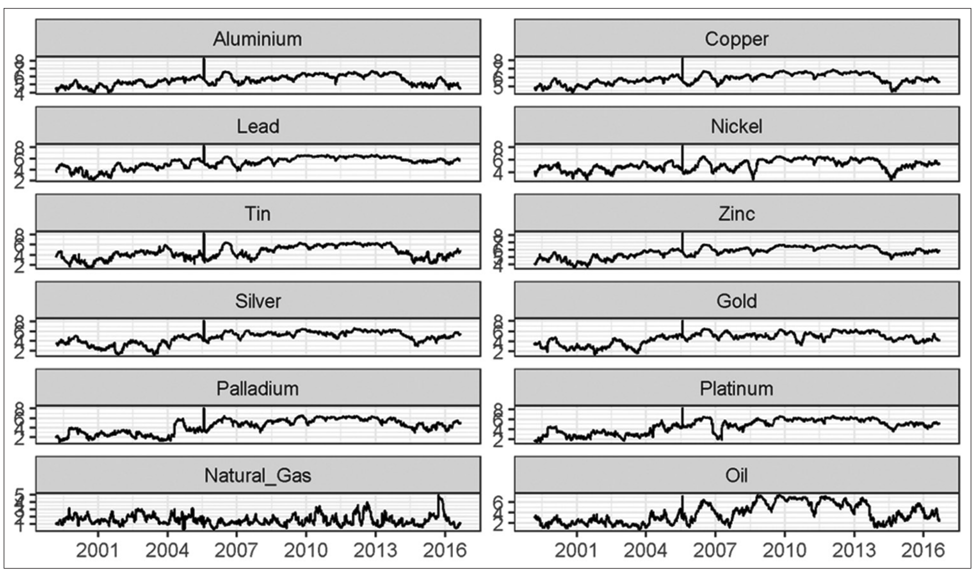
Source: Elaborated by authors

Figure 3: Volatility transmission to the market



Source: Elaborated by authors

Figure 4: Receiving market volatility



Source: Elaborated by authors

Table 3: Overnight

Commodity	Aluminium	Copper	Lead	Nickel	Tin	Zinc	Silver	Gold	Palladium	Platinum	Nat.Gas	Oil	Transmitted
Aluminium	12.23	6.32	3.92	3.28	2.49	5.55	1.52	0.66	0.70	0.81	0.00	0.00	2.11
Copper	5.81	10.93	4.35	3.86	2.81	5.98	2.19	0.88	0.78	0.83	0.00	0.00	2.29
Lead	3.71	4.65	11.09	2.84	2.26	5.07	1.23	0.55	0.69	0.72	0.01	0.00	1.81
Nickel	4.04	5.14	3.60	13.20	2.66	4.34	1.18	0.36	0.58	0.53	0.01	0.01	1.87
Tin	2.94	3.83	2.99	2.28	14.81	2.99	0.93	0.55	0.68	0.70	0.00	0.00	1.49
Zinc	4.94	6.09	4.80	3.49	2.53	10.94	1.58	0.69	0.75	0.68	0.00	0.00	2.13
Silver	1.56	2.07	1.22	0.96	0.83	1.74	13.97	5.43	1.63	2.09	0.00	0.01	1.46
Gold	0.45	0.51	0.36	0.20	0.35	0.43	4.17	16.53	1.87	3.33	0.02	0.02	0.98
Palladium	0.36	0.44	0.36	0.24	0.31	0.39	1.07	1.68	15.51	4.35	0.01	0.00	0.77
Platinum	0.38	0.46	0.32	0.21	0.32	0.33	1.26	2.74	3.51	15.73	0.01	0.02	0.80
Nat. Gas	0.00	0.02	0.02	0.00	0.00	0.00	0.01	0.01	0.01	0.01	34.13	0.00	0.01
Oil	0.87	1.13	0.92	0.49	0.62	0.68	0.83	0.49	0.61	0.74	0.00	14.99	0.61
Received	2.09	2.55	1.90	1.49	1.26	2.29	1.33	1.17	0.98	1.23	0.01	0.01	16.31

