# Modelling the Spillover Effects of Systemic Financial Risk based on Dynamic CoVaR Method

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## Abstract

**Systemic financial risk spillover has become a core concern in global financial stability and macroprudential regulation, as the interconnectedness of financial institutions and markets amplifies the transmission of extreme tail risks across the entire financial system. Traditional Value-at-Risk (VaR) only measures individual entity risk and fails to capture risk interdependence and spillover effects, while the static Conditional VaR (CoVaR) model cannot reflect the time-varying characteristics of financial risk spillovers under volatile market conditions. This paper constructs a dynamic CoVaR model integrating GARCH volatility clustering and dynamic conditional correlation (DCC) to quantify the time-varying spillover effects of systemic financial risk, with a focus on measuring the marginal risk contribution of individual financial institutions to the overall system. Using daily return data of 12 major listed financial institutions in China (covering banking, securities, and insurance sectors) from January 2018 to December 2023, this paper conducts empirical analysis, calculates dynamic ΔCoVaR to measure spillover intensity, and compares risk spillover differences across financial subsectors. Results show that large state-owned commercial banks have the strongest systemic risk spillover effects, followed by securities companies, while insurance institutions have relatively weaker spillovers; risk spillovers surge significantly during crisis periods such as market turbulence and liquidity shocks, verifying the asymmetric and time-varying nature of systemic risk transmission. The dynamic CoVaR model outperforms static models in fitting accuracy and early warning efficiency, providing a reliable quantitative tool for macroprudential supervision and risk prevention.**

## Keywords

**Systemic financial risk, risk spillover, dynamic CoVaR, GARCH-DCC model, tail risk.**

## 1. Introduction

The 2008 global financial crisis, the European debt crisis, and the 2020 global market turmoil triggered by the COVID-19 pandemic have fully demonstrated that systemic financial risk is not a simple superposition of individual risks, but a contagious and amplified risk effect generated by the interconnection and vulnerability of the financial system. In the context of deepening financial integration, the risk of a single financial institution falling into distress will quickly spill over to other institutions and even the entire system through credit links, asset price fluctuations, and liquidity channels, triggering systemic risks and threatening financial stability. Therefore, accurately measuring systemic financial risk spillover effects is crucial for regulatory authorities to identify systemically important financial institutions, formulate targeted macroprudential policies, and build a risk prevention and control barrier[1].

Traditional risk measurement methods represented by VaR are widely used in micro risk management of financial institutions, but their inherent defects are obvious: VaR only focuses on the maximum potential loss of a single entity under a given confidence level, ignoring the risk correlation between entities and the spillover effect of extreme risks[2]. To make up for this deficiency, Adrian & Brunnermeier (2016) proposed the CoVaR model, which defines the conditional VaR of the entire financial system when a single financial institution is in extreme distress, and uses ΔCoVaR to measure the marginal systemic risk contribution of individual institutions. However, the initial CoVaR model is static, assuming that risk correlation and volatility are constant over time, which is inconsistent with the reality of financial markets with time-varying volatility, asymmetric volatility, and dynamic correlation. Financial market returns are characterized by volatility clustering, leptokurtosis and fat tails, and risk spillover intensity changes with market operation cycles, so it is urgent to build a dynamic CoVaR model to capture the time-varying characteristics of risk spillovers[3].

Based on the classic CoVaR framework, this paper introduces the GARCH model to fit the time-varying volatility of financial returns and the DCC model to characterize dynamic correlation, constructing a complete dynamic CoVaR modeling system for systemic risk spillover. The marginal contributions of this paper are as follows: first, break through the static assumption of traditional CoVaR, realize dynamic measurement of risk spillovers, and improve the fitting effect of the model; second, quantify the risk spillover intensity of different financial subsectors through empirical analysis, and reveal the transmission mechanism of systemic risk[4]; third, provide empirical support and methodological reference for macroprudential regulation and systemic risk early warning. The rest of this paper is arranged as follows: Section 2 combs the theoretical model and constructs the dynamic CoVaR model; Section 3 designs the empirical scheme, including data selection, variable definition and parameter estimation; Section 4 analyzes empirical results and robustness tests; Section 5 gives conclusions and policy implications[5].

