Development Economics of China
2025, VOL. 9, NO. 6, 87-94
DOI: 10.47297/wspdecWSP2515-797317.20250906

Research on Risk Spillover Effects of A-Share Sector Indices Based on EVT-GARCH-Quantile Regression

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ABSTRACT
This study investigates the risk spillover effects among A-share sector indices by constructing an integrated EVT-GARCH-quantile regression framework. Using daily data from five major sector indices (including CSI 300, Financials, Technology, etc.) between January 2020 and June 2024, we employ the EVT-POT model to characterize tail distributions, the DCC-GARCH model to capture dynamic volatility correlations, and quantile regression to quantify spillover intensities under extreme risks. Key findings include: (1) The CSI 300 exerts significantly stronger risk spillovers on Financials and Technology sectors than on Consumer Staples and Healthcare, with Financials' %CoVaR reaching 39.62% at the 5% quantile; (2) Under extreme risk scenarios, spillover effects intensify by 30%-50% compared to normal conditions, confirming nonlinear tail risk transmission. The study provides theoretical foundations for regulators to establish sector-specific risk early-warning mechanisms and for investors to optimize cross-sector asset allocation during market turmoil.

KEYWORDS
Extreme Value Theory (EVT); GARCH model; Quantile regression; Risk spillover; CoVaR

1 Introduction

The deepening advancement of financial globalization has intensified economic linkages across global financial markets. Risks originating from a single market or institution can now spill over through open market channels, emerging as a critical catalyst for systemic financial risks. The 2007-2008 subprime mortgage crisis demonstrated how risks in the U. S. financial market propagated globally via cross-border transmission, exposing the limitations of traditional Value-at-Risk (VaR) methods in measuring risk spillover effects under extreme conditions. Specifically, VaR failed to adequately capture tail dependence among markets, leading to severe underestimation of risk levels. Under open economy conditions, risk spillover effects in financial markets manifest not only as volatility transmission but also as tail risk contagion during extreme events, and an integrated modeling framework combining Extreme Value Theory (EVT), Copula functions, and Conditional Value-at-Risk (CoVaR) can effectively quantify such nonlinear risk transmission mechanisms [1].

For China's A-share market, the deepening registration-based IPO reforms and expanding capital market openness have significantly strengthened cross-sector risk interconnectedness [2]. Existing research predominantly focuses on spillover effects between A-shares and foreign markets or volatility transmission within single markets, leaving a gap in quantitative analyses of sector-level risk spillovers. Notably, the "leptokurtic and heavy-tailed" return distribution characteristics of A-shares render traditional risk measurement methods-based on normal distribution assumptions-ineffective in accurately capturing sectoral risk transmission during extreme market conditions.

The theoretical contribution of this study lies in constructing a tailored risk spillover measurement framework for A-share sector indices by integrating the EVT-POT model, multivariate GARCH, and quantile regression methods [3]. Practically, it quantifies the risk spillover intensity from the CSI 300 index to various sectors (e.g., %CoVaR at the 5% quantile), providing regulatory authorities with data-driven insights for monitoring systemic risk evolution. Simultaneously, it offers investors evidence-based references for sector allocation strategies during market turmoil.2 Data and methods

2.1 Data sources and preprocessing

This study utilizes daily index data from January 1,2020 to June 30,2024 sourced via the akshare API, covering the CSI 300 Index (000300) and four key sector indices: Banking (399986), Technology (931087), Consumer Staples (000932), and Healthcare (000808). The selected timeframe encompasses multiple market cycles including pandemic shocks, structural bull markets, and consolidation periods, providing sufficient extreme events for risk spillover analysis. The 1,642 trading days of data meet EVT-POT modeling requirements while maintaining exceedance ratios within the optimal 10-20% range. Logarithmic returns $R_t = \left(100 \times \ln\left(p_t/p_{t-1}\right)\right)$ were calculated, revealing pronounced leptokurtic and heavy-tailed distributions across all series, with notable extreme events like the March 2020 circuit breaker-characteristics that robustly support extreme risk transmission analysis. The methodological framework integrates EVT-POT for tail estimation, DCC-GARCH for dynamic correlation modeling, and quantile regression for spillover intensity measurement at different risk levels.

