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Dynamic Interlinkages Between Precious Metal, Exchange Rate and Crude Oil: Evidence from an Extended TVP-VAR Analysis

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Abstract
In this study, we examine the dynamic connectedness among precious metals, exchange rates, and crude oil using daily data spanning from January 4, 2010, to May 10, 2023. To achieve this, we employ the time and frequency-dependent connectedness approaches. According to results, consistent with theoretical expectations, it becomes evident that global occurrences exert a substantial impact on the evolving interconnectedness of returns. As indicated by the average connectivity outcomes, silver and palladium emerge as the foremost propagators and recipients of return shocks, while Brent displays the lowest incidence of transmitting and receiving such shocks. Furthermore, gold, silver, and platinum are found as the primary sources of transmitting return shocks, whereas the remaining indices are identified as the main recipients of these shocks. Our results highlight the following: (i) the time-varying interconnectedness indices robustly capture significant financial/geopolitical events; (ii) on average, silver and palladium are the largest contributors of return shocks, while Brent has the lowest impact; (iii) gold, silver, and platinum act as net shock transmitters; (iv) short-term interconnectedness is more pronounced than persistent interdependencies; (v) frequency-dependent connectedness experience a significant surge during the announcement of the COVID-19 pandemic and the onset of the Russia-Ukraine conflict (RUC). In light of the conclusions drawn from the study, the findings underscore the evolving interconnectedness of returns among core precious metals, crude oil, and exchange rates amidst globalization. This dynamic environment not only presents opportunities for investors but also underscores the diffusion of risk across financial markets. Our findings provide policymakers with a broader economic outlook to improve both economic stability and energy-related policies.

Keywords Precious metal · Crude oil · Stock · TVP-VAR

JEL Classification C58 · D53 · G11

Extended author information available on the last page of the article

1 Introduction

Throughout history, precious metals have served various roles such as currency, investment vehicles, adornments, symbols of status, and objects of religious significance. Unlike many other commodities that have gained prominence in more recent eras, these metals have maintained a consistent level of demand since ancient times. In the contemporary context, apart from their historical applications, novel precious metals like palladium and platinum, alongside traditional gold and silver, have been identified and their utility has expanded into industrial domains. Moreover, these recently unearthed precious metals have evolved into investment assets in addition to finding extensive usage in fields like chemistry, electronics, and the automotive industry. Consequently, the demand for precious metals, both for industrial applications and as investment instruments, continues to grow (Lau et al., 2017).

The main reasons why precious metals are used as investment tools are the pursuit of profit from value gains of metals and the aim of protecting the value of assets against currencies (Sakemoto, 2018a, 2018b), since they have limited supplies in the world, they are affected by major economic crises and currency depreciation to a limited extent (Mensi et al., a, b, c). Even today, not only states and large financial institutions, but also individuals have the opportunity to easily make transactions with precious metals. The liberalization of the capital markets and the cheaper communication and calculation processes thanks to the developing technology (Shah et al., 2021) have contributed to the rapid financialization of the commodity markets (Balcilar et al., 2015). In addition, derivative markets of commodity markets have also been developed and an integrated and interdependent financial structure has emerged with instruments such as exchange rate funds, investment baskets, future derivatives markets (Kanjilal & Ghosh, 2017).

The interdependence and integration of commodity prices with other markets has increased the interaction between prices. Changes in the price of one asset affect changes in the prices of other assets, and the effect of cross-market information flows is increasing, making the commodity market more susceptible to external shocks (Mensi et al., 2022). In fact, this high integration and dependency has become such that the benefits of diversification from investment instruments have begun to decrease gradually (Mensi et al., a, b,C c), as precious metals have become rapidly affected by many factors.

The most important factor affecting the precious metals market is exchange rates, in terms of affecting the demand for them, being used by the countries in the fiscal and commercial policies and being an investment opportunity for the individuals and companies. In terms of countries, first, they keep some precious metals in their central banks as reserve assets both to stabilize the values of their own currencies and to intervene in the market in times of crisis. Second, countries can use precious metals as a trade currency in times of crisis, embargo situations or when they want to reduce their dependence on the international currency, the dollar. In terms of individuals or companies, the demand for valuable commodities changes according to the current situation and expectations in the local currency. If the currency has high inflation expectations or unstable fluctuations, there is increased interest in precious metals to hedge risks and diversify portfolios (Mensi et al., 2021a, b, c).

For these reasons, there is generally a negative relationship between the value of the global currency, the US dollar, and precious metal prices, especially gold prices. As it is well known, in the international market, most precious metals are priced in US dollars (Kunkler, 2022). The depreciation of the dollar causes metal prices to become cheaper compared to the currencies of other countries, increasing the demand for commodities (Reboredo, 2012), and investors switch to precious metals to avoid risk and protect their asset values (Mensi et al., 2022). In other words, when the exchange rate weakens, precious metals become popular investment instruments to avoid negative effects (Umar, 2017). However, in this case, there may be an increase in the prices of precious metals due to the increasing demand (Shah et al., 2021). In cases where the dollar appreciates, the opposite can happen. However, in some countries, the exchange rate risk can vary greatly depending on the value of the local currency against the US dollar (Belousova and Dorfleitner, 2012). In addition, oil prices are a determining factor for precious metal prices for countries that import oil to a large extent. Increasing oil prices cause inflationary effects as they increase costs in transportation and production. In this case, investors prefer to hedge their assets with precious metals against currency risks (Barunik et al., 2016). All these factors cause precious metals to be seen as a safe haven by investors (Mensi et al., 2022) as their values are more stable than stocks, industrial commodities, bonds, derivatives markets and other similar assets (Mensi et al., 2020a, 2020b).

Also, the exchange rates are basically one of the most important factors that determine the prices of precious metals in the country. First, currencies affect demand for precious metals as they set international prices. Second, investors may turn to precious metals as a safe haven in case of any negative expectations while evaluating the opportunities in exchange rates. Third, investors may prefer precious metals to protect their assets from the inflation caused by the increasing exchange rate. Fourth, the monetary and fiscal policies of the government may also affect the relationship between precious metals and the exchange rate. These possible situations have led to a high interest in this subject in the literature. However, this interaction may occur at different scales depending on the market situation and the country profile. Mensi et al., (2022) examined this possible situation in terms of variations in volatility, dependency and distribution using precious metal futures and the exchange rates of major countries based on US. The results revealed that the dependency between major exchange rates is positive, the dependency between exchange rates and precious metals is generally negative, so all precious metals can be used as a hedge against major currencies. The results confirm the alternativeness of these investment instruments. In addition, global crises and events in the world may also cause the relationship between exchange rates and precious metals to differ. In the research conducted by Hanif et al. (2023), the relationship between major exchange rates and precious metal futures was examined in terms of asymmetric risk spillover during and before the COVID period. The results showed that while there was a symmetrical dependence between the variables before COVID, this relationship became asymmetrical during the pandemic period, and thus the pandemic strongly changed the relationship between the exchange rate and commodity markets. Precious metals are also heavily preferred as a safe haven against exchange rates due to their close relationship with them. Sakemoto (2018a, 2018b) studied the hedge potential of precious and industrial metals and found that gold and silver have hedge properties in currency portfolios. In addition, after 2000, the properties of being a safe haven weakened and industrial metals did not have the properties of hedging. Whether precious metals are safe havens against the foreign exchange rate has also been examined by Peng (2020) for the Chinese markets. The results showed that they are a powerful diversification tool rather than a strong hedge tool. In addition, the interaction changes in times of financial crisis and has the characteristics of a stronger safe harbor for the exchange rates of silver and platinum in times of crisis.

