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Bidirectional Risk Spillovers between Chinese and Asian Stock Markets: A Dynamic Copula-EVT-CoVaR Approach

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Abstract: This study aims to investigate bidirectional risk spillovers between the Chinese and other Asian stock markets. To achieve this, we construct a dynamic Copula-EVT-CoVaR model based on 11 Asian stock indexes from 1 January 2007 to 31 December 2021. The findings show that, firstly, synchronicity exists between the Chinese stock market and other Asian stock markets, creating conditions for risk contagion. Secondly, the Chinese stock market exhibits a strong risk spillover to other Asian stock markets with time-varying and heterogeneous characteristics. Additionally, the risk spillover displays an asymmetry, indicating that the intensity of risk spillover from other Asian stock markets to the Chinese is weaker than that from the Chinese to other Asian stock markets. Finally, the Chinese stock market generated significant extreme risk spillovers to other Asian stock markets during the 2007–2009 global financial crisis, the European debt crisis, the 2015–2016 Chinese stock market crash, and the China–US trade war. However, during the COVID-19 pandemic, the risk spillover intensity of the Chinese stock market was weaker, and it acted as the recipient of risk from other Asian stock markets. The originality of this study is reflected in proposing a novel dynamic copula-EVT-CoVaR model and incorporating multiple crises into an analytical framework to examine bidirectional risk spillover effects. These findings can help Asian countries (regions) adopt effective supervision to deal with cross-border risk spillovers and assist Asian stock market investors in optimizing portfolio strategies.

Keywords: Asian stock markets; risk spillover; dynamic copula; CoVaR; COVID-19 pandemic

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1. Introduction

Along with the deepening of economic globalization and financial markets' integration, the risk contagion effect among international financial markets has been gradually enhanced, which shows a more complicated dependence structure and risk spillover (Fang et al. 2021; Ren et al. 2022; Tan et al. 2022). This may lead to localized risk events that rapidly affect the stability of global financial markets, thereby triggering systemic crises (Ellis et al. 2022). For example, the US subprime mortgage crisis not only caused a sharp decline in the American economy with a stock plunge but also aroused extreme fluctuations in global stock markets. In early 2020, the COVID-19 pandemic increased global economic uncertainty and downward pressure in the post-crisis period; combined with risk spillover effects, global stock markets plummeted one after another, and market liquidity nearly dried up.

Meanwhile, with the rapid development of the Asian economy, Asian stock markets have occupied an increasingly important position in the world's financial markets. As the world's second-largest economy, China has increasingly close financial ties with other Asian countries (regions) and plays an increasingly important role in Asian stock markets (Caporale et al. 2022). On the one hand, the greater openness of China's capital market has promoted the integration of Asian financial markets, and, on the other hand, it has also created conditions for risk contagion and spillover between the stock markets. Specifically, as an emerging market, the Chinese stock market exhibits significant herding behavior, which is apt to cause turbulence in other stock markets (Wang et al. 2022b). For instance, the Chinese stock market crashed in June 2015, and the extreme price movements caused by it aroused the linkage of Asian stock markets, which in turn caused severe losses in Asian stock markets.

Figure 1 illustrates the temporal evolution of Chinese and other Asian stock market indices. Overall, Asian stock markets exhibit strong co-movement. During the 2007–2009 global financial crisis, Asian stock markets experienced dramatic fluctuations that initially rose and then fell. Moreover, Asian stock markets experienced sharp declines during the COVID-19 outbreak, highlighting the characteristic of synchronicity. The strong co-movement of stock markets lays the groundwork for risk transmission (Chopra and Mehta 2022). As an emerging financial market with excessive speculation, the Chinese stock market significantly impacts the smooth functioning of the other stock markets, posing challenges to financial risk management (Zuo et al. 2023). Particularly in the context of the COVID-19 pandemic, investigating the dependence and risk spillover effects between Chinese and other Asian stock markets is critical to preventing risk contagion and maintaining financial market stability.

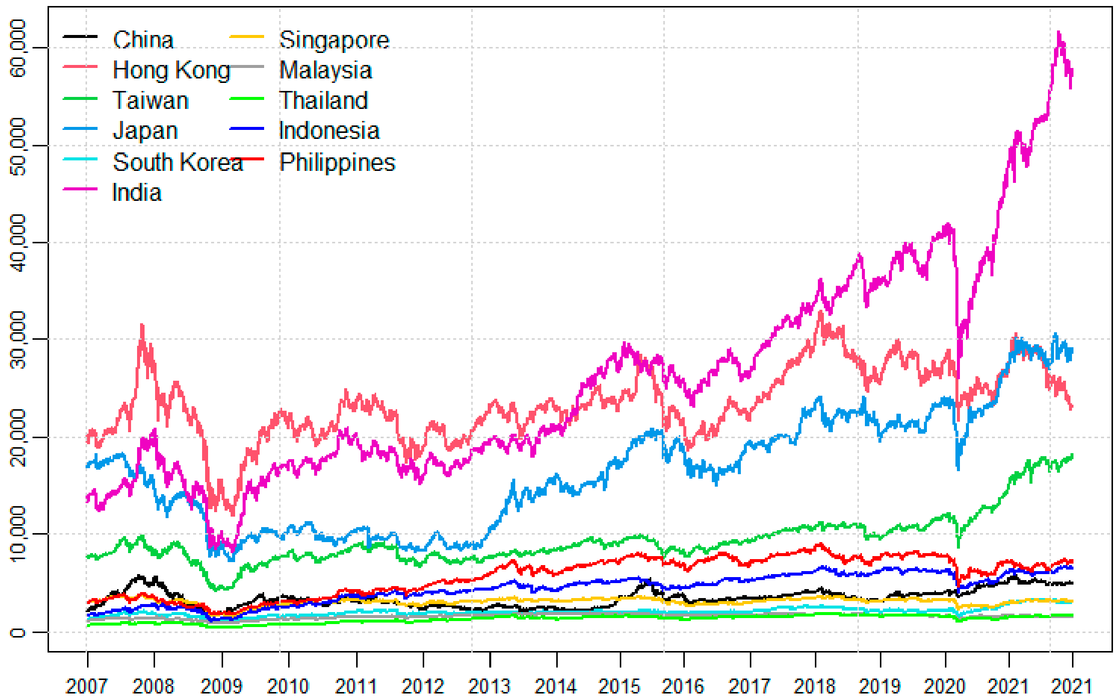

Figure 1. Time-series plot of Asian stock market indices.

The COVID-19 epidemic differs from ordinary diseases because its suddenness unprecedentedly impacted the global financial market (Belaid et al. 2023; Karamti and Belhassine 2022; Wang et al. 2022a). Due to a lack of understanding of epidemic-related information, investors have become more pessimistic and inclined to adopt conservative investment strategies. This risk aversion spreads across multiple stock markets, affecting market expectations in other countries and causing most investors to exhibit the herding effect. Ultimately, this phenomenon leads to a significant increase in dependence and risk spillover effects between stock markets in various countries. Furthermore, Asian stock markets exhibit high volatility and are particularly susceptible to major international events (Mishra and Mishra 2021). Therefore, focusing on the impact of emergencies on Asian stock markets is of practical significance for comprehensively understanding extreme risk spillovers and conducting effective risk measurement.

This paper provides several noteworthy contributions to understanding interdependencies and risk spillovers among Asian stock markets. Firstly, we examine the dynamic dependence between Chinese and 10 other Asian stock markets and find that synchronicity and risk contagion exist between them. Secondly, we quantify bidirectional risk spillovers between Chinese and other Asian stock markets, providing a rigorous analytical framework to understand how financial risks are transmitted between these stock markets. Thirdly, this study investigates the impact of emergencies on risk spillovers, including the 2007–2009 global financial crisis, the European debt crisis, the 2015–2016 Chinese stock market crash, the China–US trade war, and the COVID-19 pandemic. Finally, in terms of econometric methods, we combine the dynamic copula-CoVaR model with EVT to more effectively capture the time-varying, non-linear, and fat-tail characteristics of risk spillovers.

The rest of this paper is organized as follows: Section 2 provides the literature review; Section 3 presents the methods and materials; Section 4 shows the empirical results, along with the robustness diagnosis; Section 5 provides the discussion; and Section 6 concludes the paper.

