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Study on the Spillover of Systemic Financial Risks in Foreign Exchange Market under External Shocks

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Abstract

In today's increasingly complex financial market risks, any small risk may have an impact on other financial institutions or markets, and then lead to systemic financial risks. Based on the daily data of RMB central parity from August 2, 2006 to December 31, 2021, this paper selects US dollar, euro, Japanese yen, Hong Kong dollar and British pound to study the spillover effects of systemic financial risks in foreign exchange markets of different countries and regions. The results show that under the impact of external events such as the subprime mortgage crisis in the United States, the stock market crash in China and the COVID-19 epidemic, the foreign exchange market will fluctuate and its systemic financial risks will be significantly increased, and the role of financial spillover between markets may also change briefly due to the impact of external events.

Keywords

Systemic Financial Risk; Wavelet Analysis; Foreign Exchange Market.

1. Introduction

In the current era of globalization, the risks of financial markets are increasingly complex, economic globalization and financial integration make financial risks break through the time and space limits, resulting in spillover effects, known as systemic financial risks. Systemic financial risk mainly refers to the risk that a single financial event causes the crisis of the entire financial system and leads to significant losses of the economy and social welfare. With the increasing linkage between financial institutions and financial markets, just like the "butterfly effect", any slight financial risk may have an impact on other institutions or markets through the complex network structure of the financial system, thus triggering systemic financial risks. The path of systemic financial risk spillover and contagion shows the characteristics of network. When the stock market is extremely unstable, the spread of risks will increase sharply, endangering the stability of the whole system, and the occurrence of adverse events will trigger a chain reaction and promote the spread of pessimistic expectations. After the global financial crisis, the identification of systemic financial risks, the measurement of spillovers and risk supervision have become the issues of wide concern to governments and scholars at home and abroad. Once systemic financial risks occur in the financial system, economic development, even social stability and national security will be strongly impacted, resulting in major losses of the state and people's property. There are many countries in history that have been affected by systemic financial risks, such as the Latin American crisis in the 1980s and the Japanese financial crisis in the 1990s. At present, most studies show that extreme events related to economy and finance will affect the stability of the stock market, such as the Asian financial crisis at the end of the 20th century, the global financial crisis in 2008 and the debt crisis from 2010 to 2013, and the new coronavirus outbreak from 2020 to now also have a negative impact on the stability of the global financial market.

With the continuous development of China's financial industry, the complexity of financial risks is also increasing. Once systemic financial risks occur, they will have more serious consequences. Therefore, it is necessary to take the initiative to prevent and resolve systemic financial risks in a more important position. As China's economy is in a critical period of structural reform and new momentum of economic growth, how to prevent and resolve systemic financial risks is an important issue that needs to be solved urgently. Therefore, research on the financial risk transmission mechanism in the international foreign exchange market, identification of risk sources, and clarification of risk intensity and direction are conducive to avoiding and preventing the spread of international systemic financial risks.

After reviewing relevant literature, it is found that most scholars only study the volatility spillover effect from the perspective of time domain. Some scholars have found that there are different interaction behaviors between financial markets at different time scales, and the method of wavelet analysis can analyze financial time series data from both the perspective of time domain and frequency domain. The advantage of wavelet transform is that it can decompose financial time series data under different simultaneous frequency scales and analyze the relationship between variables, which is of great significance for the characterization of the interaction between different foreign exchange markets. Based on this, the risk volatility spillover model is established and the network topology is analyzed. It can comprehensively and effectively measure the intensity and direction of the spillover effect of systemic financial risks between foreign exchange markets, which is of great significance for China to prevent and resolve the spread of systemic financial risks.

As for the study of risk spillover, there are many research angles and methods, most of which focus on the same level, such as the systemic financial risk spillover of the market or the sector. Some scholars have studied the risk spillover effect between different markets or sectors. Xie (2010)0used the GARCH-Copula-CoVaR model to study the risk spillover effect among the three major Asian stock market indexes. Ye et al. (2018) [2]studied the risk spillover effect between the oil market and the US dollar foreign exchange market from the perspective of quantile based on the MV-CAViaR model, and analyzed the impact of the financial crisis on the risk spillover effect between the oil market and the US dollar foreign exchange market. Miao et al. (2021)[3] calculated the cross-market contagion effect of global systemic financial risks based on the interest rate and exchange rate data of 14 major countries and regions, and believed that financial risks may be transmitted through the financial network between the currency and foreign exchange markets of different countries and regions. Previous evidence suggests that extreme events can trigger downward pressure on financial markets and alter systemic adjustments in risk and return expectations (Merkle&Weber, 2014; Farhi&Gabaix, 2016; Heo et al., 2020)[4,5,6]. Rational investors who are influenced by emotional factors to rebalance their portfolios and liquidate risky assets to safe-haven assets will lead to rapid portfolio outflows and increase extreme risk exposure, which will lead to system-wide financial contagion and increase the likelihood of financial market turmoil (Ji et al., 2020; Nguyen et al., 2021) [7,8].

