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Examining market synchronicity: spillover connectedness among commodity markets and exchange rates during crisis periods

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Abstract: We investigate the dynamic spillover connectedness between commodity markets (gold and crude oil) and exchange rates in seven of the world's most influential developed and emerging economies: China, Ukraine, Germany, the United Kingdom, Japan, Russia, and the United States. Utilizing an extensive daily dataset sourced from Bloomberg, we analyze key exchange rates and commodity markets, focusing on currencies and economic indicators of significant global economies. Our findings reveal significant spillover effects across markets, with major currencies playing central roles in transmitting volatility during crisis periods. Specifically, currencies like EUR/$ and GBP/$ exhibit substantial internal spillovers, reflecting robust interconnectedness within these markets. In contrast, commodities such as crude oil demonstrate a more insulated nature, transmitting fewer spillovers compared to exchange rates. Furthermore, our analysis during distinct crisis periods, including the Covid-19 pandemic, the Russia-Ukraine conflict, and the Israel-Palestine war, highlights evolving market dynamics amidst geopolitical uncertainties. Major currencies continue to play pivotal roles during crises, transmitting the highest total spillovers, while commodities like gold emerge as significant transmitters and receivers, underscoring their role as safe-haven assets.

Keywords: *Connectedness, Exchange rates, Global crisis.*
JEL Classification: *G14; G11; G12; C58.*

1. Introduction

The interconnections between commodity markets and exchange rates are vital to understanding global financial stability, risk management, and economic policy-making. Commodities such as gold and crude oil are crucial not only due to their intrinsic economic value but also because they serve as indicators of broader economic trends (Díaz *et al.*, 2022; Rafiuddin *et al.*, 2023). Exchange rates, representing the relative values of currencies, are influenced by numerous factors, including commodity prices. Natural resources and foreign exchange reserves are deeply intertwined with a country's economic and financial security. Globalization has intensified the focus on resource security (Al Mustofa *et al.*, 2021; Amar *et al.*, 2018), with gold and oil becoming critical investment assets and heavily traded commodities in financial markets (Chen *et al.*, 2022). The foreign exchange market significantly influences other financial markets due to the close relationship between exchange rates and foreign exchange reserves (Almansour *et al.*, 2020). Researchers generally indicate dependence or risk contagion among crude oil, gold, and exchange rates (Abuzayed & Al-Fayoumi, 2021; Hung, 2022; Kalra *et al.*, 2022; Opoku *et al.*, 2023; Rastogi & Kanoujiya, 2022), although some studies suggest a degree of independence among these connections (Abuzayed & Al-Fayoumi, 2021; Xu *et al.*, 2023). Both gold and

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oil are commonly hedged due to their dual roles as financial and commodity assets (Ibrahim *et al.*, 2024; Robiyanto *et al.*, 2020)

Following the dissolution of the Bretton Woods system in 1971, which severed the link between the USD and gold, gold and crude oil transactions have remained heavily reliant on the USD (Ocampo, 2019; Pauly, 2009; Wyplosz, 2006). This reliance implies that fluctuations in the USD exchange rate can cause significant market disruptions when gold and crude oil are hedged against each other. Specifically, when crude oil prices rise, the price of gold, often considered a safe-haven asset, tends to decrease. Investors may increase their crude oil holdings and reduce their gold holdings under such conditions. However, if the USD depreciates, the increased crude oil assets may not suffice, and the reduced gold assets may also be adversely affected. Thus, the USD exchange rate can exert a dual pressure on both gold and crude oil assets, posing a potential risk for countries with foreign exchange reserves predominantly in USD (Al-Yahyaee *et al.*, 2019).

The volatility experienced in global financial markets during crises like the Covid-19 pandemic and geopolitical conflicts such as the Ukraine-Russia conflict and the Palestine-Israel war highlights the critical importance of studying and mitigating interconnected risks to maintain economic and financial resilience (Goyal & Soni, 2024; Miaari & Calì, 2020; Rubbaniy *et al.*, 2024; Yadav *et al.*, 2024). These crises can have far-reaching consequences, impacting various sectors and economies worldwide. Liu *et al.*, (2021) found that the impact of international oil prices on China's real economy has significantly increased since the 2008 financial crisis. The pandemic, causing global financial turmoil, led to the coronavirus recession and a stock market crash (Li, 2021). The pandemic induced a decline in factor inputs and shifts in consumer preferences, primarily driving the economic downturn (Kamal *et al.*, 2022; Prorokowski, 2014). During such crisis, foreign exchanges and commodity markets experience substantial price fluctuations (Al-Maadid *et al.*, 2021; Khalifa *et al.*, 2017).

Empirical econometric analyses of risk spillovers often employ time series models, with vector auto-regression (VAR), developed by Sims in 1980, being widely used due to its flexibility concerning economic assumptions. The generalized vector auto-regression framework (GVAR), an extension of VAR, mitigates the impact of variable ordering on forecast error variance decomposition (Diebold & Yilmaz, 2012). Consequently, the spillover effect model developed by Diebold and Yilmaz (2012) has been instrumental in creating spillover index frameworks to examine volatility.

This research enhances the existing literature by providing a comparative analysis of the spillover connectedness between commodity markets and exchange rates in selected economies including the world's most influential and emerging economies. Using TVP-VAR econometric models and spillover indices, we aim to illuminate the dynamic relationships and transmission mechanisms of exchange rates and commodity markets across different economies. Despite making significant contributions, the current literature still exhibits several gaps. Previous research tends to focus on specific crises or a limited range of markets, lacking a comprehensive analysis that spans multiple crises and encompasses a broader array of financial markets. Moreover, while there are considerable studies on the individual impacts of crises on market interconnectedness, there is a dearth of comparative research that examines how distinct types of crises, such as the Covid-19 pandemic and geopolitical tensions like the Russia-Ukraine conflict and Israel-Palestine tensions, influence the interconnectedness of exchange rates and commodity markets over an extended period. This study aims to fill these gaps by undertaking a comprehensive examination of spillover connectedness among various measures, including different exchange rates against the USD, crude oil prices, and gold prices across different crisis periods. The findings offer significant insights for policymakers and market participants regarding risk management, investment strategies, and the formulation of economic policies in an increasingly interconnected global market.

2. Literature Review

Contagion theory, integral to understanding financial crises, posits that economic disturbances can propagate across borders, leading to widespread market instability. This theory is particularly relevant when analyzing spillover connectedness, as it encapsulates the mechanisms through which volatility and shocks transfer from one market to another *(Majdoub et al., 2018; Naeem et al.,* 2021; Schenck *et al.*, 2021). In the context of commodity markets and exchange rates, spillover connectedness becomes a critical factor in assessing how fluctuations in one sector, such as a sudden drop in crude oil prices, can influence exchange rate volatility across major global economies. Awartani *et al.*, (2016) conducted a seminal study that emphasizes the significant volatility transmission from oil to equities, with a moderate impact on precious metals and exchange rates. This study underscores the pivotal role of oil in financial markets and its influence on various asset classes. Building on this, Zhu *et al.*, (2023) highlight the centrality of Brent oil and the US 10-year Treasury rate within global asset networks, stressing the importance of understanding dynamic spillover effects for effective financial risk regulation and asset allocation. Shah *et al.*, (2021) delve into the time-frequency domain of connectedness among crude oil, precious metals, and forex markets. They find that interconnectedness is primarily driven by short-term horizons and intensifies during periods of market uncertainty. This research highlights the temporal dimensions of market connectedness and underscores the necessity of considering different time scales in spillover analysis.

In a regional context, Opoku *et al.*, (2023) investigate the dynamic connectivity between commodities and exchange rates in Sub-Saharan Africa. Their findings reveal that crude oil is a dominant spillover propagator during economic turmoil, emphasizing the regional specificity of spillover effects and the importance of geographical context in analyzing market dynamics. Similarly, Tian *et al.*, (2022) explore the "Carbon-Commodity-Finance" system in emerging economies, discovering that stock markets are primary sources of shock contagion, while green bonds are significant shock receivers. Nefzi and Melki (2023) focus on the connectedness of carry trade currency with stock, forex, and commodity markets, identifying substantial volatility contributions from carry trade, especially during the Covid-19 pandemic. This study underscores the impact of global crises on financial market connectedness and the significant role of currency markets in transmitting volatility.

Boakye *et al.*, (2024) examine systemic risks and connectedness across commodities, stocks, exchange rates, and bond markets in Africa during the Covid-19 pandemic. Their findings indicate higher systemic risks in the forex market, highlighting the vulnerability of currency markets during global crises. Complementarily, Huang and Liu (2023) use the Diebold-Yilmaz connectedness index to explore cross-market risk spillovers, showing significant spillovers among sovereign credit default swaps, stock, forex, and commodity markets during major economic events like the Covid-19 pandemic and the Russia-Ukraine conflict.

In the context of China, Song *et al.*, (2022) and Xu *et al.*, (2023) provide valuable insights into spillover mechanisms, emphasizing the impacts of economic policy uncertainties and the Covid-19 pandemic on commodity and exchange rate markets. These studies underscore the importance of understanding market connectedness within different economic contexts and the role of external shocks in shaping these relationships. Wu *et al.*, (2023) analyze the time-frequency connectedness of policy uncertainty, geopolitical risk, and commodity markets in China, finding that monetary policy uncertainty has the most significant impact on commodity markets. This highlights the influence of macroeconomic policies on market dynamics. Qabhobho *et al.*, (2023) study the connectedness between energy markets and currency markets in the BRICS countries, noting that energy commodities are major transmitters of shocks, particularly during the Covid-19 pandemic.

