Does COVID-19 matter for systemic financial risks? Evidence from China's financial and real estate sectors

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A B S T R A C T

The occurrence of global public safety incidents often affects systemic financial risk. Based on the event analysis method, this study provides a specific analysis of COVID-19's impact on China's financial systemic risks. Additionally, the study demonstrates the different features of systemic financial risk in different financial sectors (banking, securities, insurance) and real estate during the COVID-19 outbreak. Specifically, first, COVID-19's influence on systemic financial risk in all sectors exhibits both level effect and trend effect, and the impact is particularly significant in branch sectors under real estate. Second, in the entire financial system, the securities and real estate sectors not only contribute more to the growth of systemic risk than the banking and insurance sectors but are also more persistent. Third, real estate, residential property, and park comprehensive industries with high debt, long cycles, and high financial dependence are less affected by COVID-19 on systemic financial risks than other industries. Fourth, in the transmission mechanism, COVID-19 impacts market liquidity, funding liquidity, and default risk in the financial sector and real estate sector; however, the sources of systemic risk in different sectors differ.

1. Introduction

1.1. Background

China's financial sector has been severely tested since the onset of the wide spread of COVID-19 at the end of 2019 and the start of 2020. It has predominantly been affected by a series of impacts, including the hampered circulation of industrial and supply chains; shrinking international trade and investment; the bulk commodity market's turmoil; decreasing consumption, investment, and exports; and pressure on employment (Nguyen et al., 2021; Pan et al., 2021). Specifically, the banking sector faced a decrease in credit demand and intermediate business, and an increase in overdue loans caused by the depression of production and consumption. From the insurance sector's perspective, the sales of insurance were severely impacted, and the sales of traditional insurance products fell sharply. The securities sector was affected by market sentiment, and herein, trading volume, investment, and financing activities fluctuated greatly (Agarwal and Chua, 2020; Huang et al., 2020).

Since the importance of China's economy in the world has changed, a report from Goldman Sachs stated that COVID-19's spillover effects could be significantly greater than the SARS' in 2002–2003. Wang et al. (2021) compared the impact of these two

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epidemics—COVID-19 and SARS—from the economic cycle's perspective. They found that SARS's negative impact was more evident in the later period, while COVID-19's was stronger in the initial period, which weakened due to various encouragement policies. Nguyen et al. (2021) further demonstrated that among several epidemic periods (SARS, H5N1, H7N9, and COVID-19), COVID-19 has exhibited the greatest negative impact on firms' market performance. However, "China's Monetary Policy Implementation Report for the First Quarter of 2020" from The People's Bank Of China (2020) highlighted that unconventional easy monetary and fiscal policies could be one reason for systemic financial risk, while China's uncertain international balance of payments and cross-border capital flow is another. Therefore, the following question arises: Has COVID-19 affected the systemic financial risk of China?

1.2. The real estate sector's financial nature

This study attempts to analyze the differences in China's financial systemic risks before and after the COVID-19 outbreak. This study uses data on >200 financial institutions, which account for over 90% of Chinese financial market capitalization—from December 1, 2019, to May 31, 2020.

The study adopts an innovative approach for sample selection, which includes the real estate sector in the sample. The international experience and domestic practice reveal that real estate credit and housing prices are important factors affecting the financial system. Both the real estate and financial markets are an agglomeration of risk. Their symbiosis and correlation precipitate their risk overlap and accumulation. Additionally, with the comprehensive deepening of China's financial reform, the continuous improvement of the level of financial openness, and the rapid development of financial technology, cross-related financial businesses and products are constantly launched. The financial properties of the real estate sector are amplifying. The cross-contagion and resonance of sectors may further induce systemic risks. Under COVID-19's impact, the real estate sector suffered from blocked payment collection, difficulties in capital turnover, and increased mortgage defaults caused by delayed resumption of work, which directly affected the financial sector. Therefore, we consider a larger financial system by including the real estate sector for a comprehensive analysis of the systemic risk. Moreover, we consider the systemic risk of different branch sectors of the real estate sector. The systemic risk fluctuations these branch sectors face under COVID-19's impact may differ because of their different financial attributes. Sectors with high debt or long development cycles are likely to be more vulnerable to external shocks.

1.3. Contributions

The key contribution of this study primarily lies in three aspects. First, the study contributes practically by considering the real estate industry along with the three traditional financial sectors—banking, securities, and insurance—and the systemic risk. Due to the strong financial nature of real estate in China, it has practical significance to study the influence of real estate on systemic risk. Second, the study focuses on level fluctuations and trend changes of systemic risk in the financial sector, indicating that the COVID-19 outbreak impacts Chinese systemic risk. Thus, the study has referential value as it provides a reference for other countries or regions to prevent or manage systemic risk during a disease outbreak. Third, the study contributes theoretically by using COVID-19 as a natural experimental sample to verify the relationship between external shocks and systemic risks from a practical perspective by exploring the transmission mechanism. Thus, this study compensates for a significant gap in the literature.

The remainder of the paper is organized as follows: Section 2 presents the modes used to estimate the systemic risk and impact of COVID-19. Section 3 presents the data and events. Section 4 discusses our main empirical findings. Section 5 shows the transmission mechanism. Finally, Section 6 presents our conclusions.

2. Literature review

2.1. Research on dynamic conditional value at risk

We adopted the dynamic Conditional Value at Risk ($\triangle$CoVaR) method to measure the impact of target variables (banking, securities, insurance, and real estate and its branch sectors) on China's systemic risks under COVID-19. CoVaR differs from the composite index (Illing and Liu, 2003; Lall et al., 2009) and early warning methods (Frankel and Rose, 1996; Kaminsky et al., 1998), which is based on accounting data on assets and liabilities. The CoVaR method is time-sensitive and completely considers externality, infectiousness, and spillover of systemic risk by using financial market data. Adrian and Brunnermeier (2016) provided this method to measure the loss of other financial markets or financial institutions' portfolios under crisis or high-risk conditions, based on the traditional concept of Value at Risk (VaR). CoVaR, which is an advanced model of the VaR, uses the value of conditional VaR to express the intensity of risk spillover. Adrian and Brunnermeier (2016) measured systemic risk based on risk spillover and tail dependence among financial institutions, and built a series of indicators such as $\triangle$CoVaR, Exposure-$\triangle$CoVaR, Network-$\triangle$CoVaR, and Forward-$\triangle$CoVaR.

Chinese scholars have applied CoVaR, MES and SRISK, and other new methods and technologies of systemic risk measurement to China's financial practice and have obtained a series of research results. Numerous scholars, including Li and Fan (2011), Gao and Pan (2011), Xiao et al. (2012), Bai and Shi (2014), and Zhou et al. (2014), have used the CoVaR method to measure the systemic risk level of China's financial institutions, assess the risk contribution of individual institutions and monitor the dynamic changes of China's financial systemic risks. Bu and Li (2015) and Yang et al. (2018) used various methods such as $\triangle$CoVaR and MES to measure and evaluate the overall systemic risk of China's financial institutions. In these studies, the CoVaR method combined with traditional VaR measured the impact of a single financial institution's risk on systemic risk and the risk spillover effect in the financial network more

accurately. Moreover, since the CoVaR method is derived from the VaR method, it is easier to calculate than other methods. Owing to these advantages, the CoVaR method is widely used. This study used the CoVaR method to measure the systemic risks of China's financial system. To avoid the impact of different methods of measuring systemic risk on the study's results, we applied the method Marginal Expected Shortfall (MES) proposed by Acharya et al. (2010) to measure systemic risk as a robustness test.

2.2. Research on event analysis method

For systemic risk fluctuations caused by COVID-19, we used the event analysis method. The traditional event analysis method is mainly used to analyze whether an event has a significant impact on a certain activity. Dolley (1933) evaluated a split sample of 95 stocks from 1921 to 1931 and tested stock splits' impact on stock prices by comparing stock price changes before and after the stock split event. In the late 1990s, Pilotte and Manuel (1996) further advanced the application of event analysis in the financial field. They evaluated stock splits' impact on the rate of return and used the event analysis method to study the impact of similar events that occurred before to infer similar events' possible impact in the future. Gourinchas and Obstfeld (2012) and Schularick and Taylor (2012) used an improved event analysis method for impact research. This method is different from the traditional event analysis method, similar to the double-difference method (DID) of micro-policy evaluation. It can be used to quantify a certain type of event's impact on the target variable. In essence, it is used to compare the differences of the target variables between the treatment and control groups—that is, the impact of an event's occurrence on the target variables. Brunnermeier et al. (2012) applied this method of using emergencies and analogy in DID to the field of systemic risk research.

In event analysis, the selection of time nodes for the occurrence of events will crucially impact the results. In this study, major COVID-19 events from December 1, 2019, to May 31, 2020, were selected with reference to the white paper "China's Action against COVID-19" issued by the State Council Information Office of China in June 2020. The selection of the event is mainly based on the work instructions from the National Health Commission, State Council, and national leaders. In this study, we further consider COVID-19's global spread, which would affect the systemic risk of China's financial sector. Notably, unlike the studies considering the financial sector policy announcements (Feyen et al., 2021; Demirgüç-Kunt et al., 2021), this study pays greater attention to the impact of "external shocks" by selecting key COVID-19-related public events instead of considering policy announcements of the central bank and financial sector authorities.