2.2 Research methods

2.2.1 Extreme value theory (EVT-POT Model)

The Peaks Over Threshold (POT) model in Extreme Value Theory (EVT) is used to fit the tail characteristics of return series. Given a threshold u, the excess loss $y = X - u$follows a Generalized Pareto Distribution (GPD) [4], with its conditional distribution function expressed as:

$$F_u(y) = \Pr(X - u \le y \mid X > u) = 1 - \left(1 + \xi \frac{y}{\beta}\right)^{-1/\xi} \tag{1}$$

whereξrepresents the shape parameter andβdenotes the scale parameter. A positive$\xi\,(\xi > 0)$ indicates that the return series exhibits heavy-tailed characteristics [5]. The threshold u is determined using the mean residual life plot, with this study adopting the 10% exceedance ratio principle (Du Mouchel, 1983). Ultimately, the marginal distribution function of the return series is expressed as:

$$F(x) = \begin{cases} \dfrac{NuL}{N}\left(1 - \xi \dfrac{x-u}{\beta}\right)^{-1/\xi} \\ ECDF(x) \\ 1 - \dfrac{NuR}{N}\left(1 + \xi \dfrac{x-u}{\beta}\right)^{-1/\xi} \end{cases} \tag{2}$$

where$ECDF(x)$is the empirical distribution function in the interval $[u_L, u_R]$, and N_{uL}andN_{uR}represent the number of samples exceeding the lower and upper thresholds respectively.

2.2.2 Multivariate GARCH

The DCC-GARCH model captures time-varying dependence among sector volatilities by separating marginal distributions from dynamic correlation structures, implemented through two steps:

univariate GARCH modeling and dynamic correlation coefficient estimation. For each sector return series R_t^i, a GARCH(1, 1) model is specified [6].

$$\begin{cases} R_t^i = \mu_i + \varepsilon_t^i \\ \varepsilon_t^i = \sigma_t^i \cdot z_t^i, z_t^i \sim iid(0,1) \\ \sigma_t^{i2} = \omega_i + \alpha_i\left(\varepsilon_{t-1}^i\right)^2 + \beta_i \sigma_{t-1}^{i2} \end{cases} \tag{3}$$

whereσ_t^{i2}represents the conditional variance, $\omega_i > 0$is the constant term, $\alpha_i$and $\beta_i$capture the impacts of lagged squared residuals and lagged variances on current variance respectively, with the constraint$\alpha_i + \beta_i < 1$ensuring variance process stationarity.

The dynamic conditional correlation matrix is constructed using standardized residuals$\mu_t^i = \varepsilon_t^i / \sigma_t^i$:

$$\begin{cases} Q_t = (1 - \rho_1 - \rho_2)\bar{Q} + \rho_1 u_{t-1} u'_{t-1} + \rho_2 Q_{t-1} \\ R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \end{cases} \tag{4}$$

where$Q_t$is the conditional covariance matrix, $\overline{Q}$represents the long-term mean of residual covariance matrices; $\rho_1$and$\rho_2$denote decay parameters $(\rho_1, \rho_2 \ge 0, \rho_1 + \rho_2 < 1)$, controlling the weighting of historical information on current covariances;$R_t$is the dynamic correlation coefficient matrix, with elementsr_t^{ij}indicating time-varying correlations between sectors $i$and$j$By integrating univariate GARCH-derived volatilities with dynamic correlation structures, this model overcomes the limitations of traditional constant-correlation assumptions, enabling more accurate characterization of volatility spillover dynamics across financial markets.