We focus on examining the spillover connectedness between commodity markets (gold and crude oil) and exchange rates in seven of the world's most influential developed and emerging economies: China, Ukraine, Germany, the United Kingdom, Japan, Russia, and the United States. These countries were selected due to their significant impact on global economic dynamics and their diverse economic structures, offering a comprehensive view of interconnectedness across different economic environments. By analyzing the interactions among these economies, this research aims to provide valuable insights into the transmission mechanisms of financial shocks and volatility, contributing to a broader understanding of global financial stability and risk management. The primary objective is to address several key questions: (1) To what extent does spillover connectedness drive fluctuations in commodity markets (gold and Brent crude oil) and exchange rates across China, Ukraine, Germany, the United Kingdom, Japan, Russia, and the United States? (2). Among the selected economies, which specific commodity markets and exchange rates exhibit the strongest spillover connectedness? (3) Which commodity markets and exchange rates act as net receivers or transmitters of financial shocks within the examined economies? (4) How do different geopolitical and economic crises influence the patterns of spillover connectedness among commodity markets and exchange rates in the selected economies?

3. Methodology

3.1. Data and Preliminary Analysis

Our research employed an extensive daily dataset to analyze key exchange rates and commodity markets, specifically focusing on the currencies and economic indicators of significant global economies. The exchange rates studied include CNY/USD (China), UAH/USD (Ukraine), EUR/USD (Germany), GBP/USD (United Kingdom), JPY/USD (Japan), and RUB/USD (Russia). These exchange rates were chosen to reflect a broad spectrum of economic environments and to provide insights into both developed and emerging markets. Additionally, gold and Brent crude oil prices were examined as representatives of the commodity markets. All prices in this study are either compared against or reported in USD. Data for all variables were sourced from Bloomberg, ensuring a high level of accuracy and reliability. The selection of these particular exchange rates and commodity prices was strategic. It allows for an in-depth analysis of economies hat are influential on the global stage while also including Ukraine due to its significant role in the recent geopolitical crisis with Russia. This diversified range offers several strategic advantages for investors, as it encompasses different economic conditions and crisis scenarios, thereby providing a comprehensive view of global market dynamics. The rationale for selecting these countries and commodities lies in their economic and geopolitical importance. China, the United States, Germany, the United Kingdom, Japan, and Russia are among the world's largest economies, with substantial influence on global trade and finance. Including Ukraine adds another dimension to the analysis, as it highlights the economic impact of regional conflicts and their broader implications for global markets. Table 1 presents a summary of economic conditions of selected countries in terms of GDP.

Table 2.
Summary of economic conditions of selected countries in terms of GDP (2022-2023).

Country	2022 GDP (in USD)	2023 GDP (in USD)
USA	$25.5 trillion	$26.9 trillion
China	$17.9 trillion	$17.7 trillion
Germany	$4.4 trillion	$4.1 trillion
United Kingdom	$3.1 trillion	$3.3 trillion
Japan	$4.2 trillion	$4.2 trillion
Russia	$2.2 trillion	$2.0 trillion
Ukraine	$160.5 billion	$173.41billion

Source: International monetary fund world economic outlook database

The dataset spans a substantial period from September 22, 2014, to May 31, 2024. This extensive timeframe allows for a comprehensive analysis of various market dynamics and economic conditions over nearly a decade. To capture significant events within this period, the dataset has been divided into three distinct segments. The first segment focuses on the Covid-19 pandemic, covering the period from

January 2, 2020, to May 24, 2023. This segment captures the global economic disruption caused by the pandemic, which led to unprecedented public health challenges, widespread lockdowns, and significant shifts in economic activity. This period is marked by extreme volatility in financial markets, including dramatic movements in exchange rates and commodity prices. The pandemic affected supply chains, consumer behavior, and governmental policies worldwide, leading to substantial fiscal and monetary interventions by central banks and governments (Almansour *et al.*, 2023). The second segment addresses the Russia-Ukraine conflict, beginning on February 24, 2022. This conflict has had severe geopolitical and economic repercussions, particularly in Europe and global energy markets. The war has disrupted global supply chains, particularly in energy, agriculture, and raw materials, leading to significant price fluctuations and economic uncertainty (Abid *et al.*, 2024; Cui & Maghyereh, 2024; Gabriel *et al.*, 2024). The third segment examines the Palestine-Israel conflict, which commenced on October 7, 2023. This conflict has added another layer of geopolitical instability, affecting regional markets and beyond. The ongoing nature of this conflict means that its full economic impact is still unfolding, but initial data indicates significant disruptions in financial markets and commodity prices, particularly in the Middle East (Cui & Maghyereh, 2024). Table 3 and figure 1 present the descriptive statistics and return volatility for the selected variables, respectively.

The mean values provide insights into the average daily returns for each variable. For instance, the negative mean value for CNY/USD (-0.000076) suggests a slight depreciation of the Chinese Yuan against the US Dollar on average over the observed period. Conversely, the high positive mean for UAH/USD (0.059146) indicates a significant average appreciation of the Ukrainian Hryvnia against the US Dollar, possibly influenced by economic recovery or intervention policies. Similar to CNY/USD, the slight negative means for EUR/USD (-0.000075) and GBP/USD (-0.000042) indicate marginal depreciations of the Euro and British Pound against the US Dollar, respectively. In contrast, the more noticeable negative mean for JPY/USD (-0.000221) suggests a depreciation trend for the Japanese Yen, while RUB/USD (-0.000164) also shows a depreciating trend for the Russian Ruble, likely influenced by economic sanctions and geopolitical tensions. On the other hand, the positive means for gold (0.000412) and crude oil (0.000685) reflect overall price appreciations, indicating the role of gold as a safe-haven asset and the influence of supply constraints and geopolitical factors on crude oil prices. The standard deviation measures the volatility or dispersion of returns around the mean. Variables with higher standard deviations, such as UAH/USD (2.430707), exhibit greater variability in returns, indicating higher volatility. In contrast, variables with lower standard deviations, like CNY/USD (0.002756) and EUR/USD (0.004464), suggest more stability in returns.

Table 4.
Descriptive statistics.

	CNY/USD	UAH/USD	EUR/USD	GBP/USD	JPY/USD	RUB/USD	GOLD	CRUDE OIL
Mean	-0.000076	0.059146	-0.000075	-0.000042	-0.000221	-0.000164	0.000412	0.000685
Max.	0.016100	98.490000	0.021400	0.031400	0.039400	0.121569	0.059771	0.509868
Min.	-0.016100	-0.989900	-0.020400	-0.036300	-0.031100	-0.201608	-0.049854	-0.474654
Std.	0.002756	2.430707	0.004464	0.005661	0.005257	0.013387	0.009507	0.033611
Skew.	0.136849	40.477970	0.031032	-0.105153	0.494015	-2.646368	-0.153678	0.748008
J-B	1068.08***	1840000***	151.18***	933.65***	3675.41***	177589.9***	1198.60***	329740***
ADF	-50.9***	-50.3***	-50.6***	-48.6***	-41.1***	-17.8***	-51.9***	-38.7***
Obs.	1642	1642	1642	1642	1642	1642	1642	1642

Mean represents the average daily return of the index, while Max and Min indicate the highest and lowest daily returns observed, respectively. Std. measures the volatility or dispersion of the returns around the mean. Skew denotes skewness, indicating the asymmetry of the return distribution. Kurt. signifies kurtosis, reflecting the "tailedness" of the distribution. J-B represents the Jarque-Bera test, assessing the deviation from normality. Obs. denotes the number of daily return data points, and ADF indicates the Augmented Dickey-Fuller test for stationarity. ***Significance at the 1 % level.

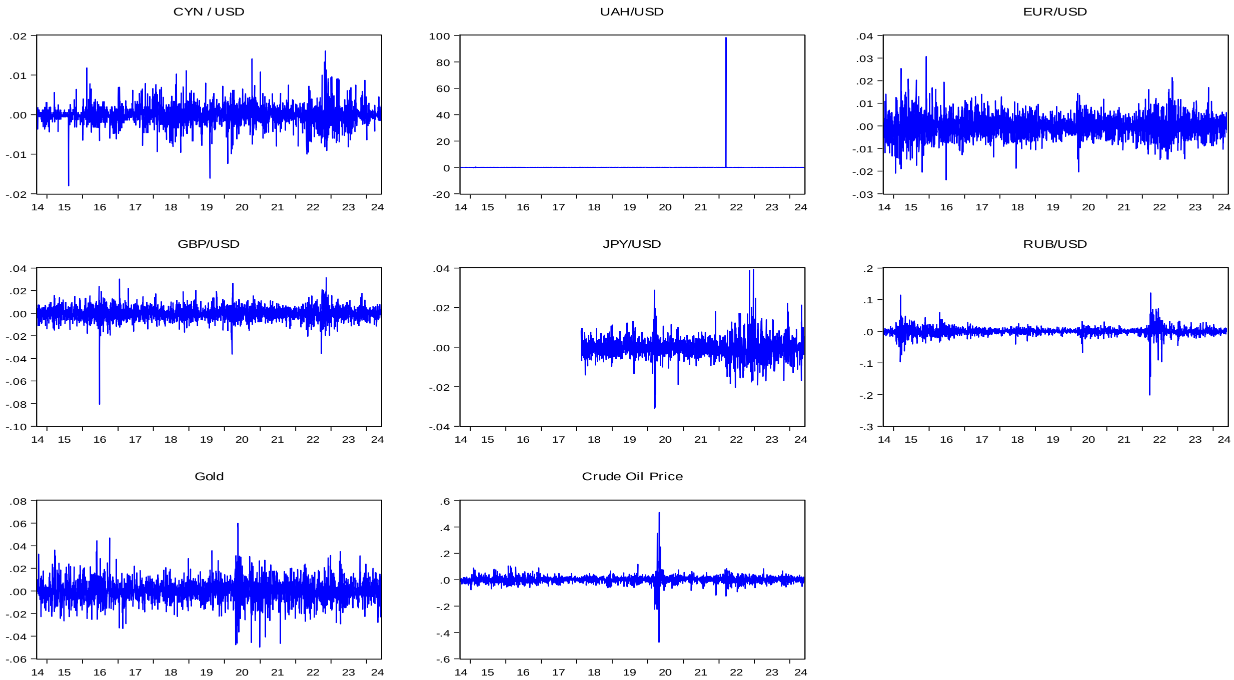

Figure 2.
Log-returns series of equity indices.