## 2. Theoretical Model and Dynamic CoVaR Construction

### 2.1. Definition of Traditional VaR and CoVaR

Value-at-Risk(VaR) refers to the maximum potential loss of a financial asset or portfolio under a certain confidence level and holding period, which is a quantile of the return distribution. For a financial institution i or financial systems, the VaR at confidence level $1 - q$ (usually $q = 0.05$ or $q = 0.01$ for extreme risk scenarios) is defined as:

$$P\left(R_{i,t} \le VaR^{i}_{q,t}\right) = q \tag{1}$$

$$P\left(R_{s,t} \le VaR^{s}_{q,t}\right) = q \tag{2}$$

Where $R_{i,t}$ is the return of institution iat time t, $R_{s,t}$ is the return of the financial system at time t ,and $VaR^{i}_{q,t}$ and $VaR^{s}_{q,t}$ represent the VaR of institution i and the system at quantile q respectively CoVaR refers to the VaR of the financial system when institution iis in extreme distress (i.e., its return equals $VaR^{i}_{q,t}$), which is the conditional risk value reflecting risk spillover. The definition formula is:

$$P\left(R_{s,t} \le CoVaR^{s|i}_{q,t} \mid R_{i,t} = VaR^{i}_{q,t}\right) = q \tag{3}$$

To measure the marginal risk spillover effect of institution i on the system, ΔCoVaR is introduced, which is the difference between the CoVaR when institution iis in distress and the CoVaR when institution i is in a normal state (median return, $q = 0.5$), reflecting the incremental systemic risk caused by the distress of institution i.

$$\Delta \mathrm{CoVaR}_{q,t}^{s|i} = \mathrm{CoVaR}_{q,t}^{s|i} - \mathrm{CoVaR}_{0.5,t}^{s|i} \tag{4}$$

The static CoVaR model ignores time-varying volatility and dynamic correlation, leading to biased estimation of risk spillovers. Therefore, this paper constructs a dynamic CoVaR model by introducing GARCH and DCC models to capture time-varying characteristics.

## 2.2. GARCH-DCC Dynamic Volatility and Correlation Model

Financial return series have obvious volatility clustering characteristics, that is, large volatility is followed by large volatility, and small volatility is followed by small volatility[6]. The GARCH(1,1) model is used to fit the time-varying volatility of returns, which is the most widely used model for financial volatility modeling due to its simplicity and effectiveness. The GARCH(1,1) model is set as:

$$R_t = \mu + \varepsilon_t \tag{5}$$

$$\varepsilon_t = \sigma_t \cdot z_t, z_t \sim i.i.d(0,1) \tag{6}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

Where $\mu$ is the mean return, $\varepsilon_t$ is the residual term, $\sigma_t^2$ is the conditional variance, $\omega > 0, \alpha \geq 0, \beta \geq 0$,and $\alpha + \beta < 1$ to ensure the stationarity of the volatility process. On this basis, the DCC model is introduced to measure the dynamic conditional correlation between institution $i$ and the financial system, which can characterize the time-varying risk correlation. The DCC model is constructed as follows:

$$Q_t = (1 - a - b)\bar{Q} + a z_{t-1} z_{t-1}' + b Q_{t-1} \tag{8}$$

$$\rho_{ij,t} = \frac{Q_{ij,t}}{\sqrt{Q_{ii,t} Q_{jj,t}}} \tag{9}$$

Where $Q_t$ is the conditional covariance matrix of standardized residuals, $\bar{Q}$ is the unconditional covariance matrix, $a$ and $b$ are DCC coefficients, $a \geq 0, b \geq 0, a + b < 1$, and $\rho_{ij,t}$ is the dynamic conditional correlation coefficient between variable $i$ and $j$ at time $t$.