The close relationship of precious metals with the economic activities in countries is also an important issue to examine. As the economy grows, individuals and firms can increase demand for precious metals to hedge their increased capital. Since economic growth also includes the risk of inflation, it is aimed to be protected from this value decreasing effect. In addition, when there is economic uncertainty, the demand for precious metals may increase to maintain asset values. Also, since economic growth is a result of increased industrial activities, the amount of precious metal demanded by the industry for use in production is in parallel with economic activities. In this case, countries rich in precious metals can be considered advantageous. In this context, in the study conducted by Bildirici and Gokmenoglu (2020), precious metal productions of selected countries were considered as resource richness in those countries and the effect of this richness on economic growth was examined. Their analyzes showed that that there is a positive interaction between metal abundance and economic growth, this interaction differs in the long and short term and also varies according to the country. This situation causes countries that are economically dominant in the world to be active in precious metal markets. Dinh et al. (2022) examined the effect of macroeconomic indicators in the G7 and BRICS countries on the volatility of precious metals markets. As a result, they determined that factors such as stock markets, money supplies, inflation rates in large countries affect volatility and confirmed the significant effect of economic factors.

Changes in international commodities also have significant effects on precious metals. As the scene where this effect is most clearly observed, oil price is one of the important macro variables that have an impact on precious metal prices. Since the shock of the increase in international oil prices increases the need for foreign exchange and costs of production and transportation, especially for oil importing countries, increases in exchange rates and inflation may occur. Investors hedge their assets with precious metals, as oil price shocks can lead to depreciation of local currencies and inflation (Baruník et al., 2016). On the other hand, since increasing oil prices will lead to capital accumulation in countries that export oil intensively, these countries may turn to precious metals, which they see as a safe haven, to protect their capital values (Tiwari & Sahadudheen, 2015). Whether oil prices are the source of volatility and risk in precious metal prices or not has been examined in terms of tail, systematic and spillover risk in the study by Ahmed et al. (2022). The results show that tail risk is generally low for precious metals in times of crisis, systematic risk is low for both oil and precious metals in times of crisis, and oil prices are the source of risk spillover in precious metals, although it varies over time. These close relationships between precious metals and oil prices also lead to the use of precious metals as a hedge against oil prices. In the study conducted by Das et al. (2022), the effects of past and current shocks in oil prices on precious metal prices were examined and it was determined which metals had better hedge properties. The results showed that other precious metals are more successful hedge tools against oil price jumps compared to traditional gold. Crude oil is a very important raw material for industrial countries and most of them are imported. Especially China realizes a very large part of the world's energy imports. In this case, it can be thought that the sensitivity of the country to shocks in oil prices has increased and its markets are open to impact. In the study conducted by Zhang et al. (2018), it was investigated how the fluctuations in oil prices affected China's precious metal markets. As a result, the effect of the expected jumps in oil prices on the precious metals market was negative, while the effect of unexpected shocks was positive. This situation revealed that the effect of shocks differs according to market expectations. In fact, this relationship between precious metals and oil is also reflected in future markets. Mensi et al., (2020,) investigated the co-movement and risk spillover between prices of precious metals and future major energy sources. The results showed that gold and oil prices are the main sources of market volatility, while other precious metals and energy sources are risk takers. The spillover of volatility between the future prices of both precious metals and oil prices has also been studied by Mensi et al. (2021a, b, c,). It has been determined that the results differ according to the bear market and bull market conditions. They determined that precious metals and oil prices are risk takers in bear market, and oil prices are the source of risk in bull markets.

The precious metals and oil prices relationship may have different regimes and the relationship may vary on time. In this context, Cunado et al. (2023) examined the relationship between oil and precious metals with the approach of quantiles. The results showed that oil price was the main source of shock in all quantiles and the relationship became more pronounced as the quantile level rose. In the study by Alomari et al. (2022), the relationship between the variables was analyzed with the quantile approach. The results indicate spillover relationship from oil prices to precious metals in market conditions where the oil price is extremely low, there is a spillover from oil to metals other than gold in market conditions where the oil price is extremely high, and there is no significant relationship under normal oil market conditions. The relationship between the variables may also differ after major macroeconomic events and crises. Before the 2008 global economic crisis, both precious metals and oil were used as hedges against inflation, as the economy overheated. Therefore, the relationship was generally positive. However, after the crisis, the money supply in the market increased very much and precious metal prices became more sensitive to the currency, and the relationship with the oil price weakened. This relationship was investigated by Huang et al. (2022) and while the relationship between precious metals and commodities was positive before the crisis, it was found to be negative after the crisis.

Investment instruments, which are seen as alternatives to precious metals in terms of protecting the value of assets and gaining in the future, are generally currencies, stocks, cryptocurrencies, derivatives and complex investment instruments. In the information age, there is a constant flow of information between these instruments, as the costs of computation and communication are very low. An event in any market can easily spread to other markets. For this reason, they have been the subject of extensive research in the literature.

In general, precious metals are thought as safe haven against other investment instruments as well due to their properties that preserve value and are less affected by fluctuations, and the demand for precious metals may increase in the face of any negative atmosphere in the market. Due to this mechanism, there is a relationship between alternative investment instruments and the export and import of precious metals. This situation was investigated by Mensi et al. (2021b) with the volatility spillover approach between the stock markets of the major precious metal exporting and importing countries and precious metal prices. The results revealed that short-term shocks are more effective than long-term shocks, and that precious metals explain the stock markets of major exporters more than the stock markets of major importers. The safe haven properties of investment instruments may also differ according to the extreme global conditions the world is in. Lahiani et al. (2021) examined the status of precious metals as a safe haven against the US stock market in the short and long term asymmetrically in the COVID period. The results showed that precious metals affected the US stock market but lost their role as a safe haven, and while some metals showed safe haven properties in the short term, none of them had these properties in the long term.

On the other hand, the relationship between stock markets and precious metals may differ according to the conditions of the markets, that is, according to the distribution of the variables. During periods when stock prices are low or precious metals are high, the flow of information may differ, because other alternative investment instruments are also included in the equation. This possible situation has been examined by Mighri et al. (2022) on US stock market indices with the quantile causality approach. The results revealed that the relationship between the stock market and precious metals differs according to the distribution, that is, it is quantile-dependent and differs according to each precious metal type, and there is a bidirectional flow of information between the US stock market and gold prices in lower and medium quantiles. Demand for stocks can also vary depending on whether the market is in a bear or bull market. In the research conducted by Mensi et al. (2021a) on the stock market of ASEAN countries, the interactions of stock markets and future prices precious metals were examined. The results show that precious metals and Vietnamese stock markets are shock receivers under bear market conditions, while Vietnamese market is the source of risk spillovers under bull market conditions. A similar study was carried out by Jain et al. (2022) using the quantile approach to differentiate the bear, bull or normal market conditions between the world's two main equity indexes and four basic precious metals. The results showed that the relationship changes according to the conditions of the market, it is strong during the periods when the markets are active, but weak during the periods when the markets stabilize.

Recently, the most prominent type of diversity in investment instruments is cryptocurrencies. Factors such as easy access, decentralization, limited supply of some currencies, high profit opportunities, making some transactions through them in business life have increased this popularity and they have become an alternative investment tool for investors. Therefore, by taking their place in investment baskets of investors, they have turned into an integrated and dependent structure with other financial instruments. Naturally, mutual information flows and risk spreads have occurred with precious metals, and various research have been made. Rehman (2020) examined the dependency and risk spillover between Bitcoin and major precious metals. The results showed that Bitcoin has the highest risk compared to other precious metals, only gold is the safe haven of precious metals, there are mutual risk spreads between precious metals and Bitcoin. On the other hand, while cryptocurrencies offer high returns, they also carry a very high risk due to uncertainty. Precious metals can be reliable investment tools for investors who do not want to be deprived of the chance of high returns but aim to minimize the risk. In this context, Hassan et al. (2021) examined the relationship between the prices of four major precious metals and the cryptocurrency uncertainty index. As a result, they determined that only gold has the characteristics of a stable and reliable port against uncertainty. In addition, the uncertainty in cryptocurrencies may also affect the precious metal future market. Research by Wei et al. (2023) examines the impact of cryptocurrency uncertainty on predicting volatility in precious metals. The results confirmed that uncertainty can predict future precious metal prices in a significant way. Investors have position in future markets according to increasing or decreasing risk in the cryptocurrencies. In addition, as with any investment instrument, the sentiments of investors can affect the movement of financial assets and their interactions with each other. Investor sentiment significantly affects risk perception, herding behavior, confirmation bias and market volatility. In this context, the effect of investor sentiment on the interaction between precious metals and the five most traded cryptocurrencies was analyzed by Fasanya et al. (2022) with a quantile approach. As a result, they found that the majority of coins are volatility transmitters and the relationship between variables is speculation driven.