To investigate the dynamic nature of the systems under examination, we initiated our analysis by computing the initial logarithmic differences log (price_t) – log (price_{t-1}).

3.2. Econometrics Model

3.2.1. Quantile Vector Autoregression

To thoroughly investigate the interconnections within foreign exchange rates and commodity markets, it is essential to comprehensively analyze the risk associated with different markets and the total and directional spillovers, both statically and dynamically. Prior research has demonstrated that the Diebold and Yilmaz spillover index, introduced by Diebold and Yilmaz (2012), offers a comprehensive suite of methods for measuring various types of spillovers. We commence by employing the quantile connectedness method, as outlined by Antonakakis *et al.*, (2020) and further developed by Chatziantoniou *et al.*, (2022). Subsequently, we assess connectedness in the frequency domain utilizing the spectral decomposition method introduced by Stiassny (1996). The Diebold and Yilmaz spillover framework, which incorporates the QVAR(p) scheme proposed by Koop *et al.*, (1996), serves as a metric for gauging both total and directional volatility spillovers. Consequently, in this study, realized volatility was employed as the modeling data for calculating the risk spillovers. The QVAR(p) scheme utilized within the Diebold and Yilmaz spillover framework mitigates the influence of variable order by employing a generalized forecast error variance decomposition (FEVD), an extension of the vector autoregressive (VAR) model. The QVAR(p) is presented as follows:

$$\mathbb{z}_t = \boldsymbol{\mu_t}(\tau) + \boldsymbol{\eth}_1(\tau)\mathbb{z}_{t-1} + \boldsymbol{\eth}_2(\tau)\mathbb{z}_{t-2} + \cdots + \boldsymbol{\eth}_p(\tau)\mathbb{z}_{t-p} + \boldsymbol{u}_t(\tau). \quad (1)$$

In our analysis, we utilize the Wold approach to convert the Quantile Vector Autoregression (QVAR(p)) into its Quantile Vector Moving Average (QVMA) (∞) form. This transformation facilitates a deeper understanding of the relationship between variables over time. The QVMA(∞) model can be represented as follows:

$$\mathbb{z}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \mathfrak{d}_j(\tau)\mathbb{z}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \mathfrak{Z}_i(\tau)\boldsymbol{u}_{t-i}.$$

In this equation, Z_t represents the dependent variable at time *t*, μ(τ) signifies the quantile-specific intercept, $d_j(\tau)$ denotes the quantile-specific autoregressive coefficients, and $u_t(\tau)$ represents the quantile-specific error term. The model incorporates a lagged structure (*p*) to account for temporal dependencies in the data. The transformation into the QVMA (∞) form allows us to capture the infinite order moving average representation of the data, enabling a more comprehensive assessment of the dynamic interactions among variables. By considering an infinite number of lagged error terms ($Z_i(\tau)$), the model accommodates for potentially long-lasting effects and intricate temporal dynamics, providing a richer characterization of the underlying relationships.

In our analysis, we place particular emphasis on estimating the decomposition of the generalized forecast error variance (GFEVD), which serves as a cornerstone of the connectedness methodology. GFEVDs offer a structured approach to assess the impact of shocks originating from individual series within the system. The GFEVD calculation involves two key equations. Firstly, Equation (2) delineates the computation of the GFEVDs; where, $\Upsilon ij(\breve{U})$ represents the GFEVD for the impact of a shock from series *j* on series *i* over a horizon of Ŭ periods. This computation entails the summation of squared terms, where each term captures the contribution of the shock from series *j* to the forecast error variance of series *i*. The summation extends over Ŭ periods, reflecting the cumulative effect of the shock over time. The denominator of Equation (2) normalizes the GFEVD by dividing by the forecast error variance of series *i*.

$$\Upsilon_{ij}(\breve{U}) = \frac{(\Sigma(\tau))_{jj}^{-1} \sum_{\breve{u}=0}^{\breve{U}-1} \left(\left(\mathfrak{Z}_h(\tau)\Sigma(\tau) \right)_{ij} \right)^2}{\sum_{\breve{u}=0}^{\breve{U}} \left(\mathfrak{Z}_h(\tau)\Sigma(\tau)\mathfrak{Z}_h'(\tau) \right)_{ii}} \tag{2}$$

Following the computation of GFEVDs, Equation (3) introduces $\tilde{\Upsilon}ij(H)$, which represents the normalized GFEVD. This normalization process is crucial for facilitating comparisons across different pairs of series within the system. By dividing each GFEVD by the sum of all GFEVDs for series *i*, Equation (3) yields a relative measure that quantifies the proportion of the forecast error variance of series *i* attributed to the shock from series *j*.

$$\tilde{\Upsilon}_{ij}(H) = \frac{\Upsilon_{ij}(\breve{U})}{\sum_{k=1}^{N} \Upsilon_{ij}(\breve{U})} \tag{3}$$

where $\tilde{\Upsilon}_{ij}(\breve{U})$ represents the impact of j^{th} series on the variance of the i^{th} series' prediction inaccuracy at horizon Ŭ. Standardizing the rows of $\tilde{\Upsilon}_{ij}(\breve{U})$is crucial because of their non-sum-to-one nature, resulting in the standardized matrix $\tilde{\Upsilon}_{ij}$. Such standardization process leads to the subsequent relationships or identities:

$$\sum_{i=1}^{N} \tilde{\Upsilon}_{ij}(\breve{U}) = 1 \text{ and } \sum_{j=1}^{N} \sum_{i=1}^{N} \tilde{\Upsilon}_{ij}(H) = N.$$

Following the initial step of standardizing the rows of the matrix $\tilde{\Upsilon}_{ij}$, we proceed to calculate the pairwise connections between the various series. This involves assessing the interactions and dependencies between each pair of series within the system. Once the pairwise connections are established, we move on to compute additional interconnectedness metrics in subsequent stages of the analysis as follow:

$$NPDC_{ij}(\breve{U}) = \tilde{\Upsilon}_{ij}(\breve{U}) - \tilde{\Upsilon}_{ji}(\breve{U}). \tag{4}$$

If $NPDC_{ij}(\breve{U}) > 0$ ($NPDC_{ij}(\breve{U}) < 0$, it implies that series j has a stronger weaker) influence on series i compared to the reverse scenario.

Total directional connectedness "to others" provides valuable insights into the propagation of shocks from a single indicator to a wider array of indicators within the system. This metric offers a comprehensive assessment of the extent to which fluctuations in a particular variable ripple through the entire network of interconnected variables. By quantifying the magnitude of spillovers from a single component to others, we gain a deeper understanding of the interdependencies and linkages present within the system.

$$TO_i(\breve{\text{U}}) = \sum_{i=1, i\neq j}^{N} \tilde{Y}_{ji}(\breve{\text{U}}) \qquad (5)$$

The metric Total directional connectedness FROM others offers a comprehensive assessment of the repercussions of a shock originating in one indicator (i) on all other indicators (j) within the system. This metric quantifies the magnitude of influence and the degree to which changes propagate throughout the interconnected network of indicators, shedding light on their interrelationships and transmission dynamics.

$$FROM_i(\breve{\text{U}}) = \sum_{i=1, i\neq j}^{N} \tilde{Y}_{ij}(\breve{\text{U}}) \qquad (6)$$

The net total directional connectedness, obtained by subtracting the influence FROM other indicators from the influence TO other indicators, provides a comprehensive portrayal of the overall impact of series i on the system under scrutiny. This metric quantifies the extent to which series i influences the broader system, considering both the transmission of shocks outward from series i and the reception of shocks from other series.

$$NET_i(\breve{\text{U}}) = TO_i(\breve{\text{U}}) - FROM_i(\breve{\text{U}}) \qquad (7)$$

When $NET_i > 0$, it signifies that all other series exert a greater influence on series i compared to the influence series i has on them. In this scenario, series i is categorized as a net shock transmitter, indicating that it predominantly transmits shocks to other indicators within the system. This implies that series i plays a significant role in driving the dynamics of the broader system, exerting a considerable impact on the behavior of other indicators. Conversely, when $NET_i < 0$, it indicates that series i is more affected by other series than it affects them. In this case, series i is classified as a net shock receiver, suggesting that it primarily receives shocks from other indicators within the system. This implies that series i is more reactive to external influences, reflecting its susceptibility to changes in other variables. The total connectedness index (TCI) is a metric to calculate the degree of interconnectedness within the network, and it is defined as:

$$TCI(\breve{\text{U}}) = N^{-1} \sum_{i=1}^{N} TO_i(\breve{\text{U}}) = N^{-1} \sum_{i=1}^{N} FROM_i(\breve{\text{U}}) \qquad (8)$$

This metric serves as a valuable tool for understanding the average impact of a shock in one series on all others, offering a means to assess market risk, with higher values indicating increased risk exposure. In our study, we initially focused on evaluating connectedness in the time domain. Concurrently, we extended our analysis to investigate connectivity in the frequency domain using spectral decomposition techniques. This approach allowed us to explore connectivity patterns from a different angle. The function is expressed as follows:

$$\mathbf{З}(e^{-i\omega}) = \sum_{\breve{u}=0}^{\infty} e^{-iwh}\, \mathbf{З}_{\breve{u}}$$

where $i = \sqrt{-1}$ and ω represents the frequency and the spectral density of x_t at frequency ω, demonstrated as the Fourier transformation of the QVMA(∞).

$$\boldsymbol{S}_{\mathbb{Z}}(\omega) = \sum_{\breve{u}=-\infty}^{\infty} E(\mathbb{Z}_t \mathbb{Z}'_{t-h})\, e^{-iwh} = \mathbf{3}(e^{-i\omega h}) \sum\nolimits_t \mathbf{3}(e^{+i\omega h}) \tag{9}$$

The Frequency Generalized Forecast Error Variance Decomposition (GFEVD) is combined with spectral density to generate the Frequency GFEVD. Following this integration, the Frequency GFEVD undergoes standardization using the formula below:

$$\Upsilon_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1} \left| \sum_{\breve{u}=0}^{\infty} \left(\mathbf{3}(\tau)(e^{-iwh})\Sigma(\tau) \right)_{ij} \right|^2}{\sum_{\breve{u}=0}^{\infty} (\mathbf{3}(e^{-iwh})\Sigma(\tau)\mathbf{3}(\tau)(e^{iwh}))_{ii}} \tag{10}$$

$$\tilde{\Upsilon}_{ij}(\omega) = \frac{\Upsilon_{ij}(\omega)}{\sum_{k=1}^{N} \Upsilon_{ij}(\omega)} \tag{11}$$

where $\tilde{\Upsilon}_{ij}(\omega)$ states that at certain frequencies in the spectrum of the *i*th variable, a shock in the *j*th series can be attributed to that portion of the spectrum. It may be viewed as a within-frequency indicator.