2. Literature Review

Effectively measuring the risk spillovers of financial markets has become an important subject in modern financial analysis. The conditional value-at-risk (CoVaR) approach proposed by Adrian and Brunnermeier (2011) has been widely used in the study of risk spillovers because it can accurately measure the risk faced by one financial market when other financial markets are in distress (Usman et al. 2023; Yao and Li 2023). Currently, there are three main methods for calculating CoVaR. Firstly, the CoVaR is calculated based on the quantile regression approach. Xu et al. (2021) applied the quantile regression method to CoVaR and took the Chinese banking industry as the research object, finding that banks with high leverage and small size exhibit stronger risk spillover effects. Secondly, CoVaR is calculated in combination with the multivariate GARCH models. Abuzayed et al. (2021) measured the systemic risk spillovers in global stock markets during the COVID-19 pandemic through the DCC-GARCH-CoVaR model and showed that developed stock markets in North America and Europe have a higher intensity of extreme risk transmission and reception to global stock markets than Asian stock markets. In addition, Zhu (2022) used the DCC-BEKK-GARCH-CoVaR model to calculate the risk spillovers from shadow banks to Chinese commercial banks. Thirdly, the copula model is used to measure CoVaR. Karadag and Golbasi Simsek (2023) utilized the Copula-CoVaR method to investigate risk spillovers between BRICS stock markets. The findings indicated that the Chinese stock market was the least affected by other BRICS countries after the COVID-19 outbreak. Additionally, Mo et al. (2023) and Hanif et al. (2023) argue that combining the copula model with CoVaR can more accurately quantify financial risk spillovers.

It is worth noting that non-linear dependence is prevalent between financial markets, which makes risk spillovers often show complex non-linear relationships. Compared with the other two methods, the copula model can more flexibly describe the non-linear dependence between financial markets and focuses on the characterization of the tail dependence structure (Liu et al. 2023a). The further introduction of time-varying parameters captures dynamic changes in dependence relationships, thereby improving the accuracy of risk spillover measures (Wang and Xu 2022; Wu et al. 2021). Yao et al. (2024) examined the risk spillovers among the Chinese mainland, Hong Kong, and London stock markets using a dynamic copula-CoVaR model and found that implementing the Shanghai–Hong Kong and Shanghai–London Stock Connections enhanced the spillovers between these markets. Additionally, extreme value theory (EVT) modeling for extreme data helps to deal with the problem of fat tails in risk measures (Alishavandi et al. 2023; Okou and Amar 2023). Zhao et al. (2023) showed that introducing the EVT model into Copula-CoVaR can effectively measure extreme risk spillovers between financial markets.

Research on the risk spillover effects of China's stock market has increased in recent years (Yadav et al. 2023; Zhong and Liu 2021; Zhou et al. 2023). Wang and Xiao (2023) found that China has significant risk spillover effects on East Asian stock markets, but this risk spillover effect is weaker during periods of high volatility. Jiang et al. (2021) found that multiple developed countries such as the United States, Britain, and Japan have significant risk spillover effects on the Chinese stock market, and regulatory agencies must monitor multiple markets simultaneously. Sun et al. (2023) identified a risk linkage between China and APEC stock markets, and China's capital market liberalization reform has strengthened this connection. Furthermore, Zhang et al. (2022) explored the spillover paths of the European, American, and East Asian stock markets using a vine-copula model, confirming that risks from European and American stock markets are transmitted to China through Japan and Hong Kong. Similarly, Du et al. (2023) found that Hong Kong's risk spillover effects on the Chinese stock market are on the rise, but there are no direct spillovers between the Chinese and US stock markets.

As an external shock, the COVID-19 pandemic has dramatically impacted the economic landscape. Yilanci and Pata (2023) found that COVID-19 had a limited impact on the exchange rates and sovereign bonds of India and Brazil, while significantly impacting their stock prices. Subsequently, Cheng et al. (2021) and Aloui et al. (2022) respectively examined China's risk spillovers to the G7 and BRICS stock markets and found that China's dependence and risk spillovers to both G7 and BRICS stock markets significantly increased during the COVID-19 pandemic. Moreover, Liu et al. (2022) used the GARCH-BEKK model to build an interaction network and found that the COVID-19 outbreak increased the volatility spillovers of the Chinese stock market, and it weakened rapidly in the middle and late stages of the pandemic. In contrast, through the TVP-VAR-connectedness method, Tan et al. (2022) argued that China's spillover effects on developed countries significantly increased in the post-COVID-19 era.

To sum up, the academic community has achieved fruitful results in describing the risk spillover effects of the Chinese stock market. However, most of the literature focuses on China's unidirectional risk spillovers to other stock markets, with fewer sample countries (regions) being selected when the research pertains to Asian stock markets. Moreover, the existing research primarily concentrates on the impact of a single crisis on risk spillovers, rarely incorporating several crises into an analytical framework. Additionally, most of the literature uses the basic copula model for analysis and seldom optimizes the model.

3. Methods and Materials

3.1. Methods

Since financial time series generally have the autocorrelation, conditional heteroscedasticity, and leverage effect, this paper establishes an AR(1)-GJR-GARCH(1,1) model for each stock return series to fit its marginal distribution. The model is defined as:

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sqrt{h_t} z_t, z_t \sim skew\text{–}t(v, \lambda) \tag{2}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3}$$

where r_t is the stock return at time t, and φ_0 and φ_1 are the autoregressive parameters. The term h_t is the conditional variance, ε_t is the random error, and z_t is the standardized residuals following a skew-t distribution[1]. The ω is a constant, ε_{t-1}^2 and h_{t-1} are the ARCH and GARCH components, with α and β being the parameters, respectively. α, $\beta > 0$ ensures the positivity of the conditional variance, and $\alpha + \beta < 1$ means that the GARCH model is stationary. $d_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, and 0 otherwise. The parameter γ captures the leverage effects.

The marginal distribution combined with EVT can more effectively describe the extreme market risk. Moreover, the peaks over threshold (POT) model focuses on the distribution $F_\mu(y)$ in which z (the random variable corresponding to z_t) exceeds the threshold, fully considering extreme data, and is widely used. $F_\mu(y)$ is the conditional excess distribution function expressed as:

$$F_\mu(y) = P(z-\mu \leq y | z > \mu) = \frac{F(\mu+y) - F(\mu)}{1-F(\mu)}, 0 \leq y \leq z_F - \mu \tag{4}$$

where μ denotes the threshold, and $y = z - \mu$ and z_F are the excess values and the right endpoint of the distribution, respectively. According to Balkema and De Haan (1974) and Pickands (1975), as the threshold μ is gradually increased, $F_\mu(y)$ will converge to the generalized Pareto distribution (GPD). Therefore, this paper adopts GPD to fit the lower and upper tail distribution of the standardized residual z_t and uses an empirical cumulative distribution function to fit the middle part. Finally, the distribution function of the standardized residual series is defined as:

$$F(z)\begin{cases} \frac{N_{\mu_L}}{N}\left(1+\xi_L\frac{\mu_L - z_t}{\beta_L}\right)^{\frac{-1}{\xi_L}} & if\ z_t < \mu_L \\ \Phi(z_t) & if\ \mu_L \leq z_t \leq \mu_U \\ 1-\frac{N_{\mu_U}}{N}\left(1+\xi_U\frac{\mu_U - z_t}{\beta_U}\right)^{\frac{-1}{\xi_U}} & if\ z_t > \mu_U \end{cases} \tag{5}$$

where ξ, β, μ_L and μ_U indicate the shape, scale, and lower and upper thresholds, respectively. N is the total number of samples, and N_μ is the number of samples that exceed the thresholds. $z_t = \varepsilon_t/\sqrt{h_t}$ is the standardized residuals filtered by the AR(1)-GJR-GARCH(1,1) model, and $\Phi(z_t)$ is the empirical distribution function.

