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Original Paper

The Co-volatility of Uncertainty Shock on Chinese Exchange Rate: Based on Time-frequency Domain and Time-varying Method

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Abstract

In recent years, with the global epidemic, the Russia-Ukraine conflict, the great power game, and so on events, the international political and economic environment has become more and more unstable, the USDCNY exchange rate fluctuates significantly, and the external uncertainty risk shocks negatively hit the foreign exchange market. Based on this, this article expands global uncertainty risk shocks into four dimensions: global geopolitical risk, U.S. economic policy uncertainty, Chinese economic policy uncertainty, and VIX index, in addition to adding international WTI crude oil and gold price as additional variables, which are significantly correlated with both, to study the linkage among uncertainty shocks, commodity volatility and USDCNY exchange rate from the time-frequency domain. Furthermore, we analyze the time-varying spillover effects among variables at different frequency scales by decomposing the data into multiple scales using the Maximum Overlap Discrete Wavelet Transform (MODWT). Findings reveal that uncertainty factors and commodity prices exert distinct influence mechanisms on the USDCNY exchange rate under different cycles of frequency fluctuations. At various time-frequency domain volatility scales, VIX and WTI generate significant risk spillovers over the USDCNY exchange rate. Moreover, when global major events occur, time-varying spillover effects of variables are also heterogeneous. The research findings presented in this paper can provide valuable insights for policymakers and investors regarding the impact of international uncertainty shocks on the Chinese exchange rate across various short, medium, and long frequencies. This understanding can aid in managing uncertainty risks in decision-making processes, ultimately facilitating the efficient functioning of the foreign exchange market.

Keywords

Uncertainty risk shocks, USDCNY exchange rate, MODWT, time-varying spillover index

1. Introduction

In recent years, with the global epidemic, trade frictions between major powers, and the Russia-Ukraine conflict, global economic downside risks have risen, the international political and economic environment has become increasingly unstable and the global economy has experienced greater uncertainty. Shocks from unfavorable global events often give rise to uncertainty risk, which significantly negatively impacts economic activities. Since entering the new century, with the accelerated evolution of the world's unprecedented changes in a century, a remarkable change is the doubling of geopolitical risks. After the outbreak of the Russia-Ukraine conflict in 2022, geopolitical risks soared sharply. After geopolitical tensions hit a country or regional economy, it will certainly affect the adjustment changes of its economic policies, making the economic policy uncertainties of major global economies rise significantly, triggering panic in financial markets and affecting the stable growth of national economies. And the state of a country's economy is prominently reflected in the exchange rate of its currency. The creation of global uncertainty risk may trigger a flight of global capital to so-called "safe assets," or geographic capital outflows from riskier areas to areas where capital is perceived to be safer, and these capital flows can cause changes in exchange rates between economies. As one of the important economic variables of a country, exchange rate fluctuations not only have an important impact on a country's macroeconomic operation and resource allocation, but also directly affect the economic system of the international community, and exchange rate fluctuations are crucial for policymakers and government regulators (Chen et al., 2020).

In 2022, international currency exchange rates moved significantly and the foreign exchange market experienced dramatic fluctuations, with global major currencies depreciating significantly (except for the U.S. dollar). Generally speaking, the factors influencing exchange rates include two main categories: the first one is long-term fundamental factors, such as economic growth (Eichengreen, 2007; Rapetti et al., 2012; Barguellil et al., 2018) and balance of payments (Narayan & Smyth, 2004; Mussa, 2019); the second is short-term disturbances, including risks (Engel, 2016), expectations (Devereux & Engel, 2006), and geopolitical uncertainties in the international arena (Duan et al., 2021; Hui, 2022; Iyke et al., 2022). In recent years, international uncertainty has increased significantly, and more and more scholars have begun to investigate the effects of global uncertainty indicators on exchange rate markets. How to identify and measure the adverse influence of external uncertainty risk shocks on the foreign exchange market is an urgent issue, which is also the main problem of this research article.

With regard to foreign exchange market selection, we pay particular attention to the USD/CNY exchange rate for the following two reasons. Firstly, as China is the world's largest exporter and second-largest importer, the USDCNY exchange rate is particularly important for the stability of China's trading cooperation with other countries. Second, the U.S. dollar has strong spillover effects due to its utilization as an invoice currency in global transactions. China's exchange rate mechanism is extremely susceptible to variations in the U.S. and the peg to the dollar is also a pillar of Chinese monetary policy (Tervala, 2019). The fluctuation of the USDCNY against the dollar has always been one of the hot issues of concern for related scholars (Funke & Gronwald, 2008). This also highlights the choice of the USD/CNY exchange rate.

The contribution of this study is mainly twofold: (1) First, it systematically collates global uncertainty high volatility factors, identifies geopolitical risk, economic policy uncertainty and financial market volatility index as the "uncertainty trinity", and adds crude oil and gold price fluctuations as additional variables to provide a more comprehensive measure of the shocks of uncertainties on the USDCNY exchange rate market. (2) Secondly, unlike existing studies that mainly discuss from a single time-domain perspective, we combine wavelet transform and time-varying spillover index methods to explore the strength and leading lags of synergistic motion among variables at different time-frequency domain and the fluctuation spillover of variables at different frequency-domain scales.

The general framework of the article is as follows: Section 2 summarizes the literature on this issue; Section 3 shows the main methodological models used; Section 4 contains the data selection and descriptive statistics; Section 5 derives the empirical results; Section 6 presents the conclusions. The study framework is shown in Figure 1.

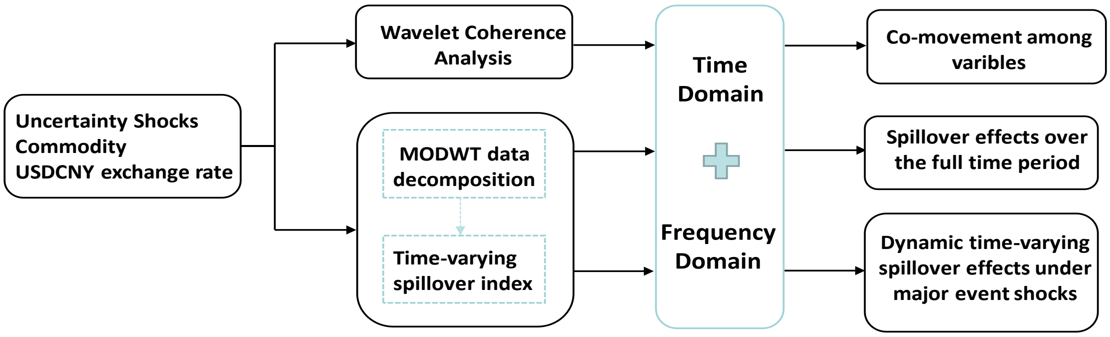


Figure 1. Study Framework

2. Literature Review

Quantifying uncertainty factors presents a unique challenge due to their subjective nature. Unlike measurable variables like inflation, uncertainty is rooted in individuals' subjective beliefs. This uncertainty stems from a variety of sources, including unforeseen shifts in economic policies, natural disasters, and conflicts. However, it is possible to use alternative indicators to indirectly observe uncertainty. Carney (2016) proposed that economic performance is influenced by various types of uncertainty, including geopolitical, economic, and policy uncertainty, which he conceptualizes as the "uncertainty trinity". The first type of uncertainty shock is geopolitical risk, which Caldara and Iacoviello (2022) have sought to quantify by analyzing the frequency of specific terms like 'geopolitical tensions,' 'terrorism threats,' and 'war risks' in global newspaper articles and create a Geopolitical Risk Index (GPR). The second type is economic uncertainty, commonly measured using the Volatility Index (VIX) since the global financial crisis (Bekaert & Hoerova, 2014; Geng & Guo, 2022). The VIX, also known as the 'investor fear index,' gauges fear levels in financial markets based on market volatility.

The last of the "uncertainty trinity" is policy uncertainty. A representative measure of this is the Economic Policy Uncertainty Uncertainty Index (EPU), which is calculated by Baker et al. (2016) by weighting terms related to economics, uncertainty, and policy found in media articles.

The three types of uncertainty are interrelated and have significant adverse effects on economic activity. When geopolitical tensions hit a country's economy, it will inevitably affect the adjustment of national economic policies and accordingly increase the uncertainty of future economic policies and expectations. This mechanism is also prevalent for financial market volatility. Chen and Siems (2004) found that panic selling by investors in the wake of a terrorist attack triggers divergent investor expectations and leads to short-term capital flows, further exacerbating market volatility. Therefore, when investigating the influential mechanism of USDCNY exchange rate fluctuations, it is important to take into account not only the direct impact of a single factor but also the indirect impact of the interlinkages among the three main uncertainties.