Source: Elaborated by authors

Table 4: Very short term

Commodity	Aluminium	Copper	Lead	Nickel	Tin	Zinc	Silver	Gold	Palladium	Platinum	Nat. Gas	Oil	Transmitted
Aluminium	13.74	6.69	4.04	3.65	2.49	5.75	1.66	0.68	0.71	0.78	0.00	0.01	2.21
Copper	5.80	11.90	4.65	4.19	2.94	6.24	1.99	0.74	0.78	0.84	0.00	0.00	2.35
Lead	4.43	5.88	14.96	3.63	2.92	6.47	1.55	0.64	0.84	0.77	0.01	0.00	2.26
Nickel	4.27	5.65	3.89	16.33	2.97	4.90	1.27	0.42	0.62	0.57	0.00	0.01	2.05
Tin	2.41	4.65	3.65	3.59	18.79	3.91	1.28	0.60	0.76	0.76	0.00	0.01	1.88
Zinc	5.35	6.71	5.53	3.90	2.63	12.83	1.73	0.63	0.71	0.66	0.00	0.01	2.32
Silver	2.23	3.09	1.86	1.47	1.24	2.45	17.68	6.79	2.37	3.04	0.01	0.01	2.05
Gold	1.39	1.80	1.15	0.76	0.82	1.40	9.18	20.42	2.49	4.50	0.01	0.02	1.96
Palladium	1.74	2.14	1.77	1.30	1.22	1.82	3.65	2.64	21.15	6.20	0.00	0.01	1.87
Platinum	1.74	2.08	1.50	1.13	1.09	1.61	4.36	4.49	6.07	19.37	0.00	0.04	2.01
Nat. Gas	0.01	0.02	0.02	0.01	0.00	0.00	0.03	0.04	0.01	0.00	41.28	0.00	0.01
Oil	1.79	2.31	1.75	1.37	1.27	1.53	1.84	1.04	1.32	1.79	0.00	25.49	1.33
Received	2.68	3.42	2.48	2.08	1.63	3.01	2.38	1.56	1.39	1.66	0.00	0.01	22.31

Source: Elaborated by authors

Table 5: Medium-term

Commodity	Aluminium	Copper	Lead	Nickel	Tin	Zinc	Silver	Gold	Palladium	Platinum	Nat.Gas	Oil	Transmitted
Aluminium	6.89	3.23	1.89	1.84	1.14	2.67	0.85	0.35	0.36	0.38	0.00	0.01	1.06
Copper	2.60	5.79	2.27	2.04	1.41	2.95	0.81	0.29	0.37	0.40	0.00	0.00	1.10
Lead	2.14	3.03	8.36	1.88	1.55	3.41	0.73	0.28	0.40	0.33	0.00	0.01	1.15
Nickel	2.00	2.76	1.85	8.66	1.46	2.46	0.63	0.22	0.30	0.29	0.00	0.01	1.00
Tin	1.74	2.47	1.93	2.29	10.19	2.22	0.76	0.32	0.40	0.41	0.00	0.01	1.05
Zinc	2.57	3.27	2.83	1.90	1.22	6.55	0.83	0.27	0.32	0.31	0.00	0.01	1.13
Silver	1.25	1.79	1.10	0.88	0.73	1.38	9.34	3.54	1.36	1.70	0.01	0.00	1.15
Gold	0.87	1.20	0.76	0.50	0.49	0.90	5.61	10.39	1.33	2.43	0.00	0.00	1.17
Palladium	1.35	1.69	1.45	1.08	0.97	1.43	2.64	1.58	11.95	3.63	0.00	0.01	1.32
Platinum	1.35	1.64	1.22	0.94	0.84	1.27	3.18	2.72	3.87	10.37	0.00	0.02	1.42
Nat. Gas	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.03	0.00	0.00	21.38	0.00	0.01
Oil	1.42	1.84	1.34	1.29	1.03	1.29	1.49	0.86	1.10	1.56	0.01	18.32	1.10
Received	1.44	1.91	1.39	1.22	0.90	1.67	1.46	0.87	0.82	0.95	0.00	0.01	12.65

Source: Elaborated by authors

Table 6: Long term

Commodity	Aluminium	Copper	Lead	Nickel	Tin	Zinc	Silver	Gold	Palladium	Platinum	Nat.Gas	Oil	Transmitted
Aluminium	0.94	0.44	0.26	0.25	0.15	0.36	0.12	0.05	0.05	0.05	0.00	0.00	0.14
Copper	0.35	0.78	0.31	0.28	0.19	0.40	0.11	0.04	0.05	0.05	0.00	0.00	0.15
Lead	0.29	0.41	1.15	0.25	0.21	0.46	0.10	0.04	0.05	0.04	0.00	0.00	0.15
Nickel	0.27	0.37	0.25	1.19	0.20	0.34	0.09	0.03	0.04	0.04	0.00	0.00	0.14
Tin	0.24	0.34	0.27	0.32	1.40	0.31	0.11	0.04	0.06	0.06	0.00	0.00	0.15
Zinc	0.35	0.44	0.39	0.26	0.17	0.89	0.11	0.04	0.04	0.04	0.00	0.00	0.15
Silver	0.17	0.25	0.15	0.12	0.10	0.19	1.27	0.48	0.19	0.23	0.00	0.00	0.16
Gold	0.12	0.17	0.10	0.07	0.07	0.12	0.77	1.41	0.18	0.33	0.00	0.00	0.16
Palladium	0.19	0.24	0.21	0.15	0.14	0.20	0.37	0.22	1.65	0.50	0.00	0.00	0.19
Platinum	0.19	0.23	0.18	0.13	0.12	0.18	0.45	0.38	0.54	1.42	0.00	0.00	0.20
Nat. Gas	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.91	0.00	0.00
Oil	0.21	0.27	0.19	0.19	0.15	0.19	0.22	0.13	0.16	0.23	0.00	2.64	0.16
Received	0.20	0.26	0.19	0.17	0.12	0.23	0.20	0.12	0.11	0.13	0.00	0.00	1.75