We assess both short-term and long-term connectedness by examining a spectrum of frequencies rather than relying on a single frequency. This spectrum is defined as $d = (a, b)\colon a, b \in (-\pi, \pi), a < b$, where a and b are values within the interval (-π, π), with a being less than b.

$$\tilde{\Upsilon}_{ij}(d) = \int_a^b \tilde{\Upsilon}_{ij}(\omega) d\omega \tag{12}$$

At this juncture, we are prepared to calculate precise connectedness measurements, employing a methodology similar to that pioneered by Diebold and Yilmaz (2012, 2014), thereby ensuring consistency in our evaluation process. However, in this context, the frequency-based interconnectedness estimates provide unique insights into the distribution of interconnections within a specified frequency range designated as '*d*'. This approach enhances our comprehension of how variables interact and propagate effects at specific frequencies, thereby expanding the scope of our analysis beyond traditional interconnectedness assessments.

$$NPDC_{ij}(d) = \tilde{\Upsilon}_{ij}(d) - \tilde{\Upsilon}_{ji}(d) \tag{13}$$

$$TO_i(d) = \sum_{i=1, i \neq j}^{N} \tilde{\Upsilon}_{ji}(d) \tag{14}$$

$$FROM_i(d) = \sum_{i=1, i \neq j}^{N} \tilde{\Upsilon}_{ij}(d) \tag{15}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{16}$$

$$TCI(d) = N^{-1} \sum_{i=1}^{N} TO_i(d) = N^{-1} \sum_{i=1}^{N} FROM_i(d) \tag{17}$$

4. Results

To account for the shocks over the chosen crisis periods, two-sample analysis methods were utilized to compute the spillover index: one involved a full sample analysis to gauge the average spillover level, while the other employed a rolling sample analysis to capture spillover trends dynamically over time.

4.1. Dynamic Spillovers Connectedness Analysis

4.1.1. Dynamic Spillovers Connectedness Among the All-Exchange Rates and Commodity Markets Across the Period of Analysis

Table 5 illustrates the dynamic spillovers connectedness among various exchange rates and commodity markets (gold and crude oil) over a specified analysis period. The results show that The Total Connectedness Index (TCI) of 40.14% represents the average spillover impact across all markets, reflecting the overall interconnectedness during the analyzed period (Awartani *et al.*, 2016).

The findings declare that the CNY/$ exchange rate has substantial internal spillovers at 57.74%, significantly influencing the GBP/$ and EUR/$ (10.32% and 9.51%, respectively), while being least influenced by crude oil (2.25%). The total spillover received from other markets is 42.26%, indicating a moderate external influence. The UAH/$ shows strong internal spillovers at 75.27%, with notable external influences coming from RUB/$ (4.78%) and JPY/$ (4.4%), and a total spillover received of 24.73%, making it one of the more internally driven markets.

The EUR/$ presents significant interconnectedness with GBP/$ (22.66%) and JPY/$ (11.83%), with only 42.9% of its spillovers being internal. It receives the highest external influence (57.1%), indicating a great susceptibility to other markets. Similarly, GBP/$ shows high interconnectedness with EUR/$ (23.2%) and JPY/$ (11.07%), with 42.97% internal spillovers, and receives considerable external influences (57.03%).

The JPY/$ has significant internal spillovers at 51.05%, with major external influences from EUR/$ (13.49%) and GBP/$ (11.9%), receiving substantial spillovers from other markets (48.95%). Examining the RUB/$, it demonstrates strong internal spillovers at 67.65%, with notable influences from UAH/$ (6.1%) and gold/$ (5.55%), and a total spillover received of 32.35%, indicating moderate external influence. gold/$ is primarily self-influenced (68.7%) but shows connections with RUB/$ (6.47%) and UAH/$ (4.94%), receiving 31.3% of its spillovers from other markets. Crude oil/$ has high internal spillovers (72.6%), with significant connections to RUB/$ (5.17%) and GBP/$ (4.41%) and is moderately influenced by external markets (27.39%). The strong internal spillovers observed within the UAH/$ exchange rate resonate with Opoku *et al.*, (2023), who emphasized similar dynamics in regional contexts. The significant interconnectedness between EUR/$ and GBP/$, alongside their susceptibility to external influences, aligns with previous research by Nefzi and Melki (2023), emphasizing the roles of major currencies in transmitting volatility across markets. Similarly, the findings regarding net spillover values correspond to the directional flow of spillovers identified by Shah *et al.*, (2021), highlighting the nuanced relationships among different market segments. The influence of crude oil appears relatively minimal, consistent with previous findings on its insular nature (Zhu *et al.*, 2023). Figure 3 shows the network plot of spillovers across the study period.

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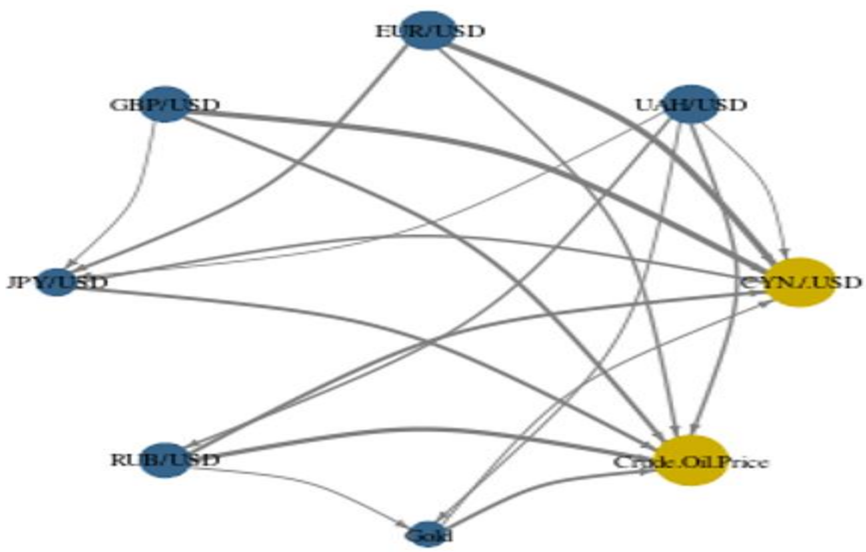

Figure 4.
Network plot of spillovers across the study period.

In terms of total spillovers transmitted and received, the highest total spillovers transmitted are from EUR/$ (63.01%) and GBP/$ (61.66%), reflecting their central roles in the interconnectedness. Crude oil transmits the least spillovers (16.1%), indicating its more insular nature. EUR/$ and GBP/$ also receive the most spillovers (57.1% and 57.03%), highlighting their high degree of interconnectedness and susceptibility to external influences. Net spillover values show EUR/$ and GBP/$ as net contributors to other markets (5.9% and 4.63%, respectively), while CNY/$ and crude oil are net recipients (-10.54% and -11.2%), indicating their positions as more influenced markets.

Table 6.
Dynamic spillovers connectedness among all exchange rates and commodity markets across the period of analysis.

	CNY/$	**UAH/$**	**EUR/$**	**GBP/$**	**JPY/$**	**RUB/$**	**GOLD/$**	**CRUDE OIL/$**	**FROM**
CNY/$	57.74	4.08	9.51	10.32	7.8	4.44	3.86	2.25	42.26
UAH/$	3.24	75.27	3.35	3.21	4.4	4.78	3.95	1.81	24.73
EUR/$	6.69	3.77	42.9	22.66	11.83	5.42	4.83	1.91	57.1
GBP/$	7.4	3.28	23.2	42.97	11.07	5.12	4.48	2.5	57.03
JPY/$	6.29	5.21	13.49	11.9	51.05	5.19	4.42	2.46	48.95
RUB/$	2.56	6.1	5.22	4.64	5.54	67.65	5.55	2.74	32.35
GOLD/$	2.9	4.94	4.97	4.53	4.98	6.47	68.7	2.5	31.3
CRUDE OIL/$	2.65	3.25	3.28	4.41	4.34	5.17	4.3	72.6	27.39
TO	31.72	30.64	63.01	61.66	49.95	36.58	31.38	16.1	321.1
Inc.Own	89.46	105.9	105.9	104.63	101	104.24	100.09	88.79	TCI
NET	-10.5	5.9	5.9	4.63	1	4.24	0.09	-11.2	40.14

The values represent the extent to which each market (rows) influences or is influenced by other markets (columns). The "FROM" column captures the total spillover received from other markets, while the "TO" row shows the total spillover sent to other markets. "Inc.Own" represents the total connectedness including own contributions, and "NET" indicates the net spillover, calculated as the difference between spillovers sent and received.

4.1.2. Dynamic Spillovers Connectedness Among the All-Exchange Rates and Commodity Markets During Covid-19 Pandemic

Table 7 illustrates the dynamic spillovers connectedness among various exchange rates and commodity markets (gold and crude oil) during the Covid-19 pandemic. The results show that the Total Connectedness Index (TCI) during this period is 56.26%, indicating a higher average spillover impact across all markets, reflecting increased interconnectedness and volatility during the pandemic, as this results is consistent with previous studies' findings (Awartani *et al.*, 2016; Huang & Liu, 2023).