First of all, geopolitical risk (GPR), widely interpreted as the related risks of war, terrorist acts and those influencing national and regional relations (Caldara & Iacoviello, 2022), is viewed as a crucial element of import and export trade policymaking, and a precursor to changes in the business cycle. Heightened geopolitical risks can affect financial markets through channels such as cross-border capital flows, import and export trade transactions, and large shocks in commodity prices such as crude oil. Kisswani and Elian (2021) considered that the exchange rate market is a proxy for the financial market and further influences investors and national economic policy-making. Cheng and Chiu (2018) studied 38 emerging countries through a VAR model, and they find that the spike in global geopolitical risk has posed a substantial implication for the business cycles of emerging economies. The recent occurrence of geopolitical conflicts such as the Ukraine conflict has led to an increase in the GPR index, resulting in significant inflationary pressures and presenting policymakers with new challenges (Cheikh et al., 2023). Understanding how exchange rates are affected during periods of uncertainty is particularly important for central banks, and this is the focus of this paper's research.

As another representative indicator of uncertainty factors, economic policy uncertainty directly and indirectly affects exchange rate fluctuations (Balcilar et al., 2016; Omrane & Savaşer, 2017; Christou et al., 2018). The more frequent the changes in a country's economic policies, the more flexible the exchange rate regime becomes, leading to greater exchange rate fluctuations. Additionally, EPU also impacts the economic condition, thus affecting exchange rate fluctuations (Chen et al., 2020). Research by Ruan et al. (2023) found that compared to several traditional long-term fundamental factors (such as GDP growth), EPU has a stronger predictive ability for exchange rate fluctuations in the sample of developing economies. However, there is limited literature on the impact of EPU on exchange rate fluctuations. This further reinforces our decision to explore how EPU affects exchange rate fluctuations in China. Through reviewing the literature, it becomes evident that existing researchers primarily focus on studying the impact of economic policy uncertainty in trading partner countries on the volatility of the domestic currency (Beckmann & Czudaj, 2017; Yang et al., 2023). Given the United States' status as a primary trading nation for many countries and its unique position in international finance, a considerable body of literature is dedicated to examining the inverse impact of economic policy uncertainty (mainly in both the home country and the United States) on exchange rates (Nilavongse et al., 2020). The reverse impact of policy uncertainty is attributed to external shocks (such as unexpected changes in monetary policy due to international political events and news shocks) and investors' behavior in the currency exchange market. Kido (2016) further investigates the spillover effects of U.S. economic policy shocks on the real exchange rate using a DCC-GARCH model. The results find a negative correlation between the U.S. EPU and high-yielding currencies. Similarly, Krol (2014) found that industrial economies can experience volatility in exchange rates due to economic policy uncertainty in their own countries and in the U.S., while emerging economies are affected by the economic policy uncertainty of their own country. However, the results of Chen et al. (2020) show that there are regional differences in the effects of EPU on fluctuations in Chinese exchange rate market: Chinese exchange rate volatility is considerably impacted by EPU in the U.S. and Europe, but less so by Hong Kong's EPU. For this divergent phenomenon, this article will introduce both the Chinese EPU and U.S. EPU to further empirically study their effects on the Chinese exchange rate market and provide useful insights for related studies.

As the process of global financial integration progresses, the shock from the U.S. will be significantly transmitted to China. Chadwick et al. (2012) revealed that financial market volatility and the spread of panic can lead to cross-border flows of domestic funds with U.S. dollars, thereby impacting foreign exchange rate market. Tsai et al. (2014) has conducted relevant research in this area, and they discovered that the U.S. stock market can exert influence on other financial markets through the VIX index. Studies link the appreciation of local currencies to the rational behavior of central banks and economic actors or the intensification of offshore and arbitrage trading activities. As a result, as a proxy for uncertainty in the U.S. financial markets, the VIX (also known as the "Investor Fear Indicator") can exert an effect on USDCNY exchange rate volatility. Chen and Sun (2022) conducted an empirical study through a high-dimensional time-varying approach and find that financial volatility from the U.S. will influence the Chinese foreign exchange market when major global risk events occur. The appreciation of the local currency is often linked to rational actions by central banks and economic agents, as well as the escalation of offshore trading and arbitrage activities. Significant international political and economic events, along with fluctuations in economic policies, can trigger market unrest and influence the rational decisions made by economic agents. VIX plays a role in absorbing the effects of high volatility stemming from GPR and EPU, consequently impacting foreign exchange market volatility. Despite this, there is a lack of extensive research on how VIX specifically affects the Chinese exchange rate market. Therefore, we have chosen to incorporate VIX into our external uncertainty shock system in order to comprehensively examine its influence on the Chinese exchange rate market.

In summary, in a period of heightened volatility in global financial markets, international geopolitical, economic, and policy uncertainties can have a significant impact on the volatility of exchange rate markets. However, through combing through the literature, it is found that the exchange rate market, as an important part of the international macro-financial system, most of the current literature focuses on the study of the impact of uncertainty and other individual factors on the foreign exchange market, while the comprehensive study on the impact factors of the underlying framework of the "Uncertainty Trinity" is relatively scarce. Lack of comprehensiveness, especially concerning China's exchange rate market. Based on these considerations, this paper comprehensively selects three types of uncertainty factors as the underlying influence framework to study the impact of uncertainty factor shocks on RMB exchange rate volatility.

In addition, many scholars' studies have also found that in times of global political and economic turmoil, uncertainty shocks, especially geopolitical risks, can have a significant spillover effect on crude oil, and that massive numbers of investors will turn to buying safe-haven funds, with rising safe-haven demand for gold, leading to a significant geopolitical risk premium. Further, oil price volatility and fluctuations in the price of gold, the main safe-haven fund, can also significantly affect international currency exchange rate movements and can transmit such risk shocks to the exchange rate market. According to Tiwari and Sahadudheen (2015), it is found that oil and gold prices can fluctuate together via import and export routes. And they can exert a remarkable influence on exchange rate volatility through a variety of channels, including imports and exports (Uddin et al., 2013; Baek, 2023). Generally speaking, The fluctuation of international oil prices is primarily influenced by supply and demand, with additional factors such as speculative funds entering the commodity market, fluctuations in the US dollar exchange rate, and impacts from events like political conflicts and military disputes also playing a role. Recent years have seen a shift in the world trade center to East Asia and South Asia, with the rapid growth of the Chinese economy making China the world's second largest importer and consumer of oil. Research by Cheng et al. (2019) highlighted that China is mainly a recipient and responder to global oil price shocks. Excessive oil dependence can leave the Chinese economy vulnerable to fluctuations in international oil prices, with risks being transmitted to China. Gold is widely considered a haven asset class by many countries, attracting investors' interest and playing a significant role in international trade (Singh & Sharma, 2018). During times of political turmoil and economic crises globally, the demand for gold tends to increase across various countries. Sari et al. (2010) discovered strong evidence of short-term feedback effects of oil prices and precious metal prices on exchange rates, with weaker evidence for long-term impacts. Given the importance of crude oil and gold, along with their high correlation with uncertainty shocks and exchange rate fluctuations, it is hypothesized that during periods of heightened international political and economic instability, as well as significant uncertainty in the global economy, crude oil and gold may transmit the risk of highly uncertain fluctuations to China's financial markets, including the foreign exchange market. Therefore, when examining the relationship between uncertainty shocks and RMB exchange rate fluctuations, it is essential to include crude oil and gold prices as additional variables to enhance the analysis of the direct and indirect impacts of uncertainty shocks on exchange rates.

The impact mechanism among the variables is shown in Figure 2. Thus, in summary, this article selects geopolitical risk (GPR), U.S. and Chinese economic policy uncertainty (UEPU, CEPU), VIX index, international WTI crude oil price(WTI), and gold price(GOLD) to investigate how uncertainty risk shocks impact the volatility of the USDCNY exchange rate. It provides useful insights for the study of contagion and spillover effects between important global economic influences and exchange rate markets, contributing to this large and important research area.