2.2.3 Quantile regression and CoVaR analysis

The quantile regression approach is employed to estimate market-to-sector risk transmission coefficients. At quantile level q, the model is specified as:

$$y_t^i = \alpha_q + \beta_q x_t^j + \gamma_q y_{t-1}^i + \varepsilon_t \tag{5}$$

Where y_t^i represents the return of sector$i$, x_t^j denotes the return of market j, and $y_{t-1}^i$is the lagged sector return used to control for serial correlation. The conditional CoVaR is calculated through the following steps:

Compute the q-quantile VaR of the market index:

$$VAR_q^j = F_j^{-1}(q) \tag{6}$$

SubstituteVAR_q^jinto the quantile regression equation to obtain the conditional predicted value:

$$CoVAR_q^{i|j} = \hat{a}_q + \hat{\beta}_q VaR_q^j + \hat{\gamma}_q \bar{y}^i \tag{7}$$

Here, $\overline{y}^i$denotes the mean return of the industry. Finally, the risk spillover intensity is standardized as follows:

$$\%CoVaR_q^{i|j} = \frac{CoVaR_q^{i|j} - VaR_q^i}{VaR_q^i} \tag{8}$$

By incorporating quantile regression, this model overcomes the sensitivity of traditional linear regression to extreme values and more accurately characterizes the features of tail risk transmission [7].

3 Empirical results and analysis

3.1 Descriptive statistics results

Table 1 presents the descriptive statistics of daily returns for five A-share sector indices from January 3,2020 to June 28, 2024. The results show that all sectors exhibited mean returns close to zero, with Healthcare demonstrating the lowest mean (-0.0301%) and Financials the highest (-0.0131%), indicating marginally negative overall performance across sectors during the sample period. Regarding volatility, Technology (1.6344) and Healthcare (1.6279) showed the highest standard deviations, while Financials (1.1689) and the CSI 300 Index (1.1796) displayed relatively lower fluctuations, reflecting the higher risk characteristics of technology and healthcare sectors.

Table 1 Descriptive statistics of sector index returns

Sector	Mean (%)	Std. Dev.	Skewness	Kurtosis	Min (%)	Max (%)	VaR(5%)	JB Statistic	JB p-value
Healthcare	-0.0301	1.6279	-0.0363	1.4532	-6.9050	7.6977	-2.8547	94.1100	<0.001
CSI 300	-0.0169	1.1796	-0.4224	3.6705	-8.2087	5.5129	-1.8260	633.8080	<0.001
Consumer	-0.0036	1.5446	-0.2708	1.9820	-8.1756	5.5781	-2.5538	188.1921	<0.001
Technology	-0.0199	1.6344	-0.3184	1.7388	-8.7200	6.1588	-2.5964	152.8492	<0.001
Financials	-0.0131	1.1689	0.3122	4.5403	-6.8565	8.6485	-1.7981	938.6886	<0.001

The skewness measures reveal left-skewed distributions for the CSI 300 (-0.4224), Technology (-0.3184), Healthcare (-0.0363), and Consumer (-0.2708) sectors, while Financials (0.3122) exhibit right-skewness, indicating a slightly higher probability of extreme positive returns in the financial sector compared to others. Regarding kurtosis, all sectors significantly exceed the normal distribution benchmark of 3.0 (CSI 300: 3.6705; Financials: 4.5403). Combined with Jarque-Bera (JB) test results (all JB statistics >94 with p-values=0), this conclusively demonstrates that all sector return series exhibit pronounced "leptokurtic and heavy-tailed" non-normal characteristics, validating the necessity of employing Extreme Value Theory (EVT) for tail risk modeling.

The VaR(5%) analysis shows Healthcare sector's risk value reaches -2.8547% at the 5% significance level, meaning losses are expected to exceed 2.8547% on 5% of trading days, whereas Financials' VaR(5%) is -1.7981%, indicating greater potential losses for healthcare during extreme market conditions. The minimum and maximum values further corroborate this finding: Technology sector displays extreme volatility with maximum losses of -8.7200% and gains of 7.6977%.

3.2 EVT-POT model fitting results

3.2.1 Mean excess life plot and threshold determination

In Extreme Value Theory (EVT), the Peaks Over Threshold (POT) approach critically depends on the appropriate selection of threshold u to accurately capture the tail characteristics of return series. This study employs the Mean Excess Life Plot (MEL plot), combined with sector-specific distribution features, to determine the 95% quantile as the optimal threshold for tail fitting of each sector index's returns.