In recent years, the outbreak of the novel coronavirus pneumonia has led some scholars to discuss the systemic risk of this public health emergency. As an extreme event, the COVID-19 pandemic represents a source of systemic risk (Sharif et al., 2020) [9]. Rizwan et al. (2020)[10] used the arithmetic mean of value at risk and connectivity to measure how COVID-19 affected the systemic risk of the banking sector in the eight countries most affected by the global epidemic, and the results showed that the systemic risk of the sample countries increased significantly. Abuzayed et al. (2021)[11] studied the systemic risk spillover between the global stock market and the individual stock market in the countries most affected by the COVID-19 epidemic, and the results showed that the bivariate systemic risk contagion between the global stock market and various stock markets evolved during the sample period and intensified with the global spread of COVID-19. Tiwari et al. (2022)[12] adopted TVP-VAR and LASSO-VAR methods to study the transfer of risk patterns among green bonds, carbon prices and renewable energy stocks, and used various portfolios to test portfolio performance. The results show that the dynamic total connectivity of assets is heterogeneous and depends on economic events over time. Clean energy dominates other markets and is seen as a major net pass-through of shocks across the network, with portfolio performance compared during the spread of COVID-19.

In terms of the current research results on the spillover of systemic financial risks, there have been a lot of research conclusions at home and abroad, all of which emphasize the importance of measuring the intensity and direction of systemic risks. As an indispensable supporting force for a country's development, the frequent occurrence of systemic risks in the financial market has alerted people to pay attention to it. Measuring the intensity and direction of systemic risk spillover is of great significance for preventing and resolving systemic risk. Foreign exchange market is an important way of international systemic risk contagion. Measuring the systemic risk spillover effect of the foreign exchange market can effectively avoid and prevent systemic financial risks while a country is opening up to the outside world. Therefore, it is increasingly important to study the systemic financial risk spillover of the foreign exchange market.

2. Theoretical Model

2.1. Wavelet Power Spectrum and Wavelet Coherence

In this paper, the wavelet method (ψ) based on wavelet Morlet family is used to study the local volatility of different markets in time domain and frequency domain and the causality between long and short term. ψ can be expressed as:

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

In this case, τ of the two wavelet components is used to highlight a specific position in time, s represents the frequency fluctuation of the wavelet. By transforming the mother wavelet formula, we can get:

$$\psi_{\tau,s}(t) = h^{-\frac{1}{2}} \psi\left(\frac{(t-\tau)}{s}\right), \tau, s \in \mathbb{R}, s \neq 0 \tag{2}$$

Firstly, the method of wavelet power spectrum (WPS) is used to visualize the volatility of the commodity market:

$$W_X(\tau, s) = \int_{-\infty}^{+\infty} x(t) s^{-\frac{1}{2}} \psi^* \left(\frac{t-\tau}{s}\right) dt \tag{3}$$

$$WPS_X(\tau, s) = \left|W_X(\tau, s)\right|^2 \tag{4}$$

$W_X(\tau,s)$ represents the continuous wavelet transform of the time series of the parent wavelet, $x(t)$ represents a time series, and ψ^* represents the complex conjugation of the parent wavelet. In the wavelet power spectrum, the brighter the color, the greater the frequency domain fluctuation at this time.

Then, on this basis, the wavelet coherence method is used to combine the time domain and frequency domain to identify the long-term and short-term causal relationship between the foreign exchange markets of different countries and regions. The main formula for the conversion of cross wavelet time series is as follows:

$$W_{XY}(\tau,s)=W_X(\tau,s)\overline{W_Y(\tau,s)} \tag{5}$$

The above equation consists of $W_X(\tau,s)$ and $W_Y(\tau,s)$, which represent the cross wavelet transform of the time series $x(t)$ and $y(t)$ of the two markets respectively. According to the theoretical research of Torrence and Compo[13] (1998), wavelet coherence (WSC) is defined as:

$$WSC=R_{XY}^2(\tau,s)=\frac{\left|S(s^{-1}W_{XY}(\tau,s))\right|^2}{S(s^{-1}\left|W_X(\tau,s)\right|^2)S(s^{-1}\left|W_Y(\tau,s)\right|^2)} \tag{6}$$

S represents the smoothing process of time and scale, W_{XY} is the cross wavelet power, which can capture the local covariance between two time series on each scale, and because of the wavelet coherence $0\le R_{XY}^2(\tau,s)\le 1$, the phase difference ϕ_{XY} is used to determine the lead-lag relationship between the two time series:

$$\phi_{XY}=\tan^{-1}\left(\frac{\operatorname{Im}\left\{S(s^{-1}W_n^{XY}(s))\right\}}{\operatorname{Re}\left\{S(s^{-1}W_n^{XY}(s))\right\}}\right),\phi_{XY}\in\left[-\pi,\pi\right] \tag{7}$$

Where Im and Re represent the virtual part and real part of the smooth cross wavelet transform respectively, the arrow on the wavelet coherence graph represents the phase difference ϕ_{XY} of the two time series stages, that is, the causality of lead and lag, the arrow pointing to the right (left) indicates the positive correlation (negative correlation) of the two time series, and the arrow points to the up, upper right or lower left. Indicates that the second time series is ahead of the first time series, and vice versa, the first time series is ahead of the second time series.

2.2. TVP-VAR-DY Overflow Index Model

Diebold and Yilmaz[14] (2012) combined the VAR model and the generalized prediction error variance decomposition model to build a DY overflow index model. This method reasonably solves the shortcomings of the traditional variance decomposition results dependent on the order of variables, and can effectively measure the time-varying trend of the size of spillover effects between different markets. Therefore, it has been widely used in many researches by scholars. However, this model cannot capture the common heteroscedasticity of financial variables and is sensitive to outliers. Therefore, this paper uses the research method of Korobilis and Yilmaz[15] (2018) to combine the time-varying parameter vector autoregression (TVP-VAR) and DY overflow index to build a time-varying vector autoregressive overflow index model (TVP-VAR-DY) for empirical research. This model can capture the common heteroscedasticity of financial variables, avoid the missing of samples in the dynamic estimation of DY overflow index, and reduce the sensitivity to outliers.