2.3. Research on transmission mechanism

The uncertainty impairs the market participants' ability to effectively share risk (Rehse et al., 2019). When discussing the transmission mechanism, this study considers that the sources of short-term systemic risks are mainly short-term liquidity risk and default risk caused by COVID-19. Brunnermeier and Pedersen (2009) stated that the liquidity risk caused by short-term debt makes shocks spread widely among market participants. In contrast, default risk affects systemic financial risk by increasing the stock's volatility. In conclusion, these three factors are the transmission mechanism of COVID-19 affecting systemic risk considered in this study. For short-term liquidity, both market and funding liquidity are considered (Brunnermeier and Pedersen, 2009). Market liquidity demonstrates how easily asset holders can sell their assets, which is reflected by the cost and speed of sales, whereas funding liquidity refers to how easily the demander can obtain funds. According to Vassalou and Xing's (2004) method, the daily default risk of financial institutions is obtained as per the Merton model.

2.4. Research on COVID-19

The recent literature on the COVID-19 shock's effects on financial markets: Rizwan et al. (2020) focused on the systemic risks of the banking sector based on data from the eight countries affected by COVID-19. In contrast, Borri and Giorgio (2022) found that in the banking system, large and commercial banks are more susceptible to trade and financial market fluctuations and contribute more to systemic risks. Lai and Hu, 2021 found the connection between the crisis' propagation speed and the relation of financial institutions using global stock market data. The increasing possibility of the outbreak of systemic financial risks caused by COVID-19 through the negative feedback mechanism of economic shock and emotional contagion effects is found in Liu and Guo's (2020) study. Unlike other studies, our study focuses on one country's financial system, examining how it performs as a system under the COVID-19 shock.

3. Model

This section includes two parts. The first part is the calculation of systemic financial risk using the $\triangle$CoVaR model. The second part involves setting the basic regression model using an improved event analysis method to study COVID-19's impact on China's financial systemic risks.

3.1. Calculation of systemic financial risks

The $\triangle$CoVaR model is based on the CoVaR method. CoVaR represents the maximum possible loss of other financial institutions under a certain probability when the VaR of a financial institution i is constant. VaR_q^i represents the maximum possible loss of institution i within the confidence interval of q and also the minimum return; that is, in the face of a crisis, there is a q% probability that the return of institution i is lower than VaR_q^i.

According to the method of measuring the systemic risk of the financial system proposed by Adrian and Brunnermeier (2016), $\Delta CoVaR_q^{system|\ i}$ represents the contribution of financial institution i to the systemic risk of the financial system. VaR_q^i represents the VAR of financial institution i. $Pr(X^i \leq VaR_q^i) = q$, where X^i represents the rate of return of institution i.

$CoVaR_q^{j|i}$ represents the VAR of institution j, when institution i is in crisis and the loss is VaR_q^i.

$$Pr\left(X^j \leq CoVaR_q^{j|i} | X^i = VaR_q^i\right) = q \tag{1}$$

The contribution of a single financial institution i to the systemic risk of financial institution j (or system) can be obtained:

$$\Delta CoVaR_q^{j|\ i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=Median^i} \tag{2}$$

According to the definition, the contribution of a single financial institution i to the systemic risk of the financial system can be derived as:

$$\Delta CoVaR_q^{system|\ i} = CoVaR_q^{system|X^i=VaR_q^i} - CoVaR_q^{system|X^i=VaR^{Median^i}} \tag{3}$$

In this study, $Median^i$ uses $VaR_{50\%}^i$ to indicate the VAR of financial institution i at the level of the 50% confidence interval, which represents that the financial institution is in a normal state.

The above is the traditional calculation method of ΔCoVaR. The contribution of a single financial institution to the systemic risk calculated by the traditional ΔCoVaR remains constant over time. It is only an overall description and is estimated based on the mean. However, financial data, in reality, are often not in the normal distribution but distributed with "leptokurtic and heavy tail" characteristics. Therefore, the traditional linear regression method is invalid in estimating financial measurement models and cannot accurately reflect the relationship between different components of the overall distribution.

The proposal of quantile regression effectively compensates for this shortcoming of the traditional linear regression. Quantile regression is performed according to different quantiles of the variables, and a regression model of all quantiles can be obtained. It extends the model—based on mean correlation—to focus on tail correlation. The financial risk is generally caused by the tail event. Therefore, the method of quantile regression is widely used in the measurement of financial risk.

According to the definition of CoVaR, it is clear that CoVaR is essentially VaR, and VaR is essentially a quantile, and thus, CoVaR is a quantile. In this study, quantile regression is used for calculating the CoVaR of various financial institutions; specifically, a quantile regression with the state variable M is used to calculate the time series of the contribution of individual financial institutions' systemic risk.

First, quantile regression is used to calculate the dynamic VaR of financial institution i at the 95% and 50% confidence levels. The quantile regression equation form is as follows:

$$X_t^i = \alpha^i + \gamma^i M_t + \varepsilon_t^i \tag{4}$$

X_t^i represents the rate of return of institution i at time t, and M_t is a state variable, which specifically covers three categories—namely liquidity risk, credit risk, and stock market risk. Liquidity risk is expressed by the month-on-month change in the yield to maturity of the 3-month Treasury bond and maturity spread, where the maturity spread is obtained by subtracting the yield to maturity of the 3-month treasury bond. Credit risk is expressed by credit spread, where the credit spread is expressed by the yield to maturity of 1-year CSI AAA corporate bonds minus the yield to maturity of 1-year treasury bonds. Stock market risk is expressed by the stock market return rate (logarithmic growth rate of the closing price of the CSI 300 index) and stock market volatility (volatility of the logarithmic growth rate of the closing price of the CSI 300 index).

Second, quantile regression is used to calculate the VAR of the financial system under the 95% confidence level when the financial institution i is under pressure and normal. The regression equation is as follows:

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_t + \varepsilon_t^{system|i} \tag{5}$$

X_t^i and M_t have the same meanings as in Eq. (4); X_t^{system} is the rate of return of the financial system at time t, expressed as the logarithmic growth rate of each financial sector index. Notably, when calculating systemic risks in different financial sectors and the real estate sector, the logarithmic growth rates of different financial indexes should be used. Specifically, when calculating the systemic risk in the banking, securities, insurance, and real estate sectors, X_t^{system} is expressed by the logarithmic growth rate of the closing prices of: the CSI 300 bank index (code: 000951SH), CSI 300 capital index (code: L11643CSI), CSI 300 insurance index (L1518CSI), and CSI 300 Real Estate Index (H30165CSI), respectively.

Through regression, we obtained the predicted value as follows:

$$\text{VaR}_t^i(q) = \widehat{\alpha}_q^i + \widehat{\gamma}_q^i M_t \tag{6}$$

$$Co\text{VaR}_t^i(q) = \widehat{\alpha}_q^{system|i} + \widehat{\beta}^{system|i} \text{VaR}_t^i(q) + \widehat{\gamma}_q^{system|i} M_t \tag{7}$$

Thereafter, the contribution of a single financial institution to systemic risk $\Delta CoVaR_q^{system|\ i} \Delta CoVaR_q^{system|\ i}$ can be expressed as:

$$\Delta Co\text{VaR}_t^{system|i}(q) = Co\text{VaR}_t^i(q) - Co\text{VaR}_t^i(50\%)$$

$$= \widehat{\beta}^{system|i} \left(\text{VaR}_t^i(q) - \text{VaR}_t^i(50\%) \right) \tag{8}$$

After obtaining the contribution of each institution in the three sectors to the systemic risks of financial institutions, calculating the systemic financial risks of the four sectors over time is necessary. This is expressed as follows:

$$\Delta CoVaR_t^{system} = \sum \frac{V_{i,t}}{V_{system,t}} \Delta CoVaR_t^{system|i} \tag{9}$$

where $\Delta CoVaR_t^{system}$ represents the systemic financial risk of a financial sector at time t; $\Delta CoVaR_t^{system|i}$ represents the contribution value of financial institution i to the systemic risk of the financial sector at time t; $V_{i,t}$ represents the market value of institution i at time t, represented by the market value of equity on that day; $V_{system,t}$ represents the total market value of the sector in which institution i belongs at time t, and the ratio of the two is the sector's weight in which institution i belongs.

3.2. Setting the improved event analysis method regression model

We used the improved event analysis method proposed by Schularick and Taylor (2012) and formation characteristics of systemic risk to construct a basic regression model. This model includes COVID-19's impact on the systemic risk level and on the trend of systemic risks in the banking, securities, insurance, and real estate sectors.

