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Research article

Transmission effect of extreme risks in China's financial sectors at major emergencies: Empirical study based on the GPD-CAViaR and TVP-SV-VAR approach

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Abstract: Major emergencies cause massive financial risk and economic loss. In the context of major emergencies, we propose the GPD-CAViaR model to depict the extreme risks of financial sectors, and utilize the TVP-SV-VAR model to analyze their transmission effect. We find that (i) the securities sector has the highest extreme risks among the four financial sectors; (ii) when major emergencies occur, the extreme risks of various financial sectors increase rapidly; (iii) the transmission effect in short term is stronger than that in medium and long term; and (iv) the transmission effects at different time points are relatively consistent.

Keywords: transmission effect; extreme risk; major emergency; financial sector

1. Introduction

With the deepening of China's economic reform and opening up, the financial system consisting of institutions, sectors and markets become increasingly crucial in recent years. As a result of the financial system's heedless and uncontrolled expansion, the various financial risks increase rapidly. Furthermore, due to the fragility, complexity and negative externalities of the financial system, its risk sources are diverse and uncertain. In addition, financial risk transmission mechanisms are distinguishable, which causes the traditional VaR (Value at Risk) model cannot adequately capture financial risks [1,2]. At the same time, major emergencies seriously threaten financial stability and economic security, and generate huge potential risks and regulatory difficulties [3]. They not only attract a sharp rise in financial risk, but also accelerate the risk transmission within the financial system, which easily induces systemic risk [4–6]. In fact, the financial sector is an essential element of the financial system, and its risk issue is important for financial risk governance in the post-crisis period. Therefore, we try to explore the extreme risks of the financial sectors and their transmission effect in the context of major contingencies, which is crucial for risk management and investment decisions.

In contrast to the traditional VaR model, the CAViaR (Conditional Autoregressive Value at Risk) model directly models the quantile series without the assumption on the return distribution, and it can effectively describe the typical properties of financial time series and overcome the shortcoming of autocorrelation in the time series [7,8]. For instance, Chen et al. [9] implement the CAViaR approach to measure the exchange-rate risk under the hypothesis of an auto-correlated distribution. On the basis of this approach, some researchers provide new insight and make some improvements. For example, White et al. [10] extend the CAViaR model and propose the MVMQ-CAViaR (Multi-variate and Multi-quantiles CAViaR) model, which makes it can simultaneously estimate parameters at different quantiles for multiple variables and perform impulse response analysis. Huang et al. [11] build a time-varying index-exciting CAViaR model based on the hypothesis that the model coefficients are connected to macroeconomic variables, which can adequately capture the spillover effect of the financial markets. In order to deal with conventional quantiles, Zhang and Duan [12] combine the CAViaR model with extreme value theory to construct the EVT-CAViaR (Extreme Value Theory CAViaR) model, and it is accurate in calculating the low quantile VaR and effective in depicting the extreme risk.

If the financial risk is not resolved in a timely and effective manner, then it will continue to accumulate and cause risk transmission [13–16]. Most authors use the VAR (Vector AutoRegression) model to examine the transmission effect of financial risk, but the parameters of this model are set to be constant and cannot identify the dynamic property of transmission [17–19]. Therefore, some scholars broaden the VAR model [20,21]. For instance, Magkonis and Tsopanakis [22] establish the SVAR (Structural VAR) model to investigate the impact of financial and fiscal stress on the macroeconomic variables, and discover that financial and fiscal shocks affect negatively the economy. Chen et al. [23] utilize the MS-VAR (Markov-switching VAR) model to analyze the nonlinear influence of financial factors on the price fluctuation of non-ferrous metals at various stages, and prove that it has considerable regime-switching characteristics. Ahelegbey et al. [24] present the Network VAR model to explore the channels of the financial risk transmission between countries through financial markets and bank lending, and confirm that both bilateral exposures and market prices are critical contagion channels. Previously, several academics utilize TVP-SV-VAR (Time-Varying Parameter Stochastic Volatility VAR) model to explore the time-varying transmission effects [25,26]. As an example, Guevara and Rodríguez [27] develop the TVP-SV-VAR model to discuss the dynamic impact of loan supply shocks on the real economic activity, and find that there are dramatically different influences during the various periods.

The existing literature provides impressive findings on the financial extreme risk and transmission effect. However, it has the following limitations. Firstly, compared with the financial institution and financial market, the financial sector is less studied by scholars, despite it plays a crucial role in the financial system. Secondly, many academics concentrate on the research of extreme risk contagion in the financial system, but seldom apply the extreme value theory to the CAViaR model, and ignore the actual condition of extreme financial risk. Finally, the traditional VAR model can only exhibit the direction and degree of the transmission between endogenous variables, and cannot further capture the nonlinear and time-varying properties. Therefore, we attempt to carry out innovation in the following aspects. (i) We primarily investigate financial extreme risks from the perspective of the financial sectors, as well as survey and compare risk differences among the financial sectors. (ii) In the context of major emergencies, we pay attention to the thick tail of financial risks, and utilize the GPD-CAViaR model to depict the extreme financial risk. (iii) In view of nonlinear, asymmetric and time-varying features, we propose the TVP-SV-VAR model to comprehensively examine the transmission effects of extreme risks in the financial sectors.

2. Methodology

2.1. GPD-CAViaR model

The CAViaR model works effectively at common probability levels, such as 5% and 1%. However, it can not perform satisfactorily at extreme quantiles, such as 0.1% or even lower. Referring to Manganelli and Engle [28], we incorporate the GPD method into the CAViaR framework to solve the above problem. Compared with the CAViaR model, the GPD-CAViaR model emphasizes the tail information of the return distribution according to the extreme value theory, which is suitable for describing financial extreme risks at major emergencies. Therefore, we decide to use it to investigate the extreme risks of financial sectors. The distribution function of the GPD is defined as

$$G(x;\mu,\sigma,\xi)=\begin{cases}1-(1+\xi\dfrac{x-\mu}{\sigma})^{-1/\xi} & \xi\neq 0\\ 1-\exp(-\dfrac{x-\mu}{\sigma}) & \xi=0\end{cases}, \tag{2.1}$$

where x is the yield sequence, μ is the location parameter, σ is the scale parameter, and ξ is the shape parameter.