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The specific formula for establishing the TVP-VAR-DY model. In the first step, the following P-order TVP-VAR-SV model is constructed for the n-dimensional vector y_t :

$$y_t = A_t z_{t-1} + \varepsilon_t, \varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t) \tag{8}$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t, \xi_t \mid \Omega_{t-1} \sim N(0, \Xi_t) \tag{9}$$

Where $z_t = (y_{t-1}, \cdots, y_{t-p})', A_t = (A_{1t}, \cdots, A_{pt})$, Σ_t and X_t are the time-varying variance covariance matrix, and vec is the vectorization operator.

The second step is to convert VAR(p) into VMA(q) according to the Wold principle:

$$y_{it} = \sum_{j=0}^{\infty} B_{jt} \varepsilon_{t-j} \tag{10}$$

The third step is to set the prediction period as H. Based on the GFDVE model, the spillover effect of variable j on variable i is as follows:

$$\theta_{ij,t}^{g}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_i' B_h \Sigma_h e_j)}{\sum_{h=0}^{H-1} (e_i' B_h \Sigma_h B_h' e_j)} \tag{11}$$

Where Σ_h is the time-varying covariance matrix of the error vector, Σ_h is the time-varying standard deviation of the JTH error term, and e_i is the selection vector (all other elements are 0 except the I-th element is 1). In order to make the row sum of the variance decomposition matrix equal to 1, it is normalized as follows:

$$\tilde{\theta}_{ij,t}^{g}(H) = \frac{\theta_{ij,t}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij,t}^{g}(H)} \tag{12}$$

Based on the normalized variance decomposition matrix, the total overflow index TSI is constructed, which represents the total overflow degree of all variables in the system:

$$TSI_t(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij,t}^{g}(H)}{N-1} \times 100 \tag{13}$$

In addition, the comprehensive directional spillover index of variable i TO and FROM other variables and affected by spillovers of other variables can also be obtained:

$$TO_{i,t}(H) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\theta}_{ji,t}^{g}(H)}{N-1} \times 100 \tag{14}$$

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$$FROM_{it}(H)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\theta}_{ij,t}^{g}(H)}{N-1}\times 100 \tag{15}$$

By combining the directional spillover index TO and FROM, the NET spillover index net of variable i to other variables can be obtained:

$$NET_{i,t}(H)=TO_{i,t}(H)-FROM_{i,t}(H) \tag{16}$$

Similarly, considering the net spillover effect between pairwise variables, the net pairing spillover index S can be constructed as follows:

$$S_{ij,t}^{g}(H)=\left(\frac{\tilde{\theta}_{ji,t}^{g}(H)-\tilde{\theta}_{ij,t}^{g}(H)}{N-1}\right)\times 100 \tag{17}$$

3. Empirical Analysis

3.1. Data Source and Description

This paper uses the daily data of the central parity rate of RMB from August 2, 2006 to December 31, 2021, and selects the corresponding data of US dollar (US), euro (EUR), Japanese yen (JPN), Hong Kong dollar (HK) and British pound (UK) for every 100 RMB, respectively, and the data comes from the State Administration of Foreign Exchange of China. All data were treated with logarithmic rate of return, and the descriptive statistical analysis of each variable was shown in Table 1 below.

Table 1. Descriptive statistical analysis of each variable

	US	EUR	JPN	HK	UK
Obs.	3750	3750	3750	3750	3750
Min	-0.010	-0.069	-0.051	-0.011	-0.072
Max	0.018	0.033	0.036	0.018	0.041
Mean	-0.000	-0.000	-0.000	-0.000	-0.000
Std. Dev.	0.002	0.006	0.006	0.002	0.006
Skewness	0.701	-0.328	-0.089	0.666	-0.855
Kurtosis	15.530	12.609	8.807	15.537	14.356
Jarque-Bera	24838.413***	14495.344***	5274.321***	24835.665***	20605.550***
ADF test	-13.678***	-14.530***	-15.740***	-13.315***	-14.394***

Note: Jarque-Bera stands for normality test, ADF stands for unit root test, and *** stands for 1% significance level.

As shown in Table 1, the skewness coefficients of US and HK are greater than 0, indicating that the two time series are right-skewness; the skewness coefficients of the other three variables are all less than 0, indicating left-skewness; all five variables present excess kurtosis (kurtosis coefficient greater than 3). The Jarque-Bera test results show that all variables reject the original hypothesis of normal distribution at the level of 1%. At the same time, the unit root test also shows that the variables are significantly stable, which can be carried out the next wavelet coherence and risk spillover effect analysis.

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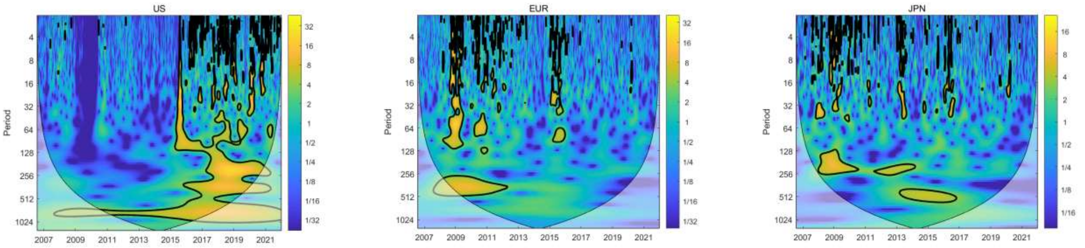
3.2. Wavelet Coherence Analysis