The formation of systemic financial risk includes two vital factors: The first factor is a negative shock factor—the source of systemic risk. The second factor is the amplification mechanism—the mechanism by which risks are amplified due to the financial system's operating characteristics after the initial negative shock is applied to the financial system. These characteristics include the leverage level of financial institutions and degree of linkage between different financial institutions. Compared with the initial negative shock, the amplification mechanism is a more important driving factor, can amplify the initial shock several times, and eventually, can form a systemic financial risk.

Noteworthily, higher operating leverage and close inter-organizational linkage contributes as a magnification mechanism, which is not achieved overnight but requires a period of accumulation. Therefore, to cover the financial sector's systemic risks through the amplification mechanism, this study establishes a dummy variable n days before and after the COVID-19 external shock and analyzes the level and trend effects of the COVID-19's impact on China's systemic financial risks.

The level effect refers to the degree to which the systemic risks of various sectors are significantly higher than the average level during the entire sample period after the emergence of COVID-19 and is expressed as follows:

$$\Delta Co\text{VaR}_{i,t}^{system} = \alpha_{i,t} + \gamma_{i,t} \times D_{-n} + \theta_{i,t} \times D_n + \varepsilon_{i,t} \tag{10}$$

The trend effect means that after the emergence of COVID-19, the trend of systemic risks in various sectors over time is significantly greater than the level before COVID-19, and is expressed as:

$$\Delta Co\text{VaR}_{i,t}^{system} = \alpha_{i,t} + \varphi_{i,t} \times T + \beta_{i,t} \times D_{-n} + \gamma_{i,t} \times D_n + \delta_{i,t} \times T \times D_{-n}$$
$$+ \varphi_{i,t} \times T \times D_n + \varepsilon_{i,t} \tag{11}$$

where $\Delta Co\text{VaR}_i^{system}$ is the systemic financial risk of sector i, which includes banking, securities, insurance, real estate, and its branch sectors. T is a time variable, starting from the beginning of the sample, standardized to 1; for each additional day, the value of T is increased by 1 until the end of the sample period. The sample period is from December 1, 2019, to May 31, 2020, excluding non-trading days, for a total of 118 days. D_{-n} is a dummy variable n trading days before the release time of all important events regarding COVID-19. D_n is a dummy variable on the day and (n-1) trading days after the release time of all important information events about COVID-19. Noteworthily, COVID-19 events in this study predominantly occurred 9 times. The time of the COVID-19 event is defined as the date of the COVID-19 news announcement. When the COVID-19 information occurs on a non-trading day, the event occurrence date is set as the first trading day after the actual occurrence of the event. The settings of D_{-n} and D_n are represented by formula (12) and formula (13), respectively:

$$D_{-n} = \sum_s D_{-n,s} \tag{12}$$

$$D_n = \sum_s D_{n,s} \tag{13}$$

where $D_{-n, s} = \begin{cases} 1, T_{f,s} - n \leq T \leq T_{f,s} - 1 \\ 0, \text{else} \end{cases}$ is the dummy variable n days before the release of the s-th important COVID-19 event (nine times in total). $D_{n, s} = \begin{cases} 1, T_{f,s} \leq T \leq T_{f,s} + n - 1 \\ 0, \text{else} \end{cases}$ is a dummy variable on the day and (n-1) days after the release of the s-th COVID-19 event. $T_{f, s}$ is the release time of the s-th important COVID-19 event. The size of n can be set according to research needs. Considering the rapid dissemination of information, most financial and real estate companies respond as soon as they receive the news. Therefore, in this study, n is selected as [1, 15]. With the change of the value of n, the dynamic changes of the level and trend effects of important COVID-19 events' impact on financial systemic risks can be obtained.

Essentially, the above formula is similar to the "Differences-in-Differences (DID)" method. As COVID-19 is a sudden external shock event, other factors affecting the systemic risks of various financial sectors and the real estate sector have not changed significantly before and in a short period of time after this event. Therefore, samples from n days before and after the outbreak of COVID-19 and other samples can be used as the treatment and control groups, respectively. Noteworthily, the improved event analysis method is superior to DID in two aspects. First, using the change in sample selection n of the treatment group, the event analysis method can obtain the event's dynamic impact on the target variable. Second, the event analysis method adopts multiple consecutive similar events to be included in the analysis, thus significantly alleviating DID's endogeneity.

Furthermore, if the regression coefficient $\theta_i\theta_i$ of D_nD_n in formula (10) is significantly greater than zero, it indicates that COVID-19 has a level effect on financial systemic risks. The size of the level effect is $\theta_i\theta_i$, which means that within n trading days after the occurrence of the COVID-19 events, the average systemic risk of each sector has increased by $\theta_i\theta_i$ relative to the average systemic risk during the entire sample period. If the regression coefficient $\theta_i\theta_i$ is significantly less than zero, it indicates a weak level effect of COVID-19 on financial systemic risks. In eq. (11), if the regression coefficient $\delta_i\delta_i$ of the interaction term between the time variable T and dummy variable D_nD_n is significantly greater than the regression coefficient $\varphi_i\varphi_i$ of the interaction term between the time variable T and dummy variable $D_{-n}D_{-n}$, it means that the COVID-19 exhibits a trend effect on financial systemic risks. The size of the trend effect is ($\theta_i\varphi_i\theta_i$-$\varphi_i$), which indicates the changes in the trend of systemic risk in various sectors over time in n trading days after the COVID-19 events, compared with n trading days before the COVID-19 events.

4. Data

This study selected non-special-treatment companies that were listed as A shares in banking, securities, insurance, and real estate sectors before December 2019, including a total of 30 listed banking companies, 46 listed securities companies, 7 insurance companies, and 119 listed real estate companies (according to the new China Securities Regulatory Commission sector classification).

Based on the initial sample, the following steps and winsorization at 1% level were followed to reduce the possible influence of outliers:

(1) We removed the companies marked ST.
(2) We excluded some companies with missing annual data.
(3) We eliminate companies with abnormal data.

Finally, the data of 202 listed companies were obtained, including 30 listed banks, 46 listed securities companies, 7 insurance companies, and 119 listed real estate companies. The sample interval is from December 1, 2019, to May 31, 2020, with a total of 118 times samples. Macroeconomic data and data from the financial sector and listed real estate enterprises were derived from the Wind database. Stata15.0 software was used for the empirical test.

To evaluate the real estate sector's impact on systemic financial risks, this study classified 119 real estate A-share listed companies (according to the CITIC sector classification standard updated in January 2020), including 89 residential property development listed companies, non-residential property development listed companies, 12 park comprehensive development listed companies, and 5 real estate services listed companies. Residential property development listed companies are the principal part of the real estate sector, including most of the real estate listed enterprises, mainly for infrastructure construction, housing construction, transfer of real estate development projects or sales, rental of commercial housing, and other activities of real estate companies. Non-residential property development listed companies include shopping malls and office buildings. Park comprehensive development listed companies include the industrial park as a carrier for conducting development, construction, investment, and financing activities. Real estate services listed companies are engaged in real estate brokerage, property management, and housing intermediaries, among others.

Table 1 shows the variables involved in the calculation of systemic risk $\Delta CoVaR_t^{system|i}\Delta CoVaR_t^{system|i}$ for each sector and branch sector.

The stock market volatility was calculated using the GARCH (1) model. The GARCH (1) model is expressed as $r_t = \alpha + \varepsilon_t$, $\varepsilon_t = \mu_t \times \sigma_t$, $\sigma_t^2 = \alpha_0 + \alpha_1 \times \varepsilon_{t-1}^2 + \beta \times \sigma_{t-1}^2$, where r_t represents the logarithmic return rate of the CSI 300 Index, and σ_t is the dynamic conditional volatility of r_t, that is, the stock market volatility. We performed GARCH modeling on the volatility of the CSI 300 Index during the sample period and found that the second-order lag is <0.05 and the return rate of the CSI 300 index during the sample period

Table 1
Data description.

Variable	Description
Syl_i	CSI 300 sector i index return rate; represents the rate of return of institution i, i = bank, sec, ins—where bank represents banking, sec represents securities sector, and ins represents insurance sector
$V_{i, t}$	Return rate of the i-th listed company in the sector at time t
M1	CSI 300 Index Growth Rate, logarithmic growth rate
M2	CSI 300 Index Volatility; reflects the fluctuation of the stock market, obtained using a GARCH (1) model.
M3	Changes in the yield to maturity of 3-month Treasury bonds; reflects changes in spreads
M4	Term spread, Shanghai Clearing House's 1-year treasury bond yield to maturity minus the 3-month treasury bond yield; reflects market liquidity
M5	Credit spread, the one-year maturity certificate AAA corporate bond yield minus the one-year maturity treasury bond yield; reflects the market's credit risk

exhibits an ARCH effect. Finally, $\alpha = 1.6367\text{e-}03$, $\alpha_0 = 2.3884\text{e-}05$, $\alpha_1 = 0.2005$, and $\beta = 0.6996$; based on these data, we obtain the volatility of CSI 300 during the sample period.

The data used to calculate the financial systemic risks (explained variables) of each sector include the logarithmic return on the total market value of each listed company's equity, logarithmic growth rate of each sector index, and all control variables. Table 2 presents the basic descriptive statistics.