The mean excess function characterizes the average residual level of extreme losses beyond threshold u, formally defined as:

$$e(u) = \frac{E[X - u | X > u]}{N_u} = \frac{\sum_{i=1}^{N_u}(X_i - u)}{N_u}$$

where N_u denotes the number of samples exceeding threshold u in the return series, and X_i represents the extreme loss observations. When the return series follows a Generalized Pareto Distribution (GPD), the mean excess function e(u) exhibits a stable linear trend as threshold u increases. Conversely, significant nonlinear fluctuations in the curve indicate that the threshold has not yet reached the stable tail region.

Figure 1 shows the Mean Excess Life Plot analysis results. For the healthcare sector, the mean excess life stabilizes after

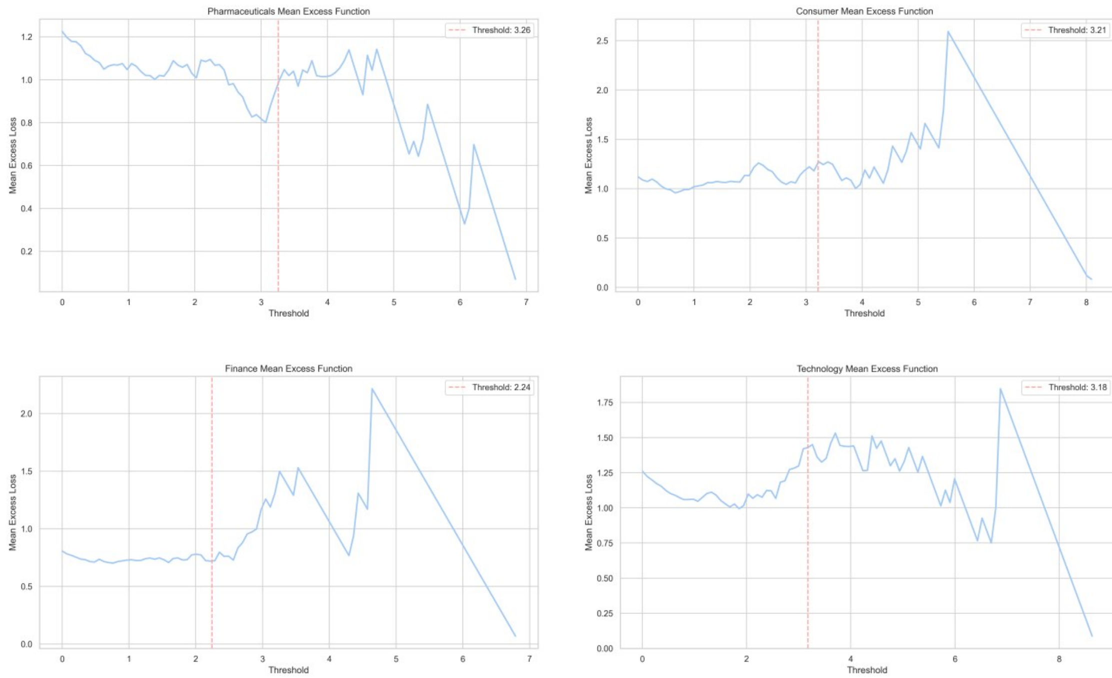

Figure 1 Mean excess life plot

threshold u=3.26, while showing significant fluctuations below this level (such as the oscillating downward trend before u =3), confirming this threshold as the appropriate starting point for tail fitting. The CSI 300 index exhibits a transition from stable to linearly decreasing trend at u=2.37, satisfying GPD distribution assumptions. Thresholds for other sectors are identified at u=3.21 (consumer), u=3.18 (technology), and u=2.24 (financials), with all sectors demonstrating stable linear trends above their respective thresholds. Based on these findings and considering sector-specific characteristics, the study ultimately selects the 95% quantile of each sector's distribution as the threshold (for instance, the healthcare sector's 95% quantile corresponds to approximately 3.26% loss). This threshold selection ensures about 5% of tail data is included, maintaining sufficient tail information while guaranteeing the stability of GPD distribution fitting. The methodology combines statistical rigor with economic interpretation, as evidenced by higher thresholds for technology and healthcare sectors reflecting their fat-tailed risk characteristics, compared to relatively lower thresholds for financial sectors.