The copula function can link the marginal distribution of two variables to obtain its two-dimensional joint distribution function, so it can describe the non-linear dependence and tail dependence between different variables. According to Sklar (1959), there exists a copula function $C : [0,1]^2 \to [0,1]$ such that:

$$F(x_1, x_2) = C(F_1(x_1), F_2(x_2)) \tag{6}$$

Therefore, the joint density function can be derived from Equation (6):

$$f(x_1, x_2) = c(F_1(x_1), F_2(x_2)) f_1(x_1) f_2(x_2) \tag{7}$$

where $c(u, v)$ and $f_n(x_n)$ are the density functions for the copula and the marginal distribution function $F_n(x_n)$, respectively. In order to obtain the dynamic CoVaR, according to Engle (2002) and Patton (2006), this paper adopts four different dynamic copula models to fit the dynamic dependence structure between the Chinese and other Asian stock markets, and, then, based on the Akaike information criterion (AIC), the optimal model is selected as the DCC-T copula given by:

$$Q_t = (1-\overline{\alpha}-\overline{\beta})\overline{Q} + \overline{\alpha} z_{t-1} z'_{t-1} + \overline{\beta} Q_{t-1} \tag{8}$$

$$z_{t-1} = \left(t_{\overline{v}}^{-1}(u_{t-1}), t_{\overline{v}}^{-1}(v_{t-1})\right) \tag{9}$$

$$R_t = \tilde{Q}_t^{-1} Q_t \tilde{Q}_t^{-1} \tag{10}$$

$$\tilde{Q}_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \tag{11}$$

where $\overline{\alpha}, \overline{\beta} \geq 0$ denotes the estimated parameters, and $\overline{\alpha} + \overline{\beta} < 1$ is required to ensure the stationarity and positive definiteness of Q_t. $\overline{Q}$ is the sample (unconditional) covariance matrix of the standardized residuals z_t, and R_t is the dynamic conditional correlation matrix. u_t and v_t are series obeying $U(0,\ 1)$ obtained by performing probability integral transformation on the standardized residuals. $t_{\overline{v}}^{-1}$ denotes the inverse T-distribution with $\overline{v}$ degree of freedom. In addition, the specifications and estimation methods for DCC-

Gaussian copula, TVP-Clayton copula, and TVP-SJC copula can be found in the work of Vogiatzoglou (2010).

According to Abuzayed et al. (2021), VaR is calculated as follows:

$$VaR_{q,t}^{i} = \Phi^{-1}(q)\sigma_t^i \tag{12}$$

where σ_t^i is the standard deviation series estimated by the marginal model, and $\Phi^{-1}(q)$ is the quantile function that obeys the normal distribution at a $1-q$ confidence level. Since VaR only represents the expected value when there is no spillover, this paper adopts the CoVaR to calculate the risk spillovers between the stock markets according to Adrian and Brunnermeier (2011) and Girardi and Ergün (2013) given by:

$$\Pr\left(r_t^j \le CoVaR_t^{j|i,q} \middle| r_t^i \le VaR_t^{i,q}\right) = q \tag{13}$$

Equation (13) indicates that, at the $1-q$ confidence level when stock market i is at extreme risk $VaR_t^{i,q}$, the conditional risk that stock market j may suffer is $CoVaR_t^{j|i,q}$. Meanwhile, according to Adrian and Brunnermeier (2016), $\Delta CoVaR_t^{j|i,q}$ is the risk spillover value of the stock market i to stock market j, defined by:

$$\Delta CoVaR_t^{j|i,q} = CoVaR_t^{j|i,q} - CoVaR_t^{j|i,50\%} \tag{14}$$

Further, ΔCoVaR is dimensionless processed to obtain %CoVaR, which can more effectively reflect the risk spillover intensity between stock markets, as follows:

$$\%CoVaR_t^{j|i,q} = \left(\Delta CoVaR_t^{j|i,q} / VaR_t^{j,q}\right) \times 100\% \tag{15}$$

According to Girardi and Ergün (2013), the $CoVaR_t^{j|i,q}$ has a closed-form distribution defined as:

$$CoVaR_t^{j|i,q} = \Phi^{-1}(q)\sigma_t^j\sqrt{1-R_t^2} + \Phi^{-1}(q)R_t\sigma_t^j \tag{16}$$

where R_t is the dynamic conditional correlation matrix based on the DCC-T copula model, σ_t^j is the standard deviation series, and q is a confidence level equal to 5%.

Given that $\Phi^{-1}(50\%) = 0$, then $\Delta CoVaR_t^{j|i,q}$ at each time point can be simplified as:

$$\Delta CoVaR_t^{j|i,q} = \Phi^{-1}(q)R_t\sigma_t^j \tag{17}$$

Finally, $\%CoVaR_t^{j|i,q}$ can be calculated according to Equation (15).

3.2. Materials

In order to study the risk spillovers between the Chinese and Asian stock markets, this paper selects the stock market indexes of 11 Asian countries (regions) as the research objects, based on data availability. The selected stock market indexes are as follows: Shanghai and Shenzhen 300 Index (China), Hang Seng Index (Hong Kong), Nikkei 225 Index (Japan), TSEC weighted index (Taiwan), KOSPI Composite Index (South Korea), S&P BSE SENSEX (India), Straits Time Index (Singapore), FTSE Bursa Malaysia KLCI (Malaysia), Jakarta Composite Index (Indonesia), Stock Exchange of Thailand Index (Thailand), and Philippines Stock Exchange Index (Philippines). The data are sourced from Investing.com and Yahoo Finance, covering 1 January 2007 to 31 December 2021. Moreover, the stock return series are calculated by $r_t = (lnP_t - lnP_{t-1}) \cdot 100$ where P_t is the daily close price at time t.

Table 1 provides the descriptive statistics of the stock return series. The standard deviation of Chinese stock returns is higher than other Asian stock markets, indicating that the Chinese stock market is more volatile. Furthermore, the skewness, kurtosis, and Jarque–Bera values confirm that all series exhibit sharp peaks, fat tails, and non-normality. This characteristic suggests that these markets are particularly vulnerable to extreme risk events. The Jarque–Bera statistic significantly rejects the null hypothesis of normal distribution at the 1% level, meaning that all series are non-normal distributions. The Q test significantly rejects the null hypothesis of white noise, indicating that all series are autocorrelated. Finally, the Q^2 and ARCH tests support that all series have ARCH effects at the 1% level, namely conditional heteroskedasticity effects. Additionally, Table 2 reports unit root tests for the stock return series. The ADF and PP statistics significantly reject the null hypothesis of the unit root processes at the 1% level, meaning that all series are stationary processes.

Table 1. Descriptive statistics for stock return series.

	Mean	Max	Min	SD	Skewness	Kurtosis	Jarque–Bera	Q (20)	Q^2 (20)	ARCH (20)
China	0.0245	8.9309	−9.6952	1.7557	−0.5194	6.8901	2389.859 ***	48.1407 ***	1613.1 ***	490.6073 ***
Hong Kong	0.0041	13.4068	−13.582	1.5362	−0.0734	11.9814	11,884.4645 ***	40.4111 ***	4020.4 ***	984.0395 ***
Taiwan	0.0234	6.5246	−9.1898	1.1951	−0.5938	8.5784	4807.5102 ***	63.0925 ***	1686.5 ***	518.094 ***
Japan	0.0147	13.2346	−12.7154	1.5561	−0.5664	11.5293	10,626.679 ***	50.2902 ***	3795.5 ***	878.0004 ***
South Korea	0.0215	11.2844	−11.172	1.2906	−0.5848	12.647	13,877.7495 ***	33.4104 **	3760.9 ***	897.7375 ***
India	0.0414	15.99	−14.1017	1.466	−0.3205	15.6961	23,237.1053 ***	60.0673 ***	1809.7 ***	506.9752 ***
Singapore	0.0009	8.8659	−10.628	1.1515	−0.3154	13.0023	14761.1008 ***	40.133 ***	3790.4 ***	900.9655 ***
Malaysia	0.0093	6.6263	−9.9785	0.7983	−0.7541	15.6559	23,500.4608 ***	44.6039 ***	588.3 ***	276.4585 ***
Thailand	0.0274	7.6531	−11.4871	1.2536	−1.1348	15.3527	22,530.4176 ***	90.1281 ***	2105.6 ***	641.9362 ***
Indonesia	0.0375	9.7042	−11.306	1.3469	−0.5082	11.4056	10,218.3681 ***	52.9503 ***	1924.2 ***	601.404 ***
Philippines	0.0259	9.3653	−14.3224	1.374	−1.0326	14.805	20,544.1125 ***	72.9788 ***	950.0 ***	395.0907 ***

Notes: Jarque–Bera denotes normal distribution test. Q (20) and Q^2 (20) are the Ljung–Box test for autocorrelation in return series and squared residual series up to the 20th order. The ARCH (20) is the Lagrange Multiplier test for conditional heteroscedasticity up to the 20th order. *** and ** denote significance at the 1% and 5% levels, respectively.

Table 2. Unit root tests for stock return series.

	China	HK	Taiwan	Japan	SK	India	Singapore	Malaysia	Thailand	Indonesia	Philippines
ADF	−58.0998 ***	−60.9688 ***	−57.6113 ***	−60.6196 ***	−59.0452 ***	−56.4758 ***	−59.0382 ***	−55.2963 ***	−57.9864 ***	−53.9687 ***	−55.3225 ***
PP	−58.1134 ***	−61.0541 ***	−57.6576 ***	−60.7685 ***	−59.0956 ***	−56.4843 ***	−59.1131 ***	−55.4702 ***	−58.1201 ***	−53.9002 ***	−55.2828 ***

Notes: ADF and PP represent the Augmented Dickey–Fuller and the Phillips–Perron unit root test, respectively. HK and SK represent Hong Kong and South Korea, respectively. *** denotes significance at the 1% level.