Examination of the relationship between precious metals, currencies and oil prices has been the subject of many studies in the literature for some reasons. First, precious metals are the most important investment tools used in portfolio diversification for currencies. Examining the information flow between them offers the opportunity for investors to diversify their investments with optimum risk. Second, precious metals are asset value protection tools. They make a great contribution to protecting purchasing power against volatility and risks in exchange rates, especially during periods of economic distress. For this reason, they are defined as safe haven. Third, precious metals have an important place in the policies of countries regarding their local currencies. They need precious metals to mitigate risks in the country's currency, to borrow from external sources, and to conduct non-exchange trading activities with other countries. Fourth, while oil is a major source of income for exporting countries, it is a major cost for importing countries. Increasing prices may accelerate capital accumulation in oil-exporting countries, causing them to turn to precious metals as an investment tool. On the other hand, as the rising prices for the importing countries may generate more foreign exchange demand, they may cause an inflationary environment in the country and cause investors to switch to safe-haven precious metals. Fifth, since oil is used as an input in many production activities, rising prices may increase production costs and cause an inflationary market. In this case, investors will turn to precious metals to protect their asset values or to reduce risk by diversifying their investments. Sixth, oil prices are one of the important indicators used for economic forecasting. Higher prices indicate an increase in economic activity and energy consumption, while lower prices indicate an economic slowdown and a decrease in energy consumption. In situations where economic slowdown expectations are formed and uncertainty increases, the transition to precious metals, which are considered as safe havens, accelerates. Therefore, the relationship, interdependence and transmission between precious metals, currencies and oil prices is of great importance for individual investors, fund managers and policy makers. However, these relations may change according to the period, regional and global events, and the economic conjuncture, namely these relations may differ according to different regimes in the sample, different parts of the distribution of the series, countries and times of global crisis. Therefore, it is of great importance that the relationship between the variables is handled with a time-varying approach while conducting research.

We opted for the time-varying parameter vector autoregressions (TVP-VAR) model due to its capability to accommodate fluctuations in the size and direction of relationships between variables across different time periods. This flexibility is essential given the potential presence of significant outliers caused by unexpected shocks. Moreover, the intricate and robust interdependencies among precious metals, exchange rates, and oil prices necessitate a systemic approach to understand their relationships comprehensively.

The TVP-VAR approach, as introduced by Antonakakis et al. (2020), is an extension of the connectedness approach originally developed by Diebold & Yilmaz (2014). The former method enables the dynamic measurement of connectedness indices using network analysis, capturing both the influence from one variable to another and the combined influence from one variable to all others within the system (Liu & Hamori, 2021). Nevertheless, its application of a rolling window mechanism can lead to excessive sensitivity to shocks or the damping of their effects. Moreover, this method is less suitable for short-term or low-frequency datasets (Ari, 2022).

In contrast, the improved approach eliminates the need for arbitrary window size selection, preserving the entirety of observations. By leveraging multiple Kalman filtering techniques, this method ensures robustness against outliers. Furthermore, its adaptability extends to the analysis of datasets with low-frequency components (Gabauer & Gupta, 2020).

Since the method provides flexibility in parameter estimations, it can provide more accurate results by capturing the evolution of the factors affecting the prices of precious metals over time. Considering the sensitivity of precious metal prices to economic, geopolitical and market factors, this is a great advantage. In this way, it can capture nonlinearities and regime changes by allowing the coefficients to change over time. In addition, since it is suitable for real-time analysis, it can update the parameters as new data is added. In the literature, this method has been used to analyze various variables such as precious metals (e.g. Antonakakis et al., 2023; Ha, 2023a), economic policy uncertainties (e.g. Antonakakis et al., 2019), stock markets (e.g. Antonakakis et al., 2023; Ari, 2022; Chowdhury & Irfan, 2022; Ha, 2023a, 2023b), energy stocks (e.g. Liu & Hamori, 2021), cryptocurrencies (e.g. Asl et al., 2021; Ha, 2023b; Huyen et al., 2023; Nasreen et al., 2021), oil markets (e.g. Antonakakis et al., 2023; Ha, 2023a), equity and debt markets (e.g. Syed, 2022), CO_2 emissions (e.g. Ha & Huyen, 2022), exchange rates (e.g. Antonakakis et al., 2023).

In our study, we analyzed the interconnectedness between four precious metals, which are Gold, Silver, Palladium, Platinum, and EUR/USD exchange rate and Brent crude oil price using TVP-VAR to capture the relationship, interdependence and transmission between them. The method can analyze the mutual risk transfer by considering all the variables as a system and by examining them pairwise. It also enables to determine the effect of the shock given to the system on the variables and which variable is the net receiver or transmitter of the risk. Thanks to the time varying parameters, it can also be analyzed whether the effect of important events affecting the regional and global economy on the interconnectedness relationship between the variables has changed.

Understanding the periodic spread of risk is of great importance for individuals, companies and governments. For individuals, precious metals are seen as safe havens. For this reason, they are preferred both for investment diversification and protection from inflationary value losses. In addition to investment diversification and protection from inflation, there are also production-related reasons for companies. Since precious metals are used as inputs and direct products in some sectors, understanding price behavior is important for them to develop risk management systems such as hedge tools and to make cost control plans. For governments, precious metals are held as a part of their foreign exchange reserves. Understanding price and risk mechanisms will facilitate the management of risks related to reserves. In addition, since the movement in the prices of precious metals reflects the trend and market sentiment in the state, they are followed by the governments to develop fiscal, monetary and commercial policies.

This paper breaks new ground by examining the dynamic (time and frequency-dependent) relationships between precious metals, exchange rates, and crude oil during major financial and geopolitical events (ESDC, COVID-19, RUC). It moves beyond static connections, delving into how these relationships evolve over time and exploring the differential impacts of positive and negative shocks using the ADCC-GARCH methodology. Additionally, the paper employs frequency-dependent networks to identify the specific frequencies that drive the system's interconnectedness. This comprehensive approach provides a fresh perspective on the interactions of these financial instruments during critical incidents.

The rest of the paper is structured as follows: Sect. 2 presents methodology and data, while Sect. 3 discusses the empirical results. Finally, Sect. 4 concludes the work.