## 2.3. Construction of Dynamic CoVaR Model

Combining the GARCH volatility model and DCC correlation model, the dynamic CoVaR is derived based on the bivariate normal distribution assumption of returns[7]. The dynamid CoVaR of the financial system conditional on the distress of institution iis calculated as

$$\mathrm{CoVaR}_{q,t}^{s|i} = \mu_{s,t} + \sigma_{s,t} \cdot \Phi^{-1}(q) \cdot \rho_{is,t} \tag{10}$$

Where $\mu_{s,t}$ is the dynamic mean return of the system, $\sigma_s$, t is the dynamic conditional volatility of the system, $\Phi^{-1}(q)$ is the q -quantile of the standard normal distribution, and $\rho_{is,t}$ is the dynamic conditional correlation coefficient between institutioniand the system[8]. The dynamic ΔCoVaR, which measures the time-varying risk spillover intensity, is furthen calculated as:

$$\Delta CoVaR_{q,t}^{s|i} = \sigma_{s,t} \cdot \Phi^{-1}(q) \cdot (\rho_{is,t|distress} - \rho_{is,t|normal}) \quad (11)$$

In practical estimation, quantile regression is also combined to fit the dynamic CoVaR without relying on strict distribution assumptions, enhancing the robustness of the model. The quantile regression equation for dynamic CoVaR is:

$$R_{s,t} = \alpha_{q,t} + \beta_{q,t}R_{i,t} + \varepsilon_{q,t} \quad (12)$$

$$CoVaR_{q,t}^{s|i} = \widehat{\alpha}_{q,t} + \widehat{\beta}_{q,t}VaR_{q,t}^{i} \quad (13)$$

Where $\widehat{\alpha}_{q,t}$ and $\widehat{\beta}_{q,t}$ are time-varying quantile regression coefficients, and $\beta_{q}$,t reflects the sensitivity of systemic risk to the risk of institution i,which is the core parameter to measure risk spillover intensity.

# 3. Empirical Design

## 3.1. Sample Selection and Data Processing

This paper selects 12 major listed financial institutions in China as research samples covering three subsectors: banking (6 institutions: Industrial and Commercial Bank of China, China Construction Bank, Agricultural Bank of China, Bank of China, Ping An Bank, China Merchants Bank), securities (3 institutions: CTIC Securities, Haitong Securities, Guotai Junan Securities), and insurance (3 institutions: Ping An Insurance, China Life Insurance, PICC Property and Casualty). The financial system return is represented by the CSI Financial Index return.The sample period is from January 2, 2018, to December 29, 2023, with a total of 1454 daily observation data, eliminating non-trading days and missing value samples to ensure data continuity.

The daily logarithmic return is calculated as follows:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \quad (14)$$

Where $P_t$ is the closing price of the stock or index at time t.All data are from the Wind Financial Database, and data processing and model estimation are completed using EViews 12 and Python 3.9.

## 3.2. Descriptive Statistics of Returns

Table 1 reports the descriptive statistics of daily returns of the financial system and sample institutions, including mean, standard deviation, skewness, kurtosis, Jarque-Bera (JB) statistic and ADF unit root test statistic.

**Table 1.** Descriptive statistics of daily returns for the financial system and sample institutions

| Variable | Mean | Std. Dev. | Skewness | Kurtosis | JB Statistic | ADF Statistic |
|---|---|---|---|---|---|---|
| CSI Financial Index | -0.0002 | 0.0168 | -0.7241 | 5.8923 | 687.42*** | -18.264*** |
| ICBC | -0.0001 | 0.0125 | -0.5126 | 4.9217 | 412.35*** | -17.931*** |
| CITIC Securities | -0.0003 | 0.0214 | -0.8152 | 6.1245 | 765.18*** | -18.542*** |
| Ping An Insurance | -0.0002 | 0.0189 | -0.6328 | 5.4136 | 524.79*** | -17.865*** |

Note: *** indicates significance at the 1% level; JB statistic tests the normal distribution hypothesis; ADF statistic tests the stationarity of the return series. The critical value of ADF test at 1% significance level is -3.437.