4. Empirical Results

This study employs the dynamic Copula-EVT-CoVaR model to quantify bidirectional risk spillovers between Chinese and other Asian stock markets, and implements it using MATLAB (R2021a) software. The model consists of three parts: the marginal model, copula model, and CoVaR model. The sample covers 11 Asian stock markets from 1 January 2007 to 31 December 2021, with the selected markets listed in Section 3.2. These markets are more representative and have roughly the same trading hours. Therefore, there is no need to address non-synchronous trading problems. Additionally, the sample interval includes multiple crisis events from the 2007–2009 global financial crisis to the COVID-19 pandemic.

4.1. Marginal Model Results

Since the return series have autocorrelation and conditional heteroscedasticity, and considering the underlying leverage effects, the AR(1)-GJR-GARCH(1,1) model is used to fit the marginal models. Meanwhile, since the return series distribution shows the characteristics of skewed and fat-tailed, this paper assumes that the residual series obeys a skew-t distribution. The estimation results of the marginal model are shown in Table 3. The parameters α are significant, indicating that each stock market is sensitive to recent information and has strong volatility characteristics. The parameters β are significant and close to 1, suggesting that each stock market has a high volatility persistence. Additionally, $\alpha + \beta < 1$, implying that the GARCH process is stationary. The parameters γ are greater than 0 and significant at the 1% level[2], which means there are asymmetric volatility and leverage effects in stock markets. Meanwhile, the bad news has a more significant impact on volatility than the good news, reflecting that price falls have a more significant impetus on the Asian stock markets. Both the degrees of freedom parameter υ and skewness parameters λ are significant at the 1% level, implying that the skew-t model can well fit the distribution features of the residual series. The p-values of the Q^2 and ARCH tests indicate no ARCH effect in the standardized residuals.

Table 3. Parameters of marginal models based on AR(1)-GJR-GARCH(1,1)-skew-t model.

	φ_0	φ_1	ω	α	β	γ	υ	λ	Q^2 (20)	ARCH (20)
China	0.0396 **	0.0018	0.0102 **	0.0577 ***	0.9415 ***	-	5.2309 ***	−0.0557 ***	26.0676	26.2258
	(0.019)	(0.016)	(0.004)	(0.009)	(0.009)		(0.449)	(0.019)	[0.1636]	[0.1585]
Hong Kong	0.0123	−0.0061	0.0262 ***	0.0241 ***	0.9222 ***	0.0791 ***	7.1126 ***	−0.0831 ***	22.3854	23.2104
	(0.018)	(0.014)	(0.009)	(0.007)	(0.014)	(0.019)	(0.829)	(0.020)	[0.3200]	[0.2786]
Taiwan	0.0355 **	0.0169	0.0159 *	0.0150 *	0.9287 ***	0.0817 **	5.5818 ***	−0.1252 ***	12.8785	12.4395
	(0.015)	(0.019)	(0.009)	(0.009)	(0.028)	(0.032)	(0.529)	(0.022)	[0.8825]	[0.9001]
Japan	0.0290	−0.0334 *	0.0761 ***	0.0277 **	0.8485 ***	0.1798 ***	6.4476 ***	−0.0907 ***	9.3406	9.4787
	(0.020)	(0.018)	(0.017)	(0.012)	(0.020)	(0.033)	(0.733)	(0.022)	[0.9786]	[0.9767]
South Korea	0.0156	−0.0148	0.0220 **	0.0290 ***	0.9027 ***	0.1038 ***	5.9915 ***	−0.1376 ***	14.9509	14.9554
	(0.014)	(0.018)	(0.009)	(0.010)	(0.023)	(0.032)	(0.605)	(0.021)	[0.7792]	[0.7790]
India	0.0412 **	0.0576 ***	0.0264 ***	0.0172 **	0.8971 ***	0.1438 ***	6.1881 ***	−0.0682 ***	18.1630	17.2615
	(0.016)	(0.017)	(0.005)	(0.007)	(0.012)	(0.023)	(0.641)	(0.025)	[0.5767]	[0.6359]
Singapore	0.0101	−0.0085	0.0089 ***	0.0239 ***	0.9233 ***	0.0893 ***	6.6428 ***	−0.0697 ***	20.9474	21.7568
	(0.013)	(0.013)	(0.003)	(0.009)	(0.012)	(0.015)	(0.711)	(0.024)	[0.4002]	[0.3539]
Malaysia	0.0048	0.0440 **	0.0071 ***	0.0555 ***	0.9019 ***	0.0679 ***	5.4710 ***	−0.0874 ***	10.9969	10.7983
	(0.010)	(0.018)	(0.002)	(0.014)	(0.018)	(0.018)	(0.499)	(0.023)	[0.9463]	[0.9513]
Thailand	0.0366 **	0.0143	0.0119 ***	0.0577 ***	0.8979 ***	0.0839 ***	5.3787 ***	−0.0765 ***	13.6191	13.1968
	(0.014)	(0.019)	(0.004)	(0.010)	(0.013)	(0.020)	(0.492)	(0.023)	[0.8493]	[0.8688]
Indonesia	0.0305 *	−0.0097	0.0290 **	0.0472 ***	0.8836 ***	0.1146 ***	4.8478 ***	−0.1302 ***	7.7680	8.2169
	(0.017)	(0.010)	(0.014)	(0.016)	(0.032)	(0.033)	(0.399)	(0.023)	[0.9933]	[0.9903]
Philippines	0.0186	0.0373 **	0.0771 ***	0.0480 ***	0.8429 ***	0.1263 ***	5.9507 ***	−0.0751 ***	10.6846	10.5426
	(0.021)	(0.018)	(0.021)	(0.016)	(0.029)	(0.029)	(0.613)	(0.025)	[0.9540]	[0.9572]

Notes: φ_0 and φ_1 are the estimated parameters of the AR(1) model. ω, α, β, and γ are the estimated parameters of the GJR-GARCH(1,1) model. υ and λ are the freedom and skewness parameters of the skew-t distribution. Q^2 (20) is the Ljung–Box test for autocorrelation in the squared standardized residuals up to the 20th order. The ARCH (20) is the Lagrange Multiplier test for conditional heteroscedasticity up to the 20th order. The standard errors are reported in parentheses, and p-values are reported in square brackets. - denotes that this parameter does not exist in the model. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4 provides the results of the BDS test. BDS statistics cannot reject the null hypothesis of i.i.d at the 1% level, meaning that all series obey i.i.d. Therefore, the standardized residuals satisfy the conditions for establishing the EVT model, and the EVT model can be used to estimate the extreme value distribution.

Table 4. BDS test results.

	China	HK	Taiwan	Japan	SK	India	Singapore	Malaysia	Thailand	Indonesia	Philippines
statistics	0.8	−0.1602	0.0298	0.4324	−0.5969	−0.9755	0.17	1.0462	−0.9846	0.2626	−0.5092
p-values	0.4237	0.8728	0.9762	0.6654	0.5506	0.3293	0.865	0.2955	0.3248	0.7928	0.6106

Notes: BDS is the Brock–Dechert–Scheinkman test for independently and identically distributed (i.i.d) series. HK and SK represent Hong Kong and South Korea, respectively.

According to the extreme value theory, this paper adopts the POT model to fit the tails of the standardized residuals for capturing the extreme risks that occur in the stock markets. The POT model requires a threshold to be set in advance, and setting the threshold too high will cause the variance of the GPD fitting result to be large, and the threshold set too low will cause the bias of the GPD fitting result to be large. Therefore, this paper selects 10% exceedances as the threshold by referring to the extant literature (Allen et al. 2013; Chavez-Demoulin et al. 2005; DuMouchel 1983; Wang et al. 2010).

From Table 5, most of the lower tail shape parameters ξ_L are larger than the upper tail shape parameters ξ_U, and the absolute values of the lower tail thresholds μ_L are larger than the upper tail thresholds μ_U, which shows that extreme events triggered by price decline are not only more numerous but also more intense. Therefore, this paper mainly focuses on the down-tail risk between stock markets. Figure 2 presents the upper-tail and lower-tail GPD fitting results for the Chinese stock market[3]. It can be seen that the fitted generalized Pareto cumulative distribution functions are very close to the empirical cumulative distribution functions, which indicates that GPD can accurately describe the fat-tailed characteristics of the standardized residuals and then effectively capture the risk status of each stock market under extreme events. Finally, the p-values of the KS test show that all new residual series obey (0, 1) uniform distribution, which satisfies the conditions for establishing the copula model.