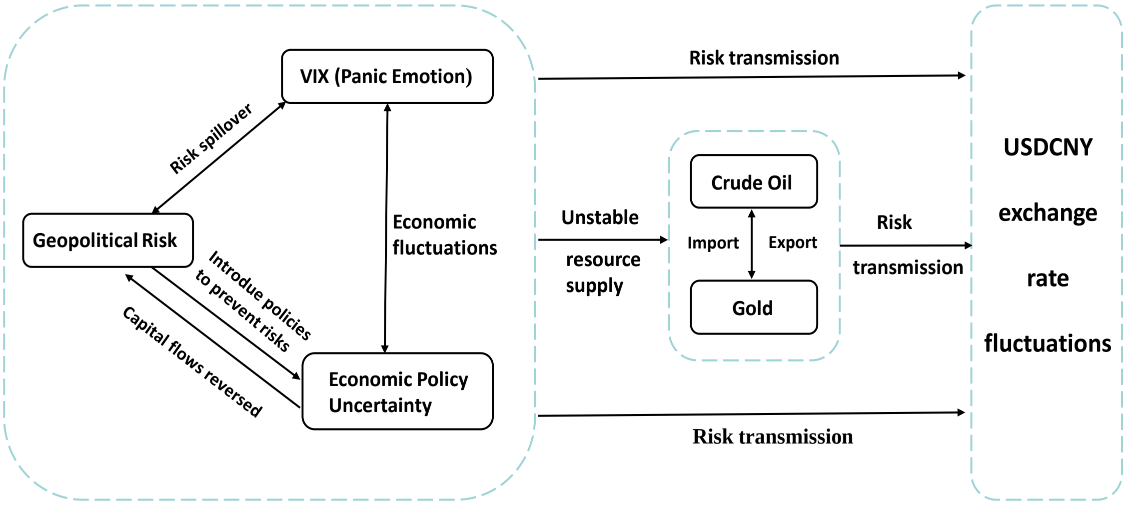


Figure 2. Impact Mechanisms of Uncertainty Risk Shocks, Commodity and USDCNY Exchange Rate Fluctuations

For the USDCNY exchange rate and uncertainty factors, most studies are based on vector autoregressive models and GARCH family models, which focus on the spillover effects of variables on the USDCNY exchange rate (Grossmann et al., 2014; Cadoret et al., 2022). With the continuous reform of the USDCNY exchange rate system, the Copula model was introduced and the dynamic spillover effect has become a research hotspot (Patton, 2001; Usman et al., 2022). However, financial data changes over time and is often influenced by a combination of factors, which are not only trendy, cyclical and other characteristics but also have a multi-level evolution pattern. Neither time domain analysis nor frequency domain analysis alone can be of any use in the study of such time series. The wavelet analysis method with a time-frequency multi-resolution function proposed by Morlet can be a good solution to this problem. There is still relatively little literature analyzing the time-varying spillover impacts of external hits on USDCNY exchange rate fluctuations from a combined time-frequency domain perspective. Given this, this article selects a combination of the wavelet model and dynamic spillover index to construct a multi-timescale analysis framework to complete the above study. Firstly, using the wavelet coherence method to explain the strength and synchronization of the co-movement between variables in the time and frequency domains. Secondly, to sufficiently identify the vital messages in different frequency scales, we use the Maximum Overlap Discrete Wavelet

Transform (MODWT) algorithm to decompose the time series into short, medium, and long-term data to represent different frequency bands. Then, using the idea of Antonakakis et al. (2020), building a time-varying volatility spillover index for the decomposed data to analyze its dynamic net risk spillover effect and dynamic net risk connectivity under different time scale conditions. The differences in the spillover of uncertainty factors and commodity volatility on the USDCNY exchange rate under different volatility periods are explored.

3. Methodology

3.1 Wavelet Coherence

The wavelet coherent rows can fully reflect the synergistic trends of variables at different time scales and frequency domain scales. A wavelet is a finite-length vibrational real-valued function defined as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right), \#(1)$$

where τ is a translation parameter, which determines the position in time, and s is a scale parameter, which determines the width of the wavelet. Morlet wavelet is chosen as the basis function. the Morlet function is defined as:

$$\psi(t) = \pi^{-\frac{1}{4}}e^{i\omega_0 t}e^{-\frac{t^2}{2}}, \#(2)$$

the parameter ω_0 determines the center frequency of the wavelet.

The continuous wavelet transform $|W_x(\tau,s)|^2$ of the time series $x(t)$ shows the relative contribution of the variance of the time series at each time and frequency to the total variance.

$$W_x(\tau,s) = \int_{-\infty}^{+\infty} x(t)\Psi^*_{\tau,s}(t)dt, \#(3)$$

* is a conjugate complex. In the binary setting, the cross wavelet transform of two time series $x(t)$ and $y(t)$is defined as follows:

$$W_{xy}(\tau,s) = W_x(\tau,s)W^*_y(\tau,s). \#(4)$$

Finally, using the wavelet power spectra of the two levels and their cross-wavelet spectra, we can define the square wavelet coherence as follows:

$$R^2(\tau,s) = \frac{\left|S\left(s^{-1}W_{xy}(\tau,s)\right)\right|^2}{S(s^{-1}|W_x(\tau,s)|^2)S\left(s^{-1}\left|W_y(\tau,s)\right|^2\right)}. \#(5)$$

Torrence and Compo (1998) further proposed phase differences that allow for the analysis of the lead-lag relationship between different time series. Based on this, the defined equations for the phase difference between wavelet functions x(t) and y(t) of two-time series are defined as follows:

$$\varphi_{xy}(\alpha,s) = tan^{-1}\left(\frac{\supset\left\{S\left(s^{-1}W_{xy}(\alpha,s)\right)\right\}}{R\left\{S\left(s^{-1}W_{xy}(\alpha,s)\right)\right\}}\right), \#(6)$$

when the arrow points left-up or right-down, it means that $y(t)$ is ahead of $x(t)$; when the arrow points left-down or right-up, it means that $x(t)$ is ahead of $y(t)$.

3.2 Maximum Overlap Discrete Wavelet Transform

MODWT minimizes the loss of data information and is more suitable for multi-time scale analysis of financial time series.

First, define the wavelet filter as $\{\tilde{h}_l\}$, $\{\tilde{h}_l\} = h_1/\sqrt{2}$, and the scale filter as $\{\tilde{g}_l\}$, $\{\tilde{g}_l\} = g_1/\sqrt{2} = (-1)^{l+1}\tilde{h}_{L-1-t}$, both of which satisfy the following properties:

$$\sum_{l=0}^{L-1}\tilde{h}_l = 0\ ,\ \sum_{l=0}^{L-1}\tilde{h}_l^2 = \frac{1}{2}\ ,\ \sum_{l=0}^{L-1}\tilde{h}_l\tilde{h}_{l+2n} = 0\ , \#(7)$$

$$\sum_{l=0}^{L-1}\tilde{g}_l = 1\ ,\ \sum_{l=0}^{L-1}\tilde{g}_l^2 = \frac{1}{2}\ ,\ \sum_{l=-\infty}^{\infty}\tilde{g}_l\tilde{g}_{l+2n} = 0\ , \#(8)$$

$$\sum_{l=-\infty}^{\infty}\tilde{g}_l\tilde{h}_{l+2n} = 0\ . \#(9)$$

Next, determine the wavelet coefficients and scale coefficients. Suppose $X = \{X_t: t = 0, \dots, N-1\}$ is the original time series data with sample number N, defined as follows:

$$\widetilde{W}_{j,t} = \sum_{l=0}^{L-1}\tilde{h}_{j,l}X_{t-lmodN}\ ,\ \tilde{V}_{j,t} = \sum_{l=0}^{L-1}\tilde{g}_{j,l}X_{t-lmodN}\ ,\ t = 0,1,\dots,N-1\ , \#(10)$$

where $\widetilde{W}_{j,t}$ and $\tilde{V}_{j,t}$ are the jth layer wavelet coefficients and scale coefficients of the MODWT of time series x(t).And $\tilde{h}_{j,l} = h_{j,l}/2^{j/2}$,$\tilde{g}_{j,l} = g_{j,l}/2^{j/2}$.The filters $\{\tilde{h}_{j,l}\}$ and $\{\tilde{g}_{j,l}\}$ are the wavelet filter and the scale filter at the jth level, with width $L_J = (2^J - 1)(L-1) + 1$ and corresponding scale $\lambda_j = 2^{j-1}$.

3.3 Time-varying Volatility Spillover Index

Antonakakis et al. (2020) constructed a time-varying volatility spillover index based on the idea of Koop and Korobilis (2014), which is obtained by extending the volatility connectivity approach proposed by Diebold and Yılmaz (2014). This overcomes the usual burden of arbitrarily chosen rolling window sizes and avoids the loss of valuable observations.