Table 1 Descriptive statistics

	Gold	Silver	Palladium	Platinum	EUR/USD	Brent
Mean	0.022	0.027	0.059*	0.001	−0.006	0.025
Variance	0.932***	3.207***	4.137***	2.012***	0.294***	5.163***
Skewness	−0.465***	−0.592***	−0.366***	−0.324***	0.019	−0.357***
Kurtosis	5.016***	6.501***	8.874***	4.925***	1.704***	13.639***
JB	3737.097***	6270.327***	11,383.695***	3543.356***	417.306***	26,784.671***
ERS	−21.094***	−14.317***	−26.398***	−23.268***	−14.871***	−22.193***
Q(20)	5.955	12.918	55.873***	29.634***	9.963	10.498
Q2(20)	201.315***	448.690***	598.272***	865.645***	371.572***	991.936***

J-B denotes the Jarque Bera statistics, ***, **, and * correspond to the 1%, 5%, and 10% levels of statistical significance. The ERS test pertains to the unit root test by Stock et al. (1996). Q (20) and Q2 (20) signify the Ljung–Box statistics used to examine serial correlation in the original series and squared residuals

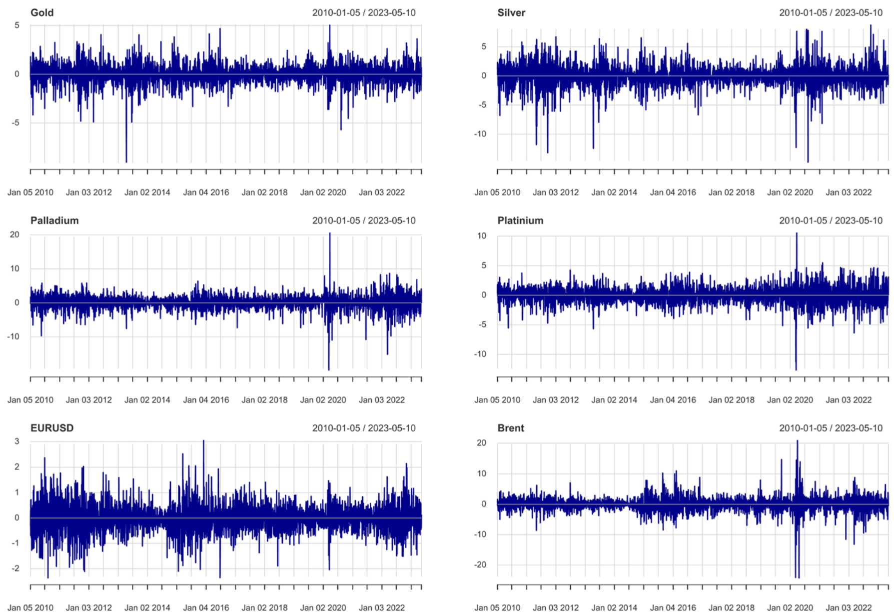

Fig. 1 Trends in the return series

2 Data and Methodology

In this study we investigate the interconnectedness between precious metal, exchange rate and crude oil. Thus, we use gold, silver, palladium and platinum as precious metal, euro/$ exchange rate and Brent petrol prices. Table 1, Figs. 1, and 2 present the descriptive statistics, evolution of returns, and the box plots of returns, respectively.

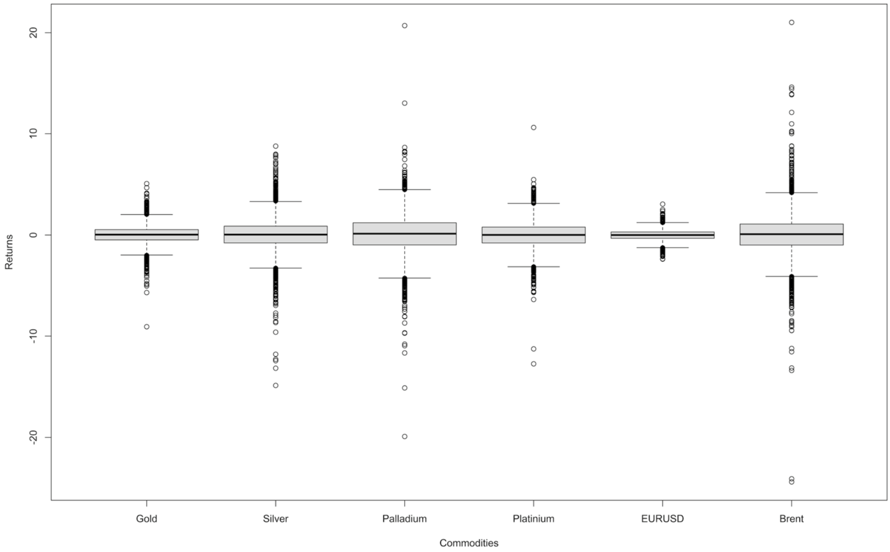

Fig. 2 Boxplots of return series

Results in Table 1 reveal that palladium and EUR/USD exhibit the highest and lowest average returns of 0.059 and − 0.006. It is worth noting that with an exception for EUR/USD, all variables provide average positive returns. Not surprisingly, Brent has the highest variance value, which aligns with the high variability of oil prices over the episode. Except for EUR/USD, all returns tail to the left and display leptokurtic distributions. Moreover, high JB values indicate that they are abnormally distributed, and show significant autocorrelations and ARCH/GARCH errors.

Figure 1 exhibits significant spikes around financial/geopolitical stress episodes such as the European sovereign debt crisis (ESDC), the global stock markets falls in August 2011, and August 2015, the Brexit referendum on June 23, 2016, the official declaration of the COVID-19 on 2020/3/11, and the start date of Russia-Ukraine war on 2022/2/24.

The boxplots of the returns for each series provide a vivid depiction of their respective characteristics. Palladium's plot shows a wide distribution with occasional outliers indicating periods of notably high returns, consistent with its average return of 0.059. In contrast, EUR/USD's boxplot centers around its lowest average return of − 0.006, illustrating a range of returns spanning both positive and negative values. Brent's plot reflects its high variance and volatile nature, showcasing a broad distribution with frequent outliers at both extremes, highlighting the substantial price fluctuations observed over the period. The boxplots for other variables with positive average returns exhibit right-skewed distributions, emphasizing more occurrences of positive returns relative to negative ones. Overall, these visual representations underscore the leptokurtic nature of the distributions, confirming the presence of heavier tails and significant variability observed in the summary statistics.

2.1 Time-Varying Connectedness

To examine the time-varying connectedness between returns, we utilize TVP-VAR model of (Antonakakis et al., 2020) which employ extended version of the connectedness approach of (Diebold & Yilmaz, 2014). This model overcomes some drawbacks of the DY, such as (i) outlier sensitivity; (ii) loss of observations; (iii) incapability of analyzing low-frequency datasets; and (iv) the issue of randomly chosen rolling-window size that is. Our TVP-VAR model estimate denoted in Eq. (1), based on the Bayesian information criterion (BIC), which can be expressed as:

$$y_t = B_t y_{t-1} + \varepsilon_t, \varepsilon_t \sim N\left(0, \mathrm{S}_t\right) \tag{1}$$

$$\mathrm{vec}\left(B_t\right) = \mathrm{vec}\left(B_{t-1}\right) + \nu_t, \nu_t \sim N\left(0, R_t\right) \tag{2}$$

where Yt, y_{t-1} and ε_t are $\mathrm{N} \times 1$ dimensional vectors and B_t and S_t are $\mathrm{N} \times \mathrm{N}$ dimensional matrices. $\mathrm{vec}\left(B_t\right)$ and ν_t are $N^2 \times 1$ and R_t is $N^2 \times N^2$ dimensional matrix. We calculate the H-step ahead generalized forecast error variance decomposition (GFEVD) based on the (Koop et al., 1996; Pesaran & Shin, 1998). We transform the TVP-VAR into a TVP-VMA model based on the Wold theorem, as follows:

$$y_t = \sum_{i=1}^{p} B_{it} y_{t-i} + \varepsilon_t = \sum_{i=0}^{\infty} A_{it} \varepsilon_{t-i} \tag{3}$$

$C_{ij}^{g}(H)$ represents the influence variable j has on a variable i, which is computed by:

$$C_{ij}^{g}(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(e\prime_i \mathrm{A}_t S_t e_j\right)^2}{\sum_{j=1}^{K} \sum_{t=1}^{H-1} \left(e\prime_i \mathrm{A}_t S_t \mathrm{A}\prime_t e_j\right)} \tag{4}$$

where $C_{ij}^{g}(H)$ represents the contribution of the jth variable to the variance of forecast error of the variable ith at the horizon H_t and e_i is a zero vector with unity on the ith position. The normalization of each element in the decomposition matrix is:

$$\tilde{C}_{ij}^{g}(H) = \frac{\mathrm{C}_{ij}^{g}(H)}{\sum_{j=1}^{k} \mathrm{C}_{ij}^{g}(H)}, \text{with } \sum_{j=1}^{k} \tilde{C}_{ij}^{g}(H) = 1 \text{ and } \sum_{i,j=1}^{k} \tilde{C}_{ij}^{g}(H) = k \tag{5}$$