Table 5. Tail threshold and GPD parameter estimation results.

	Lower Tail			Upper Tail			KS p-Value
	μ_L	ξ_L	β_L	μ_U	ξ_U	β_U	
China	−1.1925	0.1197	0.6378	1.1901	0.0084	0.5358	0.7914
Hong Kong	−1.2798	0.0355	0.5904	1.2120	−0.0397	0.5493	0.7733
Taiwan	−1.2394	0.0974	0.6759	1.1681	0.0052	0.4698	0.7131
Japan	−1.2722	0.0564	0.6328	1.2193	−0.0444	0.4925	0.8831
South Korea	−1.2369	−0.0314	0.7724	1.1922	−0.0734	0.5045	0.8388
India	−1.2243	0.0897	0.6050	1.1901	0.1395	0.4512	0.7500
Singapore	−1.2500	0.0496	0.6090	1.2047	0.0754	0.4689	0.8242
Malaysia	−1.1972	0.0813	0.6533	1.1808	0.0679	0.5022	0.8792
Thailand	−1.2115	0.0831	0.6657	1.1747	−0.0032	0.5323	0.7641
Indonesia	−1.1939	0.1370	0.6264	1.1410	0.1056	0.4782	0.7291
Philippines	−1.2140	0.1766	0.5261	1.1819	0.0826	0.5275	0.7498

Notes: μ, ξ, and β are the threshold, shape, and scale parameters, respectively. KS is the Kolmogorov–Smirnov test for the detection of a uniform distribution.

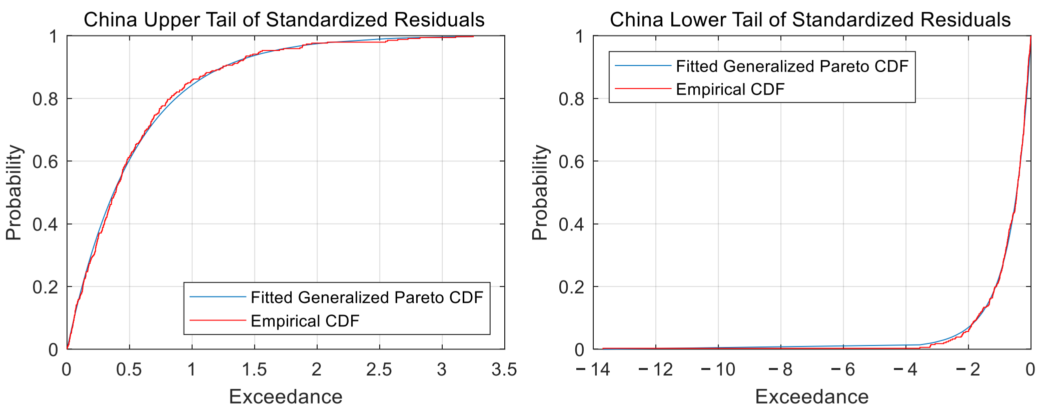

Figure 2. Upper-tail and lower-tail GPD fitting results for China.

4.2. Copula Model Results

This paper uses three static and four dynamic copula models to fit the dependence structure between the Chinese and other Asian stock markets, and, according to the AIC values in Table 6, the DCC-T copula model is selected as the optimal model[4]. The results of the DCC-T copula model are shown in Table 7, and $\overline{v}$ is significant at the 1% level, meaning that the T-copula model is appropriate. $\overline{\alpha}$ approaches 0, and $\overline{\beta}$ approaches 1, suggesting that the dynamic dependence between the Chinese and other Asian stock markets has strong persistence but is weakly influenced by past stock returns. In addition, $\overline{\alpha} + \overline{\beta} < 1$, which satisfies the constraints of the DCC model, indicating that the model is stationary. It is also shown in Table 5 that the Kendall dependences are all positive values, indicating the synchronicity between the Chinese and other Asian stock markets. That is, if an extreme event occurs in the Chinese stock market, it could cause risk spillovers to other Asian stock markets. China has the highest dependence on Hong Kong at 0.5628, which may be due to more frequent trade and mutual investment between China and Hong Kong and China's strong control and influence over Hong Kong's development (Jin 2018).

Table 6. AIC values for the static and dynamic copula models.

	T	Clayton	SJC	DCC-Gaussian	DCC-T	TVP-Clayton	TVP-SJC
Hong Kong	−1356.6493	−1145.8794	−1323.1527	−1412.3080	**−1421.0471**	−1199.7068	−1368.6927
Taiwan	−497.5774	−459.4803	−511.2854	−510.6142	**−533.6454**	−486.7947	−533.2840
Japan	−343.3495	−310.6624	−340.6391	−353.8943	**−360.4527**	−326.2321	−358.0471
South Korea	−485.0022	−459.8002	−494.4181	−496.8128	**−516.2737**	−479.8628	−511.6025
India	−238.0040	−206.9195	−241.7906	−236.0555	−241.6525	−204.0055	**−246.1028**
Singapore	−473.1127	−456.4884	−492.1070	−495.1291	**−513.6206**	−481.4896	−496.2846
Malaysia	−231.8815	−213.3022	−238.3358	−238.8721	**−248.1335**	−211.3077	−238.7798
Thailand	−245.9778	−213.0603	−245.3992	−230.6017	**−255.7786**	−209.8041	−246.8518
Indonesia	−295.9596	−277.5796	−302.8352	−291.5680	**−308.3636**	−278.0434	−303.5722
Philippines	−86.7413	−86.4480	−93.5557	−96.8564	−111.4114	−101.8417	**−118.6742**

Note: T, Clayton, and SJC represent three static copula models, and DCC-Gaussian, DCC-T, TVP-Clayton, and TVP-SJC are dynamic copula models based on DCC or TVP methods. The bold indicates the minimum Akaike Information Criterion (AIC) value among the different copula models.

Table 7. Estimated parameters of DCC-T-copula models.

	$\overline{\upsilon}$	$\overline{\alpha}$	$\overline{\beta}$	Kendall
Hong Kong	19.4103 ***	0.0136 ***	0.9842 ***	0.5628
	(6.138)	(0.004)	(0.005)	[0.0875]
Taiwan	11.6043 ***	0.0125 *	0.9814 ***	0.3627
	(2.719)	(0.007)	(0.013)	[0.0911]
Japan	19.7869 ***	0.0111	0.9810 ***	0.3036
	(5.943)	(0.009)	(0.023)	[0.0771]
South Korea	12.1023 ***	0.0416 ***	0.8864 ***	0.3479
	(2.677)	(0.012)	(0.041)	[0.0957]
India	20.0587 ***	0.0173 **	0.9055 ***	0.2570
	(6.331)	(0.008)	(0.047)	[0.0423]
Singapore	12.2519 ***	0.0214 ***	0.9642 ***	0.3474
	(2.986)	(0.006)	(0.012)	[0.1070]
Malaysia	16.3026 ***	0.0127 *	0.9737 ***	0.2515
	(5.462)	(0.007)	(0.021)	[0.0721]
Thailand	10.1254 ***	0.0089 **	0.9806 ***	0.2519
	(2.139)	(0.004)	(0.011)	[0.0619]
Indonesia	13.0804 ***	0.0072 *	0.9872 ***	0.2802
	(3.202)	(0.004)	(0.010)	[0.0666]
Philippines	12.7293 ***	0.0157 **	0.9216 ***	0.1929
	(3.080)	(0.008)	(0.042)	[0.0454]

Note: $\overline{\alpha}$ and $\overline{\beta}$ are the estimated parameters of the DCC model, and $\overline{\upsilon}$ is the degrees of freedom parameter for T-copula. Kendall is the average of the dynamic Kendall coefficients for evaluating dependence structures. The standard errors are reported in parentheses and standard deviations are reported in square brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 3 illustrates that the dynamic dependence of Chinese and other Asian stock markets has significant time-varying characteristics. According with Liu (2020), Chopra and Mehta (2022), and Li et al. (2022), this paper divides crisis events into the global financial crisis (2007–2009), the European debt crisis (2009–2012), the Chinese stock market crash (2015–2016), the China–US trade war (2018–2019), and the COVID-19 pandemic (2020–2021). During the 2007–2009 global financial crisis and the European debt crisis, Chinese and other Asian stock markets maintained a strong dependence. However, during the 2015–2016 Chinese stock market crash, the China–US trade war, and the COVID-19 pandemic, dynamic dependence experienced abnormal volatility, showing that the dependence dropped sharply and then rose rapidly.