The basic form of TVP-VAR is as follows:

$$\mathrm{A}y_t = F_1y_{t-1} + F_2y_{t-2} + \cdots + F_sy_{t-s} + \mu_t, t = s+1, \dots, n\ , \#(11)$$

where A is the dimensional associative parameter matrix; μ_t represents the error term or structural shock, $\mu_t \sim N(0, \Sigma\Sigma)$, A and Σ are denoted as:

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{k1} & \dots & \alpha_{k,k-1} & 1 \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \sigma_k \end{pmatrix}. \#(12)$$

Transforming the TVP-VAR to its vector sliding average (VMA) representation based on the Wold representation theorem:

$$y_t = J'\left(M_t^{k-1} z_{t-k-1} + \sum_{j=0}^{k} M_t^j \eta_{t-j}\right), \#(13)$$

$$M_t = \begin{pmatrix} A_t & 0_{p\times m} \\ I_{m(p-1)} & 0_{m(p-1)\times m} \end{pmatrix}, \eta_t = (\varepsilon_t, 0, \dots, 0)', J = (I, 0, \dots, 0)', \#(14)$$

$$z_{t-1} = \left(y_{t-1}, y_{t-2}, \dots, y_{t-p}\right)', A_t = (A_t, A_t, \dots, A_t). \#(15)$$

As k approximates ∞ the equation is equivalent to:

$$y_t = \sum_{j=0}^{\infty} J' M_t^{k-1} J \varepsilon_{t-j}, B_{jt} = J' M_t^j J, j = 0,1, \dots, y_t = \sum_{j=0}^{\infty} B_{jt} \varepsilon_{t-j}. \#(16)$$

$GIRFs\left(\Psi_{ij,t}(H)\right)$ denotes the response of all variables after variable i shocks j. It can be calculated by the following equation：

$$GIRF_t\left(H, \delta_{j,t}, \Omega_{t-1}\right) = E\left(y_{t+H} | e_j = \delta_{j,t}, \Omega_{t-1}\right) - E\left(y_{t+J} | \Omega_{t-1}\right), \#(17)$$

$$\Psi_{j,t}(H) = \frac{B_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\Sigma_{jj,t}}}, \delta_{j,t} = \sqrt{\Sigma_{jj,t}}, \#(18)$$

$$\Psi_{j,t}(H) = \frac{B_{H,t}}{\sqrt{\Sigma_{jj,t}}} \Sigma_t e_j, \#(19)$$

e_j is an $m \times 1$ dimensional column vector, with the j-th position. Then calculate $GFEVD\left(\widetilde{\phi_{ij,t}}(H)\right)$. It represents the directional connectivity from j to i and illustrates the effect of variable j on variable i in terms of the prediction error variance share. Then, these variance shares are normalized so that each row adds up to equal.

The calculation is as follows:

$$\widetilde{\phi_{ij,t}}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^2}, \#(20)$$

$\sum_{j=1}^{m} \widetilde{\phi_{ij,t}}(H) = 1, \sum_{i,j=1}^{m} \widetilde{\phi_{ij,t}}(H) = m$. The denominator denotes the cumulative effect of all shocks, while the molecular notes the cumulative effect of shocks in variable i. The index of spillover effects is further obtained as:

(1) Directional Spillover Index:

Variable i comes from variable :

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1, i\neq j}^{m} \widetilde{\phi_{ij,t}}(H)}{\sum_{i=1}^{m} \widetilde{\phi_{ij,t}}(H)} \times 100, \#(21)$$

Variable i to variable :

$$C_{i\rightarrow j,t}(H) = \frac{\sum_{j=1, i\neq j}^{m} \widetilde{\phi_{ji,t}}(H)}{\sum_{j=1}^{m} \widetilde{\phi_{ji,t}}(H)} \times 100, \#(22)$$

(2) Net Spillover Index:

$$C_{i,t} = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H). \#(23)$$

When the net spillover index is positive, the variable is a net exporter of risk, while a negative value indicates that the variable is a net receiver of risk.

4. Data Selection and Descriptive Statistics

4.1 Data Selection

The data used in this article include the USD/CNY Exchange Rate (USDCNY), the Global Geopolitical Risk Index (GPR), the China Economic Policy Uncertainty Index (CEPU), the U.S. Economic Policy Uncertainty Index (UEPU), the Financial Volatility Index (VIX), the West Texas Intermediate Oil Price (WTI), and the GOLD Price (GOLD). The data are selected based on data availability for the monthly time frame of June 2005 to December 2022, which includes major political and economic events since the new century.

The GPR index was calculated through automatic search of the frequency of "geopolitical risk", "geopolitical uncertainty" and other related terms in the main international electronic archives from 1985 to the present (Caldara & Iacoviello, 2022). The EPU Index was developed by Baker et al. (2016). However, the EPU indices are compiled slightly differently in the U.S. and China. The U.S. EPU Index is a weighted sum of three sub-indices: the News Index, the Tax Expiration Index and the Economic Forecaster Disagreement Index. The Chinese EPU index refers only to the first part of the composite index, i.e., the news index. Although it is only a news index, Baker et al. (2016) pointed out that the News-Based EPU is still representative because it has a strong correlation with the composite index. The VIX, also known as the 'Investor Fear Indicator', is a measure of financial market volatility and panic.

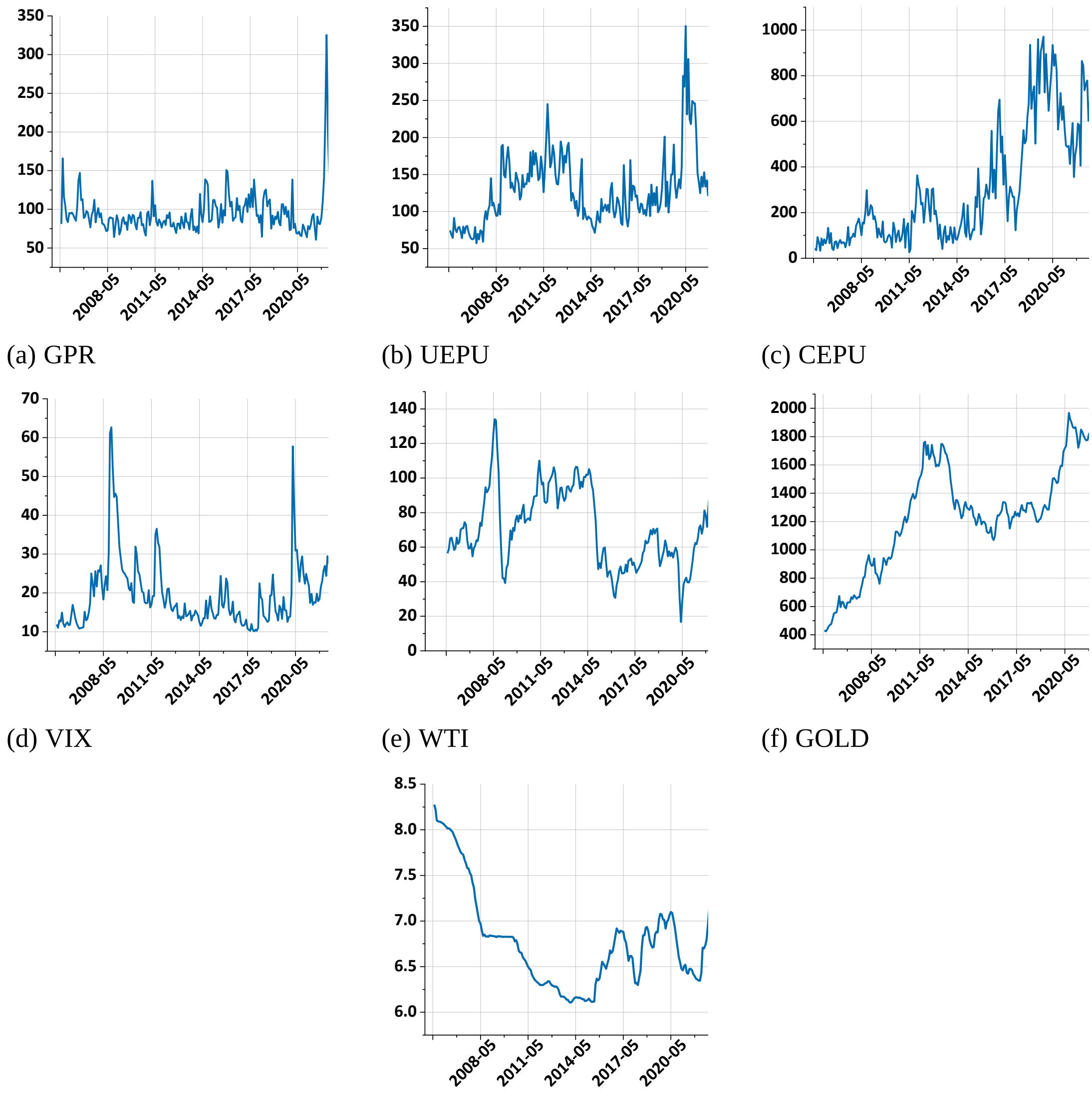
To correct for potential heteroscedasticity and dimensional differences, the variables are log-differentiated to construct exchange rate return, commodity price return and uncertainty indicator volatility as agents for risk spillover studies. Based on the subsequent need for the construction of the time-varying spillover index, an adf stability test was conducted. The results showed that all variables (log returns, log volatilities) were stable at the 5% level.