The white paper "China's Action against COVID-19"—issued by the State Council Information Office of China in June 2020—selected major events of COVID-19 from December 31, 2019, to May 30, 2020. We chose the time point of the early morning of December 31 as a start news event, when the National Health Commission planned and deployed working groups and expert groups to Wuhan to guide the management of the epidemic and conduct on-site investigations, rather than considering the earlier time when sporadic cases appeared. For foreign outbreaks, this study predominantly selected two events: 1) the World Health Organization adjusting the global risk level of COVID-19 to the highest level on February 28; and 2) the US government declaring a national emergency on March 14. Table 3 lists all events.

This study adopted the improved event analysis method, which requires shortening the sample period as much as possible. Hence, the sample period is as of the end of May. In the sample period, there were a total of nine relatively important pandemic events. This study's explanatory variables included dummy variables for n ($1 \leq n \leq 15$) trading days before and after the event and its cross-multiplication with the time variable T.

5. Empirical results

The empirical results section contains three parts. Based on systemic risk data, the first part analyzes the overall situation of systemic risks in the financial sector, which includes banking, insurance, securities, and real estate sectors. The second part shows the level effect of COVID-19 on the systemic risks based on formula (10). The third part presents the trend effect of COVID-19 on the systemic risks based on formula (11).

5.1. Systemic risks fluctuation

$\Delta Co\text{VaR}_t^{system}$ exhibits both positive and negative values. Therefore, for simplicity, we present the absolute value of $\Delta Co\text{VaR}_t^{system}$ for each sector in Figs. 1 and 2. The abscissa is the daily date variable, and the ordinate is the systemic risk value of each sector or branch sector. Fig. 1 shows the trend of systemic risk in the four sectors, and Fig. 2 shows the trend of systemic risk in branch sectors of the real estate sector. From Fig. 1, it can be concluded that COVID-19 has increased the volatility of systemic risks in the financial market. Since important COVID-19-related events were released during the holiday period (Chinese Spring Festival), the information backlog caused a sharp increase in systemic risks in early February. With the pandemic continuing after February, the fluctuation of systemic risks was significantly higher after February than in December. Due to the uncertainty precipitated by COVID-19, both the systemic financial risks level and volatility of systemic risks in the financial system have increased.

Fig. 1 and Table 4 show that the securities sector exhibits higher volatility in systemic risks than the banking, insurance, and real estate sectors. The real estate sector exhibits the largest mean value of systemic risk and smallest standard deviation, indicating that the real estate sector's systemic risk has been at a high level for a long time during the COVID-19 pandemic. These two sectors are impacted by COVID-19 more evidently. (See Table 5.)

Fig. 2 and Table 4 clearly show that the systemic risk fluctuations in the residential property development industry are the largest. Due to the short-term stagnant and high debt financial situation, the standard deviation exceeds the whole real estate sector's level. Due to the longer development cycle and payback period, the park comprehensive development industry exhibits a higher systemic risk level for a long time. Non-residential property development and real estate service companies are less affected by the pandemic.

Figs. 1, 2, and Table 4 show the systemic risk trends of the banking, securities, insurance, real estate sectors, and its branch sectors—before and after the pandemic. However, due to the mixed effects of events, COVID-19's impact on systemic risks in the financial

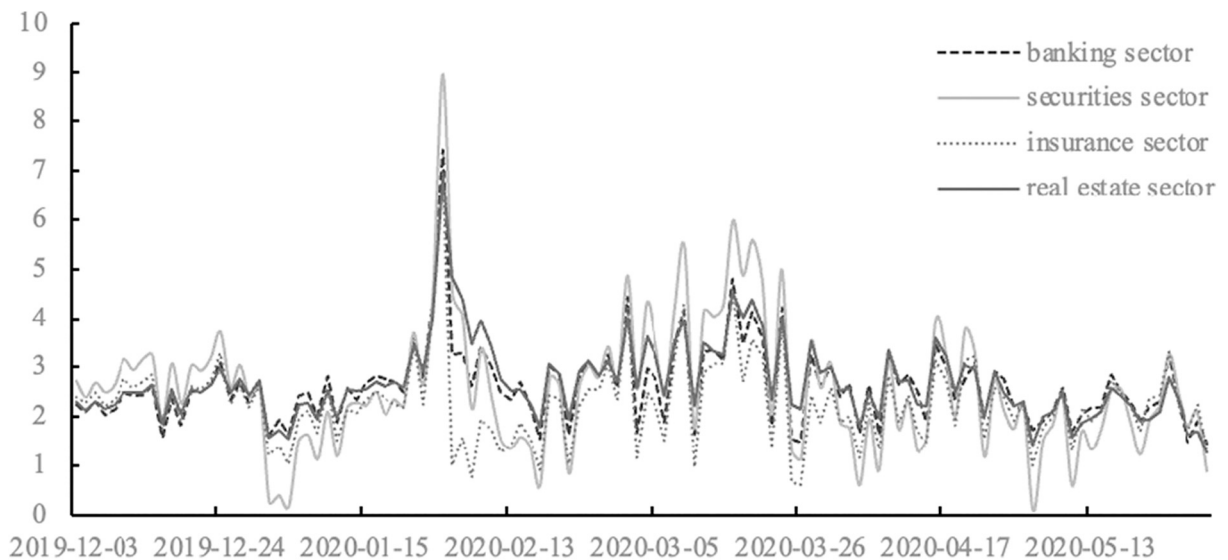**Table 2**
Descriptive statistics.

Variable	Mean	SD	Min	Max
Syl_bank	−0.0865	1.2648	−6.7125	2.6202
Syl_sec	−0.0071	2.2064	10.5277	6.0372
Syl_ins	−0.1411	1.6403	−7.6517	3.4802
CoVaR_bank	2.6131	0.8104	1.4681	7.4278
CoVaR_sec	2.5715	1.3187	0.0911	8.9346
CoVaR_ins	2.2747	0.8813	0.6130	6.9841
M1	1.4257	0.5505	0.9319	4.0852
M2	0.0068	1.5172	−8.2088	3.2368
M3	−0.2867	4.9129	18.5345	18.461
M4	0.2414	0.0850	0.0752	0.4241
M5	0.7130	0.1043	0.3903	0.9721

Note: In Panel A of this table, we provide a detailed description of the study data. Panel B reports descriptive statistics (mean, maximum, minimum, standard deviation [SD]).

Table 3
Overview of important COVID-19 events.

Date	Events
Dec 31, 2019	The National Health Commission made arrangements and dispatched working groups and expert groups to Wuhan; the Wuhan Municipal Health Commission issued the "Notice on the Current Situation of Pandemic in Wuhan" on its official website, and 27 cases were found; on the same day, the Wuhan Municipal Health Commission released pandemic information.
Jan 13, 2020	The National Health Commission held a meeting to deploy and guide Hubei Province and Wuhan City to further strengthen the temperature monitoring of personnel at ports and stations and reduce crowd gathering.
Jan 14, 2020	The National Health Commission held a national video and telephone conference to deploy, prepare for, and strengthen the prevention and control of—and response to—the pandemic in Hubei Province and Wuhan City, and, at large, the national pandemic. The meeting highlighted that there were significant uncertainties in the new infectious disease (COVID-19), and the possibility of further spread cannot be ruled out.
Jan 20, 2020	The National Health Commission organized a press conference, and a high-level expert group reported that the COVID-19 infection spreads from person to person. From this point on, the number of new cases in each province would be summarized and released. National Health Commission issued an announcement to include COVID-19 in the Class B infectious diseases stipulated by the Infectious Disease Prevention and Control Law, and adopt the prevention and control measures for the Class A infectious diseases; to include COVID-19 in the quarantine infectious diseases specified in the "Frontier Health and Quarantine Law of the People's Republic of China" management.
Jan 22, 2020	Xi Jinping, General Secretary of the Central Committee of the Communist Party of China, President of the State, and Chairman of the Central Military Commission, issued important instructions to immediately implement strict closed traffic control on the movement of people and external passages in Hubei Province and Wuhan City; the first confirmed case was found in the United States.
Jan 23, 2020	Wuhan Epidemic Prevention and Control Headquarters issued Announcement No. 1 that the airport and railway station would be temporarily closed from 10:00 am on the January 23. Ministry of Transport issued an emergency notice that the country had suspended access to Wuhan's road and water passenger transport lines; all provinces across would have successively initiated provincial-level emergency responses to major public health emergencies.
Jan 26, 2020	The General Office of the State Council issued a notice, deciding to extend the 2020 Spring Festival holiday and postpone the commencement of schools in various regions, universities, primary schools, and kindergartens.
Feb 28, 2020	World Health Organization adjusted the global risk level of the new crown pneumonia epidemic to the highest level.
Mar 14, 2020	U.S. President Trump declares a national emergency.

Fig. 1. Trends of systemic risks by ΔCoVaR model in various financial sectors and the real estate sector.

sector cannot be quantified. COVID-19 events are frequently released, and the effects of adjacent events overlap. The information on systemic risks at a one-time point may include results of plural events. To resolve this mixed effect accurately, further empirical analysis is required according to formulas (10) and (11).