The determination of the threshold is essential to building the GPD model. Currently, the most commonly utilized methods include the mean excess graph, Hill graph and sample 10% principle, but they are subjective and cannot accurately select the threshold [29]. According to Choulakian and Stephens [30], we employ W^2 and A^2 statistical methods to identify the threshold for the GPD model. In addition, the CAViaR model can explicitly calculate the extreme risk instead of estimating the tail of the distribution. The fundamental premise of this model is that the quantile series occur an evolutionary mechanism, and it is regarded as an autoregressive process. Following Engle and Manganelli [7], we define the CAViaR model as follows

$$\mathrm{VaR}_t(\beta)=\beta_0+\sum_{i=1}^{p}\beta_i\mathrm{VaR}_{t-i}(\beta)+\sum_{j=1}^{r}\beta_j l(x_{t-j}), \tag{2.2}$$

where $p = q+r+1$ is the dimension of β and l is a function of a finite number of lagged values of financial sector returns. In addition, the autoregressive terms $\beta_i\mathrm{VaR}_{t-i}(\beta)$ ensure that financial sector risk changes smoothly over time. The role of $l(x_{t-j})$ is to link $\mathrm{VaR}_t(\beta)$ to the financial sector return that belongs to Ω_{t-1} that the information set available at time $t-1$.

Generally, the CAViaR model has the following forms.

(i) The SAV-CAViaR (Symmetric Absolute Value CAViaR) model assumes that the market reacts to the good news and bad news in the same way and the expression is as follows

$$\mathrm{VaR}_t(\beta) = \beta_1 + \beta_2 \mathrm{VaR}_{t-1}(\beta) + \beta_3 \left| x_{t-1} \right| . \tag{2.3}$$

(ii) The AS-CAViaR (Asymmetric Slope CAViaR) model requires that the response to the good news and bad news should be asymmetrical and the expression is as follows

$$\mathrm{VaR}_t(\beta) = \beta_1 + \beta_2 \mathrm{VaR}_{t-1}(\beta) + \beta_3 (x_{t-1})^+ + \beta_4 (x_{t-1})^- , \tag{2.4}$$

where $(x_{t-1})^+ = \max(x_{t-1}, 0)$, $(x_{t-1})^- = -\min(x_{t-1}, 0)$.

(iii) The IGARCH-CAViaR (Indirect GARCH CAViaR) model describes the evolution of the quantile through the GARCH(1,1) model and the expression is as follows

$$\mathrm{VaR}_t(\beta) = (\beta_1 + \beta_2 \mathrm{VaR}_{t-1}^2(\beta) + \beta_3 x_{t-1}^2)^{1/2} . \tag{2.5}$$

Following Manganelli and Engle [26], we expound the basic calculation process of the GPD-CAViaR model.

Firstly, we calculate the quantile $q_{t,\theta}$ through the CAViaR model, where θ is the quantile point.

Secondly, considering the quantile residuals $\varepsilon_{t,\theta}$ and quantile, we construct the series of standardised quantile residuals

$$\frac{\varepsilon_{t,\theta}}{q_{t,\theta}} = \frac{x_t - q_{t,\theta}}{q_{t,\theta}} = \frac{x_t}{q_{t,\theta}} - 1 . \tag{2.6}$$

Finally, we assume that $q_{t,\theta}$ is the VaR series of extreme quantile level p ($p < \theta$), and it satisfies

$$\Pr(x_t < q_{t,p}) = \Pr(x_t < q_{t,\theta} - (q_{t,\theta} - q_{t,p})) = \Pr(\frac{x_t}{q_{t,\theta}} - 1 > z_p) = p , \tag{2.7}$$

where z_p is the (1−p)-quantile of the standardised quantile residuals and can be obtained through the GPD model. Furthermore, on the basis of $z_p = q_{t,p}/q_{t,\theta} - 1$, we can get $q_{t,p} = q_{t,\theta}\,(1+z_p)$.

Moreover, we evaluate the performance of the GPD-CAViaR model through the Hit and DQ test. If the GPD-CAViaR model has a good fit for financial sector risk, it is satisfied as follows

$$\Pr[x_t < \mathrm{VaR}_t(\beta)] = \theta, \ \forall t . \tag{2.8}$$

According to Engle and Manganelli [7], we propose the $\mathrm{Hit}_t(\beta)$ test for evaluating various alternatives that have better performance than other tests

$$\mathrm{Hit}_t(\beta) = I(x_t < \mathrm{VaR}_t(\beta)) - \theta , \tag{2.9}$$

where $\mathrm{Hit}_t(\beta)=1-\theta$ when the financial sector returns x_t is less than the quantile and $-\theta$ otherwise.

Clearly, the expectation of $\mathrm{Hit}_t(\beta)$ is zero ($E[\mathrm{Hit}_t(\beta)] = 0$). In accordance with the definition of the quantile function, the conditional expectation of $\mathrm{Hit}_t(\beta)$ must also be zero ($E[\mathrm{Hit}_t(\beta)]|I_{t-1} = 0$). In particular, $\mathrm{Hit}_t(\beta)$ is defined without the existence of autocorrelation with its own lagged values and uncorrelated with $\mathrm{VaR}_t(\beta)$. Only if $\mathrm{Hit}_t(\beta)$ satisfies these conditions, then the autocorrelation in the hits and the measurement error don't exist.

In order to test the adequacy of the GPD-CAViaR model, we construct an in-sample dynamic quantile test (DQ_{IS}) and an out-of-sample dynamic quantile test (DQ_{OS}).

$$\mathrm{DQ}_{IS} \equiv \frac{\mathrm{Hit}'(\hat{\beta})\mathrm{X}(\hat{\beta})(\hat{\mathrm{M}}_T\hat{\mathrm{M}}_T')^{-1}\mathrm{X}'(\hat{\beta})\mathrm{Hit}'(\hat{\beta})}{\theta(1-\theta)} : \ \chi_q^2, \tag{2.10}$$

$$\mathrm{DQ}_{OS} \equiv N_R^{-1}\mathrm{Hit}'(\hat{\beta}_{T_R})\mathrm{X}(\hat{\beta}_{T_R})[\mathrm{X}'(\hat{\beta}_{T_R})\cdot\mathrm{X}(\hat{\beta}_{T_R})]^{-1}\times\mathrm{X}'(\hat{\beta}_{T_R})\mathrm{Hit}'(\hat{\beta}_{T_R})/(\theta(1-\theta)) : \ \chi_q^2, \tag{2.11}$$

where

$$\hat{\mathrm{M}}_T \equiv \mathrm{X}'(\hat{\beta}) - \left\{(2T\hat{c}_T)^{-1}\sum_{t=1}^{T} I\left(\left|x_t - \mathrm{VaR}_t(\hat{\beta})\right| < \hat{c}_T\right)\times\mathrm{X}'(\hat{\beta})\nabla\mathrm{VaR}_t(\hat{\beta})\right\}\times\hat{D}_T^{-1}\nabla'\mathrm{VaR}_t(\hat{\beta}). \tag{2.12}$$