The findings indicate that the CNY/$ exchange rate has substantial internal spillovers at 35.34%, significantly influenced by the JPY/$ and GBP/$ (13.63% and 11.42%, respectively), while being least influenced by crude oil (6.4%). The total spillover received from other markets is 64.66%, indicating a high sensitivity to external influences. The findings reveal notable internal spillovers within various markets, with the CNY/$ exchange rate significantly influenced by the JPY/$ and GBP/$, consistent with previous research highlighting the role of major currencies during times of crisis (Zhu *et al.*, 2023). The UAH/$ shows strong internal spillovers at 56.2%, with notable external influences coming from RUB/$ (15.51%) and JPY/$ (13.82%), and a total spillover received of 43.8%, making it one of the more balanced internally and externally influenced markets. The EUR/$ presents significant interconnectedness with GBP/$ (20.78%) and JPY/$ (11.86%), with only 36.78% of its spillovers being internal. It receives a high external influence (63.22%), indicating a great susceptibility to other markets. Similarly, GBP/$ shows high interconnectedness with EUR/$ (17.28%) and JPY/$ (13.44%), with 33.65% internal spillovers, and receives considerable external influences (66.35%). The JPY/$ has significant internal spillovers at 34.32%, with major external influences from UAH/$ (13.82%) and CNY/$ (13.46%), receiving substantial spillovers from other markets (65.68%). Examining the RUB/$, it demonstrates strong internal spillover at 47.64%, with notable influences from UAH/$ (15.51%) and GOLD/$ (6.87%), and a total spillover received of 52.36%, indicating moderate external influence. GOLD/$ is primarily self-influenced (55.18%) but shows connections with RUB/$ (6.87%) and UAH/$ (9.7%), receiving 44.82% of its spillovers from other markets. Crude oil/$ has high internal spillovers (50.8%), with significant connections to RUB/$ (7.92%) and GBP/$ (5.29%), and is moderately influenced by external markets (49.2%), the crude oil demonstrates relatively low influence, indicative of its more insulated nature, echoing findings from previous studies on market insularity during periods of heightened uncertainty (Shah *et al.*, 2021). Figure 5 shows the network plot of spillovers during the Covid-19 pandemic.

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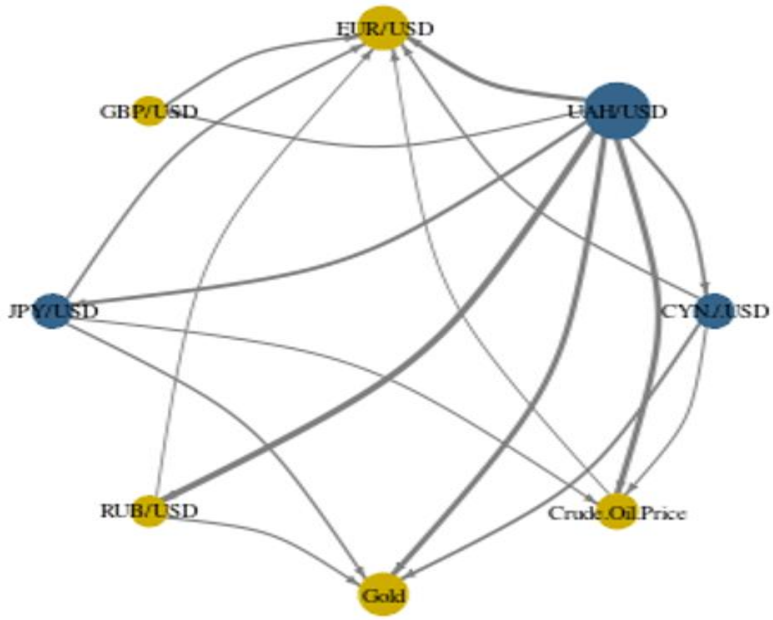

Figure 6.
Network plot of spillovers during Covid-19 pandemic.

In terms of total spillovers transmitted and received, the highest total spillovers transmitted are from UAH/$ (80.05%) and JPY/$ (73.23%), reflecting their central roles during the pandemic. Crude oil transmits the least spillovers (26.86%), indicating its more insular nature. EUR/$ and GBP/$ also receive the most spillovers (63.22% and 66.35%, respectively), highlighting their high degree of interconnectedness and susceptibility to external influences. Net spillover values show UAH/$ as a significant net transmitter (36.26%), while EUR/$ and gold are notable net receivers (-19.9% and -17.96%, respectively).

Table 8.
Dynamic spillovers connectedness among the all exchange rates and commodity markets during Covid-19 pandemic

	CNY/$	**UAH/$**	**EUR/$**	**GBP/$**	**JPY/$**	**RUB/$**	**GOLD/$**	**CRUDE OIL/$**	**FROM**
CNY/$	35.34	13.56	7.95	11.42	13.63	7.63	4.07	6.4	64.66
UAH/$	9.59	56.2	2.26	5.26	9.33	8.31	3.74	5.31	43.8
EUR/$	10.87	7.69	36.78	20.78	11.86	4.64	3.21	4.17	63.22
GBP/$	12.58	8.17	17.28	33.65	13.44	5.83	3.67	5.38	66.35
JPY/$	13.46	13.82	8.51	11.92	34.32	7.79	3.78	6.4	65.68
RUB/$	8.89	15.51	2.5	5.76	9.13	47.64	4.01	6.57	52.36
GOLD/$	7.89	9.7	2.64	4.94	6.9	6.87	55.18	5.89	44.82
CRUDE OIL/$	8.96	11.62	2.1	5.29	8.94	7.92	4.37	50.8	49.2
TO	72.25	80.05	43.24	65.37	73.23	48.98	26.86	40.12	450.1
Inc.Own	107.59	136.26	80.01	99.02	107.54	96.62	82.04	90.92	TCI
NET	7.59	36.26	-19.9	-0.98	7.54	-3.38	-17.96	-9.08	56.26

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4.1.3. Dynamic spillovers connectedness among the all exchange rates and commodity markets during Russia-Ukraine conflict

Table 9 illustrates the dynamic spillovers connectedness among various exchange rates and commodity markets (gold and crude oil) during the Russia-Ukraine conflict. The results indicate a Total Connectedness Index (TCI) of 34.34%, reflecting the interconnectedness and volatility of these markets during the conflict.

The findings reveal that the CNY/$ exchange rate has substantial internal spillovers at 57.24%, with significant influences from EUR/$ and GBP/$ (13.27% and 13.22%, respectively), while being least influenced by crude oil (0.62%). The total spillover received from other markets is 42.76%, indicating moderate external influence. The UAH/$ exchange rate shows strong internal spillovers at 70.06%, with notable external influences from EUR/$ (6.36%) and JPY/$ (6.29%), and a total spillover received of 29.94%. The EUR/$ exhibits significant interconnectedness with GBP/$ (28.68%) and JPY/$ (11.69%), with 41.09% of its spillovers being internal. It receives the highest external influence (58.91%), indicating a high susceptibility to other markets. Similarly, GBP/$ demonstrates high interconnectedness with EUR/$ (30.26%) and JPY/$ (11.03%), with 43.33% internal spillovers, and receives substantial external influences (56.67%). The JPY/$ has significant internal spillovers at 52.32%, with major external influences from EUR/$ (14.58%) and CNY/$ (9.97%), receiving substantial spillovers from other markets (47.68%). Examining the RUB/$, it demonstrates strong internal spillover at 88.31%, with minor influences from JPY/$ (2.25%) and EUR/$ (1.8%), and a total spillover received of 11.69%, indicating minimal external influence. GOLD/$ is primarily self-influenced (83.23%) but shows connections with UAH/$ (4.18%) and EUR/$ (2.91%), receiving 16.77% of its spillovers from other markets. Crude OIL/$ has high internal spillovers (89.68%), with minor connections to JPY/$ (1.1%) and EUR/$ (1.18%) and is least influenced by external markets (10.32%). Figure 7 shows the network plot of spillovers during Russia-Ukraine conflict.

The significant internal spillovers observed within the CNY/$ exchange rate, particularly influenced by the EUR/$ and GBP/$, reflect the central role of major currencies in transmitting volatility during geopolitical crises (Awartani *et al.*, 2016) . Conversely, crude oil exhibits minimal influence, indicative of its relative insulation from geopolitical tensions, consistent with findings from previous studies on market behavior during geopolitical conflicts (Huang & Liu, 2023). Moreover, the disparities in spillover transmission and reception among currencies and commodities underscore the nuanced relationships within global financial markets, further emphasized by the network plot of spillovers during the Russia-Ukraine conflict. The identification of EUR/$ and GBP/$ as significant net transmitters, alongside UAH/$ and JPY/$ as net receivers, reflects the differential impacts of geopolitical tensions on various market segments (Boakye *et al.*, 2024).

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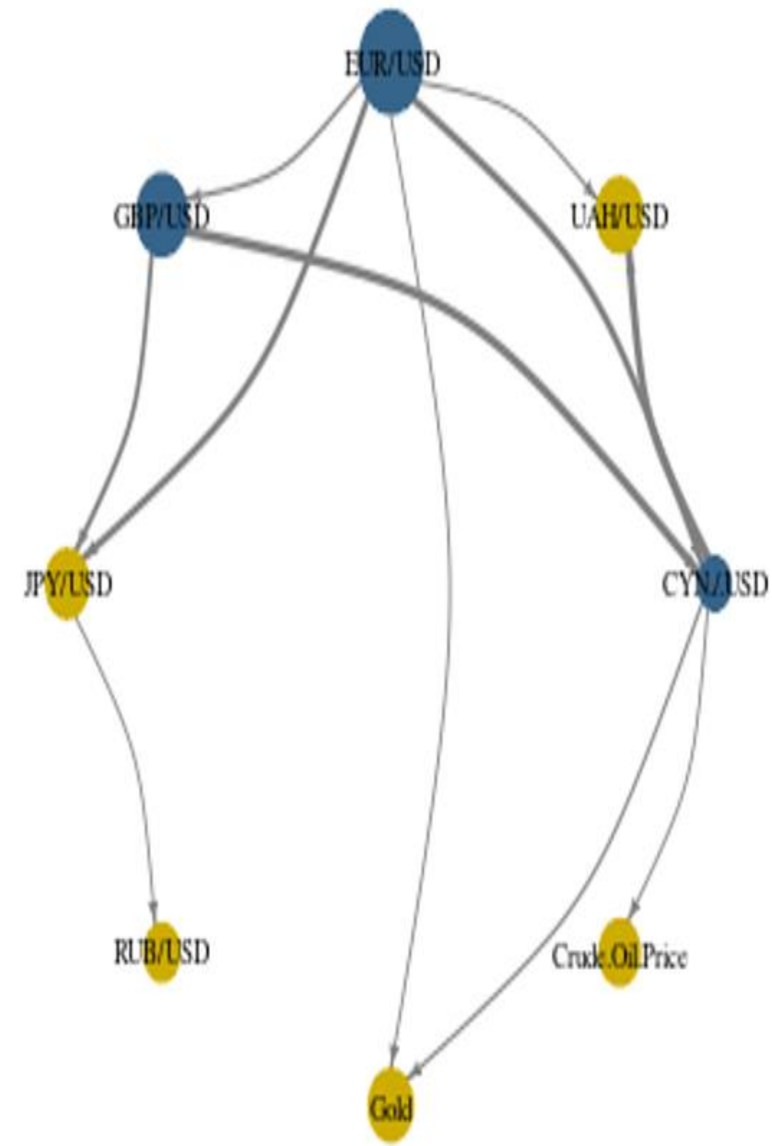

Figure 8.
Network plot of spillovers during Russia-Ukraine conflict.