4.2 Time Series Trend of Variable

Wavelet coherence analysis reveals a notable association between uncertainty factors, commodities, and the RMB exchange rate. The strength of this relationship varies across different frequencies. Next, we will employ the MODWT algorithm to create a time-varying volatility spillover index, examining the dynamic net risk spillover effects and interconnectedness under various time-frequency domain. By quantifying these relationships, we aim to investigate the risk spillover dynamics between variables in both time and frequency domains.

Figure 3 plots the time series trend for each indicator within the data sample. First, in a single time dimension, there were five noticeable ups and downs in the USDCNY exchange rate, which are the global financial crisis in 2008, the 8.11 exchange rate reform and China's stock market crash in 2015, the U.S.-China trade friction in 2018, COVID-19 pandemic outbreak in 2020, the Russia-Ukraine conflict and the Shanghai epidemic outbreak in 2022.

Since the adoption of a managed float system for the USDCNY exchange rate in July 2005, the USDCNY has experienced more flexible and significant exchange rate fluctuations, with 2005-2015 being a period of substantial appreciation of the USDCNY. However, there was a period of stagnation in the appreciation of the USDCNY in the 2008 global financial crisis. Meanwhile, UEPU and VIX rose sharply and financial market panic peaked. The Chinese economy has also been affected, with volatility in exchange rate markets and higher global energy prices, as well as the highest price of WTI crude oil in two decades. CEPU rose sharply following two significant depreciations of the USDCNY during the China stock market crisis and 8.11 exchange rate reform in 2015, and the 2008 US-China trade friction, which had a significant impact on domestic economic policy. There was also some spillover impact on the United States, with the UEPU, VIX, WTI and GOLD all rising somewhat, but with little impact on GPR.



(a) GPR (b) UEPU (c) CEPU

(d) VIX (e) WTI (f) GOLD

(g) USDCNY

Figure 3. Time Series Trend of GPR, UEPU, CEPU, VIX, WTI, GOLD, USDCNY

After this, there were two other large fluctuations in the USDCNY, which occurred in early 2020, and in 2022. In early 2020, COVID-19 pandemic broke out, the exchange rate broke seven again, and the RMB maintained its depreciation trend. The UEPU, CEPU. VIX, WTI and GOLD all rose sharply as a result of the global outbreak of the epidemic. All other variables showed substantial increases due to the global outbreak of the epidemic. The bilateral volatility of the USDCNY has increased significantly going into 2022. Under the combined effect of the geopolitical risk spillover from the Russia-Ukraine conflict, the Fed's tightening policy ramping up, the multi-point distribution of the domestic epidemic and other over-expected factors, the USDCNY trend began to shake lower from mid-March and fell below the round number mark of 7.0 in late December, which was the largest annual drop in nearly 20 years. On the one hand, China's economy is facing a serious shock from the outbreak and economic downturn, while on the other hand, the Russia-Ukraine conflict that broke out in February 2022 has exacerbated global economic uncertainty, rising resource and energy prices, reduced external friendliness and increased geopolitical risks.

Looking at the graphs of the indicators over the last 20 years, it can be seen that periods of major adverse global economic events and turbulent U.S.-China relations correspond to high fluctuation levels in USDCNY exchange rate. And it was accompanied by varying increases in the UEPU, CEPU and VIX indices. And when the GPR rises sharply during the period, other indicators also fluctuate to different degrees, especially when crude oil prices have fallen more sharply, which also corresponds to a period of greater devaluation of the USDCNY. But it seems that GPR fluctuations are less affected by fluctuations in other variables.

5. Empirical Results

5.1 Co-movement among Variables Based on Wavelet Coherence

This section further explores the dynamical impact of uncertainty factor shocks and commodity fluctuations on the USDCNY exchange rate and the lead-lag relationship based on the wavelet coherence method. The wavelet coherence plots are given in Figure 4.

Figure 4(a) plots the wavelet coherence between the Chinese EPU and the USDCNY exchange rate. We find that the CEPU and USDCNY show yellow islands at lower frequencies (16-32 month frequency band) between 2015 and 2018, exhibiting a high degree of interdependence. The stock market crisis in 2015 and the U.S.-China trade friction in 2018 all led to a significant increase in CEPU, and this turmoil was also reflected in the exchange rate market. Significant regions were also found in the lower frequency bands during this period, indicating a contagion effect between variables. Unlike the lower frequency bands, the arrows in the significant areas of the medium-term frequency bands (6-8 month frequency band) are mostly to the right and upward, suggesting that volatility in the Chinese EPU spills over into the exchange rate market during the semi-annual period, causing volatility in the USDCNY, with the CEPU leading the movement in the USDCNY. However, The arrows turn mostly to the right and down on low-frequency band (16-32 month frequency band), illustrating that exchange rate movements during the one-year period in turn cause fluctuations in China's EPU, and the two show a high degree of interdependence.

Figures 4(b) and (d) plot the wavelet coherence between the U.S. EPU, the financial fluctuations index VIX with the USDCNY exchange rate. Obviously, the linkage between the UEPU and the USDCNY is clearly weaker compared to the CEPU. This also confirms the claim of Krol (2014) that exchange rates of emerging countries have been significantly influenced by their own EPU, but the UEPU has a relatively weak effect on them. Yet, in the 2008 global financial crisis, we can see a significant island with a period of one and a half years for the UEPU, VIX with USDCNY. As can also be seen in Figure 4(b)(d), the significant island region arrows to the right and upwards, indicating that this uncertainty and panic within the U.S. during the financial crisis spilled over into China and had an impact on USDCNY exchange rate. Equally similar, this prominent region emerged in the 2015 Chinese stock market crisis, with a contagion effect between the UEPU, VIX index and the USDCNY (significant islands in the 4-8 month frequency band) and an arrow downward, implying that fluctuations in the USDCNY exchange rate were also contagious to the U.S. during the Chinese stock market crash. Following the gradual opening of China's financial markets, the Chinese economy is gradually integrating into the developed economies. This means that the Chinese and U.S. financial markets are becoming increasingly intertwined and have an impact on each other in the event of a major crisis. This phenomenon is even more evident in the volatility of the VIX, where the wavelet coherence plot between the VIX and USDCNY during the 2008 financial crisis shows that Chinese exchange rate fluctuations can have a long-term negative impact on fluctuations in the U.S. financial markets (significant area in the high-frequency band of 32 months).