5.2. COVID-19's level effect on systemic risks

The level effect is used to measure the degree of difference between the systemic risk of one sector and average systemic risk of the entire financial sector in a chosen period. The average systemic risk of each sector and the entire financial sector are represented by γ_i and θ_i, which are the regression coefficients of dummy variables D_{-n} and D_n in formula (10), respectively. Fig. 3 shows the changes in the regression coefficients in n trading days before and after the occurrence of the COVID-19 event, where the abscissa represents the
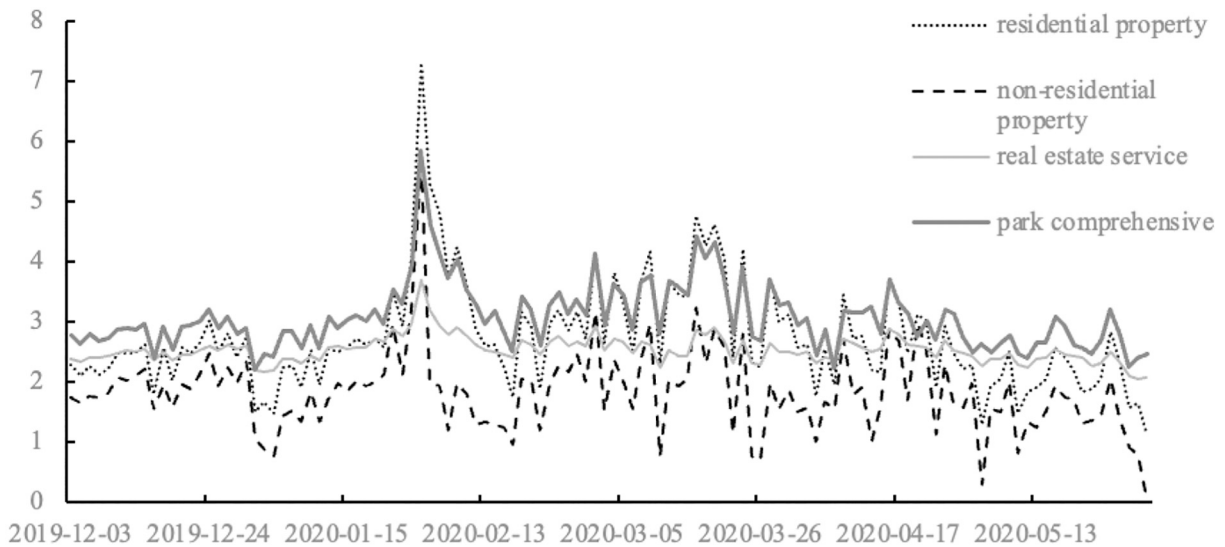
Fig. 2. Trends of systemic risk by ΔCoVaR model in the branch sectors of real estate.

Table 4
Descriptive statistics of systemic risks.

Variables	Description	Mean	SD	Min	Max
CoVaR_bank	Systemic risks in the banking sector	2.6131	0.8104	1.4681	7.4278
CoVaR_sec	Systemic risks in the securities sector	2.5715	1.3187	0.0911	8.9346
CoVaR_ins	Systemic risks in the insurance sector	2.2747	0.8813	0.6130	6.9841
CoVaR_est	Systemic risks in the real estate sector	2.6881	0.8041	1.1442	6.8764
CoVaR_zz	Systemic risks of residential property development	2.7245	0.9210	0.0654	7.3159
CoVaR_fzz	Systemic risks of non-residential property development	1.8420	0.6739	0.2972	5.6107
CoVaR_fdcfw	Systemic risks in real estate services	2.5360	0.2189	2.0492	3.6936
CoVaR_yq	Systemic risks of park comprehensive development	3.0570	0.5932	0.6289	5.8507

time before and after events. A positive number n represents n trading days after the COVID-19 events, and (−n) represents n trading days before the COVID-19 events. The ordinate represents the regression coefficients of D_{-n} and D_n in formula (10), which, respectively, represent the level effects before and after COVID-19.

The left side of Fig. 3 shows that COVID-19 exhibits a level effect on the systemic risks in all sectors. Specifically, before the outbreak of the COVID-19 events, the regression coefficient γ_i of the dummy variable D_{-n} was negative in almost all sectors, while the regression coefficient θ_i of D_n increased within 3–4 trading days after the outbreak of the COVID-19 events. The value of θ_i was above zero for 3 weeks after the outbreak, even though it decreased later. It is indicated that after the COVID-19 outbreak, the mean of systemic risks in every sector has increased compared with the entire sample, especially in the securities and real estate sectors. This suggests that the systemic risk growth of the securities and real estate sectors has been severely impacted, and that these sectors contribute more to the growth of systemic risk in the entire financial system than the banking and insurance sectors.

The right side of Fig. 3 shows that after the COVID-19 outbreak, the real estate branch sector's average systemic risk has increased significantly. Specifically, the mean value of the systemic risk of residential property development and park comprehensive development exhibits the most increment and longest persistence. Affected by the rent reduction policies for large shopping malls, markets, and shops during COVID-19, the level effect in the non-residential properties industry declined rapidly. Although the average systemic risk of real estate services has increased, the level effect in the whole period is weak.

The level effect of the COVID-19 events on these sectors is reflected in the rapid rise of the mean value of systemic risk after the release of information. The regression coefficient increases in 1–5 trading days before the outbreak of the epidemic, but not significantly. Although COVID-19's news shock to the financial sector is continuous, the initial expectations of information digestion, unlike other persistent emergencies, did not help significantly. The financial sector remained on alert for a prolonged period, until the announcement of some decisive good news—for example, the introduction of an effective and safe vaccine.

Noteworthily, after the occurrence of COVID-19, the upward trend of systemic risk in every sector may also push the mean of the overall sample, thus concealing the level effect of COVID-19 on systemic risk, which is also observed in the empirical result as a decline in the later period.

Table 5
Significance level of γ_i and θ_i in formula 10.

n	Banking sector	Securities sector	Insurance sector	Real estate sector	Residential properties	Non-residential properties	Real estate services	Park comprehensive
−15	−0.071	−0.192**	−0.052	−0.108**	−0.125**	−0.036**	−0.023	−0.073**
−14	−0.070	−0.195**	−0.046	−0.112**	−0.130**	−0.033**	−0.023	−0.075**
−13	−0.083	−0.216**	−0.053	−0.127**	−0.149**	−0.040**	−0.027	−0.087**
−12	−0.091	−0.229**	−0.056	−0.138**	−0.161**	−0.044**	−0.029	−0.093**
−11	−0.105**	−0.249**	−0.064	−0.154**	−0.179**	−0.051**	−0.033	−0.105**
−10	−0.107**	−0.256**	−0.061	−0.161**	−0.188**	−0.051**	−0.034	−0.109**
−9	−0.136**	−0.304**	−0.076	−0.197**	−0.230**	−0.068**	−0.043	−0.134**
−8	−0.158**	−0.354**	−0.086	−0.233**	−0.271**	−0.084**	−0.051	−0.155**
−7	−0.155**	−0.362**	−0.072	−0.243**	−0.283**	−0.080**	−0.053	−0.160**
−6	−0.144	−0.346**	−0.062	−0.230**	−0.269**	−0.065**	−0.047	−0.154**
−5	−0.100	−0.296	−0.030	−0.187**	−0.222**	−0.033**	−0.034	−0.126
−4	−0.074	−0.245	−0.026	−0.141	−0.169	−0.002	−0.017	−0.098
−3	−0.055	−0.218	−0.030	−0.107	−0.131	0.017	−0.002	−0.073
−2	0.017	−0.095	0.048	−0.032	−0.049	0.100	0.022	−0.031
−1	0.177	0.063	0.204	0.087	0.078	0.229	0.063	0.048
1	0.211	0.209	0.234	0.144	0.138	0.258	0.089	0.116
2	0.552**	0.631	0.554	0.424	0.449	0.465	0.149**	0.309**
3	0.534**	0.698	0.464	0.492**	0.535**	0.435**	0.159**	0.352**
4	0.539**	0.758**	0.405	0.556**	0.616**	0.415**	0.171**	0.394**
5	0.475**	0.699**	0.291	0.543**	0.610**	0.344**	0.162**	0.384**
6	0.445**	0.660**	0.242	0.534**	0.603**	0.313**	0.158**	0.375**
7	0.429**	0.632**	0.210	0.527**	0.598**	0.291**	0.154**	0.368**
8	0.383**	0.554**	0.169	0.480**	0.546**	0.251**	0.140**	0.334**
9	0.311**	0.427**	0.106	0.401**	0.458**	0.190**	0.118**	0.283**
10	0.296**	0.388**	0.108	0.369**	0.421**	0.178**	0.109**	0.262**
11	0.285**	0.364**	0.101	0.352**	0.402**	0.165**	0.103**	0.251**
12	0.252**	0.318**	0.072	0.321**	0.368**	0.137**	0.093**	0.230**
13	0.231**	0.280**	0.053	0.297**	0.341**	0.118**	0.086**	0.214**
14	0.212**	0.246**	0.036	0.275**	0.317**	0.103**	0.081**	0.201**
15	0.197**	0.220**	0.026	0.257**	0.297**	0.094**	0.077**	0.189**