3.2.1. Wavelet Power Spectrum Results

Firstly, wavelet power spectrum is used to study the long and short term volatility of the foreign exchange markets of the United States, the European Union, Japan, Hong Kong, China and the United Kingdom. Morlet is used as the mother wavelet and plots are drawn as shown in Figure 1 below. The ordinate represents the frequency domain and the abscess represents the time domain, which reflect the correlation information of frequency changes over time. A warmer hue (yellow) indicates a higher correlation, and a cooler hue (blue) indicates a weaker correlation. The black narrow curve in the figure is called the influence cone. In the process of wavelet calculation, the coefficient of wavelet is convolved by the window function and wavelet. When the window is at the edge of the signal, there will be a part of it without signal, and the wavelet transform assumes that the data is cyclic, but usually the time series we need to process is limited, in order to meet this precondition of wavelet transform, In the process of wavelet transform, MATLAB will automatically zero-fill the incomplete signal in the window, and make up enough length. Due to forced zero-fill, it will lead to signal distortion and edge effect. In order to determine the influence of edge effect, an influence curve is drawn, which is also known as the influence cone. Therefore, in the interpretation of the wavelet coherence graph, the results in the influence cone are mainly used. The black closed contour in the figure is achieved using Monte Carlo simulation, indicating that it passes the significance test at a significance level of 5%.

As shown in Figure 1, the volatility of the foreign exchange markets of the United States and Hong Kong, China is highly consistent, both of which began to show a significant short-term volatility trend in 2015, and showed a significant long-term volatility of more than 512 days from 2011 to 2019, while the volatility of the foreign exchange markets of the European Union, Japan and the United Kingdom was relatively similar. In 2009 and 2011, there were significant short-term and long-term volatility trends. Among them, the EU foreign exchange market showed a short-term volatility trend of 64 days or less in 2015, while the Japanese foreign exchange market showed short-term volatility in 2013, 2017 and 2020 respectively. During this period, there was a long-term volatility of 512 days. The UK forex market showed significant short-term volatility in 2017 and 2020. According to the results of the wavelet power spectrum, the subprime crisis in 2007 had a long-term impact on the US foreign exchange market and the foreign exchange market in Hong Kong, China, which lasted for many years, while it had a certain long-term impact on the foreign exchange market in the European Union, Japan and the United Kingdom, but the impact lasted for a short time. The new coronavirus has swept the world in 2020, and these events have had a certain impact on the foreign exchange market.



(a) (b) (c)

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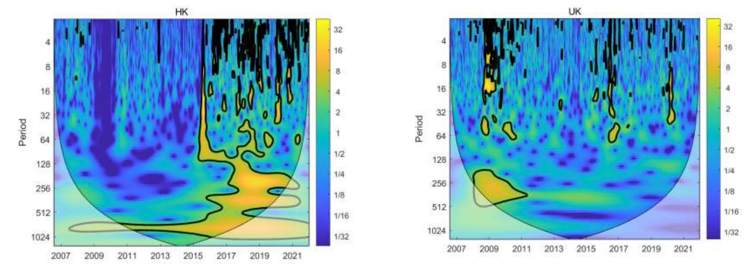
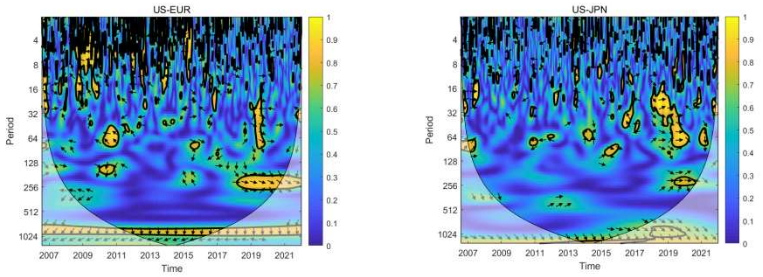


(d) (e)

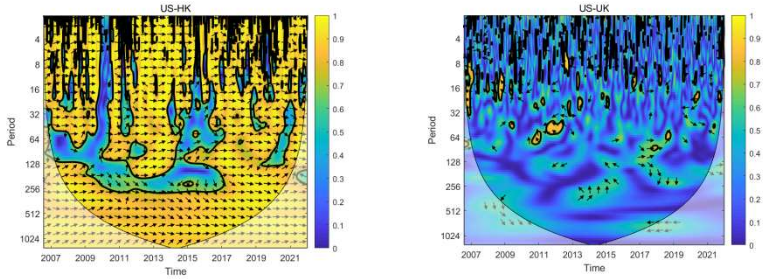
Figure 1. Wavelet power spectrum of each foreign exchange market

3.2.2. Wavelet Coherence Results

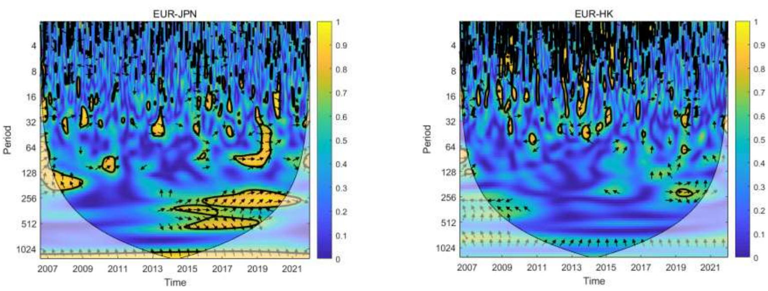
Next, wavelet coherence graph is used to analyze the correlation between the two pairs in the foreign exchange market. It can be seen from Figure 2(c) that there is a highly correlated interaction between the US foreign exchange market and the Hong Kong foreign exchange market, whether it is a short-term trend of 64 days or less or a long-term trend of 128 days or more. The arrow points to the right, indicating that the US foreign exchange market and the Hong Kong foreign exchange market are mutually reinforcing. Figure 2(a) shows that the US forex market leads the EU forex market in a long-term trend of 1024 days, and Figure 2(g) shows that the Hong Kong forex market leads the EU forex market in a long-term trend of 256-512 days from 2008 to 2016, and the other markets have some correlation on different scales.