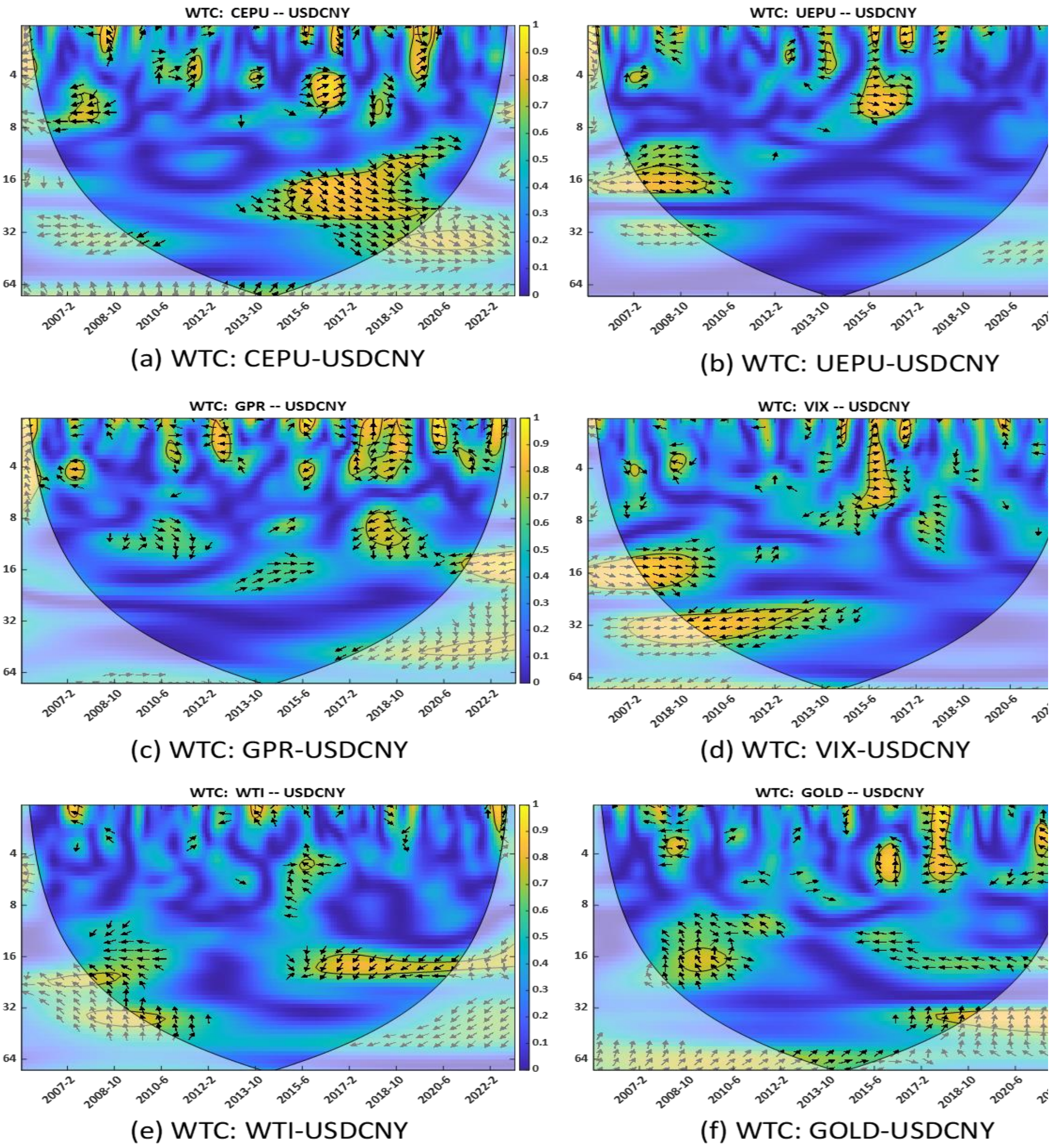


Figure 4. The Wavelet Coherence Plot of CEPU,UEPU,GPR,VIX,WTI,GOLD with USDCNY

For geopolitical risk, looking at Figure 4(c), we noticed that the co-movement of GPR and the USDCNY is mostly concentrated in the high-frequency interval (2-6 month frequency band), exhibiting a high contagion effect: when volatility occurs in GPR, the USDCNY exchange rate responds within a few months. And this contagion, with significant yellow islands seen at the beginning, middle and end of the sample cycle, demonstrates that short-term exchange rate fluctuations can be predicted based on GPR. The phase arrows in Figure 4(c) are mostly upward, suggesting that GPR leads the exchange rate and that rising geopolitical risk exacerbates USDCNY fluctuations and GPR is a risk spillover. Especially in 2022, after the outbreak of the Russia-Ukraine conflict, the arrow is more skewed upwards and the contagion effect is more pronounced

As for the association of WTI crude oil return and USDCNY exchange rate, we can see that in the beginning of the sample cycle, i.e., the 5-year period from 2005 to 2010, and the later part of the sample cycle (after 2015), WTI and USDCNY show a continuous long-term co-movement in the low-frequency band of 16-32 month with yellow significant islands, and the phase arrows point mostly downwards to left after 2010, illustrating that the volatility of WTI will have a long-term negative impact on USDCNY, and this impact lasts for a longer time frame. With the outbreak of the Russia-Ukraine conflict in early 2022, geopolitical risks have increased, international tensions have increased, and there has been a significant short-term contagion effect between WTI and USDCNY.

Figure 4(f) plots the wavelet correlation between the gold return and the USDCNY exchange rate. We find that the fluctuations between the precious metal return and USDCNY are correlated in short-run, but the long-run correlation is weaker. Most of the yellow significant islands of GOLD and USDCNY occur at higher frequency (2-6 month frequency band), pointing to a short-term correlation. And these high-frequency significant regions appear in the time frame during international events such as the 2008 global financial crisis, the 2015 China stock market crash, the 2018 U.S.-China trade friction, and the 2022 Russia-Ukraine conflict. It indicates that the strong contagion linkage between international gold prices and USDCNY exchange rate in times of financial crisis and international gold prices can have a negative short-term impact on USDCNY exchange rate fluctuations, indicating the impact of financial contagion.

In general, GPR and GOLD are more correlated with USDCNY fluctuations over the short and medium periods, and this correlation is more pronounced when major global events occur. In contrast, WTI and USDCNY exhibit a strong long-term linkage and weaker effects for the short-term. And for UEPU and VIX, before 2012, U.S. policy changes and financial market fluctuations would exert a long-term impact on USDCNY exchange rate. But after 2012, when there are changes in the U.S.-China relationship or fluctuations in the U.S. economy, the USDCNY exchange rate will react within a short period of time. Furthermore, the Chinese EPU has the strongest linkage with the USDCNY exchange rate, showing significant correlations in both the short and medium term, and a more risk-spillover role for the USDCNY exchange rate.

5.2 Time-varying Spillover Effects Based on Wavelet Decomposition

Through the wavelet coherence analysis, we can clearly see that there is an obvious joint volatility relationship between the uncertainty factors and commodities and the RMB exchange rate, but the linkage relationship between different factors and the RMB exchange rate varies at different frequency lengths. In the following, we will MODWT algorithm to construct a time-varying volatility spillover index to analyze its dynamic net risk spillover effect and dynamic net risk connectivity under different time scale conditions. Specific values quantify the risk spillover relationship between variables in the time and frequency domains.

First, based on the data characteristics, this study uses MODWT to decompose each variable sequence into 6 scales (D1-D6 scales), presented in integer powers of number 2. Scale 1 indicates 2 months, scale 2 indicates 4 months and so on, fully identifying the important information in the frequency domain from short to long term. Combining the strength of the linkage between the variables in the previous section at each frequency, we finally selected D1 (2 months), D3 (8 months i.e. semi-annual), and D4 (16 months i.e. one and a half years) to indicate short, medium, and longsequences.

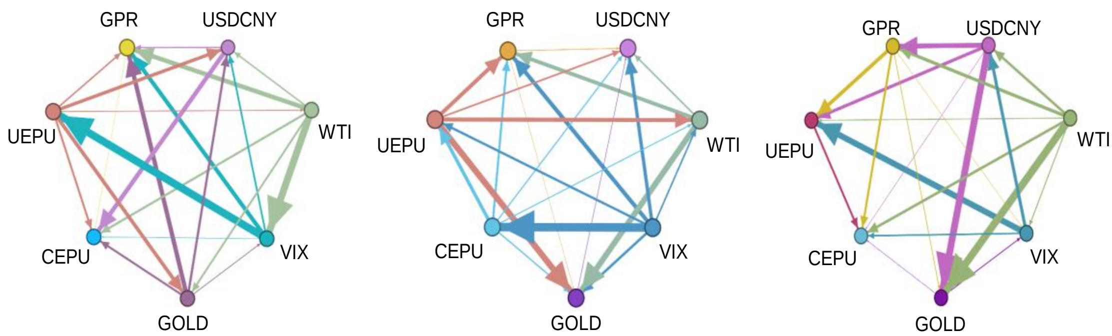
5.2.1 Spillover Effects over the Full-time Period

Table 1 gives a matrix of spillover indices of global uncertainty risk shocks, commodites and USDCNY exchange rate fluctuations in the short-medium-long term, mainly including TO, FROM and NET spillover index. The data in every row indicates that variable receives spillover shocks from other variables (the degree of influence), the data in each column indicates the degree of spillover from the variable to other variables (the contribution rate). The Net spillover index will be obtained by the TO minus the FROM (NET=TO-FROM). A positive net spillover index represents the variable as a net exporter of risk, and a negative value represents the variable as a net receiver of risk. These data represent the correlation between variables within the system and the degree of influence, and further based on this data, the net pairwise risk spillover direction plot between the variables is drawn. Combined with spillover index matrix and net pairwise risk spillover direction plot, a more visual representation of this interaction mechanism among variables can be gained.

