

Risk spillover effect between the stock markets of China and Europe

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Abstract. Global integration has had a significant impact on stock markets, promoting cross-border investment and capital flows, leading to closer connections between international stock markets. In this study, the SSEC index, SCI index, FTSE 100 index, DAX 30 index, and CAC 40 index were selected as research objects. Calculating the Value at Risk (VaR) of the stock market, and subsequently obtain indicators such as ΔCoVaR to measure the risk spillover effect of major European stock markets on the Chinese stock market.

Keywords: risk spillover; VaR; CoVaR.

1. Introduction

With the further advancement of economic globalization, trade and economic exchanges between countries have become more frequent. If a country completely isolates itself and refuses any interaction with the outside world, it is impossible to rely solely on self-reliance for economic development, and it will likely fall into poverty. After 30 years of development, the Chinese stock market has formed a distinctive path that is in line with the country's economic development. The market has continuously expanded in size, the number of listed companies has increased, and investor enthusiasm has improved. The institutional framework has also been increasingly perfected.

According to data released by the European Union's statistical office, in the first half of 2022, the trade volume between the 27 EU countries and China reached 413.9 billion euros, a year-on-year increase of 28.3%. China continues to be the EU's largest trading partner, and strengthening cooperation and exchanges with China have become increasingly important for European countries. Furthermore, with the opening of the Shanghai-London Stock Connect in 2019, investment products between different time zones and exchanges can be interconnected, allowing investors in the A-share market and the European market to invest in each other's products. This has further enhanced the depth and breadth of China's capital market opening, indicating that China's influence on European stock markets is becoming increasingly significant.

2. Literature References

The stock market crash in October 1987 intensified researchers' interest in the transmission of risks between international stock markets. When the US stock market experienced a significant decline, it triggered a widespread domino effect on global stock markets. King and Wadhwani (1990) were the first to study the stock market crash of 1987. Their research suggested that there is a contagion effect between different markets, and regardless of the value of information, these markets tend to overreact to fluctuations in other stock markets.

The effects of price and risk transmission between stock markets can be explained in two ways. Firstly, there may be a causal relationship between stock markets, where the volatility of one market is influenced by the volatility of another market. This is known as a lead-lag relationship, which occurs when the trading hours of the two countries do not overlap. The second way is through the influence of international factors that affect both markets, leading to a causal relationship between the two markets (Mishra et al., 2007). The research conducted by Diebold & Yilmaz (2012) suggests that the Diebold-Yilmaz volatility spillover index can be used to accurately predict the direction of volatility spillovers between markets. This index can identify which markets play a dominant role in increasing volatility (i.e., "giving" spillovers) and which markets passively receive the increase in

volatility (i.e., "receiving" spillovers). Additionally, the study found that this index performs well in predicting market volatility. Bae & Karolyi (2013) explored the risk transmission and volatility spillovers among global stock markets and discovered the impact of economic factors on stock market volatility. Feng et al. (2015) studied the risk spillover effects between the A-share market and global markets based on a multivariate volatility model. Kim & Rhee (2017) analyzed the risk transmission relationship between the US and European stock markets and investigated the interrelationship between stock returns and volatility. Yang & Zhang (2017) conducted modeling and calculations using data from the Shanghai and Shenzhen 300 Index and other major stock market indices in the US, Europe, and Asia. They found significant risk spillover effects, indicating that the Chinese stock market is influenced by major global stock markets, and the volatility spillovers from other major markets affect it. Deng et al. (2018) found a bidirectional risk transmission relationship between the Chinese stock market and major global stock markets at different frequency bands, indicating that their volatilities mutually influence each other. Uddin et al. (2018) investigated the dynamic spillover effects among crude oil, precious metals, and agricultural commodity futures markets, revealing the risk transmission relationships among different commodity markets. Zhang et al. (2019) studied the dynamic risk spillover effects between the Chinese stock market and the foreign exchange market, providing empirical evidence on risk transmission between different asset classes. Huang & Zhang (2020) used the dynamic conditional correlation method to analyze the risk spillover effects between the Chinese and US stock markets. By modeling and calculating data from the Shanghai Composite Index and the S&P 500 Index, they found significant risk spillover effects.