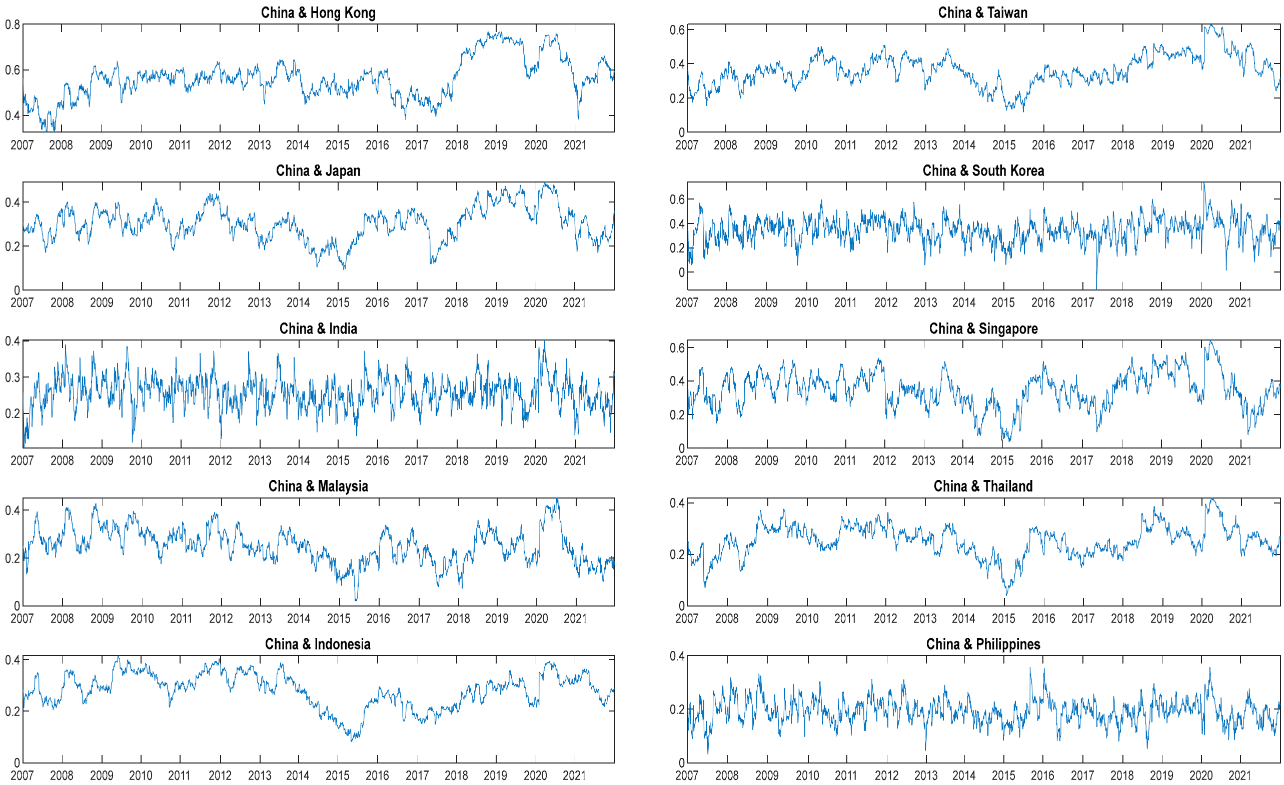

Figure 3. Dynamic dependence between the Chinese and Asian stock markets. Note: The blue lines indicate the dynamic Kendall correlation coefficients between the Chinese and other Asian stock markets.

4.3. Risk Spillover Results

Table 8 presents measures of risk spillovers for Chinese and Asian stock markets at the 5% quantile. On average, the CoVaR values for each stock market are smaller than the VaR values, indicating that the VaR method underestimates the risk spillover effects between the stock markets.[5] ΔCoVaR is negative, indicating a positive risk spillover between the stock markets; that is, when any one of the stock markets falls into extreme risk, other stock markets will also face greater risks. Meanwhile, considering the significant difference in VaR values between stock markets, this paper focuses on analyzing the %CoVaR obtained after normalization, which more intuitively shows the risk spillover intensity between the Chinese and other Asian stock markets.

Firstly, the risk spillovers from China to other Asian stock markets are heterogeneous, in order from strong to weak: Hong Kong, Malaysia, Singapore, Taiwan, South Korea, Thailand, Indonesia, Japan, India, and the Philippines. Specifically, China has the strongest risk spillover intensity to the Hong Kong stock market at 69.05%. China's risk spillovers to Malaysia and Singapore among the five ASEAN countries are the strongest at 59.86% and 59.71%, respectively, but the weakest to the Philippines at 26.79%. This result may be because China is Malaysia's largest source of investment and had been Malaysia's largest trading partner for 13 continuous years by 2021. In addition, since 2013, Singapore has been China's largest foreign investor, and China has been Singapore's largest trading partner. The risk spillover intensity of China to the Philippine stock market is the weakest, which may be because the limited resources of the Philippines make China's investment in it relatively unusual, so the scope of the capital impact is negligible.

Table 8. Average risk spillovers between the Chinese and Asian stock markets.

	VaR	**CoVaR**	**ΔCoVaR**	**%CoVaR**
China→Hong Kong	−2.2496	−3.3292	−1.4907	0.6905
China→Taiwan	−1.7702	−2.5811	−0.9461	0.5607
China→Japan	−2.3101	−3.0182	−0.8315	0.3809
China→South Korea	−1.8661	−2.663	−0.937	0.5326
China→India	−2.0497	−2.6738	−0.6998	0.3735
China→Singapore	−1.6345	−2.4445	−0.9408	0.5971
China→Malaysia	−1.1983	−1.8486	−0.6978	0.5986
China→Thailand	−1.8268	−2.4434	−0.6876	0.4122
China→Indonesia	−2.0045	−2.6846	−0.7719	0.4086
China→Philippines	−2.0454	−2.536	−0.5353	0.2679
Hong Kong→China	−2.6971	−3.4671	−1.2735	0.5107
Taiwan→China	−2.6971	−3.1318	−0.6545	0.2651
Japan→China	−2.6971	−3.2991	−0.722	0.2875
South Korea→China	−2.6971	−3.1786	−0.681	0.2688
India→China	−2.6971	−3.1452	−0.5426	0.2074
Singapore→China	−2.6971	−3.0704	−0.6106	0.2336
Malaysia→China	−2.6971	−2.8881	−0.3195	0.1222
Thailand→China	−2.6971	−3.117	−0.4877	0.1866
Indonesia→China	−2.6971	−3.195	−0.5842	0.2235
Philippines→China	−2.6971	−3.0665	−0.4117	0.1633

Note: This paper focuses on the lower-tail risk between stock markets, namely, the risk spillover effect at the 5% quantile.

The risk spillover intensity from China to Taiwan and South Korea is also relatively strong at 56.07% and 53.26%, respectively. This can be explained by economic fundamentals. China is the largest trading partner and the largest source of trade surplus for Taiwan and South Korea, and when China's economy downturns, it will lead to a drop in foreign trade, which can negatively impact the economic situation of Taiwan and South Korea, and the stock markets, as a macroeconomic barometer, generally will trend downward as well. Finally, the risk spillover intensity of China to Japan and India is relatively weak at 38.09% and 37.35%, respectively. It may be that Japan is a developed economy, and its economic structure is quite different from that of China, which does not satisfy the economic cycle synchronicity, thus slowing down the risk spillovers between stock markets. In addition, geopolitical tensions between China and India in recent years have led to a decline in trade ties, which has weakened the intensity of risk spillovers from the Chinese stock market.

Secondly, there are bidirectional risk spillovers between Chinese and other Asian stock markets, showing asymmetric risk spillovers; that is, the risk spillover intensity of other Asian stock markets to the Chinese is weaker than that of the Chinese to other Asian stock markets. This may be because the Chinese market is relatively closed, and the capital account has not been fully opened. Although financial liberalization has achieved certain results, there are still many problems, such as strict capital account controls and limited openness in the financial sector, which have led to relatively little participation by foreign investors in the Chinese stock market, thus limiting the free flow of capital and the short-term impact of hot money, which in turn has improved China's ability to resist risk spillovers. In addition, the Chinese stock market implements a strict price limit system, which can limit stock market turbulence caused by external shocks to a certain extent.