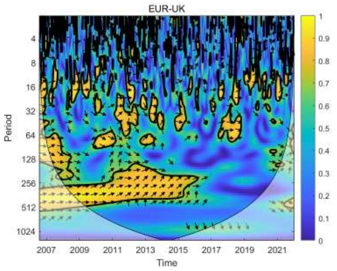
(a) (b)



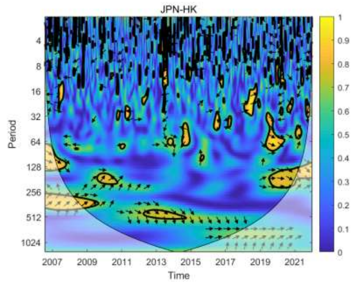
(c) (d)



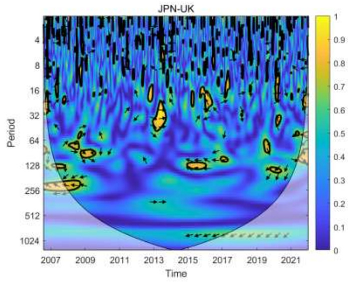
(e) (f)



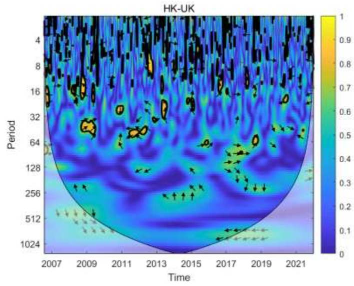
(g)



(h)



(i)



(j)

Figure 2. Wavelet coherence between pairwise foreign exchange markets

3.2.3. Systemic Financial Risk Spillover Effect and Network Topology of Foreign Exchange Market

Table 2 lists the static spillover indexes of the five foreign exchange markets, and it can be seen that TCI=36.73%, indicating that 36.73% of the risk changes in each market are explained by the risk changes in other markets. According to the correlation between the foreign exchange markets of different countries and regions, the correlation between the foreign exchange markets of the United States and Hong Kong is the strongest, followed by the foreign exchange markets of the European Union and the United Kingdom. From the perspective of directional spillover, the spillover and inflow levels of foreign exchange markets in different countries and regions fluctuate within the range of 13.112%~58.106% and 16.932%~52.243%, respectively. From the perspective of spillover (TO), the spillover effects of the US foreign exchange market and the Hong Kong foreign exchange market on other markets are relatively high. FROM the perspective of inflow, the highest inflow effect on other countries and regions is still the US foreign exchange market and the Hong Kong foreign exchange market, which are 52.243% and 50.482%, respectively. From the perspective of NET spillover (NET spillover), the net spillover value of the United States and Hong Kong of China is positive, and they are net risk exporters, while the net spillover value of the European Union foreign exchange market, the Japanese foreign exchange market and the British foreign exchange market is negative, and they are net risk recipients.

Table 2. Static spillover index of Foreign exchange market (%)

	US	EUR	JPN	HK	UK	FROM
US	47.757	6.398	3.19	40.273	2.382	52.243
EUR	8.306	63.968	4.614	5.943	17.169	36.032
JPN	4.816	5.17	83.068	4.026	2.92	16.932
HK	41.351	4.611	2.913	49.518	1.607	50.482
UK	3.633	19.364	2.396	2.567	72.039	27.961
TO	58.106	35.543	13.112	52.809	24.079	183.65
NET	5.863	-0.489	-3.82	2.327	-3.881	TCL=36.73

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Then, the dynamic spillover effect analysis of systemic financial risks in the foreign exchange market is carried out. AIC criterion is adopted to determine the order, the lag order is selected as 1 order, and the dynamic spillover effect of systemic financial risks is calculated 100 steps forward.

Since the static spillover feature in Table 2 can only analyze the average level of each foreign exchange market during the whole sample period, and cannot represent the time-varying characteristics of the interaction between various markets, this paper further analyzes the dynamic characteristics of each foreign exchange market. Figure 3 to Figure 7 are the dynamic trend charts of the total spillover index of the system, the directional spillover index, the net spillover index and the net pairing spillover index of each market respectively.

Figure 3 shows the total spillover index of systemic financial risk in the foreign exchange market. It shows that the spillover index of systemic financial risk in 2008 and 2015 showed an obvious surge, which was related to the 2008 financial crisis and the 2015 stock market crash in China. The impact of external events would lead to the increase of systemic financial risk.