Based on GFEVD, we compute several connectedness measures as follows.

$$TO_{j,t} = \sum_{i=1, i \neq j}^{k} C_{ij,t}^{g}(H) \tag{6}$$

$$FROM_{j,t} = \sum_{i=1, i \neq j}^{k} C_{ji,t}^{g}(H) \quad (7)$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \quad (8)$$

$$TCI_t(q) = k^{-1} \sum_{j=1}^{k} TO_{j,t} = k^{-1} \sum_{j=1}^{k} FROM_{j,t} \quad (9)$$

Equation 6 shows the total directional connectedness index to others (denoted by 'TO'), or the impact of a shock in variable j has on all other variables i. Equation 7 shows the total directional connectedness from others (denoted by 'FROM'), or the influence all other variables have on variable j. The net total directional connectedness in Eq. 8 is derived by subtracting the impact variable j has on others by the influence others have on variable j. A positive (negative) value indicates a net transmitter (net receiver), hence driving (driven by) the network. Finally, the total connectedness index (TCI) measures the average influence of one variable on all others.

2.2 TVP-VAR Frequency Connectedness Networks

Concerning different economic agents and market participants are interested in the spillover at different frequencies, the next phase of this study aims at examining the connectedness in the frequencies (Ellington & Barunik, 2020), henceforth, the EB, which is based on a TVP-VAR model with a time-varying covariance structure using a Quasi-Bayesian Local Likelihood (QBLL) method. It disintegrates the overall connectedness into different frequencies, providing information at the specific frequencies that most contribute to the connectedness of a system. This provides valuable insights for investors in their short-run or the long-run investment decisions. In particular, participants, driven by various beliefs, preferences, objectives, risk tolerance, and constraints, are heterogeneous in their time horizons. Despite day traders with short-term horizons are more concerned about short-term connectedness; institutional investors with long-term horizons are more interested in long-term connectedness. Therefore, this methodology provides granular information that is useful for investors as it computes the short-, medium-, and long-term network connectedness taking into account the time-varying coefficient and variance–covariance structure.

It should be noted that recent literature has extensively explored frequency-dependent connectedness using various econometric methodologies, as demonstrated by studies by Frimbong et al. (2021), Mensi et al. (2021c), and Boroumand and Porcher (2023). These studies have utilized methodologies such as wavelet analysis, which is notable for its focus on both time and frequency domains. This approach allows for assessing the correlation between two time series over different time intervals (e.g., short-term versus long-term). In contrast, Barunik and Ellington (2020) employed spectral decomposition of time-varying variance matrices in their methodology. The Bayesian framework of their approach incorporates prior shrinkage and provides information about estimation uncertainty through the posterior distribution of connectedness metrics. This methodological approach diverges from traditional studies that typically offer single-point estimates and rely on bootstrapping for confidence interval.

The EB approach introduces a dynamic network structure, that shows the effects of transient and persevering shocks from j on the future variance of k as follows:

Define $\left(Y_{t,T}\right)_{1\le t\le T, T\epsilon N}$ with $Y_{t,T}=\left(Y^{1}_{t,T},\dots,Y^{N}_{t,T}\right)^{T}$, where t represents the time index and T as the "*sharpness of the local approximation of the time series* $\left(X_{t,T}\right)_{1\le t\le T, T\epsilon N}$ *by a stationary one*" (Ellington & Baruník, 2020).

$\left(Y_{t,T}\right)_{1\le t\le T, T\epsilon N}$ is formed as follows:

$$Y_{t,T}=\varphi_1(t/T)Y_{t-1,T}+\dots+\varphi_p(t/T)Y_{t-p,T}+\Sigma_{t,T} \tag{10}$$

where $\Sigma_{t,T}=\Sigma^{-\frac{1}{2}}(t/T)\rho_{t,T}$ with $\rho_{t,T}\sim NID\left(0,I_N\right)$, and $\varphi(t/T)=\left(\varphi_1(t/T),\dots,\varphi_p(t/T)\right)^{T}$ are time-varying autoregressive coefficients. In fixed time neighbourhood of $\mu_0=t_0/T$, a stationary process $\widetilde{Y}_t\left(\mu_0\right)$ approximates the process $Y_{t,T}$ as

$$\widetilde{Y}_t\left(\mu_0\right)=\varnothing_1\left(\mu_0\right)\widetilde{Y}_{t-1}\left(\mu_0\right)+\dots+\varnothing_p\left(\mu_0\right)\widetilde{Y}_{t-p}\left(\mu_0\right)+\Sigma_t \tag{11}$$

with $t\in\mathbb{Z}$, satisfying the suitable regularity conditions $\left|Y_{t,T}-\widetilde{Y}_t\left(t_0\right)\right|=O_P\left(\left|t/T-\mu_0\right|+1/T\right)\cdot$ The $VMA(\infty)$ representation of it:

$$X_{t,T}=\sum_{\mathrm{h}=-\infty}^{\infty}\psi_{t,T}(\mathrm{h})\Sigma_{t-\mathrm{h}} \tag{12}$$

Here, $\psi_{t,T}\approx\psi(t/T,h)$ and $sup_l\|\psi_t-\psi_l\|^2=O_p(h/t)$ for $1\le h\le t$ as $t\to\infty$. "*The spectral density of* $Y_{t,T}$ *at frequency* d *is defined as*" (Ellington & Baruník, 2020):

$$S_X(\mu,\varpi)=\sum_{h=-\infty}^{\infty}E\left[Y_{t+h}(\mu)X_t^{T}(\mu)\right]e^{-i\varpi h}=\left\{\psi(\mu)e^{-i\varpi}\right\}\Sigma(\mu)\left\{\psi(\mu)e^{+i\varpi}\right\}^{T} \tag{13}$$

The dynamic adjacency matrix is defined as:

$$[\theta(\mu,d)]_{j,k}=\frac{\sigma_{kk}^{-1}\int_a^b\left|\left[\psi(\mu)e^{-i\varpi}\epsilon(\mu)\right]_{j,k}\right|^2d\varpi}{\int_{-\pi}^{\pi}\left[\left\{\psi(\mu)e^{-i\varpi}\right\}\Sigma(\mu)\left\{\psi(\mu)e^{+i\varpi}\right\}^{T}\right]_{j,j}d\varpi} \tag{14}$$

where $d=\{(a,b):a,b\epsilon(-\pi,\pi),a<b\}$.

For The 'local network connectedness':

$$C(\mu,d) = 100 \times \sum_{\substack{j,k=1 \\ j \neq k}}^{N} [\theta(\mu,d)]_{j,k} \Big/ \sum_{j,k=1}^{N} [\theta(\mu)]_{j,k} \tag{15}$$

Here,

$$[\theta(\mu,d)]_{j,k} = [\theta(\mu,d)]_{j,k} / \sum_{k=1}^{N} [\theta(\mu)]_{j,k} \tag{16}$$

FROM connectedness for $k \neq j$, is defined as:

$$C_{j\leftarrow \bullet}(\mu,d) = 100 \times \sum_{\substack{k=1 \\ k \neq j}}^{N} [\theta(\mu,d)]_{j,k} / \sum_{j,k=1}^{N} [\theta(\mu)]_{j,k} \tag{17}$$

TO connectedness for $k \neq j$, is defined as:

$$C_{j\rightarrow \bullet}(\mu,d) = 100 \times \sum_{\substack{k=1 \\ k \neq j}}^{N} [\theta(\mu,d)]_{k,j} / \sum_{k,j=1}^{N} [\theta(\mu)]_{k,j} \tag{18}$$

In this research, the TVP-VAR connectedness index is partitioned into distinct time frames: short-term, medium-term, and long-term. These time frames align with intervals of 1–5 days (spanning from 1 day to 1 week), 5–20 days (ranging from 1 week to a month), and 20 + days (exceeding 1 month), respectively.