The DQ_{IS} test is a specification test for the particular GPD-CAViaR process and can be useful for the model selection. Meanwhile, the DQ_{OS} test can be applied for the regulators to examine whether the VaR estimates submitted by a financial sector satisfy the minimum requirements of a good quantile, such as unbiasedness, independent hits and independence of the quantile estimates.

2.2. TVP-SV-VAR model

In contrast to the VAR model, the TVP-SV-VAR model can accurately describe the nonlinearity, asymmetry and time-variability of risks. Therefore, we choose this model to analyze the transmission effect of extreme risks of financial sectors.

The TVP-SV-VAR model is developed from the SVAR (Structural VAR) model, whose parameters are time-varying and obey a random walk process. The basic definition of the SVAR model is as follows

$$AY_t = F_1Y_{t-1} + \cdots + F_sY_{t-s} + u_t,\ t = s+1,\cdots,n, \tag{2.13}$$

where Y_t is the $k\times1$ vector of observed variables, and A, F_1, …, F_s are $k\times k$ matrice of coefficients. s is lag times. The disturbance u_t is the $k\times1$ vector of structural shock.

We assume $u_t \sim N(0, \Sigma\,\Sigma)$, where Σ is a $k\times k$ dimensional diagonal matrix, and the elements on the diagonal are ($\sigma_1, \sigma_2, \ldots, \sigma_k$). In addition, A is a lower triangular matrix of order $k\times k$, and the elements of the lower triangle are α_{kk-1}, which satisfies the following relationship

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \alpha_{k1} & \cdots & \alpha_{kk-1} & 1 \end{pmatrix}. \tag{2.14}$$

On the basis of Eq (2.13), we introduce the time-varying parameters $\beta_t = A^{-1}F_s$ and define $X_t = I_k \otimes (Y'_{t-1}, Y'_{t-2}, \ldots, Y'_{t-s})$, where $\otimes$ is the Kronecker product.

Therefore, the basic definition of the TVP-SV-VAR model is as follows

$$Y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t, \tag{2.15}$$

where the coefficient matrix β_t, the parameters matrix A_t and the error covariance matrix $\sum_t$ are all time-varying. In addition, ε_t is the random disturbance term, and $\varepsilon_t \sim N(0, I_k)$.

Following Primiceri [31], we assume that α_t is the stacking vector of the lower triangular matrix A_t and satisfies $\alpha_t = (\alpha_{21}, \alpha_{31}, \alpha_{32}, \alpha_{41}, \ldots, \alpha_{kk-1})'$. Concurrently, we define $h_t = (h_{1,t}, h_{2,t}, \ldots, h_{k,t})'$, where $h_{j,t}=\ln\sigma^2_{j,t}, j = 1,2, \ldots, k$. The time-varying parameters are assumed to obey a first-order random walk process

$$\beta_{t+1} = \beta_t + u_{\beta t}, \tag{2.16}$$

$$a_{t+1} = a_t + u_{at}, \tag{2.17}$$

$$h_{t+1} = h_t + u_{ht}, \tag{2.18}$$

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} : N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right), \tag{2.19}$$

where $\beta_{s+1} \sim N(u_{\beta_0}, \sum_{\beta_0})$, $a_{s+1} \sim N(u_{a_0}, \sum_{a_0})$ and $h_{s+1} \sim N(u_{h_0}, \sum_{h_0})$.

According to Nakajima [32], we use the MCMC (Markov Chain Monte Carlo) method to estimate the time-varying parameters of the TVP-SV-VAR model. In addition, the initial value of the parameter is $u_{\beta_0} = u_{a_0} = u_{h_0}$, $(\Omega_{\beta_0}) = (\Omega_{a_0}) = (\Omega_{h_0}) = 10 \times I$. The MCMC method is carried out under the framework of Bayes inference, and its prior distribution is set as follows

$$(\Sigma_\beta)_i^{-2} : \ Gamma(40, 0.02), \tag{2.20}$$

$$(\Sigma_a)_i^{-2} : \ Gamma(4, 0.02), \tag{2.21}$$

$$(\Sigma_h)_i^{-2} : \ Gamma(4, 0.02), \tag{2.22}$$

where $(\sum_\beta)_i$, $(\sum_a)_i$ and $(\sum_h)_i$ are the ith element of the variance diagonal matrix.

3. Empirical analysis

3.1. Data selection and descriptive statistics

We divide the financial sector into the banking sector, securities sector, insurance sector and diversified financial sector, and examine their extreme risks and transmission effects. The Shenwan

Industry Index is used as a proxy for each sector. It conforms to the sector classification standards of the CSRC (China Securities Regulatory Commission) and reflects the actual situation of various financial sectors [33]. Among them, the banking sector, securities sector and insurance sector are the traditional main components of the financial system, and the diversified financial sector includes trust, internet finance and consumer finance and so on. Considering data availability, we set the sample period from January 17, 2007 to June 30, 2021, and there are 3514 observations for each sector. We obtain data from the Wind database.

Table 1 reports the summary statistics for the return series of financial sectors. We find that the average values of the return series are all greater than zero, implying that their returns are in good condition. Specifically, the securities sector has the highest returns, but its volatility is also the largest. The skewness, kurtosis and JB statistics show that the return series have sharp peaks and thick tails, reflecting the non-normality of the unconditional distribution. According to the ARCH test, we believe that the return series of financial sectors exhibit the ARCH effect, and the volatility clustering features are significant. The p-value corresponding to the LB test proves that there is no autocorrelation in the return series of financial sectors. The results of the ADF test demonstrate that there is no unit root in the return series of financial sectors, meaning that they are all stationary series. In conclusion, the return series of financial sectors have non-normality and conditional heteroscedasticity, which are suitable to be resolved by the extreme value theory.