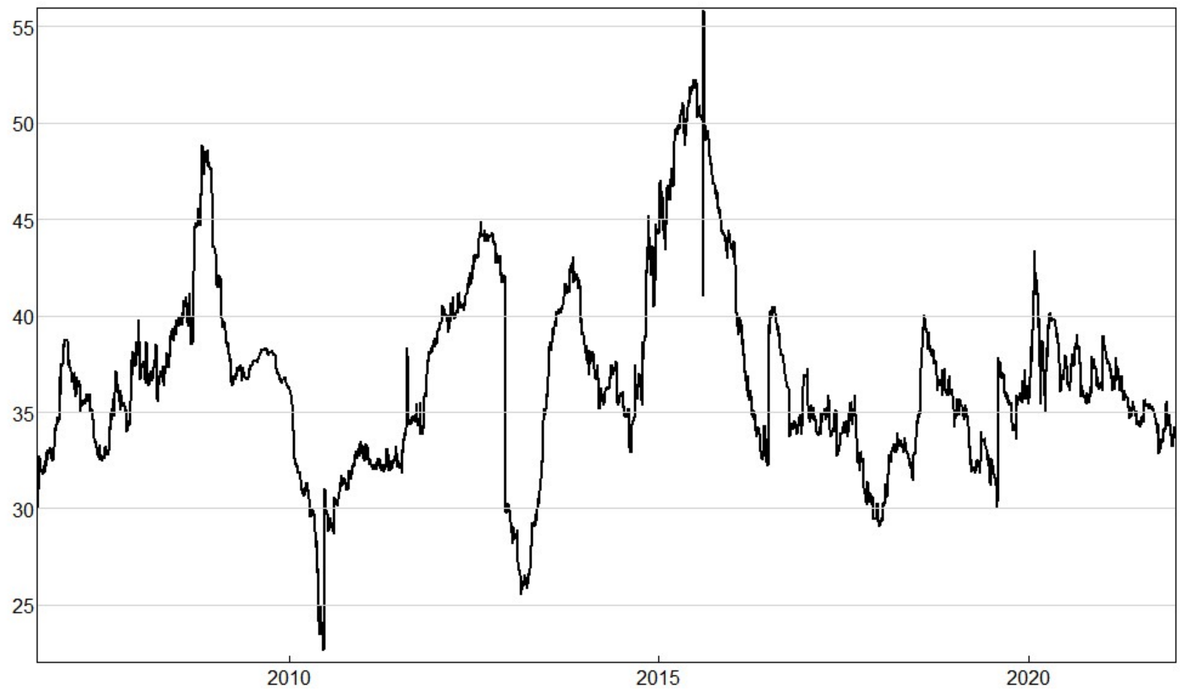

Figure 3. The total connectedness

Figure 4 and Figure 5 respectively show the dynamic temporal trend of the external directional spillover index of each foreign exchange market. Figure 4 represents the dynamic spillover effect of a certain market fluctuation on other markets (TO others), and Figure 5 represents the dynamic spillover effect of a certain market on other markets (FROM others). As can be seen from the figure, there are obvious differences in the spillover or spillover effect of various foreign exchange markets, among which the spillover effect of the US foreign exchange market and the Hong Kong foreign exchange market are highly consistent, and the change trend of spillover effect of the other three markets is similar.