2.3 ADCC (Asymmetric DCC) Analysis

ADCC model of Cappiello et al. (2006) is employed to analyze the time-varying correlation coefficients between returns of assets. We employ the mean equation on the I_{t-1}:

$$r_t = \mu + \varphi r_{t-1} + \varepsilon_t \tag{19}$$

where r_t is the $n \times 1$ returns vector The e are denoted by $\varepsilon_t = H_t^{1/2} z_t$ where H_t is the conditional covariance matrix of r_t and z_t is an $n \times 1$ vector i.i.d. errors. H_t can be reformulated as:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{20}$$

where $D_t = diag\left(h_{i,t}, \ldots, h_{n,t}\right)$ represents the diagonal conditional variances. The conditional correlation matrix R_t is given as:

$$R_t = diag\left(q_{q,t}^{-1/2}, \ldots, q_{n,t}^{-1/2}\right) \Omega_t \left(q_{q,t}^{-1/2}, \ldots, q_{n,t}^{-1/2}\right) \tag{21}$$

where θ_t is asymmetric positive definite matrix with $\Omega_t = (1 - \theta_1 - \theta_2)\overline{\Omega} + \theta_1 z_{1-1} z_{t-1}\prime + \theta_2 \Omega_{t-1}$. Later, $\overline{\Omega}$ shows the $n \times n$ unconditional standardized residuals matrix z_{it},θ_1 and θ_2 are non-negatives providing the $\theta_1 + \theta_2 < 1$ condition. The correlation is defined as:

$$\rho_{ij,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \tag{22}$$

Cappiello et al. (2006) proposed asymmetric DCC approach adding an asymmetric term to Engle (2002) DCC model. The conditional volatility obtained from GARCH(1,1) is given as:

$$h_{i,t} = w_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \gamma_i \varepsilon_{i,t-1}^2 I(\varepsilon_{i,t-1}) \tag{23}$$

where the indicator function $I_{t-1} = 1$ if $\varepsilon_{i,t-1} < 0$ otherwise $I_{t-1} = 0$. Ω_t is represented by:

$$\Omega_t = \left(\overline{\Omega} - A\prime\overline{\Omega}\mathrm{A} - B\prime\overline{\Omega}\mathrm{B} - G\prime\overline{\Omega}\mathrm{G}\right) + A\prime z_{t-1} z_{t-1}\prime A + B\prime \Omega_{t-1}\mathrm{B} + G\prime z_t^- z_{t-1}\prime G \tag{24}$$

where A, B, and G are $n \times n$ matrices for parameters and z_t^- are zero-threshold standardized residuals with unconditional $\overline{\Omega_t^-}$ matrix.

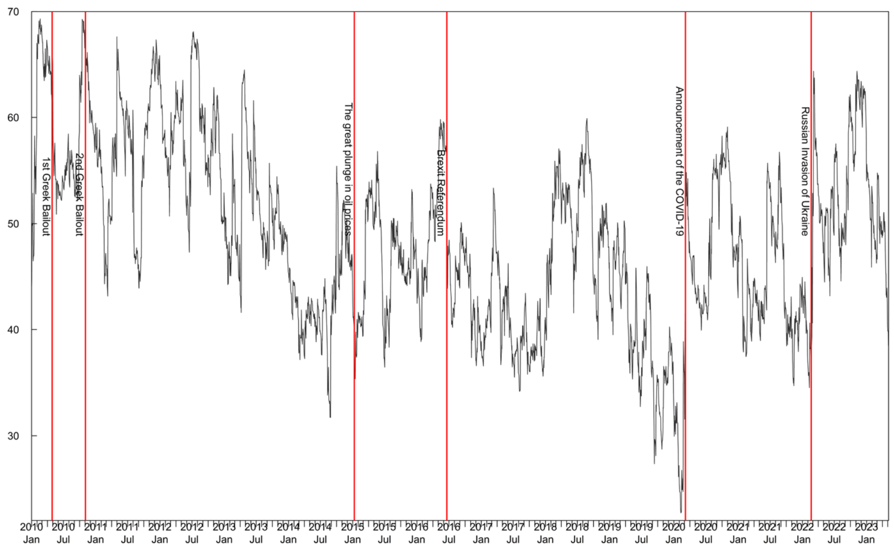

Fig. 3 TCI for returns

Table 2 Average spillovers for the returns

	Gold	Silver	Palladium	Platinum	EUR/USD	Brent	FROM
Gold	40.47	25.92	7.01	16.54	7.35	2.71	59.53
Silver	25.13	38.93	8.79	17.39	6.18	3.58	61.07
Palladium	8.44	10.97	53.02	17.73	4.71	5.12	46.98
Platinum	16.42	18	14.43	40.55	6.35	4.25	59.45
EURUSD	10.61	8.9	5.68	8.83	61.95	4.04	38.05
Brent	4.29	5.83	6.93	6.82	3.99	72.14	27.86
TO	64.89	69.62	42.84	67.3	28.58	19.7	292.93
NET	5.36	8.56	– 4.13	7.85	−9.47	– 8.16	TCI = 48.82

The off-diagonal values depict the impacts of the ith element o the jth element in the network. The outcomes are derived using the TVP-VAR (1) model with a lag of 1 (selected by BIC), along with a 10-step ahead forecast error variance decomposition (FEVD)

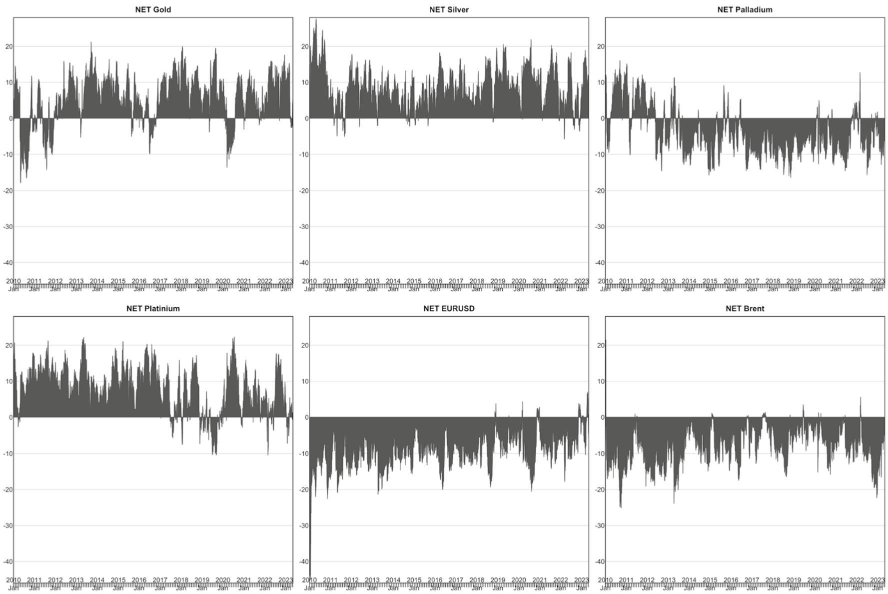

Fig. 4 Net spillovers

3 Results

3.1 Time-Varying Connectedness Results

Examining time-varying connectedness of returns, Fig. 3 displays the total connectedness index (TCI) with prominent incidents.