In terms of total spillovers transmitted and received, the highest total spillovers transmitted are from EUR/$ (70.35%) and GBP/$ (63.58%), reflecting their central roles during the conflict. Crude oil transmits the least spillovers (6.99%), indicating its more insular nature. EUR/$ and GBP/$ also receive the most spillovers (58.91% and 56.67%, respectively), highlighting their high degree of interconnectedness and susceptibility to external influences. Net spillover values show EUR/$ and GBP/$ as net transmitters (11.43% and 6.91%, respectively), while UAH/$ and JPY/$ are net receivers (-5.32% and -4.06%, respectively).

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Table 10.
Dynamic spillovers connectedness among the all exchange rates and commodity markets during Russia-Ukraine conflict.

	CNY/$	UAH/$	EUR/$	GBP/$	JPY/$	RUB/$	GOLD/$	CRUDE OIL/$	FROM
CNY/$	57.24	3.52	13.27	13.22	9.92	0.92	1.3	0.62	42.76
UAH/$	7.42	70.06	6.36	3.04	6.29	2.01	3.29	1.53	29.94
EUR/$	10.24	5.04	41.09	28.68	11.69	0.99	1.7	0.58	58.91
GBP/$	9.68	2.57	30.26	43.33	11.03	0.91	1.2	1.03	56.67
JPY/$	9.97	6.8	14.58	13.38	52.32	1.09	1.05	0.81	47.68
RUB/$	1.52	1.22	1.8	1.47	2.25	88.31	2.03	1.4	11.69
GOLD/$	2.72	4.18	2.91	1.98	1.35	2.61	83.23	1.03	16.77
CRUDE OIL/$	1.8	1.28	1.18	1.81	1.1	1.61	1.54	89.68	10.32
TO	43.34	24.61	70.35	63.58	43.62	10.14	12.1	6.99	274.73
Inc.Own	100.58	94.68	111.43	106.91	95.94	98.45	95.33	96.67	TCI
NET	0.58	-5.32	11.43	6.91	-4.06	-1.55	-4.67	-3.33	34.34

4.1.4. Dynamic Spillovers Connectedness Among the All-Exchange Rates and Commodity Markets During Israel-Palestine War

Table 11 displays the dynamic spillovers connectedness among various exchange rates and commodity markets (gold and crude oil) during the Israel-Palestine war. The Total Connectedness Index (TCI) during this period is 35.62%, reflecting the interconnectedness and market dynamics amidst the conflict.

The analysis reveals that the CNY/$ exchange rate exhibits significant internal spillovers at 59.68%, with notable influences from EUR/$ and GBP/$ (13.2% and 13.6%, respectively), while being least influenced by gold (0.34%). The total spillover received from other markets is 40.32%, indicating a moderate external influence. Conversely, the UAH/$ exchange rate shows strong internal spillover at 76.85%, with notable external influences from Crude OIL/$ (6.68%) and RUB/$ (1.99%), and a total spillover received of 23.15%. The EUR/$ demonstrates substantial interconnectedness with GBP/$ (32.04%) and JPY/$ (10.69%), with 41.83% of its spillovers being internal. It receives a high external influence (58.17%), indicating susceptibility to other markets. Similarly, GBP/$ shows high interconnectedness with EUR/$ (32.23%) and JPY/$ (9.04%), with 41.7% internal spillovers, and receives substantial external influences (58.3%). The JPY/$ has significant internal spillovers at 57.88%, with major external influences from EUR/$ (14.14%) and GBP/$ (12.14%), receiving substantial spillovers from other markets (42.12%). Examining the RUB/$, it demonstrates strong internal spillover at 78.08%, with minor influences from JPY/$ (4.79%) and EUR/$ (3.67%), and a total spillover received of 21.92%, indicating minimal external influence. GOLD/$ is primarily self-influenced (79.99%) but shows connections with RUB/$ (5.55%) and Crude OIL/$ (3.37%), receiving 20.01% of its spillovers from other markets. Crude OIL/$ has high internal spillovers (79.06%), with minor connections to EUR/$ (2.43%) and GBP/$ (4.94%) and is least influenced by external markets (20.94%). Figure 9 shows network plot of spillovers during Israel-Palestine war.

The strong internal spillovers observed within the UAH/$ exchange rate, alongside notable external influences, underscore the complex dynamics shaping market interconnectedness during periods of geopolitical turmoil (Opoku *et al.*, 2023). The substantial interconnectedness between EUR/$ and GBP/$, coupled with their susceptibility to external influences, mirrors broader patterns observed in previous studies on market interconnectedness during geopolitical conflicts (Zhu *et al.*, 2023).

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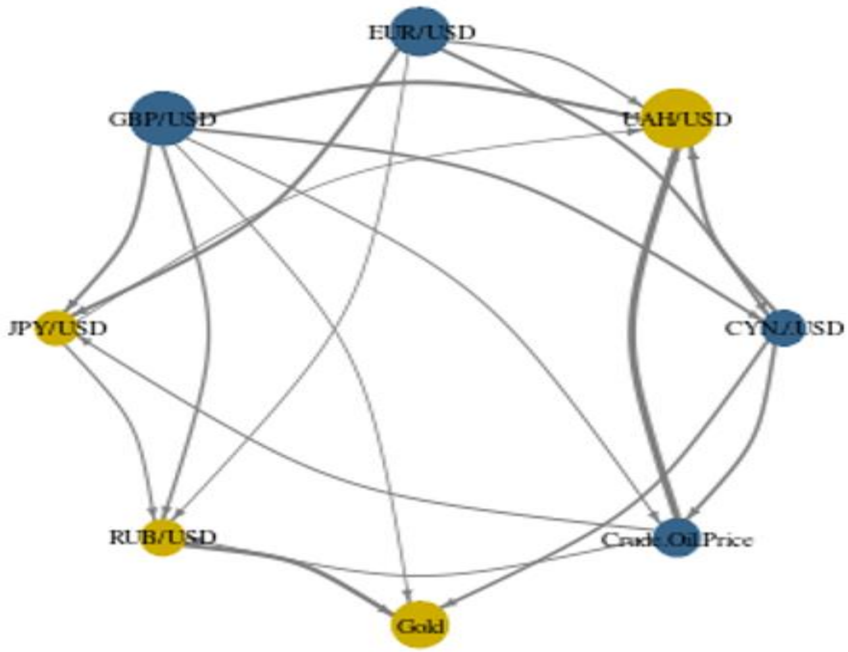

Figure 10.
Network plot of spillovers during Israel-Palestine war.

In terms of total spillovers transmitted and received, the highest total spillovers transmitted are from EUR/$ (70.41%) and GBP/$ (73.92%), reflecting their central roles during the conflict. Gold transmits the least spillovers (9.19%), indicating its more insular nature. EUR/$ and GBP/$ also receive the most spillovers (58.17% and 58.3%, respectively), highlighting their high degree of interconnectedness and susceptibility to external influences. Net spillover values show GBP/$ as the largest net transmitter (15.63%), while UAH/$ is the largest net receiver (-19%).

Table 12.
Dynamic spillovers connectedness among the all exchange rates and commodity markets during Israel-Palestine war

	CNY/$	UAH/$	EUR/$	GBP/$	JPY/$	RUB/$	GOLD/$	CRUDE OIL/$	FROM
CNY/$	59.68	0.61	13.2	13.6	8.65	1.06	0.34	2.85	40.32
UAH/$	4.04	76.85	2.67	3.97	1.7	1.99	2.09	6.68	23.15
EUR/$	10.1	0.33	41.83	32.04	10.69	2.11	0.67	2.23	58.17
GBP/$	10.67	0.2	32.23	41.7	9.04	1.84	1.2	3.12	58.3
JPY/$	7.92	0.26	14.14	12.14	57.88	2.64	1.04	3.97	42.12
RUB/$	2.47	0.86	3.67	4.43	4.79	78.08	1.49	4.22	21.92
GOLD/$	3.17	0.98	2.06	2.79	2.08	5.55	79.99	3.37	20.01
CRUDE OIL/$	5.91	0.92	2.43	4.94	1.97	2.42	2.35	79.06	20.94
TO	44.28	4.15	70.41	73.92	38.93	17.6	9.19	26.44	284.93
Inc.Own	103.96	81	112.24	115.63	96.81	95.68	89.19	105.49	TCI
NET	3.96	-19	12.24	15.63	-3.19	-4.32	-10.81	5.49	35.62

The comparative analysis of dynamic spillovers connectedness among exchange rates and commodity markets during three distinct crisis periods the Covid-19 pandemic, the Russia-Ukraine conflict, and the Israel-Palestine war provides valuable insights into the evolving dynamics of financial markets amidst geopolitical and global uncertainties. Amidst the Covid-19 pandemic, financial markets experienced unprecedented turmoil, characterized by heightened interconnectedness and volatility across exchange rates and commodities. Major currencies like EUR/$ and GBP/$ demonstrated significant internal spillovers, indicating a robust interconnectedness within these markets. Conversely, crude oil exhibited a more isolated nature, transmitting the least spillovers compared to exchange rates. During the Russia-Ukraine conflict, while exchange rates like EUR/$ and GBP/$ continued to play pivotal roles, transmitting the highest total spillovers, the net spillover values revealed varying degrees of influence among currencies. Some currencies acted as significant net transmitters, while others served as net receivers, reflecting the nuanced dynamics of market interconnections amidst geopolitical tensions. Notably, the conflict underscored the importance of major currencies as conduits for transmitting market shocks across global financial systems. In contrast, the Israel-Palestine war exhibited a moderate level of interconnectedness during the crisis, with major exchange rates continuing to transmit substantial spillovers. Gold emerged as a significant transmitter and receiver, highlighting its role as a safe-haven asset during geopolitical uncertainties. Additionally, crude oil demonstrated resilience amidst regional conflicts, with high internal spillovers but relatively low external influence.