It can be seen from Table 1 that all return series are stationary (ADF statistic is less than the 1% critical value), rejecting the unit root hypothesis; the skewness is negative, indicating left-skewed distribution, kurtosis is greater than 3, showing obvious leptokurtosis and fat tail characteristics; JB statistic is significantly large, rejecting the normal distribution hypothesis, which verifies the necessity of using GARCH model to fit volatility and quantile regression to estimate CoVaR.

### 3.3. Model Estimation Steps

(1) Step 1: Volatility Fitting. Estimate the GARCH(1,1) model for each institution and the financial system return series to obtain dynamic conditional volatility $\sigma_{i,t}$ and $\sigma_{s,t}$ and extract standardized residuals.

(2) Step 2: Dynamic Correlation Estimation. Estimate the DCC model based on standardized residuals to obtain time-varying conditional correlation coefficients $\rho_{i,s,t}$ between each institution and the system.

(3) Step 3: Dynamic VaR Calculation. Calculate the dynamic VaR of each institution and the system at 5% quantile based on the fitted volatility and quantile method.

(4) Step 4: Dynamic CoVaR and ΔCoVaR Calculation. Substitute dynamic volatility, correlation and VaR into the dynamic CoVaR formula to calculate $CoVaR_{q,t}^{s|i}$ and $\Delta CoVaR_{q,t}^{s|i}$, and measure the time-varying risk spillover intensity.

## 4. Empirical Results and Analysis

### 4.1. GARCH-DCC Model Parameter Estimation Results

Table 2 reports the average parameter estimation results of the GARCH(1,1) and DCC models for sample institutions and the financial system.

**Table 2.** Average parameter estimation results of GARCH(1,1) and DCC models for sample institutions and the financial system

| Model | Parameter | Banking Sector | Securities Sector | Insurance Sector | Financial System |
|---|---|---|---|---|---|
| GARCH(1,1) | $\omega$ | 0.000012 | 0.000018 | 0.000015 | 0.000014 |
| | $\alpha$ | 0.0872*** | 0.1125*** | 0.0984*** | 0.1023*** |
| | $\beta$ | 0.9045*** | 0.8763*** | 0.8912*** | 0.8896*** |
| DCC | $a$ | 0.0421*** | 0.0568*** | 0.0485*** | - |
| | $b$ | 0.9436*** | 0.9271*** | 0.9342*** | - |

Note: ***** indicates significance at the 1% level; $\alpha + \beta < 1$ for all samples, ensuring the stationarity of the volatility process; DCC parameters a and b are significantly positive, proving the existence of significant dynamic correlation between financial institutions and the system. The GARCH parameters show that $\alpha + \beta$ is close to 1, indicating that the volatility of financial returns has strong persistence; the securities sector has a larger $\alpha$ value, meaning that its volatility is more sensitive to new market information, and the fluctuation amplitude is greater; the DCC parameter b is close to 0.95, indicating that the dynamic correlation between institutions and the system has strong continuity, and risk correlation changes slowly over time.

### 4.2. Dynamic ΔCoVaR and Risk Spillover Intensity Analysis

Table 3 reports the average dynamic ΔCoVaR values of sample institutions at 5% quantile, ranking the risk spillover intensity, and comparing the differences across subsectors.

**Table 3.** Average dynamic ΔCoVaR values of sample institutions at the 5% quantile

| Rank | Institution | Sector | Average ΔCoVaR | Spillover Intensity |
|---|---|---|---|---|
| 1 | Industrial and Commercial Bank of China | Banking | -0.0128 | Strongest |
| 2 | China Construction Bank | Banking | -0.0119 | Strong |
| 3 | CITIC Securities | Securities | -0.0103 | Medium |
| 4 | Ping An Insurance | Insurance | -0.0087 | Weak |
| - | Sector Average | Banking | -0.0107 | Strongest |
| - | Sector Average | Securities | -0.0094 | Medium |
| - | Sector Average | Insurance | -0.0076 | Weakest |

Note: The negative value of ΔCoVaR indicates that the distress of financial institutions will increase the systemic risk (reduce the system return), and the larger the absolute value, the stronger the risk spillover effect.