Table 1. Descriptive statistics of return series of financial sectors.

	Banking sector	Securities sector	Insurance sector	Diversified financial sector
Mean	0.0377	0.0484	0.0338	0.0351
Std. dev.	1.8521	2.6551	2.2807	2.3420
Skewness	0.1925	0.1495	0.1319	0.3293
Kurtosis	7.7751	5.6991	5.8362	5.9544
JB	3260.3999	1079.8080	1188.0560	1341.5540
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ARCH	27.5136	26.9621	22.9163	40.3212
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LB	1.9659	6.0655	0.4902	0.3893
	(0.5795)	(0.1085)	(0.9210)	(0.5233)
ADF	59.7186	57.5354	59.3231	54.6292
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: JB denotes the Jarque-Bera statistic for normality. ARCH is the ARCH-LM test. LB is the Ljung-Box test, and ADF is the unit root test. The p values corresponding to the test statistics are shown in parentheses.

3.2. Measurement of financial sectors risk

Considering the previous time series features, we utilize the GPD model to analyze the distribution of the return series of financial sectors and estimate the parameters through the MLE (Maximum Likelihood Estimation) method. Taking the banking sector as an example, we illustrate the implementation process of the parameter estimation of the GPD model. When the threshold $\mu = 1.9802$, the sample excess data best follows the Generalized Pareto Distribution shown in Table 2. Consequently, the final selected threshold is 1.9802.

Table 2. Parameter estimation of the GPD model for banking sector return series.

μ	N_μ	σ	ξ	W^2	A^2
1.9426	354	1.5641	0.0219	0.1458 (α < 0.10)	1.1481 (α < 0.05)
1.9512	353	1.5523	0.0272	0.1322 (α < 0.10)	1.1143 (α < 0.05)
1.9802	352	1.5513	0.0273	0.1056 (α > 0.10)	0.9382 (α > 0.05)
1.9805	351	1.5500	0.0278	0.0968 (α > 0.10)	0.9013 (α > 0.05)
1.9961	350	1.5445	0.0312	0.0901 (α > 0.10)	0.8756 (α > 0.05)

Notes: N_μ denotes the number of samples that exceed the threshold. α is the p-value corresponding to the W^2 and A^2 test.

Based on the estimated results, it can be concluded that the banking sector return series obeys the GPD distribution with parameters (μ, σ, ξ) = (1.9802, 1.5513, 0.0273). Similarly, the securities sector return series obeys the GPD distribution with parameters (3.0221, 2.7530, 0.2458). The insurance sector return series obeys the GPD distribution with parameters (2.6123, 1.8444, 0.0389). The diversified financial sector return series obeys the GPD distribution with parameters (2.5728, 1.8398, 0.1028). As shown in Figure 1, the GPD model has good fitting effectiveness, which can not only accurately determine the size of the threshold, but also properly describe the distribution of the return series.

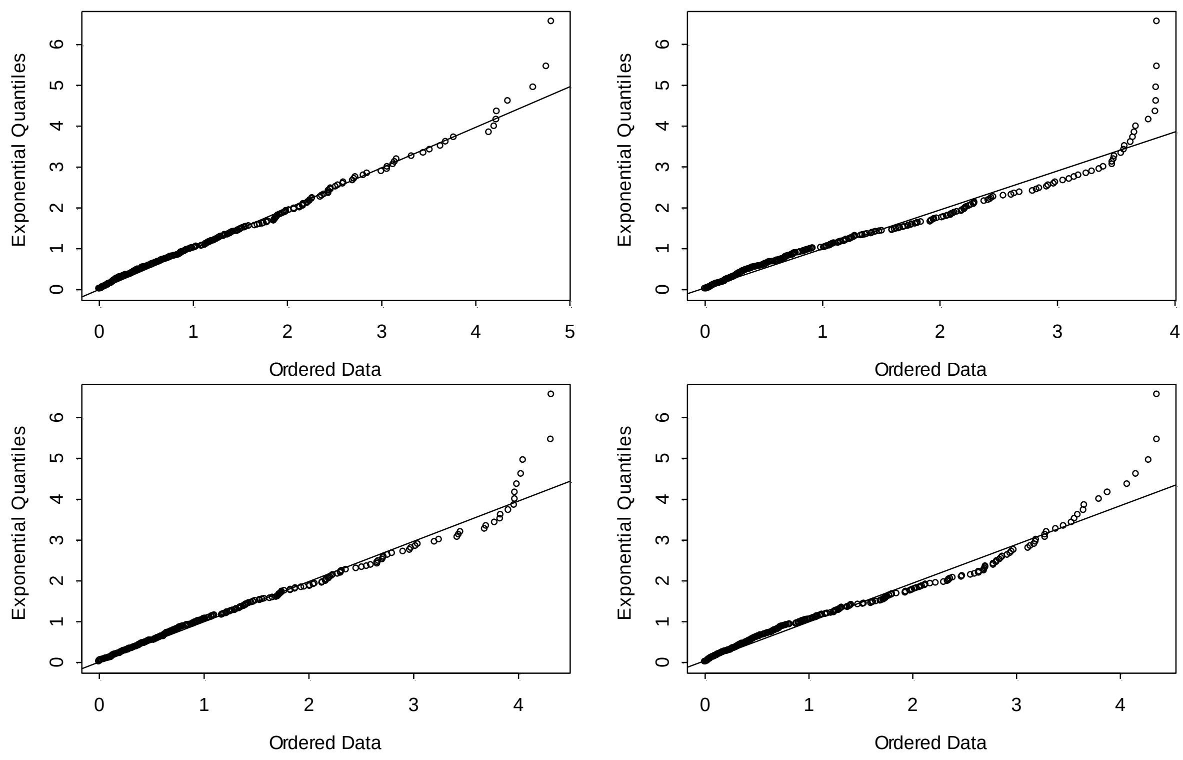

Figure 1. Residual series QQ plot of the GPD model.