4.2. Rolling Sample Dynamic Analysis Over the Crisis Periods

4.2.1. Rolling Sample Dynamic Analysis during Covid-19 pandemic

The dynamic analysis of spillover connectedness among key exchange rates and commodity prices from early 2021 to mid-2023, using 100-day rolling intervals is shown in figure 11. Initially, the graph shows moderately high levels of connectedness, fluctuating around 20-40%, which suggests that the markets were moderately interlinked during this period, reflecting some degree of synchronization and mutual influence among the examined assets. However, a significant spike in mid-2021, reaching values close to or exceeding 80%, indicates a period of exceptionally high connectedness. This spike can be attributed to heightened market reactions to major events, such as the emergence of Covid-19 variants like Delta, significant economic policy adjustments, and geopolitical developments. During this time, the high connectedness suggests that the markets moved in a more synchronized manner, with strong spillover effects across the different assets.

Following the spike, the graph shows a decrease and stabilization of connectedness levels, settling back to around 20-40% through late 2021 and into 2022. This trend reflects the markets' gradual adaptation to the new economic conditions, supported by vaccine rollouts and the reopening of economies, which led to more stable, albeit still interconnected, market conditions. The gradual decline in connectedness continuing into 2023 indicates a move towards normalization and recovery, with markets becoming less tightly coupled as economic uncertainties reduced. The occasional small peaks in this period highlight that while the overall connectedness was declining, markets still responded collectively to certain events, albeit with less intensity than the mid-2021 spike.

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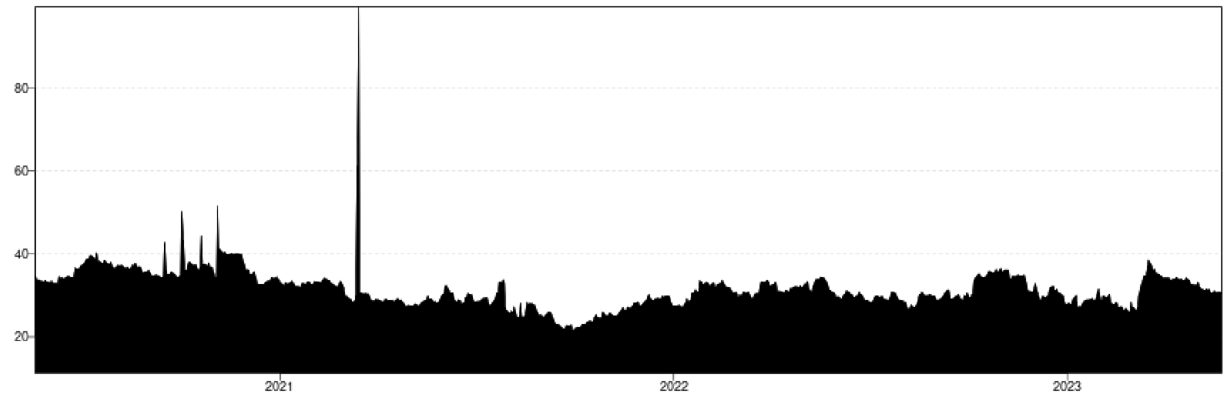

Figure 12.
Total volatility spillover index during Covid-19 pandemic.

4.2.2. Rolling sample dynamic analysis during Russia-Ukraine conflict

Figure 13 presents the spillover connectedness among key exchange rates and commodity prices from early 2023 to early 2024, analyzed using a rolling sample with 100-day intervals. The x-axis represents the timeline, while the y-axis measures the level of connectedness, ranging from 20 to 100. This analysis focuses on the impact of the Ukraine-Russia conflict on global markets, highlighting periods of increased market synchronization in response to geopolitical events.

In the initial period of early 2023, the graph shows moderately stable connectedness levels around 20-40%, indicating a relatively calm market environment with consistent but moderate interdependencies among the examined assets. This stability suggests that markets were operating under normal conditions, with no significant disruptions from the Ukraine-Russia conflict. However, as we move into mid-2023, while connectedness levels show minor fluctuations, they remain relatively stable. This period likely reflects markets adapting to ongoing geopolitical tensions, maintaining a degree of normalcy despite the underlying conflict. Entering late 2023, the graph reveals several spikes in connectedness, indicating periods of increased market synchronization. These spikes are likely linked to specific events related to the Ukraine-Russia conflict, such as escalations in violence, significant policy changes, or the imposition of economic sanctions. The increased connectedness during these spikes suggests that markets were reacting in a more unified manner, with strong spillover effects across different assets. This heightened sensitivity indicates that geopolitical developments were having a pronounced impact on market behavior.

Towards early 2024, a sharp spike in connectedness is observed, reaching levels close to 100%. This dramatic increase likely corresponds to a major event or series of events that caused markets to move in a highly synchronized manner, reflecting intense interconnectedness. Such a spike could be due to significant geopolitical developments, major economic policies, or other critical incidents affecting the Ukraine-Russia situation. The overall trend of moderate to high connectedness underscores the interdependent nature of global markets, where significant geopolitical events can lead to widespread and synchronized market reactions.

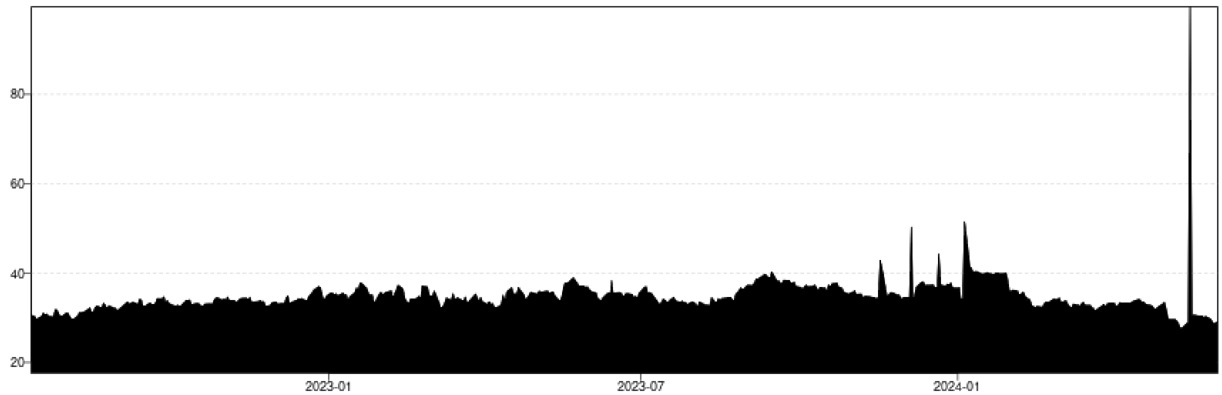

Figure 14.
Total volatility spillover index during Russia-Ukraine conflict

4.2.3. Rolling Sample Dynamic Analysis During Israel-Palestine War

Figure 15 illustrates the spillover connectedness among key exchange rates and commodity prices during the Israel-Palestine conflict, covering the period from October 7, 2023, to May 31, 2024. Using a rolling sample dynamic analysis with 100-day intervals, the x-axis represents the timeline, while the y-axis measures the level of connectedness, ranging from 20 to 34. This analysis aims to capture how geopolitical tensions in this region affect global financial markets.

In October 2023, the graph shows relatively stable connectedness levels around 30, indicating that markets maintained moderate interdependencies despite the initial escalation of the conflict. This stability suggests that while the conflict had some impact, it did not cause significant disruptions in the interconnectedness of the examined assets. Minor fluctuations within this period reflect the usual market responses to geopolitical tensions, where certain events might trigger slight increases or decreases in connectedness.

As we move into the early months of 2024, there is a noticeable rise in connectedness, peaking above 34. This increase likely corresponds to specific escalations in the Israel-Palestine conflict, such as intensified military actions, significant political developments, or heightened international responses. The rising connectedness indicates that markets were reacting more uniformly to these events, with stronger spillover effects observed across different financial assets. This period highlights how significant geopolitical events can enhance market synchronization, leading to increased interdependencies. Towards May 2024, the graph shows a slight decline in connectedness levels, though they remain higher than in October 2023, fluctuating around 32. This decline might suggest a period of relative de-escalation or stabilization in the conflict, allowing markets to somewhat adjust to the new conditions. However, the higher baseline level compared to the initial period indicates that the impact of the conflict continued to exert influence, keeping markets more interconnected than before.