Finally, according to Figure 4, the risk spillovers between the Chinese and other Asian stock markets are time-varying and fat-tailed. Specifically, the Chinese stock market generated significant extreme risk spillovers to other Asian stock markets during the 2007–2009 global financial crisis, the European debt crisis, the 2015–2016 Chinese stock market crash, and the China–US trade war. This may be because investors often rely on heuristics to make decisions when faced with emergencies, and this irrational behavior is amplified by herding effects, causing negative shocks to other countries' stock markets, thus generating extreme risk spillovers. However, during the COVID-19 pandemic, the risk spillover intensity of the Chinese stock market was weaker, and it was the risk recipient of the Asian stock markets. This means that, although China was the first country to have a large-scale outbreak of COVID-19, the extreme risks in the stock market during the pandemic were not caused by China, but rather China was the country that suffered the severest risk spillovers from the crisis.

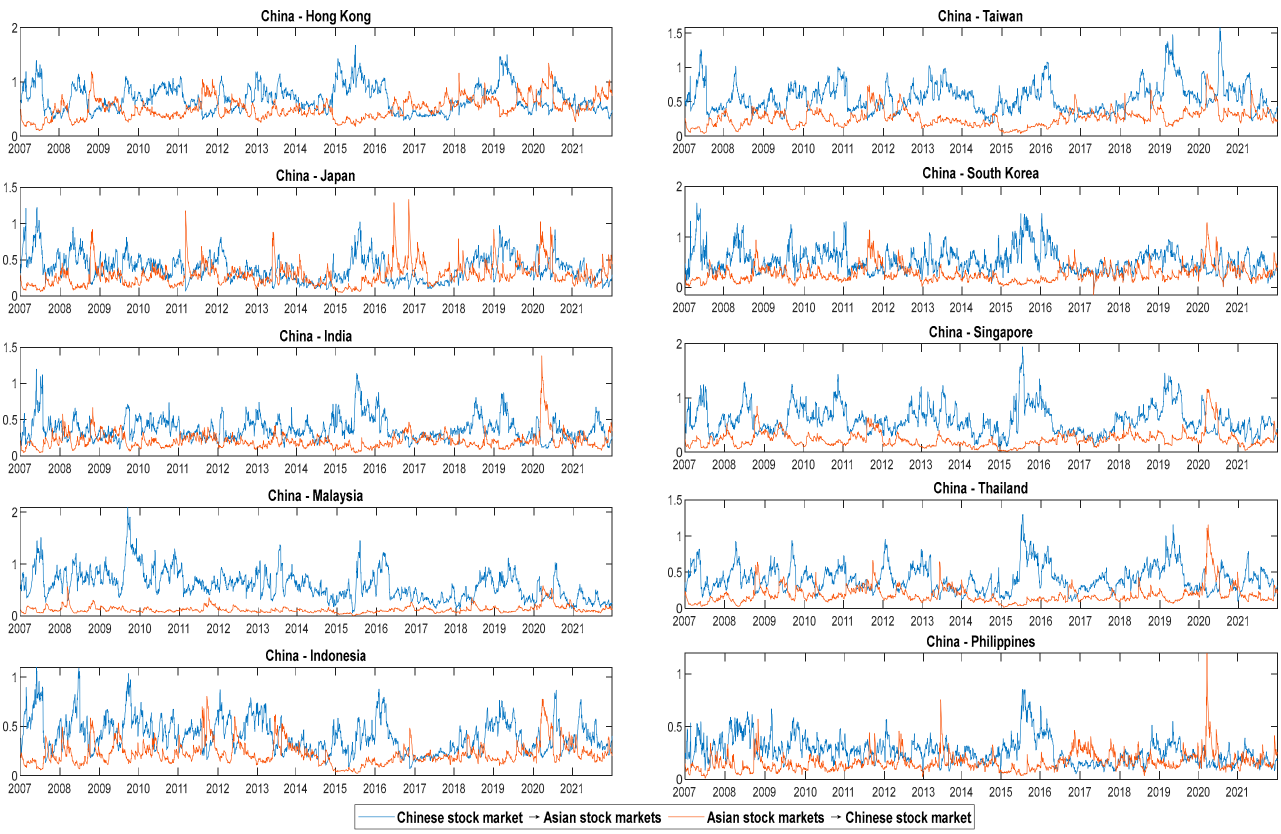

Figure 4. Dynamic %CoVaR between the Chinese and Asian stock markets.

In addition, natural disasters can also generate extreme risk spillovers to the stock markets, such as the 2011 earthquake in Japan. Japan also generated extreme risk spillovers to the Chinese stock market during the 2016 Brexit referendum. This may be because the yen gained popularity as a safe haven during the Brexit referendum, resulting in a sharp appreciation of the yen and pressure on exports, which in turn caused the stock markets to plunge and generate the risk spillover effect. Finally, China and South Korea had negative %CoVaR during the 2017 Sade event, suggesting that risk absorption existed between the two countries.

4.4. Robustness Diagnosis

From Table 4, the AIC values of the optimal and the suboptimal copula models are similar. Therefore, without losing generality, this paper uses the suboptimal copula model to check the results, as shown in the Appendix A (Table A1 and Figure A1)[6]. Figure 4 is similar to Figure 3, so empirical results are robust and can accurately measure risk spillovers between the Chinese and Asian stock markets.

5. Discussion

The results of the dynamic dependence analysis show that the dependence between the Chinese and other Asian stock markets increased rapidly after the crisis event. This observation indicates a high level of synchronicity between the Chinese and other Asian stock markets, consistent with the findings of Zaidi and Rupeika-Apoga (2021). This synchronicity creates conditions for risk contagion, whereby risks originating in one region can quickly spread to other regions, exacerbating instability across the entire market.

The results of risk spillovers indicate that China is relatively less affected by other Asian stock markets. China has implemented strict capital controls. These controls have restricted the free flow of capital and the short-term impact of hot money, thereby improving China's ability to resist risk spillovers. In contrast, other countries may have more open economic systems, freer markets, and less government intervention. Consequently, they cannot control risk spillovers as effectively as China.

Additionally, China's risk spillovers to other Asian stock markets are strong, highlighting its importance as Asia's largest economy. Specifically, the risk spillover intensity from China to the Hong Kong stock market is the strongest, which is consistent with the results of Xiao (2020). This phenomenon could be attributed to the higher degree of financial market integration between China and Hong Kong. Many companies are listed in both China and Hong Kong together. This makes the Hong Kong stock market more susceptible to economic and policy shocks emanating from China. Furthermore, risk spillovers from China to Japan and India are relatively weak, possibly due to differences in economic structures or ongoing geopolitical tensions.

Finally, China had significant extreme risk spillovers to other Asian stock markets during the 2007–2009 global financial crisis, the European debt crisis, the 2015–2016 Chinese stock market crash, and the China–US trade war. However, amid the COVID-19 pandemic, the Chinese stock market suffered strong risk spillovers from other stock markets and was a risk recipient. Additionally, Liu et al. (2023b) pointed out that the COVID-19 pandemic had a significant negative impact on the Chinese stock market, particularly impacting labor-intensive state-owned firms. Overall, the direction and intensity of risk transmission between China and other Asian stock markets may vary across different emergencies. Therefore, regulatory agencies must consider the dynamic nature of risk spillovers when formulating risk prevention strategies.

6. Conclusions

6.1. Conclusions and Policy Implications

This paper investigates bidirectional risk spillovers between Chinese and Asian stock markets by constructing a dynamic copula-EVT-CoVaR model. The main conclusions are as follows: Firstly, synchronicity exists between the Chinese and other Asian stock markets, providing conditions for risk contagion. Secondly, the risk spillovers from the Chinese to other Asian stock markets are heterogeneous, in order from strong to weak: Hong Kong, Malaysia, Singapore, Taiwan, South Korea, Thailand, Indonesia, Japan, India, and the Philippines. Meanwhile, the risk spillover has an asymmetry, which means that the risk spillover intensity of other Asian stock markets to the Chinese is weaker than that of Chinese to other Asian stock markets. Finally, during the 2007–2009 global financial crisis, the European debt crisis, the 2015–2016 Chinese stock market crash, and the China–US trade war, China created a significant extreme risk spillover for other Asian stock markets. However, during the COVID-19 pandemic, the risk spillover intensity of the Chinese stock market was weaker, and it was the risk recipient of the Asian stock markets.