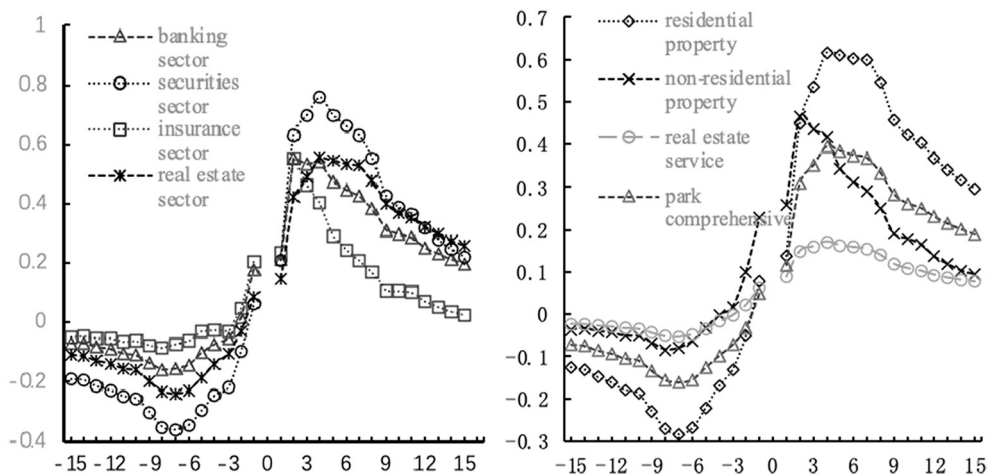Note: **denotes the level effect is significant at the 5% significance level.

Fig. 3. Level effect of the COVID-19 epidemic on systemic risks by the ΔCoVaR model.

5.3. COVID-19's trend effect on systemic risks

According to formula (11), the size of the trend effect is represented by $(\delta_i - \varphi_i)$, where δ_i is the regression coefficient of the interaction term between the dummy variable D_n and time variable T, and φ_i is the regression coefficient of an interaction term between the dummy variable D_{-n} and time variable T. i refers to different sectors–banking, securities, insurance, real estate sectors, and its branch sectors.

The abscissa in the left graph of Figs. 4 and 5 represents the value of n in formula (11). A positive value of n means "after the event," and a negative value of n means "before the event." The ordinate represents the values of the regression coefficients δ_i and φ_i of $T \times D_{-n}$ and $T \times D_n$ in formula (11), respectively. In the right graph of Figs. 4 and 5, the ordinate represents the value of the difference $(\delta_i - \varphi_i)$
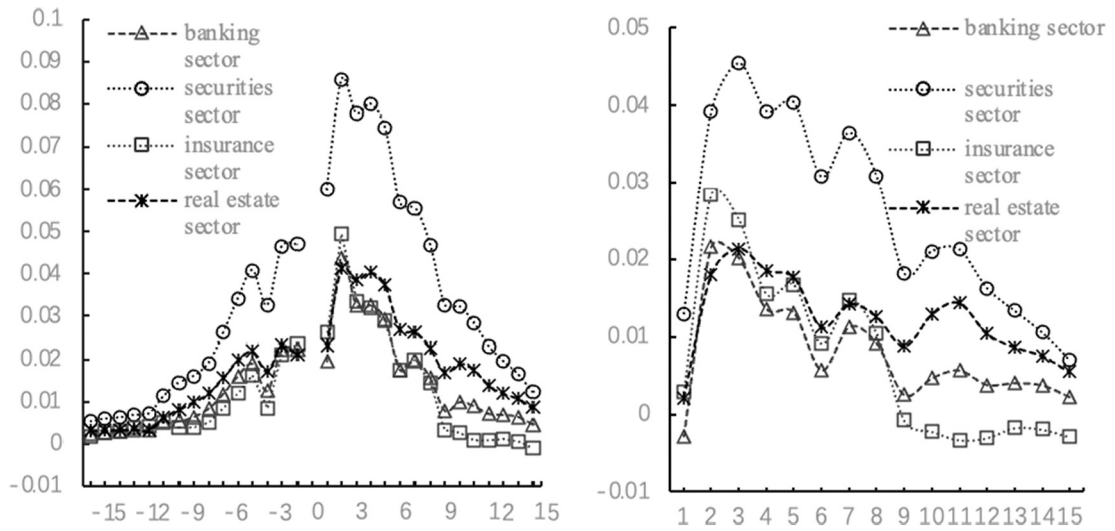
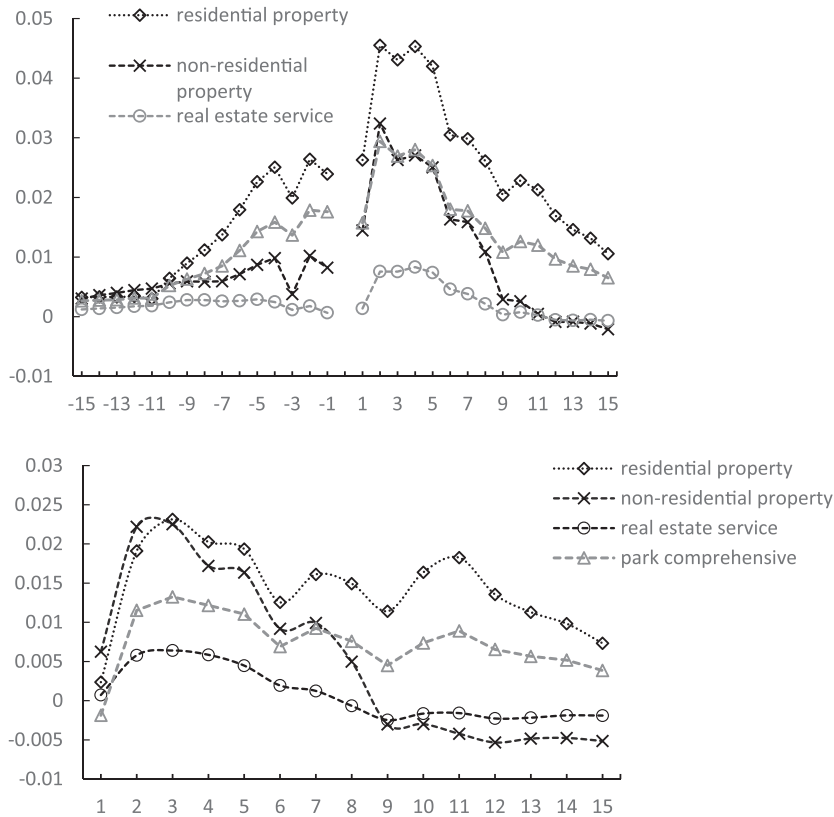**Fig. 4.** Trend effect of COVID-19 on systemic risks by the ΔCoVaR model in financial sectors.

Fig. 5. Trend effect of COVID-19 on systemic risks by the ΔCoVaR model in branch sectors of real estate.

between the regression coefficients of $T \times D_{-n}$ and $T \times D_n$ in formula (11), indicating COVID-19's trend effects on systemic risks in various sectors.

Fig. 4 and Table 6 show that COVID-19 exhibits a trend effect on systemic risk in four sectors. Before the news shock, the trend in the banking, securities, and real estate sectors is significantly positive; the reason may be that the systemic risk of the financial sector is difficult to digest in a short period, and the overlap of previous events is continuously effective. There was no significant upward trend of systemic risk in the insurance sector before the COVID-19 events. After the COVID-19 news shock, the systemic risk of the four

Table 6
Significance level of δ_i and φ_i in formula 11.