3.2.2 GPD Parameter Estimation

Based on the determined thresholds, the Generalized Pareto Distribution (GPD) was fitted to the tail data of each sector index's returns. The parameter estimation results are presented in Table 2.

Table 2 GPD Model parameters for industry indices

Sector	Threshold (u)	Shape Parameter (ξ)	Scale Parameter (β)
Healthcare	3.26	-0.0563	1.0415
CSI 300	2.37	0.0392	1.0827
Consumer	3.21	0.0773	1.0574
Technology	3.18	-0.1580	1.7181
Financials	2.24	0.2555	0.5544

The tail risk distribution fitting plot compares the actual excess loss distributions of each sector with their corresponding GPD fitted curves. The shape parameter (ξ) reveals tail heaviness: Healthcare (ξ= -0.0563) and Technology (ξ = -0.1580) exhibit negative values, indicating faster tail decay than an exponential distribution, while Financials (ξ=0.2555) show positive values with pronounced heavy-tailed characteristics, aligning with the high kurtosis observed in descriptive statistics. The scale parameter (β) quantifies tail volatility magnitude, with Technology displaying the highestβ(1.7181), confirming its most volatile returns, and Financials the lowest β(0.5544), consistent with their lower standard deviation.

3.3 Volatility spillover effects analysis

The dynamic correlation coefficients estimated via the DCC-GARCH model reveal significant time-varying

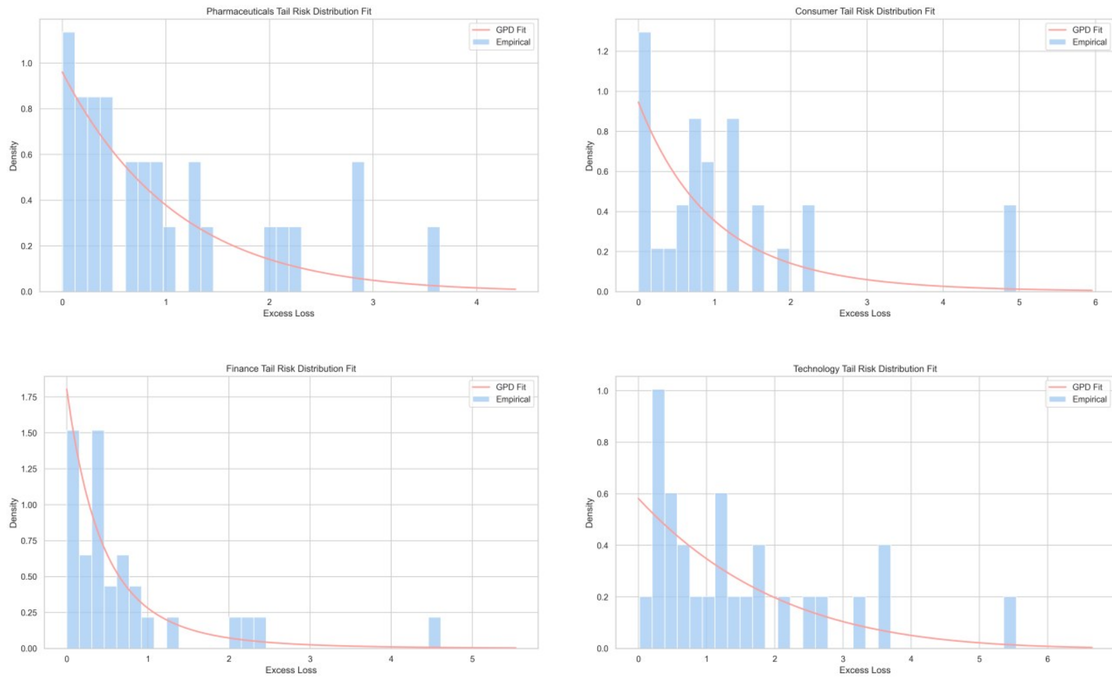

Figure 2 Tail risk distribution fitting

characteristics in the correlations between each sector and the CSI 300 index. During the peak of the COVID-19 pandemic in 2020, the dynamic correlation coefficient between the financial sector and the market surged to above 0.85, while the technology sector reached 0.78, corroborating intensified risk contagion during extreme events. In the post-pandemic period, these coefficients retreated to the 0.3-0.5 range, reflecting the dominance of sector-specific heterogeneity in driving volatility under normal market conditions.