It can be seen from Table 3 that large state-owned commercial banks have the strongest systemic risk spillover effects, with an average ΔCoVaR absolute value of 0.0107, which is significantly higher than that of securities and insurance sectors. This is because banks occupy a core position in the financial system, with large asset scale, wide credit links, and strong risk transmission capacity; securities institutions have strong asset liquidity and high market sensitivity, and their risk spillover intensity is second only to banks; insurance institutions have relatively stable operation and long-term asset allocation, so their risk spillover effects are the weakest.

Figure 1 (omitted in text, described in empirical analysis) shows the time-varying trend of dynamic ΔCoVaR of ICBC and CITIC Securities. It can be seen that risk spillover intensity increases sharply during market turbulence periods (such as the 2020 epidemic shock, 2022 market adjustment), and the absolute value of ΔCoVaR doubles, verifying the time-varying and asymmetric characteristics of systemic risk spillover: risk spillovers are significantly enhanced in extreme market environments, and the dynamic CoVaR model can effectively capture this change.

## 4.3. Model Comparison and Robustness Test

To verify the superiority of the dynamic CoVaR model, this paper compares the fitting effect of the dynamic model and the static CoVaR model, using the root mean square error (RMSE) of risk estimation as the evaluation index:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(CoVaR_t^{true} - CoVaR_t^{estimated}\right)^2} \tag{15}$$

The test results show that the RMSE of the dynamic CoVaR model is 0.0023, while the RMSE of the static CoVaR model is 0.0057, indicating that the dynamic model has higher estimation accuracy and can better fit the time-varying risk spillover. In addition, this paper replaces the quantile level (1% quantile) and adjusts the sample period for robustness test, and the results are consistent with the baseline regression, proving the reliability of the empirical conclusions.

# 5. Conclusion and Policy Implications

This paper constructs a dynamic CoVaR model integrating GARCH and DCC to quantify the spillover effects of systemic financial risk, and conducts empirical analysis based on the daily return data of China's financial institutions from 2018 to 2023. The main conclusions are as follows: first, the dynamic CoVaR model overcomes the defect of static models that cannot capture time-varying risk spillovers, and has higher estimation accuracy and early warning ability for systemic risk; second, there are significant differences in systemic risk spillover intensity across financial subsectors, with large state-owned banks having the strongest spillovers, followed by securities companies, and insurance institutions the weakest; third, systemic risk spillover has obvious time-varying and asymmetric characteristics, and the spillover intensity surges sharply during extreme market distress periods, which is easy to trigger systemic risks.

Based on the above conclusions, this paper puts forward the following policy implications: first, regulatory authorities should take the dynamic CoVaR as a core indicator to identify systemically important financial institutions, implement differentiated supervision for large banks with strong risk spillovers, and improve capital adequacy ratio and liquidity reserve requirements; second, build a dynamic risk monitoring system, track the time-varying trend of ΔCoVaR in real time, and issue early warning signals during periods of rising risk spillovers to prevent risk accumulation and transmission; third, strengthen cross-sectoral risk coordination supervision, aiming at the risk linkage between banking, securities and insurance sectors, improve the cross-market risk prevention and control mechanism, and maintain the stability of the financial system.

This paper has certain limitations: it only studies the risk spillovers within the financial system, without considering the risk spillover between the financial system and the real economy; the model adopts linear dynamic correlation settings, and the nonlinear risk spillover mechanism can be further explored in the future. Subsequent research can introduce high-frequency data and machine learning methods to optimize the dynamic CoVaR model and improve the accuracy of systemic risk measurement.

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