The CAViaR model is estimated by quantile regression that displays tail risk appropriately. Consequently, we employ the CAViaR model to measure the extreme risks of financial sectors at 5% quantile, and the parameters of the model are calculated through the Nelder-Mead Simplex and Quasi-Newton method in accordance with the fitted distribution. Specifically, referring to Engle and Manganelli [6], we divide the sample into two sub-samples: in-sample and out-of-sample. The first

3014 data are utilized as training samples for the model estimate, and the last 500 data are used as out-of-sample observations for the extrapolation test. The results of parameter estimating and model testing are shown in Table 3. The Hit test values of the AS-CAViaR model are closest to the 5% quantile level, implying that this model has good fitting effectiveness on the data inside and outside the sample. The DQ test values are all greater than 5%, showing that the parameter estimations are robust and can accurately depict the risk profile. Therefore, we choose the AS-CAViaR model to investigate the extreme risks of financial sectors. In terms of the autoregressive term β_2, the quantiles of the financial sectors exhibit the presence of serial correlation. The current quantile is affected by the previous quantile, and all the values are above 0.75, reporting that the volatility aggregation effect of the tail quantile is significant. In addition, the negative shock coefficient β_4 is greater than the positive shock coefficient β_3, reflecting that the impact of the shock on the extreme risks of financial sectors is asymmetric. Particularly, bad news has a greater influence on the extreme risks of financial sectors than good news.

Table 3. Parameter estimation of the GPD-CAViaR model.

		β_1	β_2	β_3	β_4	RQ	Hit(in)	Hit(out)	DQ(in)	DQ(out)
SAV	BS	0.0006 (0.0690)	0.9563 (0.0397)	0.0957 (0.0569)		569.0386	5.0138	4.8232	0.7846	0.6773
	SS	0.0027 (0.0146)	0.9636 (0.0081	0.0790 (0.0135)		834.8265	5.0484	3.2154	0.4774	0.5496
	IS	0.0096 (0.0061)	0.9601 (0.0049)	0.0789 (0.0063)		708.7396	5.0138	2.8939	0.8661	0.1943
	DS	0.0022 (0.0102)	0.9497 (0.0126)	0.1181 (0.0257)		787.2598	4.9847	3.6977	0.1439	0.2720
AS	BS	0.0006 (0.0066	0.9578 (0.0084	0.0713 (0.0182)	0.1159 (0.0171)	567.7372	5.0138	4.9839	0.8699	0.5392
	SS	0.0042 (0.0072)	0.9600 (0.0082)	0.0718 (0.0058)	0.1003 (0.0353)	833.2742	5.0138	3.2154	0.7102	0.5368
	IS	0.0120 (0.0169)	0.9600 (0.0109)	0.0646 (0.0112)	0.0899 (0.0263)	707.7827	5.0138	2.8939	0.9966	0.1587
	DS	0.0095 (0.0122	0.9506 (0.0057)	0.0658 (0.0576)	0.1536 (0.0257)	782.7466	5.0138	3.8762	0.2057	0.1762
IG	BS	-0.0104 (0.0090)	0.9608 (0.0105)	0.1113 (2.2047)		571.0704	4.9793	4.5016	0.7576	0.8288
	SS	-0.0053 (0.0537)	0.9594 (0.0126)	0.1121 (2.5288)		834.2547	4.9793	2.8939	0.5087	0.3328
	IS	-0.0101 (0.0134)	0.9663 (0.0027)	0.0868 (0.0624)		708.6852	5.0138	3.2154	0.8847	0.1305
	DS	-0.0029 (0.0132)	0.9445 (0.0026)	0.1885 (0.0554)		785.5733	4.9793	3.0547	0.0163	0.2440

Notes: BS, SS, IS and DS represent banking, securities, insurance and diversified financial sector, respectively. RQ indicates the minimum quantile regression function when the local optimal parameters are obtained. Hit(in) and Hit(out) denote the probability of in-sample and out-of-sample extreme events, respectively. DQ(in) and DQ(out) tests are used to determine the overall significance of the in-sample and out-of-sample models, respectively. Standard errors corresponding to each parameter estimate are shown in parentheses.

We explore the dynamic extreme risks of financial sectors after identifying the optimal CAViaR model and completing parameter estimation in Figure 2. The extreme risks of the four financial sectors are listed in descending order: securities sector f diversified financial sector f insurance sector f banking sector. Among them, the extreme risk of the securities sector is generally the largest, because it is most vulnerable to the negative impact of external news, especially bad news. Furthermore, it is most sensitive to financial crisis events, and its price fluctuates significantly. On the contrary, since the banking sector's asset scale is the largest, the loan duration is medium and long term, the influence of external information is relatively limited, and the fluctuation is smooth, its extreme risk is at the lowest level.