Table 1. Spillover Index Matrix (%)

		USDCNY	GPR	VIX	UEPU	CEPU	WTI	GOLD	FROM
short	USDCNY	72.3	2.9	6.1	6.7	2.3	3.4	6.3	27.7
	GPR	4.2	68	7.5	4.7	2.3	6.5	6.9	32
	VIX	4.3	3.1	57	7.1	5.8	14.2	8.5	43
	UEPU	3.2	3.2	15.3	50.9	7.6	8.6	11.3	49.1
	CEPU	7.1	2.5	6.1	9.7	59.8	6.4	8.2	40.2
	WTI	1.9	1.8	6.3	9.3	4.1	58.6	18	41.4
	GOLD	3.8	2.1	7.8	15.2	6.1	20	45	55
	TO	24.4	15.6	49.1	52.7	28.1	59.2	59.2	TCI
	NET	-3.2	-16.4	6.1	3.7	-12.1	17.7	4.2	41.2
medium	USDCNY	44.9	14.7	11	7.6	5.8	7.7	8.3	55.1
	GPR	13.8	33.4	13.5	13.1	9.1	12.7	4.5	66.6
	VIX	4	5.3	50.6	13.3	11.8	8	7	49.4
	UEPU	4.4	5.3	17.8	36	13	13.8	9.6	64
	CEPU	3.7	4.8	28.5	6.1	40.1	10	6.8	59.9
	WTI	4.8	5.3	11	21.5	11.7	36.7	9	63.3
	GOLD	7.8	4.8	11.9	22.3	9.2	21	23	77
	TO	38.6	40.1	93.8	83.9	60.5	73.1	45.2	TCI
	NET	-16.5	-26.5	44.4	19.9	0.7	9.9	-31.8	62.2

long	USDCNY	29.6	10.1	13.1	7.9	7.3	24.3	7.7	70.4
	GPR	17.2	29.3	8.1	8.8	7.2	20.4	8.9	70.7
	VIX	7.7	8.6	45.6	14.6	8.2	7.9	7.3	54.4
	UEPU	12.8	14.6	23.9	22.7	8.8	10	7.1	77.3
	CEPU	7.9	10.9	10.5	12.1	36.3	10.4	11.8	63.7
	WTI	20.3	15.5	6.3	8.9	6.3	29	13.7	71
	GOLD	19.9	10	6.1	7.1	11.4	26.2	19.3	80.7
	TO	85.9	69.7	68.2	59.4	49.2	99.3	56.5	TCI
	NET	15.5	-1	13.8	-17.9	-14.5	28.3	-24.2	69.8



(a) short-term (b) medium-term (c) long-term

Figure 5. Net Pairwise Risk Spillover Direction Plot

Firstly, for the total spillover index, the short-term spillover index reaches 41.2%, indicating that 41.2% of the volatility within the spillover system, composed of the USDCNY exchange rate together with uncertainty factors and commodities, is caused by the interaction between the variables. Moreover, the total spillover index is 62.2% and 69.8% for the medium and long term respectively. The increasing spillover index indicates that interactions between variables are gradually increasing over time and have a continuous influence.

In the short term, the net risk spillover indices for USDCNY, GPR, and CEPU are -3.2%, -16.4%, and -12.1%, respectively, all of them negative, being the main receivers of risk and more influenced by other variables. And the USDCNY is mainly influenced by spillovers from the UEPU (6.7%), VIX (6.1%) and GOLD (6.3%), and less influenced by the spillover from CEPU. Furthermore, it can be seen from Figure 5(a) that the USDCNY also counteracts the fluctuation of CEPU. Not only that, the arrows of the net spillover index between China's EPU and all other variables in the figure point to itself, suggesting that China's economic policy uncertainty is subject to greater external influence. As for the commodities crude WTI and GOLD, in a short-term perspective, apart from being affected by the uncertainty of U.S. economic policy, they are major spillovers of risk for other uncertainty indicators as well as for the USDCNY exchange rate. Due to the leading position of the USA in the global political and economic arena, UEPU and VIX have obvious risk spillover effects on the others.

In the medium term, the spillover effect of other factors on USDCNY strengthens significantly, from short-term at 27.7% to medium-term at 55.1%, and the interaction between variables in the medium-term phase strengthens. In Figure 5.(b), the medium-term net pairwise spillover arrows of the USDCNY exchange rate with all other variables point to themselves, indicating that USDNY is the main risk spillover recipient and is vulnerable to the risk fluctuations of other variables in the medium term. Second, it can be seen that the VIX generates a direct risk spillover on USDCNY in addition to a varying degree of risk spillover on all other variables. Thus the VIX, directly and indirectly, affects the volatility of USDCNY in terms of semi-annual fluctuations. Another significant change at this point is that the CEPU is no longer the main recipient of risk, and it also causes a net risk spillover to other variables, but is affected by the sharp and significant volatility of VIX. Extra vigilance should be exercised over the spillover effects of volatility on the USDCNY exchange rate from the U.S. financial markets during the semi-annual period.

From a long-term perspective, USDCNY is subject to an enhanced total systemic spillover of 70.4%, but it can be seen that this enhanced spillover comes mainly from the fact that the WTI spillover on USDCNY increases significantly in the long term (from short-term at 3.4% to medium-term at 7.7% to long-term at 24.3%). International crude oil can have a long-term and far-reaching impact on the USDCNY exchange rate. Meanwhile, USDCNY spillover to other variables also appears to increase in varying degrees, becoming a risk sender for GPR, UEPU and GOLD. And the impact of GPR on other factors has gradually increased over time.

5.2.2 Dynamic Time-varying Spillover Effects under Major Event Shocks

The spillover index mentioned in the previous section for the full-time period can indicate the level of internal interaction among global uncertainty factors, commodity prices, and the RMB exchange rate. However, it may overlook the systematic fluctuations triggered by significant adverse international events, resulting in uncertainty risks and an inadequate measurement of the time-varying spillover effects between variables. Therefore, based on the above analysis, this paper adopts the method proposed by Koop and Korobilis (2014) to create a time-varying volatility spillover index. This index is utilized for a dynamic analysis of the spillover effects among global uncertainty factors, commodity prices, and the RMB exchange rate.