n	Banking sector	Securities sector	Insurance sector	Real estate sector	Residential properties	Non-residential properties	Real estate services	Park comprehensive
−15	0.0023	0.0052	0.0018	0.0031	0.0032	0.0030	0.0012	0.0027
−14	0.0026	0.0059	0.0025	0.0032	0.0033	0.0036	0.0014	0.0028
−13	0.0028	0.0062	0.0030	0.0033	0.0033	0.0040	0.0015	0.0028
−12	0.0033	0.0068	0.0037	0.0034	0.0034	0.0045	0.0017	0.0031
−11	0.0033	0.0071	0.0042	0.0032	0.0030	0.0047	0.0018	0.0031
−10	0.0052	0.0113	0.0049	0.0061	0.0064	0.0056	0.0024	0.0052
−9	0.0053	0.0144	0.0039	0.0082	0.0090	0.0059	0.0028	0.0063
−8	0.0064	0.0161	0.0040	0.0100	0.0112**	0.0059	0.0028	0.0072**
−7	0.0083	0.0191**	0.0052	0.0120**	0.0137**	0.0059	0.0026	0.0085**
−6	0.0118	0.0261**	0.0082	0.0156**	0.0179**	0.0071	0.0027	0.0111**
−5	0.0160**	0.0342**	0.0121	0.0197**	0.0226**	0.0087	0.0029	0.0143**
−4	0.0189**	0.0409**	0.0164	0.0219**	0.0251**	0.0098	0.0025	0.0159**
−3	0.0125	0.0325**	0.0085	0.0171	0.0199	0.0038	0.0012	0.0137**
−2	0.0222	0.0466**	0.0212	0.0232	0.0264	0.0102	0.0018	0.0179**
−1	0.0224	0.0470	0.0234	0.0211	0.0239	0.0082	0.0006	0.0176
1	0.0195	0.0600	0.0263	0.0232	0.0263	0.0145	0.0014	0.0157
2	0.0438**	0.0858**	0.0496**	0.0413**	0.0455**	0.0324**	0.0076**	0.0294**
3	0.0327**	0.0779**	0.0336**	0.0385**	0.0431**	0.0263**	0.0076**	0.0269**
4	0.0325**	0.0801**	0.0319**	0.0404**	0.0453**	0.0270**	0.0083**	0.0280**
5	0.0291**	0.0746**	0.0288**	0.0373**	0.0420**	0.0250**	0.0074**	0.0253**
6	0.0175**	0.0569**	0.0174**	0.0269**	0.0305**	0.0163**	0.0046**	0.0180**
7	0.0196**	0.0556**	0.0199**	0.0263**	0.0298**	0.0159**	0.0038**	0.0178**
8	0.0155**	0.0469**	0.0144	0.0226**	0.0261**	0.0108	0.0021	0.0148**
9	0.0078	0.0325**	0.0031	0.0170**	0.0204**	0.0029	0.0003	0.0108**
10	0.0099	0.0323**	0.0027	0.0190**	0.0228**	0.0026	0.0008	0.0126**
11	0.0089	0.0283**	0.0009	0.0176**	0.0213**	0.0005	0.0002	0.0120**
12	0.0071	0.0230**	0.0007	0.0138**	0.0169**	−0.0009	−0.0005	0.0097**
13	0.0068	0.0195**	0.0012	0.0120**	0.0146**	−0.0009	−0.0006	0.0085**
14	0.0064	0.0164**	0.0006	0.0108**	0.0132**	−0.0012	−0.0005	0.0080**
15	0.0046	0.0122	−0.0011	0.0086**	0.0106**	−0.0021	−0.0007	0.0065**

Note: **denotes the trend effect is significant at the 5% significance level.

sectors exhibited a significant upward trend, and the upward trend was much greater than the trend before the release of COVID-19 news.

Regarding time efficiency, it has been proved that epidemics' effect on firms' stock returns is persistent up to 10 days after the event dates (Quang Thi Thieu Nguyen et al., 2021). However, the significant upward trend effect in systemic risk reaches a peak in 2–3 days and, thereafter, becomes weak. The significant increasing trend effect in the banking and insurance sector disappears in 7–8 trading days, whereas it still exists in the securities and real estate sector even after 15 days (δ_i is positive but decreasing). After the information impact of one event is digested, the mean of systemic risk in the financial sector is still increasing.

Fig. 5 and Table 6 show that COVID-19 exhibits a significant positive trend effect on the real estate industry. Among the branch sectors, the positive trend of systemic risk in the residential property and park comprehensive industry lasted for a long time. While the non-residential property and real estate services do not show a significant upward trend before the event (δ_i is not significant), they show a significant upward trend 2–8 trading days after the event and, then, are no longer significant. Under the COVID-19 events' impact, the rising trend of systemic risk in the real estate sector is mainly affected by the continuous rising of residential property and park comprehensive industry.

COVID-19's trend effect on systemic financial risks in the real estate branch sector is different in value and significance level. Within five trading days after the release of COVID-19 information, the trend effect of systemic risk of residential and non-residential properties was higher than that of park comprehensive property, and the trend effect of real estate service was the lowest. After five trading days, the trend effect of systemic risk in non-residential property and real estate services decreased rapidly and, then, disappeared (the value of ($\delta_i - \varphi_i$) becomes negative after 8–9 trading days, as seen in the right graph of Fig. 5). Although the trend effect in residential property and park comprehensive property declined, it still remained at a higher level than other branch sectors. It takes a long time to digest the impact in residential property and park comprehensive property, and the real estate service industry exhibits a better ability to resist negative external impact.

6. Transmission mechanism

COVID-19, as an uncertain factor, makes investors unsure about the real economy's prospects. Uncertainty leads to a sell-off of the stock (Rehse et al., 2019). Consequently, market liquidity contracts, which is reflected through falling stock prices. When markets are illiquid, market liquidity is highly sensitive to further changes in funding conditions. This is due to two liquidity spirals: a margin spiral and a loss spiral (Brunnermeier and Pedersen, 2009). Since short-term assets are insufficient to pay the short-term liabilities, the enterprises have to sell assets, thus precipitating a sharp fall in asset prices. As the probability of a solvency crisis increases, the default

risk also affects the volatility of the stock. In conclusion, these three factors are the transmission mechanism of COVID-19 affecting the systemic risk considered in this study.

This section examines COVID-19's impact on market liquidity, funding liquidity, and default risk. It further explains that the sources of systemic risk in different sectors are different. Among the sectors, the securities sector is imposed by constraints of liquidity factors in the COVID-19 outbreaking period. The real estate sector—due to its dual nature of finance and the real economy—is most severely impacted by market liquidity. The risk of default in all sectors has also increased significantly, except for the banking sector, where default risk has remained extremely low.

6.1. Market illiquidity

Amihud (2002) proposed the illiquidity ratio as an indicator of the illiquidity of the stock market:

$$M\_ILLIQ_{i,t} = |R_{i,t}| \Big/ VOLD_{i,t} \tag{14}$$

where $R_{i,t}$ is the return on stock i on time t, and $VOLD_{i,t}$ is the respective daily volume (in millions).

COVID-19's impact on the market liquidity of the financial sectors and real estate sector using the event analysis method is shown in Fig. 6. The COVID-19 events had a significant positive impact on the market illiquidity of the financial sectors and real estate sector, among which the real estate and securities sectors were the most severely affected. The real estate sector's coefficient is larger than that of the other three sectors, shown separately on the left vertical axis in Fig. 6. Clearly, under COVID-19's impact, the real estate and securities sectors are facing the most lack of market confidence.

6.2. Funding liquidity

Funding liquidity refers to the ability of an institution or company to raise funds in a short period. In this study,

$$F\_LIQ_i = (a_i - l_i) \Big/ A_i \tag{15}$$

where a_i is short-term assets, l_i is short-term liabilities, and A_i is total assets. Thereafter, F_LIQ_i is the ratio of the gap between short term
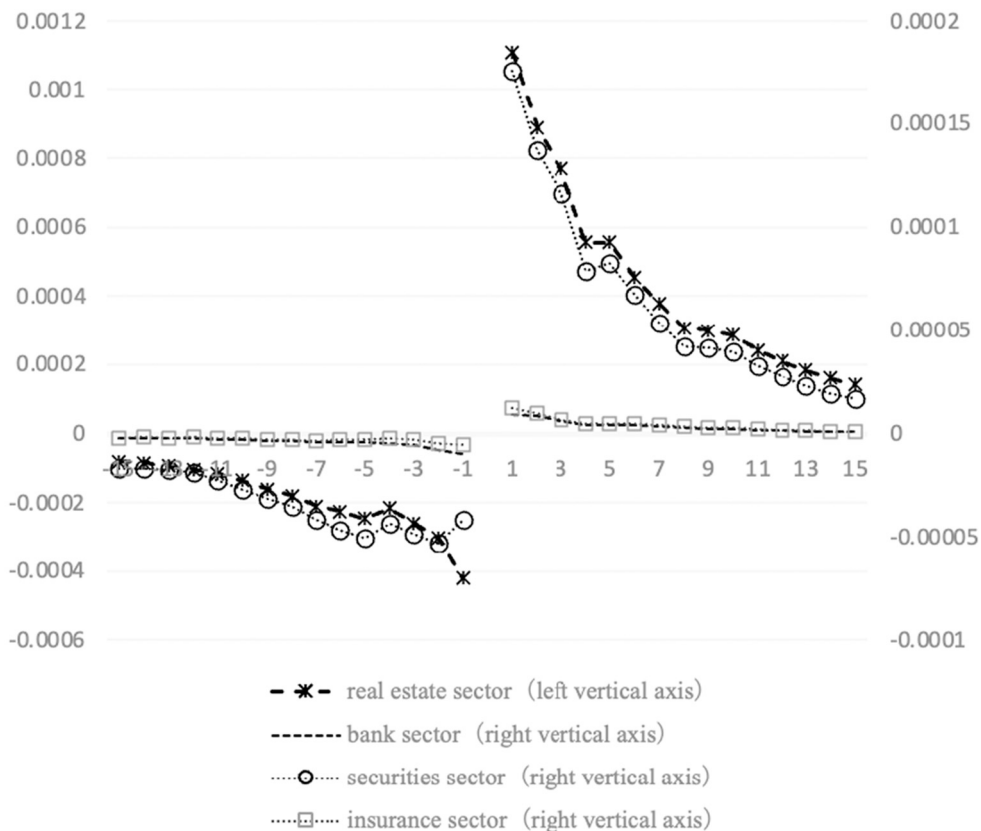

Fig. 6. Level effect of the COVID-19 epidemic on Market illiquidity.

assets and short term liabilities to the total assets. The data from the quarterly statements are used. The larger the funding gap, the more the circulating fund the enterprises have, and the better the financing liquidity. Since this indicator is long-term data, event analysis cannot be used. The changes in funding liquidity risk of each sector in 8 quarters from 2019 to 2020 can reflect the impact during the period of COVID-19 outbreak, as shown in Fig. 7.