In addition, the research also found that risk spillovers between financial markets are more pronounced during crisis periods. Wu & Li (2019) used a risk spillover indicator based on the VAR model and conducted empirical analysis using correlation analysis and IRF methods. The results showed significant risk spillover effects between Chinese and European major stock markets. This spillover effect is particularly evident during financial crises. During these periods, there may be strong contagion effects between markets that go beyond what can be explained by economic fundamentals. This market contagion phenomenon indicates that shocks and volatility in financial markets have universal and global impacts. Therefore, the research results remind us that although each country and region has its unique economic and financial system, the volatility of stock markets in different countries seems to be interconnected. In investment and risk management, it is important to recognize the interdependence among international stock markets and the possibility of contagion effects between markets during crisis periods.

3. Theoretical design

3.1. VaR

The Vector Autoregressive Model (VAR model) is a non-structural equation system model, proposed by Sims in 1980. This model is not based on economic theory and is formulated as a system of multiple equations. In each equation of the model, the endogenous variables are regressed on the lagged terms of all endogenous variables in the model. This allows for the estimation of the dynamic relationships among all endogenous variables. VAR models are commonly used for forecasting interconnected time series systems and analyzing the dynamic impact of random disturbances on the variable system.

Value at Risk (VaR) is literally interpreted as the "value at risk" which represents the maximum potential loss that a financial instrument or portfolio may face under a certain confidence level and holding period, given future asset price fluctuations.

Assuming there is a relationship among variables y_{1t}, y_{2t} , if we separately establish two autoregressive models,

$$y_{1,t} = f(y_{1,t-1}, y_{1,t-2}, \dots)$$

$$y_{2,t} = f(y_{2,t-1}, y_{2,t-2}, \dots)$$

If we do not consider the variables together, we cannot capture the relationship between the two variables. By adopting a simultaneous approach, we can establish the relationship between the two variables. The structure of the VAR model depends on two parameters: the number of variables included (N) and the maximum lag order (k).

Taking an example of a VAR model with two variables, where variable $y_{1,t}, y_{2,t}$ lags one period, it can be represented as:

$$\begin{cases} y_{1,t} = \mu_1 + \pi_{11.1}y_{1,t-1} + \pi_{12.1}y_{2,t-1} + \mu_{1t} \\ y_{2,t} = \mu_2 + \pi_{21.1}y_{1,t-1} + \pi_{22.1}y_{2,t-1} + \mu_{2t} \end{cases}$$

$\mu_{1t}, \mu_{2t} \sim \text{IID}(0, \sigma^2), \text{Cov}(\mu_{1t}, \mu_{2t}) = 0$. In matrix form, it can be written as:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \pi_{11.1} & \pi_{12.1} \\ \pi_{21.1} & \pi_{22.1} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \end{bmatrix}$$

Assuming that: $Y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix}, \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \pi_1 = \begin{bmatrix} \pi_{11.1} & \pi_{12.1} \\ \pi_{21.1} & \pi_{22.1} \end{bmatrix}, \mu_t = \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \end{bmatrix}$

$$Y_t = \mu + \pi_1 Y_{t-1} + \mu_t$$

The VAR (Vector Autoregressive) model with N variables lagged by k periods is represented as follows:

$$Y_t = \mu + \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \dots + \pi_k Y_{t-k} + \mu_t, \mu_t \sim \text{IID}(0, \Omega)$$

$$Y_t = (y_{1,t}, y_{2,t}, \dots, y_{N,t})', \mu = (\mu_1, \mu_2, \dots, \mu_N)', \mu_t = (\mu_{1t}, \mu_{2t}, \dots, \mu_{Nt})'$$

$$\pi_j = \begin{bmatrix} \pi_{11.j} & \pi_{12.j} & \dots & \pi_{1N.j} \\ \pi_{21.j} & \pi_{22.j} & \dots & \pi_{2N.j} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{N1.j} & \pi_{N2.j} & \dots & \pi_{NN.j} \end{bmatrix}, j = 1, 2, \dots, k$$

Y_t is an $N \times 1$ order time-series column vector, $\pi_1, \dots, \pi_k$ is an $N \times 1$ order constant term column vector, b is an $N \times N$ order parameter matrix, $\mu \sim \text{IID}(0, \Omega)$ is an $N \times 1$ order column vector of random errors, where each element is non-autocorrelated, but there may be correlations between the error terms corresponding to different equations. In the VAR model, each equation's right-hand side only contains lagged terms of endogenous variables, which are uncorrelated with μ_t . Therefore, each equation can be estimated using the Ordinary Least Squares (OLS) method, and the resulting parameter estimates will be consistent.

3.2. CoVaR

The CoVaR (Conditional Value at Risk) method is based on the concept of conditional VaR. It measures the systemic risk of each financial institution by estimating its contribution, given the VaR of the entire system. By considering the sensitivity and correlation of financial institutions, CoVaR can help identify those institutions that have a larger negative impact on the stability of the entire financial system.