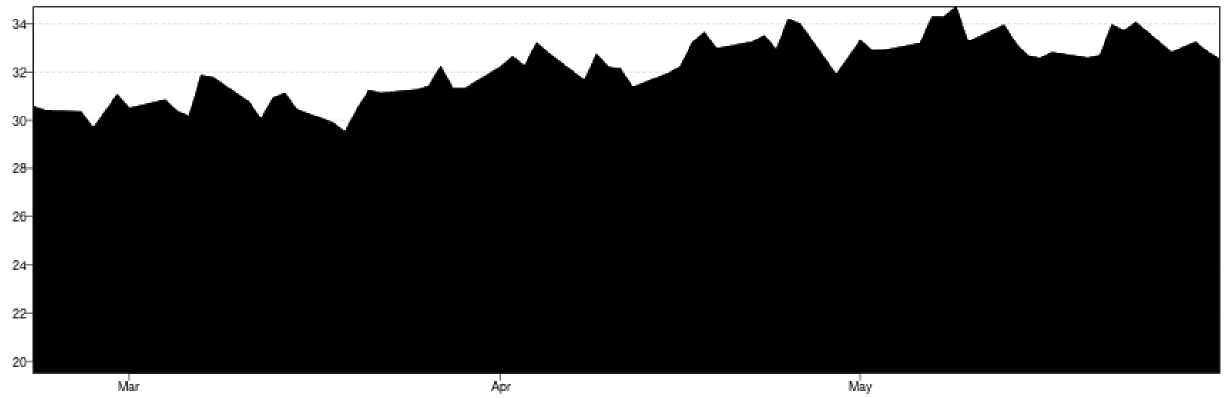

Figure 16.
Total volatility spillover index during Israel-Palestine war

4.2.4. Robustness Test

Figure 17 presents a comprehensive analysis of the dynamic pairwise connectedness between commodity markets (gold and crude oil) and the exchange rates of seven major global economies: China (CNY/USD), Ukraine (UAH/USD), Germany (EUR/USD), United Kingdom (GBP/USD), Japan (JPY/USD), and Russia (RUB/USD). This analysis spans from 2016 to 2024, allowing for an in-depth understanding of how interconnected these financial entities are over time, especially under various economic conditions and events.

The subplots comparing different exchange rates reveal significant dynamic connectedness among the currencies. For instance, the relationship between CNY/USD and EUR/USD shows periods of high connectedness, particularly during global economic disruptions, reflecting how shocks in one major economy can transmit to another. The GBP/USD and JPY/USD subplot similarly indicates that the British Pound and Japanese Yen have periods of heightened interconnectedness, which may correspond to Brexit-related uncertainties and other geopolitical events affecting both currencies. The RUB/USD exchange rate shows strong connections with other currencies, especially with EUR/USD and GBP/USD, likely influenced by geopolitical tensions and energy market dependencies.

The analysis shows substantial connectedness between exchange rates and commodity prices. Notably, the CNY/USD and crude oil price subplot suggests a strong relationship, likely due to China's significant role as a major importer of crude oil. This interconnectedness is crucial for understanding how fluctuations in oil prices can affect the Chinese currency and vice versa. Similarly, the RUB/USD exchange rate shows a strong connection with crude oil prices, reflecting Russia's economy's heavy dependence on oil exports. The JPY/USD and gold price subplot also reveals notable interconnectedness, indicating that gold is often a safe-haven asset during periods of economic uncertainty affecting the Japanese Yen.

The connectedness between gold and crude oil markets is particularly noteworthy. The subplot showing gold and crude oil prices illustrates periods of significant spillover effects, highlighting how these two critical commodities influence each other. This relationship is essential for investors and policymakers as it underscores the impact of changes in the energy sector on precious metals and vice versa. For example, during periods of geopolitical instability, both markets may show increased connectedness as investors seek safe-haven assets like gold while reacting to oil supply disruptions.

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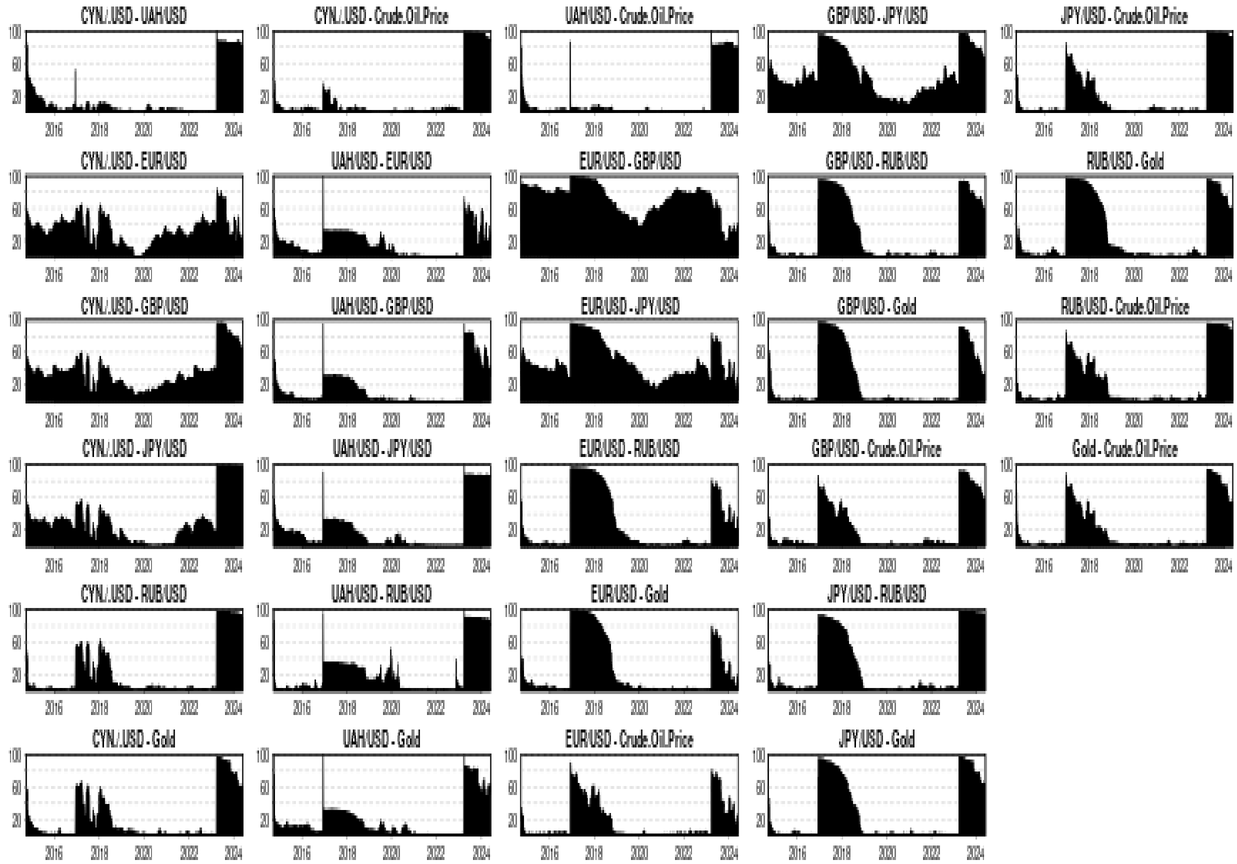

Figure 18.
Dynamic pairwise connectedness.

5. Conclusion

Our findings have significant theoretical and empirical implications that enrich our comprehension of financial market dynamics, particularly during crisis periods. By uncovering the intricate patterns of spillovers across exchange rates and commodity markets, we contribute to a deeper understanding of how financial systems respond to geopolitical and global uncertainties. The observed patterns of spillovers underscore the pivotal role played by major currencies in transmitting volatility across markets. During times of crisis, such as the Covid-19 pandemic and geopolitical conflicts like the Russia-Ukraine conflict and the Israel-Palestine war, major currencies like the EUR/$ and GBP/$ act as conduits for transmitting market shocks. This highlights the interconnectedness of global financial systems and emphasizes the importance of understanding the transmission mechanisms underlying currency movements. Moreover, our analysis sheds light on the resilience of certain commodities amidst geopolitical tensions. Despite the volatility and uncertainty surrounding events like the Russia-Ukraine conflict and the Israel-Palestine war, commodities like gold and Brent crude oil exhibit varying degrees of resilience. Gold, often regarded as a safe-haven asset, demonstrates its role as a store of value and a hedge against geopolitical risks by maintaining its significance as a transmitter and receiver of spillovers. On the other hand, crude oil's relatively low external influence amidst regional conflicts suggests its insulation from geopolitical tensions, reflecting its complex dynamics and unique market behavior.

By uncovering these dynamics, our research contributes to the development of theoretical frameworks that elucidate the mechanisms driving market interconnectedness during crisis periods.

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These insights can inform policymakers, investors, and market participants about the potential implications of geopolitical events on financial markets, helping them to better navigate and manage risks. In addition to the theoretical and empirical contributions, our findings offer practical insights that can directly benefit investors and financial practitioners in managing risk and optimizing portfolio performance, especially in the face of heightened geopolitical uncertainties, by understanding the dynamics of spillovers provides investors with valuable information for making informed decisions regarding risk management and portfolio diversification strategies. Also, by recognizing how shocks propagate across different markets during crisis periods, investors can anticipate potential sources of volatility and take proactive measures to protect their portfolios. One key implication is the ability to identify opportunities for hedging against volatility. By analyzing the direction and magnitude of spillovers, investors can pinpoint assets or markets that tend to act as leading indicators or amplifiers of market turbulence. Armed with this knowledge, investors can strategically deploy hedging strategies, such as options, futures, or inverse ETFs, to mitigate the impact of adverse market movements on their portfolios. Moreover, understanding spillover dynamics enables investors to construct diversified portfolios that are resilient to systemic risks. By diversifying across assets with different spillover characteristics, investors can reduce the correlation among portfolio components and minimize the risk of simultaneous downturns across multiple holdings. For example, if certain assets exhibit low spillover effects or negative correlations with broader market movements during crises, they can serve as effective diversifiers that help cushion the impact of adverse events on overall portfolio performance.

For future research, it would be valuable to delve deeper into the underlying drivers of spillovers during crisis periods, including the role of market sentiment, policy responses, and technological advancements. Additionally, investigating the impact of regional and global economic integration on market interconnectedness could provide further insights into the evolving dynamics of financial systems in an increasingly interconnected world.

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