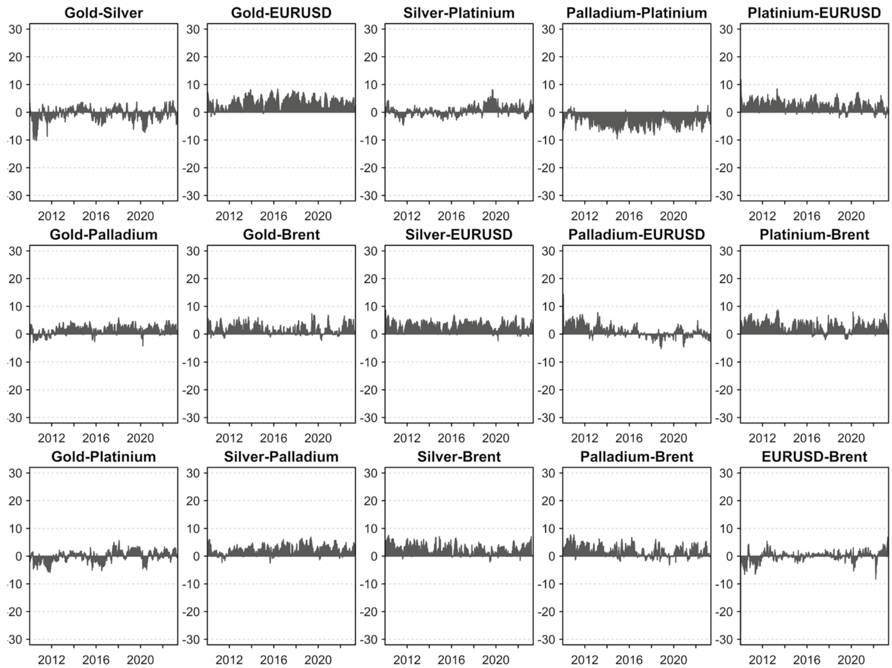

Fig. 5 Net pairwise spillovers for the returns

The TCI swung between 22 and 70% and hit its apex on February 23, 2010, coinciding with the ESDC. In line with the theoretical expectation, it is seen that international events have a significant effect on time-varying connectedness of returns. Oscillating between 43 and 70% until late 2012, the index gradually alleviated and reached 31.74% on August 29, 2014. It is worthwhile remarking that the TCI skyrocketed around the beginning of the COVID-19 outbreak on March 11, 2020, and the start date of the Russia-Ukraine war on February 24, 2022. Table 2 presents the average spillovers between return series.

Average connectedness results indicate that, on average, all indices exhibit a greater influence on their own shocks than on those of others. The largest transmitters/recipients of return shocks are silver and palladium, while Brent transmits/receives the fewest of the shocks. This finding is consistent with the results of Shah et al. (2021). Gold, silver, and platinum are determined to be the net transmitter of return shocks, whereas the rest of the indexes are the net recipients of shocks. The average connectedness index is 39.58%. Next, we examine the net directional spillovers among the indexes and display in Fig. 4.

The net directional spillover effects highlight the subsequent notable outcomes. Firstly, consistent with our prior results, gold, silver, and platinum consistently propagate return shocks for the majority of the duration, whereas other indices predominantly experience an influx of shocks. Notably, EUR/USD encounters a substantial influx of return shocks in January and February, which coincides with the early European Systemic Debt Crisis (ESDC).

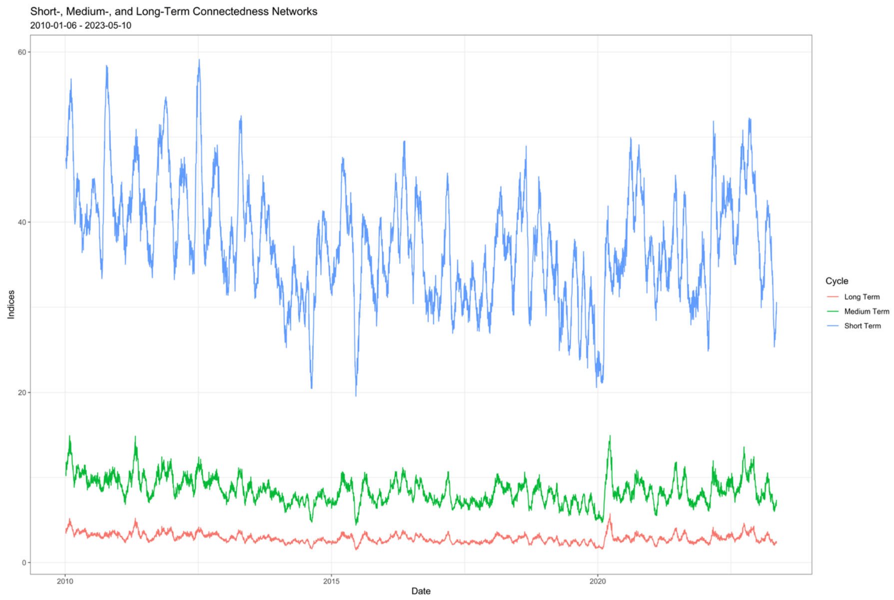

Fig. 6 Frequency-dependent interlinkages

Net pairwise spillovers among the returns are depicted in Fig. 5.

The findings in Fig. 5 reveal the following results. First, sharing a common feature, the net return connectedness among precious metals and EUR/USD exchange rate are mainly positive throughout the period. Second, Brent is relatively lesser interconnected with other indexes over the study period, which can indicate its hedging potential. Finally, gold and silver have relatively strong linkages with the exchange rate EUR/USD, underpinning significant return spillovers among them.

3.2 Frequency-dependent Dynamic Interlinkages

In this section, we examine the transient-, medium-, and persistent connectedness networks and plot them with well-known geopolitical/financial incidents in Fig. 6.

Frequency-dependent connectedness networks reveal that the transient interdependencies is tighter than the persistent interlinkages, which aligns with

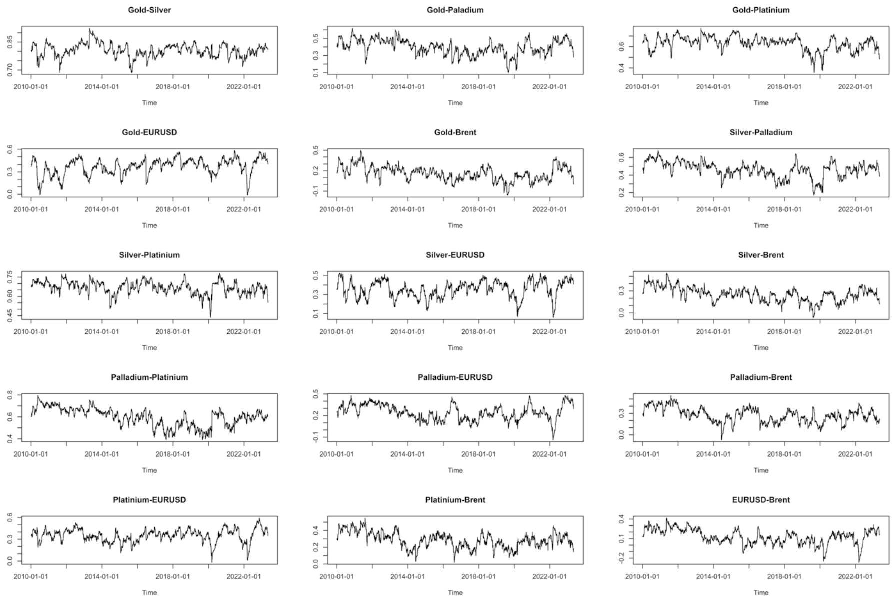

Fig. 7 ADCC-GARCH correlations. *Notes* Results are based on ADCC-GARCH(1,1) model relied on the AIC (Akaike information criterion

the related studies (Mo et al., 2022; Mensi et al., 2023). Additionally, frequency-based interconnectedness indices accurately signal significant events. Notably, these indices exhibit a sharp surge at the beginning of the COVID-19 outbreak and the Russia-Ukraine war. To conclude, in line with Shah et al. (2021), our results propose that over the extended term, investors can gain benefits from diversification and the utilization of precious metals as a safeguard against shocks in Brent oil prices and exchange rates.