The Chinese stock market exhibits strong risk spillovers to other Asian stock markets, with the most significant spillovers observed in the Hong Kong stock market. Therefore, financial regulatory agencies in Asian stock markets such as Malaysia, Singapore, Taiwan, and South Korea must not only supervise cross-border capital flows from China but also be wary of Hong Kong as a potential channel for transmitting risks. While the current stringent capital controls in China contribute to mitigating risk spillovers from other countries, this should not be considered a long-term solution. The Chinese stock market should further open up the financial market and attract more foreign investors to increase market liquidity and activity, thereby improving its ability to withstand external shocks. Moreover, the Chinese stock market, as a recipient of risk during the COVID-19 pandemic, should be vigilant against risk spillovers from other Asian stock markets that are dominated by the Indian market. Compared with other Asian stock markets, Chinese investors may consider increasing portfolio weightings with Japanese, Indian, or Philippine stock markets to achieve risk diversification and optimize returns amid potential market volatility.

6.2. Limitations and Future Research Recommendations

Although this paper makes contributions to the existing literature, it still has some limitations. First, this study focuses on the aggregate level of the stock market and does not deeply explore the potential heterogeneous spillovers among various stock industries. Second, this study does not decompose the risk spillover effects from a frequency domain perspective. Therefore, future research can introduce a wavelet transform to examine the impact of risk spillovers in the short and long term. Third, although CoVaR can measure risk spillovers between two variables, it is necessary to construct a risk spillover network to investigate the risk transmission direction and spillover mechanism in complex financial systems.

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Appendix A

Table A1. Estimated parameters of the suboptimal copula models.

	Model	$\overline{\omega}_L$	$\overline{\alpha}_L$	$\overline{\beta}_L$	$\overline{\omega}_U$	$\overline{\alpha}_U$	$\overline{\beta}_U$	$\overline{\alpha}$	$\overline{\beta}$
Hong Kong	DCC-Gaussian	-	-	-	-	-	-	0.0145 *** (0.004)	0.9825 *** (0.006)
Taiwan	TVP-SJC	0.7250	−7.0520 ***	−0.5377	0.8000	−10.0000	0.0752	-	-
		(0.543)	(2.547)	(0.409)	(0.985)	(7.179)	(0.755)		
Japan	TVP-SJC	0.1231 ***	−0.5705 ***	0.9746 ***	−0.8562	−9.9998	−0.5462	-	-
		(0.037)	(0.171)	(0.008)	(2.064)	(8.660)	(0.426)		
South Korea	TVP-SJC	0.6935	−6.0411 ***	−0.3243	0.6762	−9.4605 **	0.2312	-	-
		(0.487)	(2.160)	(0.243)	(0.631)	(3.804)	(0.314)		
India	TVP-SJC	−2.6189 ***	−0.0461	−0.6515 ***	1.0991 ***	−6.7035 ***	0.7574 ***	-	-
		(0.917)	(3.763)	(0.242)	(0.381)	(1.977)	(0.066)		
Singapore	TVP-SJC	0.0379 (1.292)	−5.2209 (4.136)	−0.9527 *** (0.057)	−1.9171 (4.406)	−9.9998 (17.562)	−0.9978 *** (0.010)	-	-
Malaysia	DCC-Gaussian	-	-	-	-	-	-	0.0123 * (0.007)	0.9735 *** (0.022)
Thailand	TVP-SJC	0.1507 ** (0.075)	−1.0471 * (0.555)	0.9069 *** (0.086)	−1.9173 (2.348)	−1.4408 (3.130)	0.1177 (0.550)	-	-
Indonesia	TVP-SJC	−0.0674 (0.860)	−8.4142 ** (3.417)	−0.9554 *** (0.027)	−2.7839 (2.919)	−8.3967 (9.814)	−0.9126 *** (0.128)	-	-
Philippines	TVP-SJC	0.1017 (0.208)	−1.6277 * (0.947)	0.7873 *** (0.138)	−3.2370 (6.443)	−9.2955 (13.859)	−0.1378 (0.451)	-	-

Note: The parameters $\overline{\omega}_L$, $\overline{\alpha}_L$, $\overline{\beta}_L$, $\overline{\omega}_U$, $\overline{\alpha}_U$ and $\overline{\beta}_U$ correspond to the parameters of the lower and upper tails of the TVP-SJC copula model. $\overline{\alpha}$ and $\overline{\beta}$ are the estimated parameters of the DCC-Gaussian copula model. The standard errors are reported in parentheses. - denotes that this parameter does not exist in the model. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

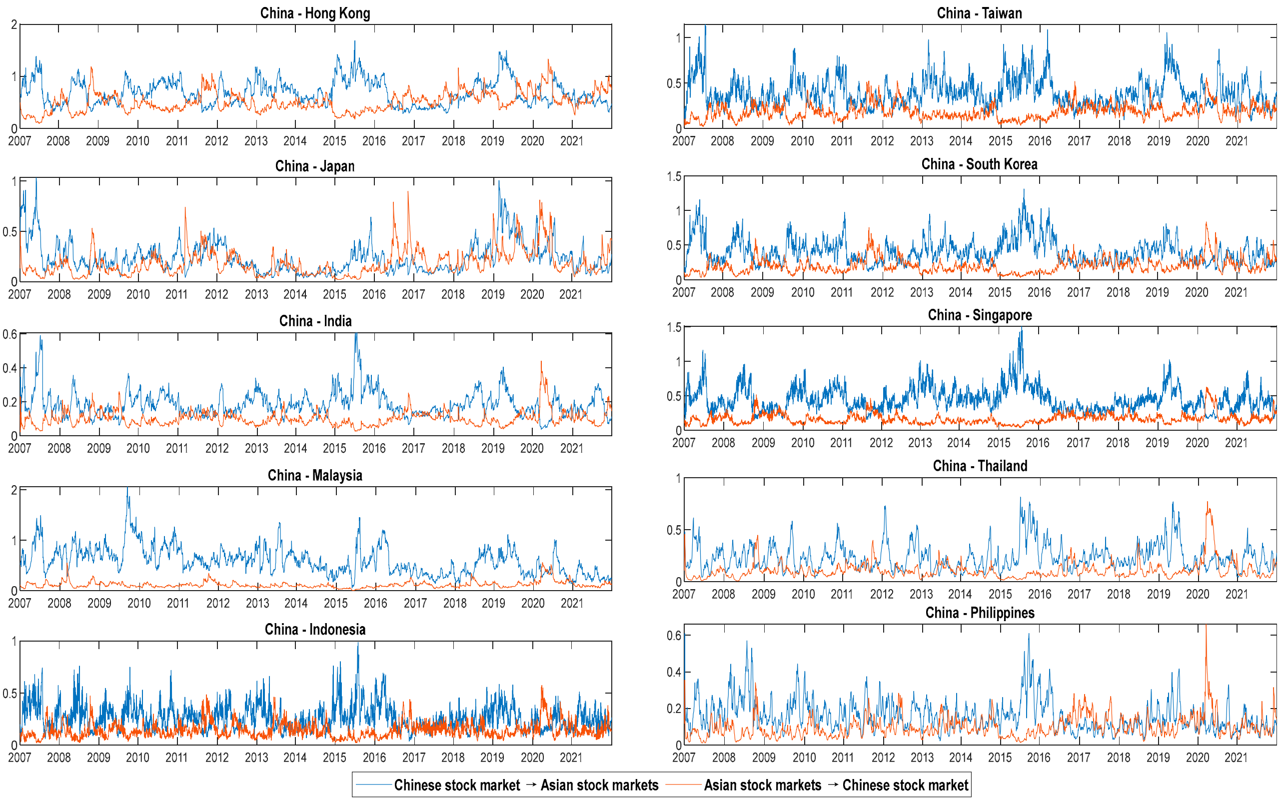

Figure A1. Dynamic %CoVaR between the Chinese and Asian stock markets based on the suboptimal copula models.

Notes

1. Considering the non-normality of GARCH residuals, this paper assumes that standardized residuals obey skew-t distribution to capture asymmetries and fat tails.
2. Since the parameter γ of the Chinese stock return series is not significant, the AR(1)-GARCH(1,1)-skew-t model is used to estimate the Chinese stock market.
3. Due to space limitations, this paper only lists the fitting results of the Chinese stock market, and the results of other stock markets are available upon request.
4. Different copula models have different sensitivities to the tails, and, in order to make the dynamic dependence comparable, the DCC-T copula model is used uniformly for the calculation.
5. VaR represents the expected value without spillovers from other stock markets, that is, its own risk value. Therefore, the VaR calculation result of other Asian stock markets for the Chinese stock market is unanimously -2.6971.
6. Because of space limitations, this paper only lists some main results and focuses on the lower-tail risk between stock markets.

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