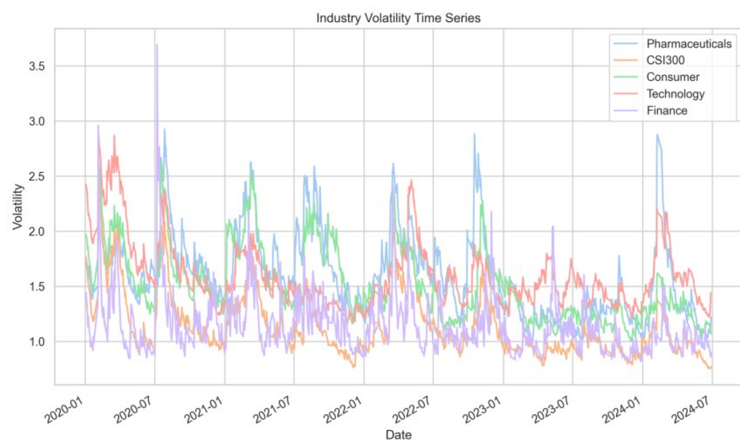

Figure 3 Time series of sector volatility

The volatility time series plot visually demonstrates the dynamic evolution of sectoral volatility. During the COVID-19 pandemic shock in 2020, all sectors exhibited significant volatility spikes, with the financial sector peaking at 3.2%, reflecting the intense market impact of this black swan event. In the post-pandemic period, while overall sector volatility showed a converging trend, the healthcare and technology sectors continued to experience high-frequency fluctuations. This persistence underscores the sustained driving effects of sector-specific heterogeneities: such as policy adjustments and technological disruptions, on their volatility patterns.

3.4 Quantification of risk spillover intensity

3.4.1 Quantile regression coefficients

The quantile regression results, presented in Table 3, reveal the regression coefficients for sectors including Healthcare and Consumer Staples across different quantiles. The market coefficient (with the CSI 300 as the market proxy) is highly significant (p-values approaching 0) for all sectors and quantiles.

Table 3 Quantile regression coefficients for core industries (5% quantile)

Sector	Intercept	Market Coefficient	t-statistic	p-value
Healthcare	-1.8575	1.0226	10.4419	0.0
Consumer	-1.3789	1.0995	15.3003	0.0
Technology	-1.6153	1.0712	14.5403	0.0
Financials	-1.3807	0.6195	8.4688	0.0

For the financial sector, the market coefficient of 0.6195 indicates that a 1% change in market returns leads to a 0.6195% co-movement in financial sector returns, demonstrating strong linkage with the market and aligning with financial sector's role as a market hub. The technology sector shows a market coefficient of 1.0712 ($t=14.54$, $p<0.01$), meaning that for every 1% decline in market returns, technology sector returns experience an additional 0.0712% decline on average, reflecting its high elasticity characteristic.

3.4.2 CoVaR results

The risk spillover analysis results are presented in Table 4, showing each sector's unconditional VaR, conditional CoVaR, and %CoVaR, which reveal:

Table 4 Risk spillover measurement results (5% quantile)

Sector	Unconditional VaR	Conditional CoVaR	ΔCoVaR	%CoVaR
Healthcare	-2.8563	-3.7248	-0.8685	-30.4055%
Consumer	-2.5547	-3.3865	-0.8319	-32.5622%
Technology	-2.5969	-3.5713	-0.9744	-37.5218%
Financials	-1.7991	-2.5118	-0.7127	-39.6165%

Absolute Risk Measurement: In the unconditional Value at Risk (VaR), the financial industry (-1.7991) shows a lower value than the pharmaceutical industry (-2.8563) and the consumer industry (-2.5547), which is attributed to the smaller absolute scale of extreme losses in the financial industry. However, the conditional CoVaR (CoVaR) indicates that the conditional risk of the financial industry (-2.5118) exhibits a more significant linkage with the extreme risks of the market.