3.3 ADCC-GARCH Model Results

Continuing with our analysis of dynamic correlations, Fig. 7 shows the pairwise correlations[1] between returns estimated by the ADCC-GARCH model.[2]

According to Fig. 7, there is seen big drops in the asymmetric dynamic correlation coefficients between EURUSD and commodities (as silver, palladium and gold) especially in the periods of the Russia-Ukraine war. Also, it is seen some decreases

[1] We employed the GJR-GARCH (Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity) model (Glosten et al., 1993) within the ADCC-GARCH model framework. For the sensitivity analysis, we incorporated various GARCH volatility models, including sGARCH, eGARCH, and iGARCH, into the ADCC-GARCH model. The results consistently revealed similar patterns in time-varying correlations.

[2] The ADCC-GARCH model estimations are given in Appendix A.1. Note that the stability condition of the DCC-GARCH holds since alpha + beta < 1.

periods in the asymmetric correlation coefficients consistent with the connectedness results including the beginning of Covid-19 pandemic, August 2011 stock market fall and 2015 oil price plunge and stock market selloff. When asymmetric dynamic correlations between the commodities are investigated, it is seen decreases in the Covid-19 pandemic periods and increases in Russia-Ukraine war periods. Also, it is seen that the other periods presented in Fig. 2 have an effect on the dynamic correlation coefficients between the commodities consistent with the connectedness results.

The results provide important findings for investors, financial markets and policy makers. For investors, gold, silver and platinum can be defined as investment instruments with high hedging potential because they are transmitters of shocks. Investors can use these precious metals to mitigate risks in the oil price and exchange rate. In addition, diversification using precious metals is very important for investors and can be especially protective against volatility caused by global events such as the pandemic and the Russia-Ukraine war. The results also reveal that investors should focus more on short-term market movements during periods of increased volatility.

Using TCI, financial markets can track the connectedness among key assets and thus predict the impact of global events on market stability. The fact that TCI varies between 22 and 70% and peaks when there are global events such as ESCD, COVID-19 and the Russia-Ukraine war demonstrates the need for more dynamic risk management practices as it shows the impact of global events on the connectedness of returns. The sharp increase in the TCI index in times of crisis also reveals the need for more resilient crisis management policies. In addition, developing indices that measure the connectedness of key financial assets will provide both transparency and market information, and reduce uncertainty. Policy makers should develop effective crisis management mechanisms by considering time-varying connectedness and thus promote long-term economic growth by reducing short-term volatility.

Considering the average spillovers, Silver and Palladium are the largest transmitters and receivers of return shocks and therefore have central roles in the interconnectedness network. Brent oil, on the other hand, can be considered a stable asset in portfolio diversification as it has the lowest profile in terms of receiving and transmitting shocks. Regarding net directional spillovers, since gold, silver and platinum are net transmitters of return shocks, investors and policy makers should take their influential roles into account when evaluating the market and developing risk management strategies. Since short-term dependencies are more dominant in frequency dependent relationships, there is a need to develop strategies for short-term market fluctuations.

The oil market is a liquid market and large amounts of trading activities can be carried out without much change in price, which can reduce volatility. In addition, countries' energy policies such as production, consumption and alternative energy are long-term policies and their effects on oil prices are diffuse effects rather than immediate effects. Also, since the oil market includes many different stakeholders, the reactions of each stakeholder to the change in oil prices may differ, and this may smooth volatility. On the other hand, since precious metals are seen as a safe haven investment tool, they cause a large amount of shock propagation, especially in times of economic uncertainty. Exchange rates can also show high fluctuations and propagation because they are highly sensitive to macroeconomic indicators, monetary policies and geopolitical events. While investor sentiments about oil prices largely depend on long-term trends and fundamental factors, sentiments in precious metals and exchange rates may react more to short-term news and events.

4 Conclusion

As globalization progresses, leading to the integration of financial markets, it presents diverse opportunities for investors. However, it also results in the diffusion of risk. Consequently, comprehending the dispersion of risk holds significance for assessing risk among varying financial assets, facilitating hedging and risk distribution for portfolio managers. Conversely, for policy makers, this scenario carries importance for the effectiveness of critical strategies. In this study, we explore the connectedness among core precious metals, crude oil, and exchange rates, utilizing daily data spanning the period from January 4, 2010-May 10, 2023. When examining the interrelationships within financial data, it becomes evident that heightened volatility, particularly during crisis periods, accentuates the significance of risk management. In this context, we employ the TVP-VAR approach coupled with a connectedness procedure, accommodating the evolving relationships over time.

The research aimed to systematically uncover the impacts of significant events during the post-2010 era on financial markets, with particular attention on crisis periods. This approach aimed to provide timely insights, offering valuable guidance for portfolio managers and decision-makers. This guidance pertains to scrutinizing the patterns and origins of volatility in financial markets, valuating financial assets, executing global hedging strategies, and formulating choices regarding portfolio preferences.

First of all, consistent with theoretical expectations, it becomes evident that global occurrences exert a substantial impact on the evolving interconnectedness of returns. As indicated by the average connectivity outcomes, silver and palladium emerge as the foremost propagators and recipients of return shocks, while Brent displays the lowest incidence of transmitting and receiving such shocks. Furthermore, gold, silver, and platinum are found as the primary sources of transmitting return shocks, whereas the remaining indices are identified as the main recipients of these shocks.

Net directional spill-over effects reveal the subsequent significant outcomes. Firstly, aligning with our prior discoveries, gold, silver, and platinum consistently act as the enduring sources of transmitting return shocks across the majority of the period, while the remaining indices predominantly function as the primary recipients of such shocks.

Based on the frequency-dependent interlinkages, the transient interdependencies are more pronounced than the long-term ones, which aligns with the former literature (Mo et al., 2022; Mensi et al., 2023) and underscores the heightened propagation of shocks within short-term returns. Furthermore, the frequency-based connectedness indices appropriately signify well-known occurrences over the course of the study.

It is observed that the indices experience surges subsequent to significant events. Notably, these indices exhibit a sharp rise surrounding the inception of the COVID-19 pandemic and the commencement of the Russia-Ukraine war, with similar index reactions occurring for other events as well. Ultimately, in accordance with Shah et al. (2021), our findings offer that over an extended timeframe, investors can attain benefits through diversification and the utilization of precious metals as a safeguard against shocks in Brent oil prices and exchange rates.

In light of the conclusions drawn from our study, the findings underscore the evolving interconnectedness of returns among core precious metals, crude oil, and exchange rates amidst globalization. This dynamic environment not only presents opportunities for investors but also underscores the diffusion of risk across financial markets. Understanding these dynamics is crucial for risk assessment, hedging strategies, and portfolio management. Our research, utilizing a TVP-VAR approach and connectedness procedures over the period from January 4, 2010, to May 10, 2023, reveals that global events significantly influence these interrelationships, particularly during crisis episodes. The analysis highlights silver and palladium as key propagators and recipients of return shocks, with gold, silver, and platinum consistently transmitting shocks while other indices predominantly receive them. Moreover, the frequency-dependent interlinkages emphasize transient dependencies, suggesting heightened volatility in short-term returns following major events such as the COVID-19 pandemic and the Russia-Ukraine conflict. These insights, corroborated by prior studies, underscore the benefits of diversification and the role of precious metals in mitigating risks associated with fluctuations in Brent oil prices and exchange rates, offering valuable guidance for investors and policymakers alike in navigating turbulent financial landscapes.

Our research has potential limitations. First, sample selection bias may arise due to our focus on specific assets and a particular timeframe, possibly affecting the generalizability of our findings. Second, the external validity of our conclusions might be limited, as the findings are most applicable to the studied period and assets, and may not extend to different timeframes or other financial instruments.

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Declarations

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