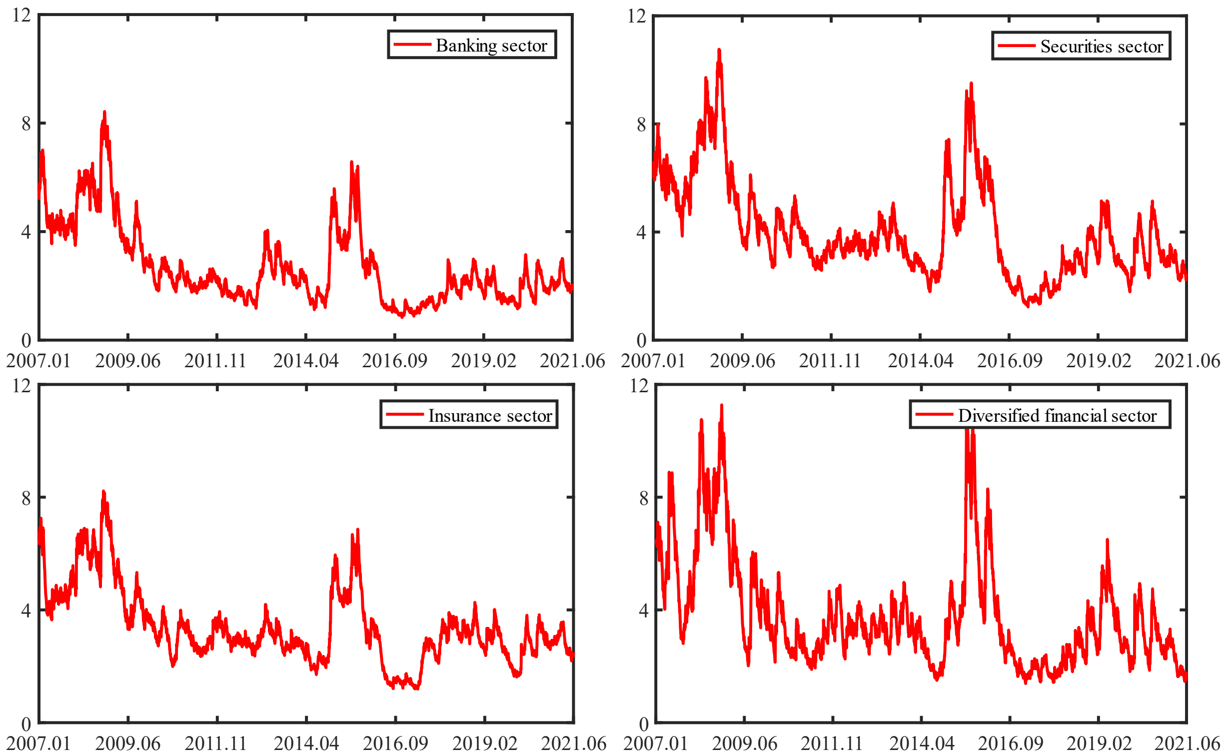

Figure 2. The extreme risks of financial sectors.

Judging from the various risk series, we find that major emergencies have significant influence on the extreme risks of financial sectors. When major emergencies occur, especially the subprime mortgage crisis in 2008, the stock market crash in 2015, the Sino-US trade friction in 2018 and the COVID-19 epidemic in 2020, the extreme risks of financial sectors dramatically rise. The influence of the four major emergencies is presented in descending order: subprime mortgage crisis f stock market crash f Sino-US trade friction f European debt default. After the outbreak of major emergencies, the various financial sectors are negatively impacted by the economic downturn and the market decline, and their profitability gradually decreases. From a microscopic point of view, investors hold pessimistic expectations on the market, resulting in a sharp increase in potential risk and a continuous accumulation of systemic risk.

3.3. Estimation of the TVP-SV-VAR model

The effective premise of the TVP-SV-VAR model is that the time series is stationary, while non-stationary time series are prone to resulting in spurious regression. In this paper, we employ the ADF method to test the stationarity of the extreme risk of financial sectors, and the lag order of the test is determined by the SIC criterion. The ADF test results are shown in Table 4.

The ADF statistic values are all greater than the critical value at the significance level of 5%, indicating that the extreme risks series of financial sectors are non-stationary and cannot be directly modeled. Nevertheless, the null hypothesis that the risks series have a unit root cannot be rejected. After the first-order difference processing, they become stationary, and there is a first-order single integration. The first-order difference is equivalent to an incremental analysis of variables, which reflects the rate of change of the extreme risks. Therefore, considering the first-order difference data, we propose the TVP-SV-VAR model to analyze the transmission effect of extreme risks.

Table 4. Stationarity test of the TVP-SV-VAR model.

Variable	Inspection form	ADF statistic	5% critical value	Conclusion
BI	(C, T, 0)	3.0934	3.4110	non-stationary
ΔBI	(C, T, 0)	59.5612	3.4110	stationary
SI	(C, T, 0)	3.1116	3.4110	non-stationary
ΔSI	(C, T, 0)	58.7796	3.4110	stationary
II	(C, T, 0)	3.3881	3.4110	non-stationary
ΔII	(C, T, 0)	60.2746	3.4110	stationary
OI	(C, T, 0)	3.3258	3.4110	non-stationary
ΔOI	(C, T, 0)	39.1837	3.4110	stationary

Notes: The test form (C, T, K) is the intercept term, the trend term and the lag order, respectively, and Δ represents the first difference.

Referring to the lag criterion of the VAR model, we determine that the lag order of the TVP-SV-VAR model is 2 to deal with over-parameterization and residual autocorrelation. The parameters of the model are estimated through the MCMC method, and the number of simulations is set to 10000. In order to eliminate the interference of the initial value on the model estimation, we discard the first 1000 pre-burned samples.

Table 5. Parameter estimation results of the TVP-SV-VAR model.

Parameter	Mean	Std. dev.	95% percent interval	CD	Inefficiency
$(\sum_\beta)_1$	0.0022	0.0003	[0.0018, 0.0029]	0.110	19.19
$(\sum_\beta)_2$	0.0023	0.0003	[0.0018, 0.0030]	0.127	18.19
$(\sum_a)_1$	0.0336	0.0085	[0.0163, 0.0531]	0.326	22.90
$(\sum_a)_2$	0.0070	0.0020	[0.0046, 0.0126]	0.000	35.97
$(\sum_h)_1$	0.2813	0.0166	[0.2500, 0.3166]	0.803	75.81
$(\sum_h)_2$	0.3002	0.0197	[0.2628, 0.3386]	0.002	81.46

Table 5 displays the parameter estimation results of the TVP-SV-VAR model. The Convergence diagnostics (CD) and inefficiency factors are critical for testing the estimation performance of the TVP-SV-VAR model through the MCMC method. Specifically, the CD is suitable for testing the convergence of the model, and is less than the critical value of 1.96 at the significance level of 5%, implying that the null hypothesis of convergence to the posterior distribution cannot be rejected at this significance level. The inefficiency factors are applicable to test the validity of simulated samples. Generally, the smaller the inefficiency factors value is, the greater the number of irrelevant samples is, and the better the sampling outcome is. This indicator's value in Table 5 is small, and is sufficient to infer the posterior distribution. In summary, the TVP-SV-VAR model estimated by the MCMC simulation is reliable, and can be used for impulse response analysis.

3.4. Transmission effect of extreme risks at different lead periods

Considering the time-varying of parameters, we derive transmission effects at different lead periods and time points. For transmission effects at different lead periods, we define 1 period, 6 periods and 12 periods as short term, medium term and long term, respectively. Figure 3 illustrates the transmission effect of the extreme risks at different lead periods.