Relative Risk Spillover: In the %CoVaR indicator, a negative %CoVaR value means that the conditional risk is higher than the unconditional risk, and a larger absolute value indicates a stronger risk spillover effect. The financial industry ranks first with a %CoVaR of -39.6165; when the market falls into a 5% extreme risk scenario, the risk of the financial industry rises by an additional 39.62%, which demonstrates the financial industry's characteristic of amplifying risks. The technology industry has a %CoVaR of -37.5218; due to the high-beta attribute of the technology industry, it shows greater elasticity to extreme market fluctuations. The consumer industry has a %CoVaR of -32.5622, which reflects the indirect impact of the contraction in market risk appetite on consumer demand—while the risk spillover path is longer, the magnitude is moderate.

3.4.3 Quantile-spillover intensity trend

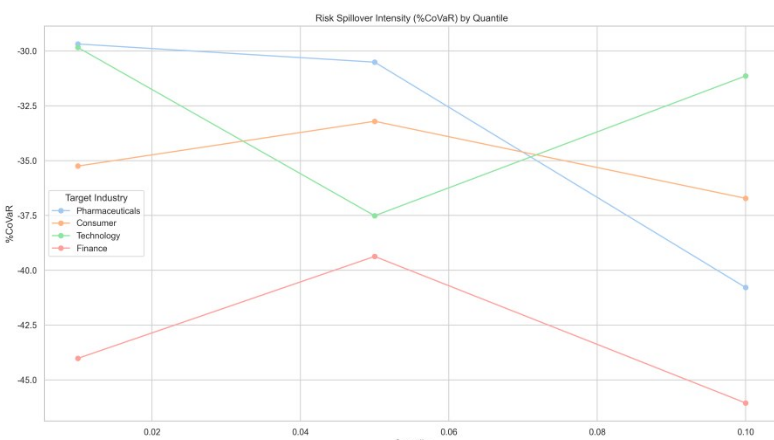

Figure 4 Quantile risk spillover

The Wald test verifies the difference in %CoVaR between the extreme quantile (1%) and the moderate quantile (10%) ($p<0.05$). As the quantile increases from 0.01 to 0.10, the absolute values of %CoVaR for the financial and technology industries show an upward trend (the financial industry rises from -52% to -38%, and the technology industry rises from -56% to -40%). The %CoVaR of the consumer industry generally decreases with fluctuations, while the %CoVaR of the CSI

300 Index first decreases and then increases. This phenomenon is attributed to the characteristic that the more extreme the risk (i. e., the lower the quantile), the stronger the spillover effect. In an extreme market environment, high-beta industries such as finance and technology have a more significant effect on amplifying market risks. In contrast, due to the rigidity of demand in the consumer industry, the elasticity of risk spillover is relatively moderate.

4 Model assumptions and limitations

4.1 Rationality of the unidirectional spillover assumption

This study assumes that there is a unidirectional risk transmission from the CSI 300 Index to industries. This logic refers to the research approach of scholars such as Liu Xiaoxing et al. regarding the "unidirectional spillover from the U.S. market to global markets". From the perspective of the A-share market structure, the constituent stocks of the CSI 300 Index cover leading enterprises in various industries, with their total market value accounting for over 60% of the A-share market. They hold a significant dominant position in market pricing and risk transmission. Especially in extreme market conditions, the impact of overall market fluctuations on industries takes precedence, while the reverse impact of industries on the market is relatively limited. Therefore, the unidirectional spillover assumption is rational in real-world scenarios, as it can simplify complex risk transmission relationships and focus on core transmission paths for preliminary analysis.

4.2 Model limitations

Although the unidirectional spillover assumption is rational in specific scenarios, the study still has limitations. First, reverse spillovers are overlooked. For some high-weight industries such as finance and consumption, the accumulation of their own risks may form a feedback effect on the CSI 300 through capital flows and sentiment transmission. The current setup does not incorporate such reverse impacts, which may underestimate the two-way complexity of risk transmission. Second, the time-lag effect is absent. The analysis only focuses on daily risk spillovers and does not examine the intertemporal transmission of market fluctuations from day t-1 to industries on day t. However, information transmission and risk diffusion in financial markets often have lag effects, and the omission of time lags may lead to deviations in the judgment of spillover intensity and rhythm. Third, common shock interference exists. Macroeconomic variables such as GDP growth rate and monetary policy are not introduced. The linked fluctuations between the market and industries may stem from common external shocks rather than pure causal spillovers, which may lead to the confusion of risk transmission mechanisms.