Source: Elaborated by authors

From the analysis, we can assume that the assets that display the most considerable interconnectivity are Copper, Gold, Silver, and Zinc. According to Vardar et al (2018), silver is an asset that has become highly vulnerable to market movements after the 2008 crisis. Similarly, according to Bouei et al. (2016), volatility in Gold is observed to be significantly correlated with previous market returns. As noted by Sadorsky (2014), the volatility in copper demonstrates a marked susceptibility to the dynamics of conditional correlations (CCs) with emerging market stock prices, oil, and wheat.

Notably, the influence of CCs becomes particularly pronounced during periods of economic crises and recessions. For instance, the author points to the significant impact of the 2008-2009 period on copper prices. Our study aligns with this observation as it encompasses this very timeframe, underscoring the pivotal role that economic crises play in shaping copper's volatility. These findings are further substantiated by the research of Creti et al. (2013) and Mollick and Assefa (2013), who similarly demonstrate the interconnected volatility between diverse asset classes.

Furthermore, in a recent study conducted by Umar et al. (2021), it was revealed that demand shocks and risk shocks take the forefront as the prominent recipients (transmitters) of shocks within the realm of metal returns. Furthermore, in line with this insight, Zinc, much like its counterparts in the industrial and precious metals category, experiences the inflow of volatility from net transmitters such as Tin, Gold, Nickel, Lead, and Aluminum. These intricate dynamics are vividly illustrated in the tables provided that follow the Diebold and Yilmaz (2012) Method.

Lastly, in the very short term, the total market connectivity stands at 16.31%, increasing to 22.31% in the short term, 12.65% in the medium term, and 1.75% in the long term. This is attributed to the rapidity of market agents' response to shocks, evident in shorter intervals. As time progresses, market participants assimilate these shocks, causing connectivity to wane. These findings align with those of Baruník and Krehlík (2018), who demonstrated that market connectivity is heightened in shorter periods and diminishes with extended timeframes.

5. CONCLUSION

This paper aims to quantify volatility transmission within the market of metallic commodities (aluminum, copper, lead, nickel, tin, zinc, silver, gold, palladium, and platinum) and energy commodities (natural gas and oil). We utilize the spillover index devised by Diebold and Yilmaz (2012) alongside daily closing price data from London Metals Exchange futures trading and the Handy & Harman index spanning 1998 to 2018.

The interconnectedness within the metallic and energy commodity market surpasses that of previously analyzed markets, signifying substantial volatility transfers between asset pairs. This underscores their interdependence, complementarity in usage, and shared characteristics in extraction, indicating the propagation of shocks from one commodity to another. This analysis aligns with established research by Vardar et al. (2014), Creti et al. (2013), Mollick and Assefa (2013), and Umar et al. (2021). The intricate dynamics are visually represented through Diebold and Yilmaz's method tables. Correspondingly, Baruník and Krehlík's (2018) findings affirm heightened connectivity in shorter timeframes, gradually waning.

Furthermore, our findings highlight notable interactions between specific pairs. Gold and silver, as well as platinum and palladium, showcase substantial transmission levels (16.24 and 13.99, respectively), indicating robust connections. Nickel's 13.92 transmission to copper underscores its impact. Conversely, minimal interactions are observed for natural gas and specific storage-tied commodities due to their isolation. Oil, though less interactive, contributes to metals' extraction, exemplified by nickel's role in oil storage.

Prominently, copper, gold, silver, and zinc demonstrate significant interconnectivity. The 2008 crisis rendered silver vulnerable to market shifts, while gold's volatility is tied to past returns. Copper's volatility notably responds to conditional correlations, especially during economic crises. Recent research underscores shocks' considerable influence on metal returns, with zinc absorbing volatility from net transmitters like tin, gold, nickel, lead, and aluminum. Moreover, temporal market connectivity plays a pivotal role in shaping this study's long-term trends. Short-term connectivity peaks at 16.31%, gradually declining to 1.75% in the long term, reflecting the swift market response to shocks, which diminishes over time.