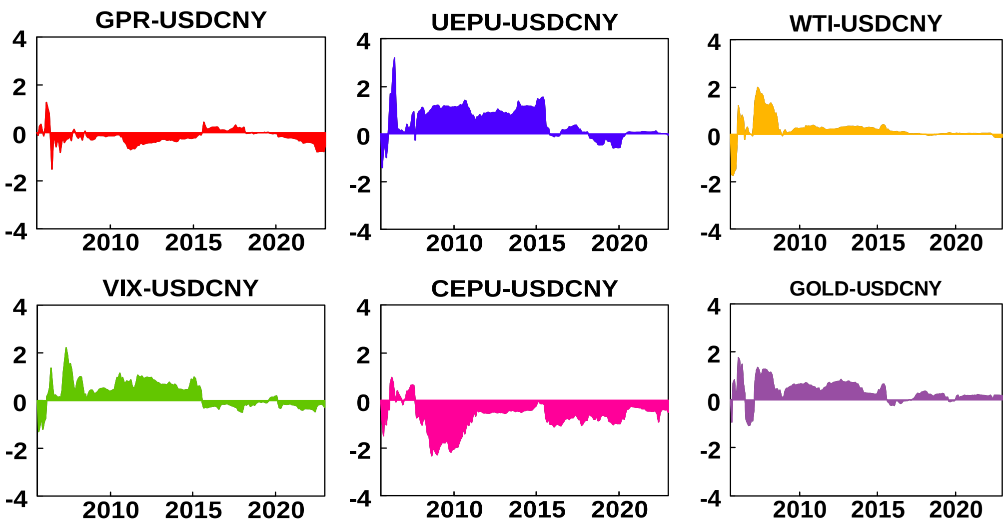


Figure 6 (a). Short-term Net Pairs Spillover Index

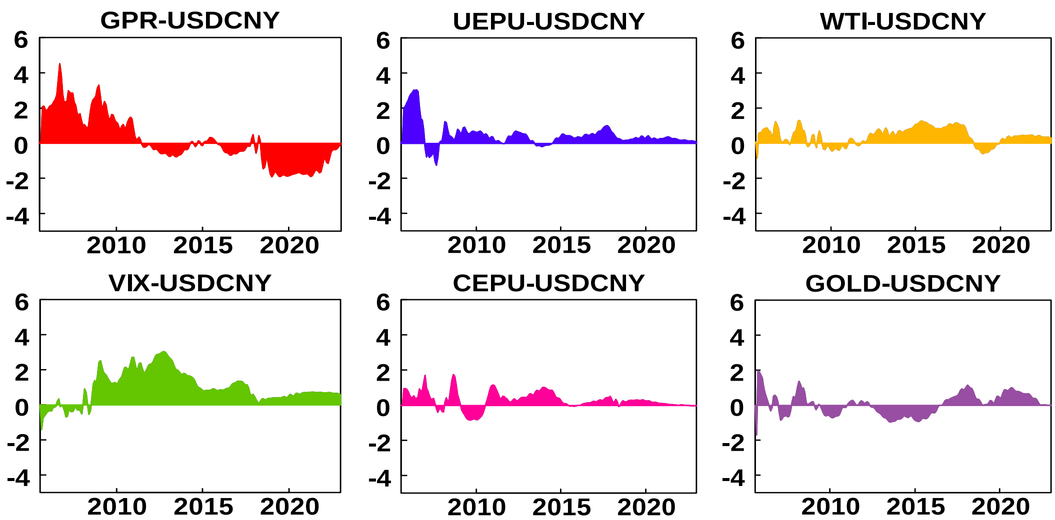


Figure 6 (b). Medium-term Net Pairs Spillover Index

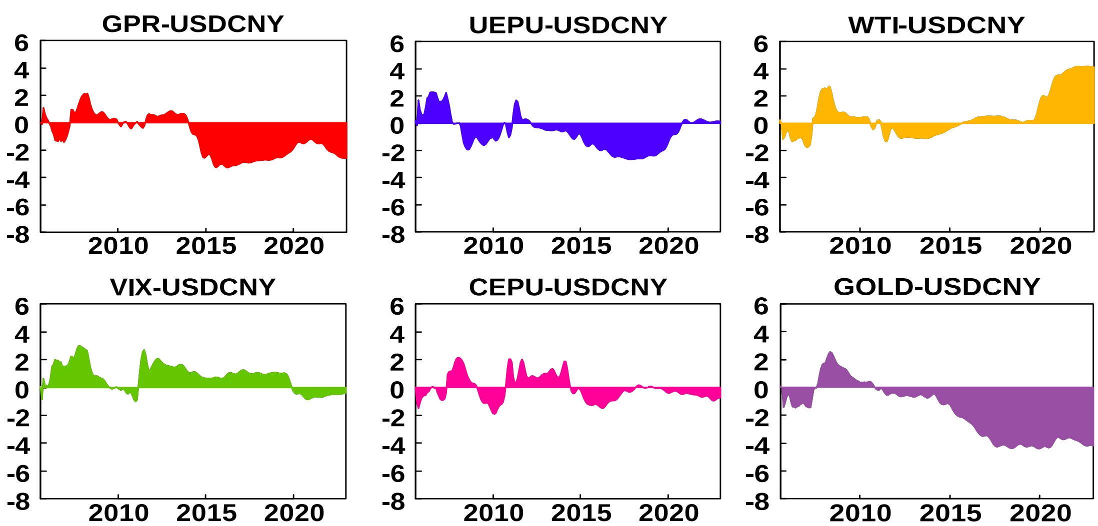


Figure 6 (c). Long-term Net Pairs Spillover Index

Figures 6 plot the net pairwise spillover index between the variables in the short-medium-long term. We can see that during the period of the global financial crisis in 2008, the USDCNY received spillovers from UEPU, VIX, WTI, and GOLD in the short-term, and this risk can still be seen in the medium to long term. And in the short run the USDNY in turn spills this risk to CEPU and GPR. Nevertheless, in the medium to long term, almost all variables during the global financial crisis have spillover effects on USDCNY exchange rate volatility.

When there are twists and turns in the U.S.-China relationship or major economic events in China, the VIX will be affected by USDCNY volatility in the short term, but in the medium to long term the VIX remains a risk spiller to USDCNY volatility, leading it. UEPU is in a different situation, as it is affected by economic policy changes from China in all frequency cycles, and thus by risk spillovers from USDCNY, and this effect is more pronounced in the long-term. CEPU on most time-frequency scales is a recipient of risk from USDCNY volatility, influenced by USDCNY fluctuations. While the outbreak of the COVID-19 pandemic in 2020, it can be seen that the CEPU presents a risk spillover impact on the USDCNY mainly in the semi-annual period.

The direct spillover effect of GPR on USDCNY volatility is not obvious during the period of the Russia-Ukraine conflict in 2022, but it can be seen that the risk spillover of WTI on USDCNY is significantly higher during this period. Numerous existing literature have found that GPR is associated with an impact on crude oil return, for example, Liu et al. (2022) argued that geopolitical risk has a significant negative impact on the volatility of the crude oil spot market. In times of high geopolitical risk volatility, GPR can indirectly affect USDCNY exchange rate volatility by influencing international crude oil price fluctuations. And the risk of WTI price volatility on all frequency scales during major global event weeks spills over into USDCNY volatility.

6. Conclusion

Based on the sample data from July 2005 to December 2022, this article constructs a multi-time scale analytical framework by using wavelet coherence analysis and time-varying spillover index model based on wavelet decomposition to analyze and compare the different impact mechanisms of global uncertainty factors, commodity prices and USDCNY exchange rate in different time and frequency domains as well as the strength of linkages and spillover differences. Our research found that under different frequency cycles and shocks of significant events, the associations between variables vary. (1) The USDCNY exchange rate is a major risk recipient in both the short and medium term. However, over time, with a long-term volatility frequency of 16 months, USDCNY exchange rate volatility will counteract U.S. economic policy uncertainty, gold prices, and geopolitical risks, creating a long-term negative impact. (2) Geopolitical risk and gold have stronger synergistic movements with the USDCNY exchange rate in the short-medium term, generating risk spillovers on the USDCNY exchange rate mainly in the short-medium term. (3) On each of the short-medium-long term volatility scales, both U.S. financial market volatility (VIX) and international oil prices (WTI) generate significant risk spillovers on the USDCNY exchange rate, especially in the long run the volatility spillover of international oil prices on the USDCNY exchange rate is most pronounced. The VIX, on the other hand, has an impact on USDCNY exchange rate volatility through direct or indirect contagion pathways during the medium-term (Semi-annual) volatility period.

The spillover effects of the variables will also vary when major global events occur: (1) During the contagion of the global financial crisis, in the short-term, the USDCNY exchange rate was subject to significant spillover effects from the USA and commodity price fluctuations, reacting quickly and applying such spillover effects to its own domestic EPU, increasing the instability of Chinese economic policy during the global economic turmoil. Therefore, in times of global economic instability, China should actively adjust its strategy to improve its ability to cope with international economic shocks. (2) Most time scales of Chinese economic policy uncertainty are receiving risk spillovers from USDCNY exchange rate fluctuations and are affected by USDCNY exchange rate fluctuations. However, when a major adverse event occurs in China such as the 2015 stock market crash or the COVID-19 epidemic in 2020, the uncertainty of China's domestic economic policy can have a significant spillover effect on USDCNY exchange rate volatility during the Semi-annual period. (3) In times of high geopolitical risk volatility, it can indirectly affect USDCNY exchange rate volatility by influencing international crude oil price fluctuations. Be alert to the possibility of high volatility risks in China's exchange rate market during times of global geopolitical instability.

The escalation of uncertainty levels impacts decision-making in various sectors of the economy, including households, businesses, banks, financial markets, and policymakers, potentially leading to adverse effects on RMB exchange rate fluctuations. Decision-makers need to take into account both current and future economic uncertainties when crafting policies. Monitoring cross-border capital flows and objectively assessing their risks is crucial. Additionally, it is important to clarify central bank policy strategies and bolster the financial system's resilience. Departments should work towards establishing long-term mechanisms in banks to improve currency shock management services, provide better support for currency hedging, maintain the RMB exchange rate at a stable level, and mitigate internal and external uncertainty shocks to promote currency and financial stability. Analyzing the spillover effects of internal and external uncertainty shocks on Chinese exchange rate market volatility is highly significant. This analysis can help identify external risk factors affecting Chinese exchange rate fluctuations more accurately, enhance the precision and forward-looking nature of macroeconomic regulation, reduce systemic risk, and uphold economic and financial stability.

The increase in uncertainty levels impacts decision-making in various sectors of the economy, such as households, businesses, banks, financial markets, and policymakers, potentially leading to adverse effects on RMB exchange rate fluctuations. Therefore, policymakers should take into account current and future economic uncertainty when creating policies, closely monitoring cross-border capital flows, and objectively evaluating prospects and their associated risks. It is important for relevant departments to further encourage the establishment of long-term mechanisms in banks to enhance currency shock management services, provide increased support for hedging against major exchange rate movements, maintain the RMB exchange rate at a stable equilibrium level, mitigate internal and external uncertainty shocks, and promote currency and financial stability. Researching the spillover effects of internal and external uncertainty shocks on China's exchange rate market volatility is crucial for accurately identifying external risk factors that influence exchange rate fluctuations in China, improving the precision and foresight of macroeconomic regulation, reducing systemic risk, and ensuring healthy economic development.

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