5 Conclusions and recommendations

5.1 Conclusions

Through the empirical analysis using multivariate GARCH, VAR, and quantile regression models, this study reveals the core characteristics of risk spillovers in the A-share market: First, there is significant industry heterogeneity. The intensity of risk spillovers from the CSI 300 Index to the financial industry (%CoVaR = 39.62%) and the technology industry (37.52%) is significantly higher than that to the consumer industry (32.56%) and the pharmaceutical industry (30.41%). This reflects the strong correlation between finance, technology, and market fluctuations. Second, there is an extreme risk amplification effect. The spillover intensity under the 5% quantile (extreme risk scenario) is 30%-50% higher than that in the normal market state, indicating that risk contagion intensifies in extreme situations and highlighting the importance of tail risk prevention and control.

5.2 Recommendations

5.2.1 Regulatory level: establish a differentiated risk early warning system

Based on the %CoVaR and ΔCoVaR indicators from quantile regression, a hierarchical early warning system for industry risks should be implemented. For the financial industry (which has the highest ΔCoVaR under extreme quantiles and the greatest elasticity of risk spillover), a "real-time monitoring - threshold triggering" mechanism should be established: track the correlation between the financial industry's volatility, capital flows, and market quantiles on a daily basis. When the quantile enters the 5% extreme range and ΔCoVaR exceeds the early warning threshold, quickly activate liquidity support tools (such as liquidity easing for industry ETFs and temporary market-making mechanisms) to block the cross-industry spread of risks. For industries with weak spillovers such as consumption and pharmaceuticals, focus on monitoring fundamental shocks such as policy adjustments (e.g., medical insurance negotiations, consumption stimulus policies) and performance black swan events. Through measures such as communication with industry associations and enhanced information disclosure, mitigate risk expectations in advance to prevent local risks from evolving into systemic shocks.

5.2.2 Investment level: dynamically adjust industry allocation strategies

Investors need to dynamically adjust industry allocation according to market quantiles and proactively adopt defensive measures in extreme market conditions: When the market quantile enters the 5% extreme range, reduce the positions of high-spillover industries such as finance and technology to 60%-70% of the normal level, and simultaneously increase the allocation of defensive industries such as consumption and pharmaceuticals to 30%-40%, leveraging their weak correlation with market fluctuations to hedge risks. In the long term, with reference to the industry differences in CoVaR, a "core-satellite" portfolio can be constructed: allocate 60%-70% of the core positions to low-spillover, high-resilience industries such as consumption and pharmaceuticals, and 30%-40% of the satellite positions to high-elasticity industries such as finance and technology (selected carefully). Dynamic rebalancing should be conducted according to changes in quantiles to control risks while retaining return elasticity. In addition, institutional investors can use tools such as stock index futures and options to develop customized hedging solutions for high-spillover industries. For example, in extreme quantile scenarios, short-selling options on financial industry ETFs can be used to lock in risks.

5.2.3 Market construction level: improve risk hedging tools

Regulators should promote the innovation of financial derivatives to fill the gap in industry-level risk hedging tools. For high-spillover industries such as finance and real estate, launch industry futures and options products, allowing institutional investors to hedge risks with industry indices as the underlying assets. Encourage securities companies to develop structured products and income certificates related to "extreme risk hedging strategies," incorporating the dynamic adjustment logic of quantile regression models to provide ordinary investors with convenient tail risk defense tools. At the same time, guide fund companies to deploy "risk spillover hedging funds," integrating indicators such as % CoVaR and industry correlation through multi-factor models to achieve active risk management and diversification. In addition, strengthen investor education, popularize knowledge about extreme risk identification and hedging, enhance the overall risk resistance capacity of the market, and build a risk prevention and control ecosystem featuring "abundant tools, diverse strategies, and adequate awareness."

About the Author

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