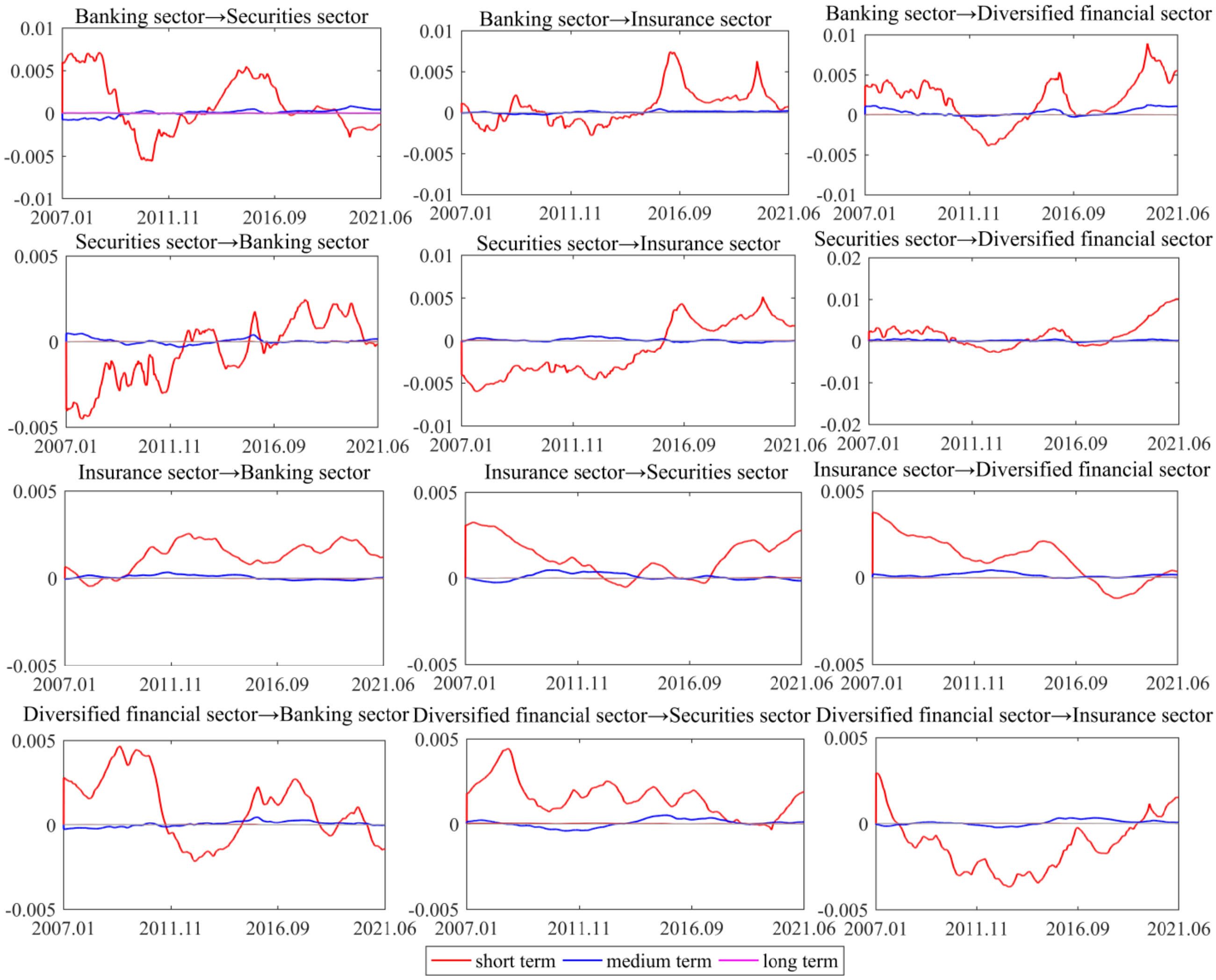

Figure 3. Transmission effect of the three-lead periods.

On the whole, there are significant differences in the transmission effect of the extreme risks of financial sectors during various lead periods. Specifically, the transmission effect in short term is stronger than that in medium and long term, reflecting that the impacts of the extreme risk of a financial sector on the risks of the other three financial sectors are concentrated in the short term, while the medium-term and long-term transmission effects are similarly weak. This finding is consistent with the regulation of financial risk evolution. In other words, when the extreme risk of a financial sector occurs, it causes a strong impact on the risks of the other three financial sectors in the short term. However, due to the internal weakening of financial risks and the external intervening of risk supervision, the transmission effect of the extreme risks of financial sectors gradually declines or even disappears in the medium term and long term over time.

In the short term, there are significant diversities in the transmission effect of the extreme risks of financial sectors. In terms of the scale of transmission, the extreme risks of the banking sector and the diversified financial sector exhibit a considerable transmission effect on the other financial sectors, which represents the strong spillover capability of the extreme risks of the banking sector and the diversified financial sector. One possible explanation is that the asset scale of the banking sector is large and the risk sources of the diversified financial sector are various, which results in a substantial impact of these two financial sectors on the risks of the other financial sectors. It is worth noting that the transmission effect under certain time conditions is negative. For example, when the extreme risk of the securities sector fluctuates, the impact on the extreme risk of the insurance sector is negative before 2016, and then turns into a positive effect. The reason is that the securities sector is small in scale before 2016, leading to the few influence on the extreme risks of the insurance sector. At this stage, the extreme risk of the insurance sector comes from the inside and is less affected by external factors. On the contrary, the securities sector develops rapidly, and the price fluctuations are more abnormal and frequent after 2016, which aggravates the infectivity of financial risks and the vulnerability of the system.

The transmission effect of extreme risks of the financial sectors is greatly affected by major emergencies. For example, the transmission effect of the extreme risk from the banking sector to the securities sector is substantially exacerbated by the subprime mortgage crisis in 2008, the European debt crisis in 2010 and the stock market crash in 2015, while the transmission effect of the extreme risk from the banking sector to the insurance sector is significantly influenced by the stock market crash in 2015, Sino-US trade friction in 2018 and the COVID-19 epidemic in 2020. The transmission effect of extreme risk from the banking sector to the diversified financial sector is seriously triggered by major emergencies, which reflects the strong correlation between banking extreme risks and other financial extreme risks at major emergencies. The occurrence of major emergencies increases the extreme risk of the banking sector, and enhances the transmission effect of the extreme risk from the banking sector to the other three financial sectors.