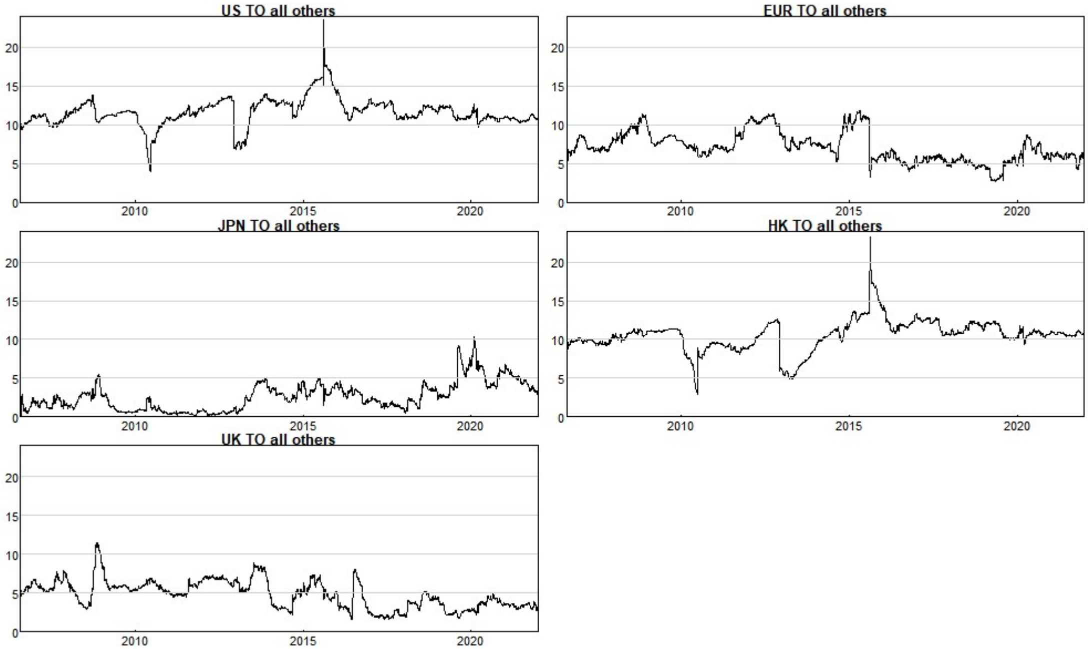

Figure 4. Dynamic spillovers of each forex market from other markets

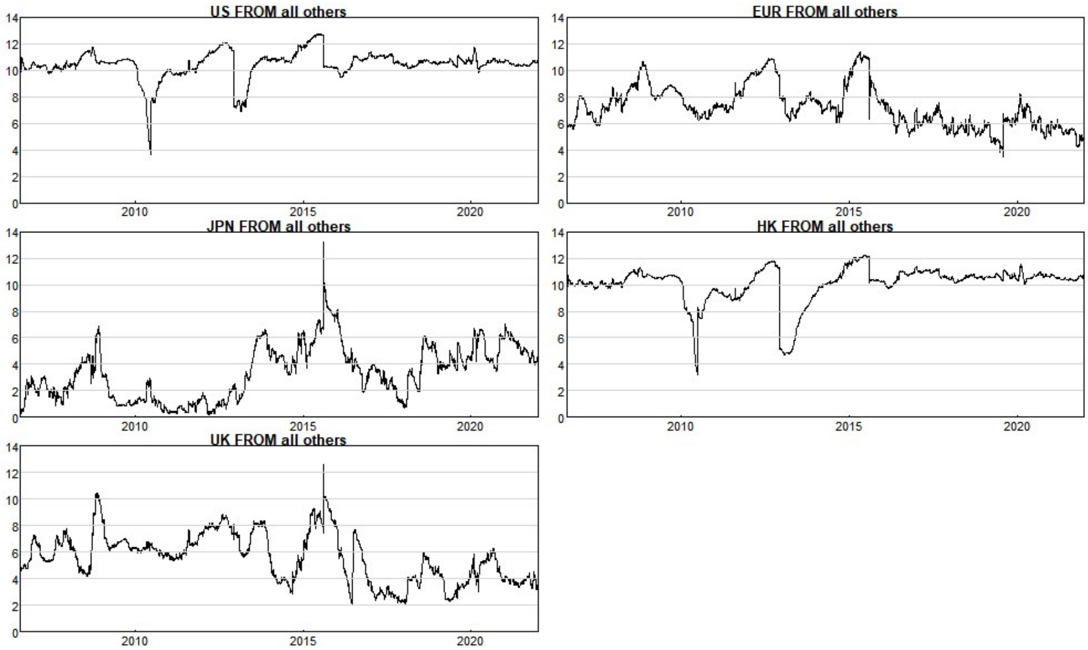

Figure 5. Dynamic spillover from other markets in each foreign exchange market

Figure 6 shows the time-varying characteristics of the net directional spillover index for each foreign exchange market. It can be seen that during the whole sample period, the net spillover index of the US foreign exchange market (US) and the Hong Kong foreign exchange market (HK) is positive in most cases, indicating that the volatility spillover effect of the US and Hong Kong foreign exchange market on other markets is significantly greater than the volatility spillover effect received from other markets, and they maintain the role of net risk exporters in risk transmission. The net spillover index of the EU Foreign Exchange market (EUR), Japan Foreign Exchange Market (JPN) and UK Foreign Exchange market (UK) is negative in most cases and acts as a net recipient of risk in risk transmission.

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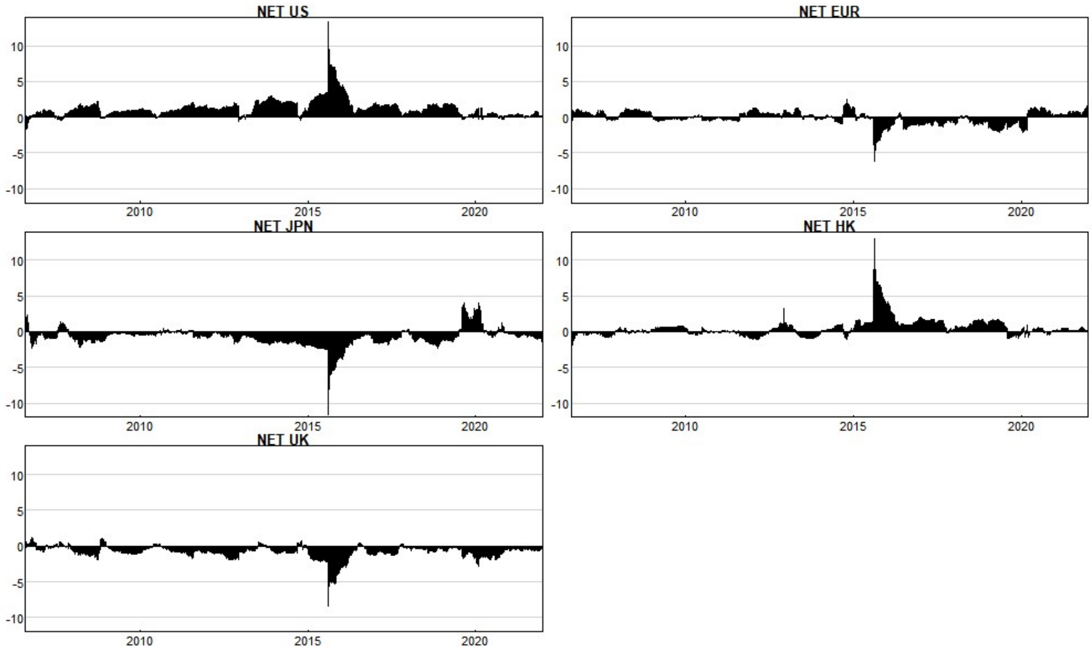

Figure 6. Net spillovers by foreign exchange market

It can be seen from the analysis that each market has different levels of spillover and spillover into other markets, but the above can only see the volatility spillover effect of one market on all the remaining markets, and cannot observe the volatility spillover effect between pairwise paired markets. Therefore, we will conduct pairwise paired analysis between different markets. Further study the correlation between the two markets and the specific direction of volatility spillover between them, as shown in Figure 7.