$CoVaR^{sys|X_i=VaR_q^i}$ represents the conditional value at risk of the system i , given a confidence level of $1-q$, when institution i 's loss value is used as the VaR:

$$pr(X^{sys} \leq CoVaR^{sys|X_i=VaR_q^i}) = q$$

The risk contribution of institution i to the system sys is represented as:

$$\Delta CoVaR_q^{sys|i} = CoVaR_q^{sys|X^i=VaR_q^i} - CoVaR_q^{sys|X^i=Mediam^i}$$

4. Empirical research

4.1. Data

The objective of this study is to examine the interdependence and risk spillover effects between China's A-share market and major European stock markets. Based on the analysis of the current development of European stock markets, three representative stock indices were selected: the Financial Times Ordinary Shares 100 Index (FTSE100) from the UK, the DAX30 Index from Germany, and the CAC40 Index from France. In addition, the Shanghai Securities Composite Index (SSEC) and the Shenzhen Component Index (SCI) from China were also included as research subjects. To mitigate the influence of other factors on the experimental results, the daily closing prices of each stock market were logarithmically transformed:

$$r_{i,t} = \ln P_{i,t} - \ln P_{i,t-1}$$

Where $r_{i,t}$ is the stock index return at time t , and $P_{i,t}$ is the stock price at time t .

4.2. Empirical results

Table 1 Summary statistics of the returns

	mean	std	min	max	skew	kurt	J-B
SCI	-0.00004	0.0158	-0.08824	0.062542	-0.68084	3.745968	9820**
SSEC	0.00003	0.01300	-0.08873	0.056036	-0.93604	6.738657	7653**
DAX30	0.00022	0.01294	-0.13055	0.104143	-0.47197	7.562739	7335**
FTSE100	0.00007	0.01025	-0.11512	0.086668	-0.71104	10.1032	7301**
CAC40	0.00017	0.01278	-0.13098	0.080561	-0.60546	7.880309	11671**

This table reports the descriptive statistics of the stock index returns. Normality is rejected at the 5% significance level. Mean is statistically not different from zero at the 5% significance level.

To calculate the risk excess using the quantile regression method, first estimate the parameter values α and β in the equation. Then calculate the VaR (Value at Risk) for each financial market. Further compute $CoVaR$ (Conditional Value at Risk) and $\Delta CoVaR$ (Adjusted Conditional Value at Risk). Normalize the results to obtain $\% \Delta CoVaR$. The specific results are shown in Table below: The quantile regression method is used to calculate the risk excess value at a 5% significance level.

Table 2 The spillover effect of major European stock markets on the Chinese stock market

	Market	CoVaR	$\Delta CoVaR$	$\% \Delta CoVaR$
SSEC	FTSE100	-0.0229	-0.00397	26.98%
	DAX30	-0.250	-0.00604	30.78%
	CAC40	-0.0259	-0.00254	18.36%
SCI	FTSE100	-0.0275	-0.00417	28.36%
	DAX30	-0.331	-0.00298	24.99%
	CAC40	-0.255	-0.00254	18.37%

According to the calculated risk spillover values, it can be observed that at a significance level of 5%, there are significant risk spillover effects among different markets. This indicates that during extreme risks in international financial markets, risk spillover is likely to occur. Based on the data in the table, it can be seen that for the Chinese mainland markets, the Shanghai Composite Index and the Shenzhen Composite Index are significantly influenced by the German stock market and the UK stock market. The standardized risk spillover value ($\% \Delta \text{CoVaR}$) from the German stock market to the Shanghai Composite Index reaches 30.78%, and to the Shenzhen Composite Index it reaches 24.99%. This indicates a close connection between these two European markets and the mainland market, with a significant impact on the risk spillover effect.

5. Summary

This article conducts an empirical analysis of the risk spillover effects between the Chinese and European stock markets based on daily closing price data from January 1, 2011, to December 31, 2022. The ΔCoVaR and $\% \Delta \text{CoVaR}$ indicators are calculated to measure the risk spillover effects of the European stock markets on the Chinese market. To maintain financial market stability, regulatory authorities need to focus on the risk issues in domestic stock markets and strengthen supervision over the stock market. Financial institutions also need to enhance risk management awareness. Government departments must recognize the severe situation of risk prevention and control in China and establish and implement long-term mechanisms for systemic risk prevention and mitigation.

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