3.5. Transmission effect of extreme risks at different time points

For examining the transmission effect at different time points, we select the following three dates: September 17, 2008, August 25, 2015, and February 4, 2020, which correspond to the maximum value of extreme risks in the three periods of the subprime mortgage crisis, the stock market crash and the COVID-19 epidemic, respectively. Figure 4 exhibits the dynamic transmission effect of the extreme risks in the financial sectors at three-time points. On the one hand, the transmission effect of extreme risks in the financial sectors at each time point remains essentially constant, illustrating that they are consistent at different time points. For example, when there is a significant change in the extreme risk of the banking sector, the impact on the other three financial sectors is positive, and the transmission effects at the three-time points are relatively similar. Specifically, the transmission effect on February 4, 2020 is slightly greater than that on August 25, 2015 and September 17, 2008, which indicates that the impact of the extreme risk of the banking sector on the other three financial sectors at different time points is parallel, and the variation in transmission effects is negligible. On the other hand, the transmission effect of extreme risks of the financial sectors at different time points is time-sensitive, and gradually tends to be stable or even disappear after the lag of three periods. For instance, after the transmission effect of the extreme risk of the insurance sector on the other three financial sectors reaches a maximum value at the lag of two periods, their effect weakens rapidly and converges to zero after the lag of three periods. It demonstrates that the extreme risk of the banking sector has a strong but transient impact on the extreme risks of the other three financial sectors. Since the prevention and control against the extreme risks of financial sectors are significant, the risk transmission effect gradually declines over time.

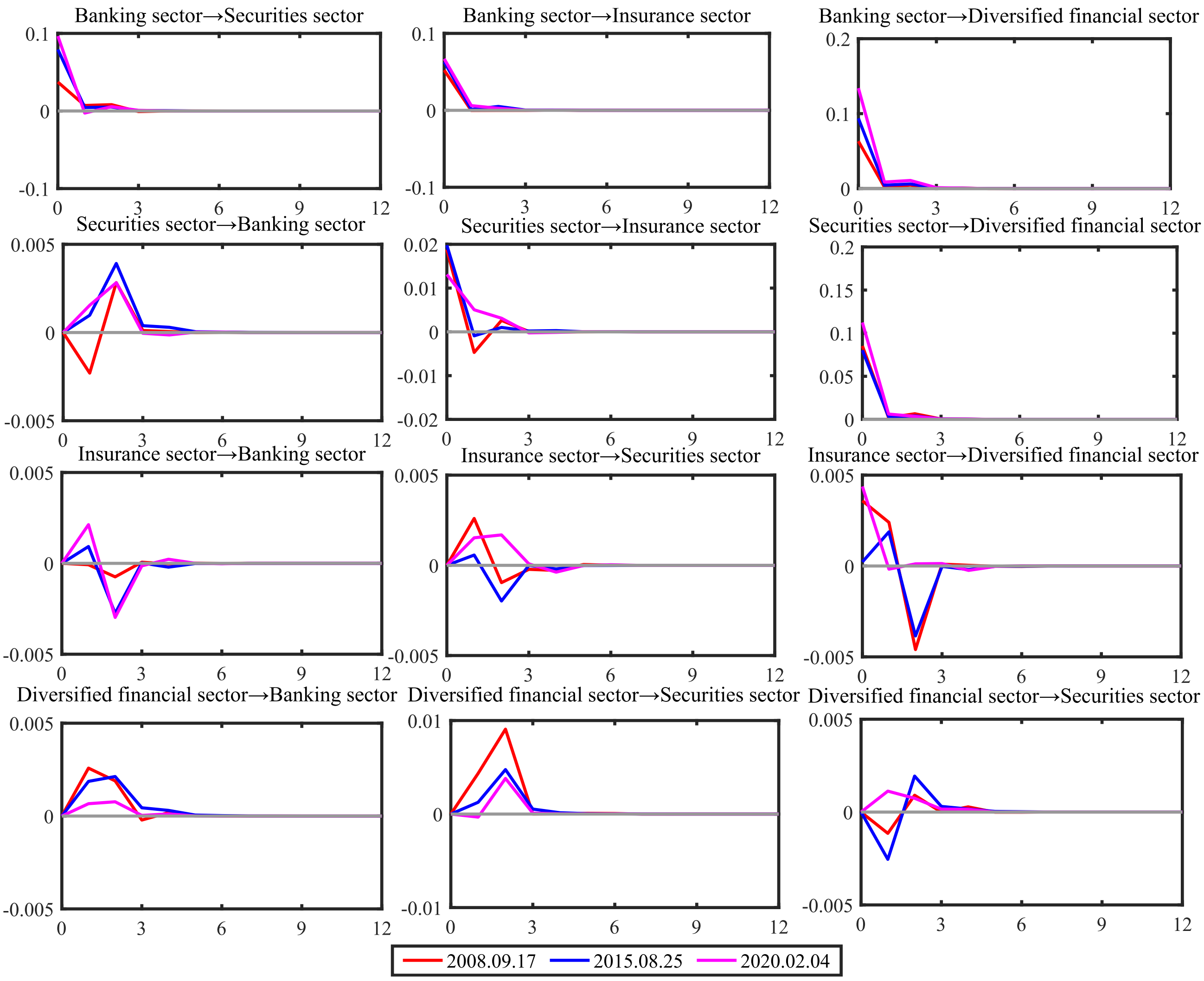

Figure 4. Transmission effect of the three-time points.

4. Conclusions

In the context of major emergencies, we propose the GPD-CAViaR model to describe the extreme risks of financial sectors, and construct the TVP-SV-VAR model to investigate their transmission effect. The main research results are as follows. (i) The impact of market information on the extreme risks of financial sectors is asymmetric. Compared with to the good news, the extreme risks of financial sectors are more sensitive to the bad news, such as price decline and pessimistic expectations. (ii) The extreme risks of financial sectors increase sharply and continue enduringly when major emergencies occur. In general, the extreme risks of the subprime mortgage crisis in 2008 and the stock market crash in 2015 are greater than those of the European debt crisis in 2010, Sino-US trade friction in 2018 and the COVID-19 epidemic in 2020, demonstrating that the risk impact of the finance-related major emergencies is stronger than the other major emergencies. (iii) There are significant differences in the transmission effect of various lead periods. Specifically, the transmission effect in short term is stronger than that in medium and long term, while the medium-term and long-term transmission effect become weaker and weaker over time. (iv) The transmission effects at various time points are relatively consistent. Generally, the transmission effects of financial sectors differ significantly, although they are quite small after a three-period lag.

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Conflict of interest

The authors declare there is no conflict of interest.

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