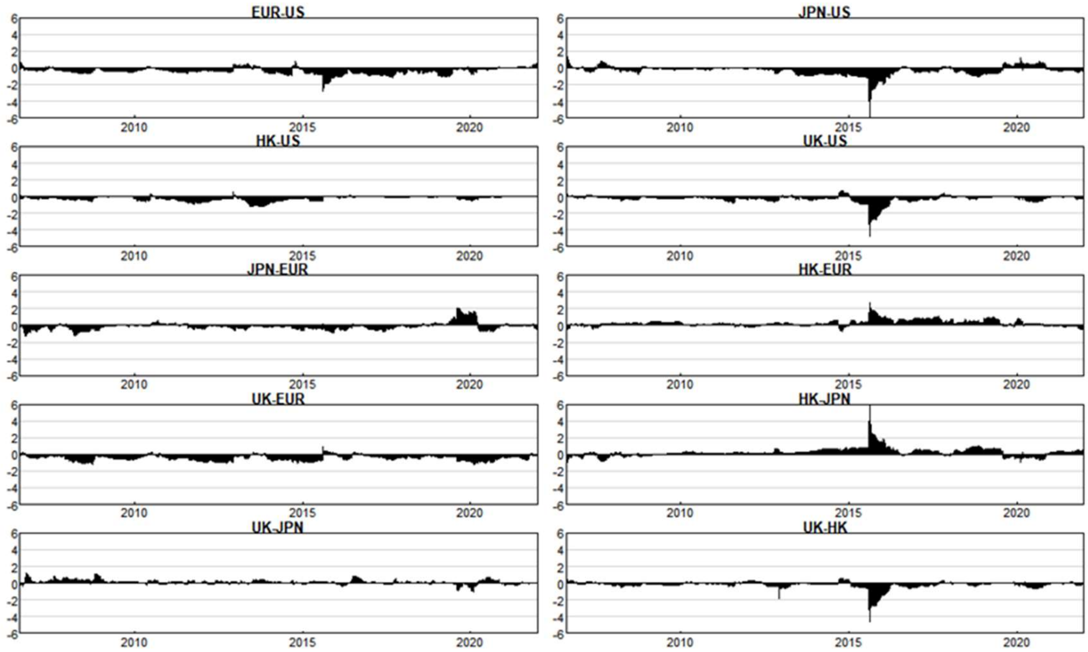

Figure 7. The pairwise connectedness

As can be seen from Figure 7, the US foreign exchange market and other foreign exchange markets basically show the position of net exporter of volatility spillovers. Except the US foreign exchange market, the Hong Kong foreign exchange market is the net exporter of risk spillovers from other foreign exchange markets, while the UK foreign exchange market is the net recipient

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of risk in the EU foreign exchange market and the Hong Kong foreign exchange market. Before 2020, Japan's foreign exchange market was basically a net recipient of risk in other foreign exchange markets. In 2020, Japan's foreign exchange market briefly changed its status and became a net exporter in other foreign exchange markets, which may be related to the COVID-19 pandemic in 2020, which began to break out on a large scale in Asia. The resulting increase in financial risks in the Japanese foreign exchange market has created a systemic financial risk spillover to the rest of the foreign exchange market.

4. Conclusion and Suggestions

This paper uses the daily time series data of foreign exchange markets in five different countries and regions from August 2, 2006 to December 31, 2021, including US dollar (US), euro (EUR), Japanese yen (JPN), Hong Kong dollar (HK) and British pound (UK), to study the representative systemic financial risk spillover effects of foreign exchange markets.

Firstly, wavelet power spectrum and wavelet coherence are used to analyze the volatility and interaction of each market affected by exogenous events. It is found that the volatility of the foreign exchange market of the United States and Hong Kong, China is highly consistent, and there is a mutual promotion relationship. The volatility of the other three markets is similar, and there is an interaction relationship in a certain frequency domain scale. Each foreign exchange market has a certain reaction to the impact of exogenous events.

Then, the time-varying vector autoregressive spillover index model (TVP-VAR-DY) is used for empirical research to capture the risk spillover characteristics of the foreign exchange market. The study found that 36.73% of the change in risk in each market is explained by the change in risk in other markets. From the correlation degree of foreign exchange markets in different countries and regions, it can be seen that the correlation between the US and Hong Kong foreign exchange market is the strongest, followed by the EU and the UK foreign exchange market; From the perspective of dynamic characteristics, during the "subprime mortgage" crisis in the United States in 2008 and the "stock market crash" in China in 2015, the systemic financial risk spillover index rose sharply, and the spillover or spillover effect of each foreign exchange market was significantly different, among which the spillover effect of the foreign exchange market in the United States and the foreign exchange market in Hong Kong was highly consistent. The spillover effect of the other three markets has a similar change trend. The US and Hong Kong foreign exchange markets maintain the role of net risk exporter in the risk transmission, while the EU, Japan and UK foreign exchange markets are net risk recipients in the risk transmission. Around 2020, the Japanese foreign exchange market has undergone a brief change of identity. Net recipients from other foreign exchange markets have become net exporters from other foreign exchange markets, which is related to the occurrence of the COVID-19 event in 2020.

In today's global economic integration, financial and economic turbulence in any country or region will cause overall changes in the world economy, and the financial risks generated in the foreign exchange market are inevitable. We can only minimize the probability of systemic financial risks and prevent external events from causing a country's economy and finance to suffer a huge impact, which will lead to a series of butterfly effects. Government departments of all countries should strengthen systemic financial supervision, coordinate development with financial regulators of other countries and regions, minimize the occurrence of domestic systemic financial risks caused by external financial turbulence, and achieve stable development and win-win results.

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