Our findings hold significance for economic and financial literature, aiding risk management, portfolio allocation, and policy decisions regarding commodity utilization in national structures. A potential avenue for future research is delving into the volatility transmission dynamics among investment funds encompassing commodities, stocks, foreign exchange, and interest rates.

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REFERENCES

Aghababa, H., Barnett, W.A. (2016), Dynamic structure of the spot price of crude oil: Does time aggregation matter? Energy Economics, 59, 227-237.

Ahmadi, M., Behmiri, N.B., Manera, M. (2016), How is volatility in commodity markets linked to oil price shocks? Energy Economics, 59, 11-23.

Algieri, B., Leccadito, A. (2019), Price volatility and speculative activities in futures commodity markets: A combination of combinations of p-values test. Journal of Commodity Markets, 13, 40-54.

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

Baruník, J., Krehlík, T. (2015), Measuring the Frequency Dynamics of Financial and Macroeconomic Connectedness. Pod Vodarenskoy Vezu, Version 4.

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

Bouri, E., Awartani, B., Maghyereh, A. (2016), Crude oil prices and sectoral stock returns in Jordan around the Arab uprisings of 2010. Energy Economics, 56, 205-214.

Cevik, S., Sedik, T.S. (2014), A barrel of oil or a bottle of wine: How do global growth dynamics affect commodity prices? Journal of Wine Economics, 9(1), 34-50.

Chen, M.H. (2010), Understanding world metals prices-returns, volatility and diversification. Resources Policy, 35, 127-140.

Chen, J., Zhu, X., Zhong, M. (2019), Nonlinear effects of financial factors on fluctuations in nonferrous metals prices: A Markov-switching VAR analysis. Resources Policy, 61, 489-500.

Creti, A., Joets, M., Mignon, V. (2013), On the link between stock and commodity markets' volatility. Energy Economics, 37, 16-28.

Dadzie, P., Nambie, N.B., Obobi, B.A. (2023), Impact of petroleum energy price volatility on commodity prices in Ghana. International Journal of Economics and Financial Issues, 13(1), 73-82.

De Oliveira Passos, M., Tessmann, M.S., Ely, R.A., Uhr, D., Taveira, M.T. (2020), Effects of volatility among commodities in the long term: Analysis of a complex network. Annals of Financial Economics, 15(03), 2050014.

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

Fernandez, V. (2018), Price and income elasticity of demand for mineral commodities. Resources Policy, 59, 160-183.

Guedj, I., Li, G., McCann, C. (2011), Futures-based commodity ETFs. The Journal of Index Investing, 2(1), 14-24.

Hammoudeh, S., Mcaleer, M. (2012), Risk management and financial derivatives: An overview. North American Journal of Economics and Finance, 25, 109-115.

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

Mollick, A.V., Assefa, T.A. (2013), US stock returns and oil prices: The tale from daily data and the 2008-2009 financial crisis. Energy Econonomics, 36, 1-18.

Ross, S.A. (1989), Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. The Journal of Finance, 44(1), 1-17.

Sadorsky, P. (2014), Modeling volatility and correlations between emerging market stock prices and the prices of copper, oil, and wheat. Energy Economics, 43, 72-81.

Sow, T.S. (1996), Multivariate forecasting of mineral commodities prices: Implications for natural resource scarcity. United States: The University of Arizona.

Tessmann, M.S., Ely, R.A., Canever, M.D. (2021),Volatility transmissions between commodity futures contracts in short, medium and long term. International Journal of Financial Markets and Derivatives, 8(1), 79-99.

Todorova, N., Clements, A.E. (2018), The volatility-volume relationship in the LME futures market for industrial metals. Resources Policy, 58, 111-124.

Umar, Z., Jareño, F., Escribano, A., (2021), Oil price shocks and the return and volatility spillover between industrial and precious metals. Energy Economics, 99, 105291.

Vardar, G., Coşkun, Y., Yelkenci, T. (2018), Shock transmission and volatility spillover in stock and commodity markets: Evidence from advanced and emerging markets. Eurasian Economic Review, 8, 231-288.

Zhang, C., Shi, X., Yu, D. (2018), The effect of global oil price shocks on China's precious metals market: A comparative analysis of gold and platinum. Journal of Cleaner Production, 186, 652-661.

Zhu, X.H., Chen, J.Y., Zhong, M.R. (2015), Dynamic interacting relationships among international oil prices, macroeconomic variables and precious metal prices. Transactions of Nonferrous Metals Society of China, 25(2), 669-676.