Fig. 7 shows that the funding liquidity in all financial sectors and the real estate sector exhibit an evident decreasing trend during the COVID-19 outbreak. Particularly, the securities and real estate sectors exhibit a downward trend throughout 2020. This suggests that the two sectors faced severe funding liquidity risk due to COVID-19. At the same time, the funding liquidity of the banking and insurance sectors fluctuated but recovered in mid-2020.

6.3. Default risk

MertonDD model based on market information is a mainstream method of enterprise financial distress. As an improvement of MertonDD, NaïveDD by Bharath and Shumway (2008) has been widely adopted by scholars.

They set the market value of debt

$$\text{Naïve D} = F \tag{16}$$

where F is the face value of debt. Thereafter, the value of assets V = E + F, where E is the equity value.

Since firms that are close to default exhibit highly risky debt, and the risk of their debt is correlated with their equity risk, the volatility of debt is

$$\text{Naïve } \sigma_D = 0.05 + 0.25 \times \sigma_E \tag{17}$$

where σ_E is volatilities of the firm. 0.05 represent term structure volatility, and 0.25 is times equity volatility.

Thereafter, the total volatility is expressed as follows:

$$\text{Naïve } \sigma_V = \frac{E}{E + \text{Naïve D}} \sigma_E + \frac{\text{Naïve D}}{E + \text{Naïve D}} \text{Naïve } \sigma_D \tag{18}$$

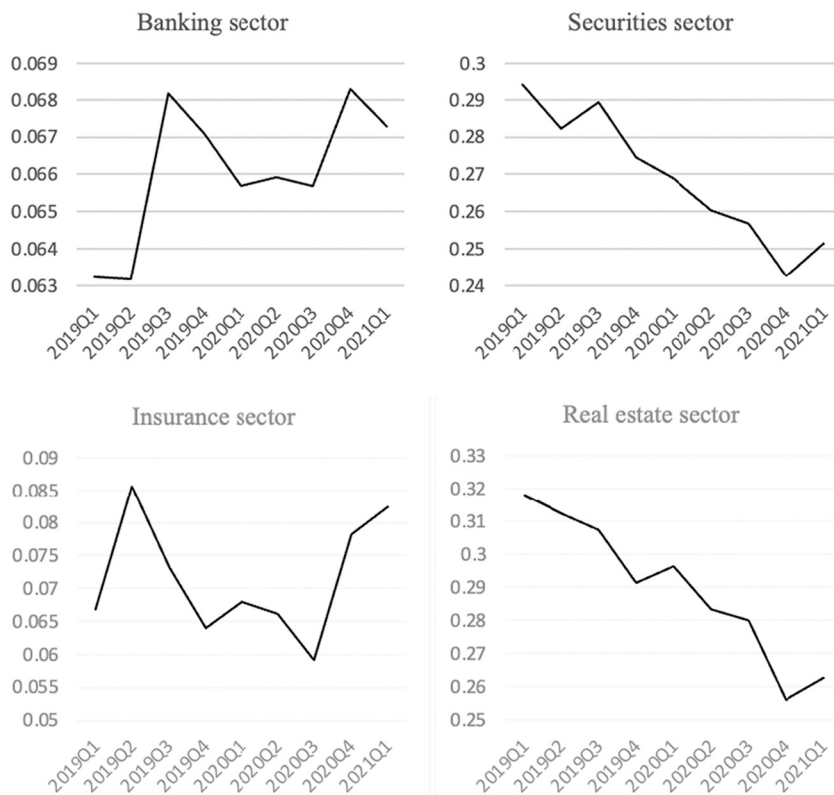Set the expected return on assets equal to the stock return over the previous term.

Fig. 7. Funding liquidity risk in various financial sectors and real estate sector.
Note: **denotes the trend effect is significant at the 5% significance level.

$$\text{Naïve } \mu = r_{i,t-1} \tag{19}$$

The naïve distance to default is then.

$$\text{Naïve DD} = \frac{ln[(E+F)/F] + \left(r_{it-1} - 0.5\text{Naïve } \sigma_V^2\right)T}{\text{Naïve } \sigma_V \sqrt{T}} \tag{20}$$

where T is time-to-maturity. Thereafter, the expected default probability is:

$$\pi = \mathcal{N}(-\text{naïve D}) \tag{21}$$

The empirical results by event analysis method on the daily data of expected default probability on the banking, insurance, securities, and real estate sectors according to the Merton model—from the end of 2019 to the middle of 2020—are shown in Fig. 8, which depicts that COVID-19 significantly impacts default rates in all financial sectors and the real estate sector.

According to coefficients, the insurance sector faced the greatest impact. Both rising loss rates and falling sales due to public safety incidents have increased the potential defaults in the insurance sector.

In the real estate sector, COVID-19 significantly impacts on all the transmission mechanisms because of its dual nature of real economy and finance. The result reflects that the difficulties faced by the real estate sector economy, such as work stoppings and insufficient sources of funds.

COVID-19's impact on the expected default probability of the securities sector is significant. In contrast, in the banking sector, the expected default probability has remained at a low level—close to 0. The sharp corner seen in Fig. 8 could be due to the data itself. The banking sector has been the most stable sector under COVID-19's impact.

7. Robustness test

To avoid the impact of different methods of measuring systemic risk on the study's results, we applied the Marginal Expected Shortfall (MES) method proposed by Acharya et al. (2010) as a robustness test to measure systemic risk. The DCC-GARCH model by Brownlees et al. (2010) was used to calculate MES.

Compared with the $\triangle$CoVaR model, the MES model has the following differences: 1) The MES model measures all losses below the quantile, including tail risks under extreme conditions. 2) The MES model can accurately measure systemic risk by summing up the risk contribution of individual financial institutions, which is additive.

Brownlees et al. (2010) defined MES as:

$$\text{MES}_{i,t}(C) = \frac{\partial \text{ES}_{m,t-1}(C)}{\partial \omega_i} = E_{t-1}\left(r_{i,t}|r_{m,t} < C\right) \tag{22}$$

where $r_{i,t}$ is return rate of financial institution i at time t.

Thereafter, market return rate

$$r_{m,t} = \sum_{i=1}^{N} \omega_i r_{i,t} \tag{23}$$

$\text{ES}_{m,t-1}(C)$ is expected return rate when the market return rate $r_{m,t}$ is below critical value C, defined as:

$$\text{ES}_{m,t-1}(C) = E_{t-1}\left(r_{m,t}|r_{m,t} < C\right) = \sum_{i=1}^{N} \omega_i E_{t-1}\left(r_{i,t}|r_{m,t} < C\right) \tag{24}$$

The TARCH model was used to calculate dynamic volatility, and the dynamic conditional correlation coefficient (DCC) model was used to calculate the correlation coefficient between institutional returns and market returns. The results are shown in Figs. 9 and 10.

It can be confirmed that the systemic risk of the securities sector is the highest during COVID-19's impact, followed by the real estate—like the results of $\triangle$CoVaR model. Among the branch sectors of real estate, the residential property sector's risk is the highest due to the high debt risk and the real estate development stagnating during the COVID-19 pandemic.

The MES model gives the systemic risk contribution of financial institutions' unit assets. It shows the differential performance of individual financial institutions under the pressure of a significant decline in the return rate of the entire financial market. The curves are more volatile at the events and calm down faster after the events than the results of the $\triangle$CoVaR model. The $\triangle$CoVaR model is not suitable for observing the event analysis method's trend effects. In contrast, the $\triangle$CoVaR model is the most suitable for the event analysis method with a dynamic time window.

Fig. 11 shows the results of the level effects of the event analysis method.

According to Fig. 11 (left), Level effect still exists when using the MES model to measure systemic risks. Before the COVID-19 events, the regression coefficients of dummy variables in all sectors were negative or not significant, while after the outbreaks of the events, the regression coefficients were significantly positive, indicating that systemic financial risks in all sectors increased by COVID-19's impact. Similarly, the real estate and securities sectors were more affected than the banking and insurance sectors. According to Fig. 11 (right), among the branch sectors of real estate, the systemic risk of the residential property sector is the most impacted. The event analysis method's results remain unchanged by the MES model. Therefore, this study's conclusion—that COVID-
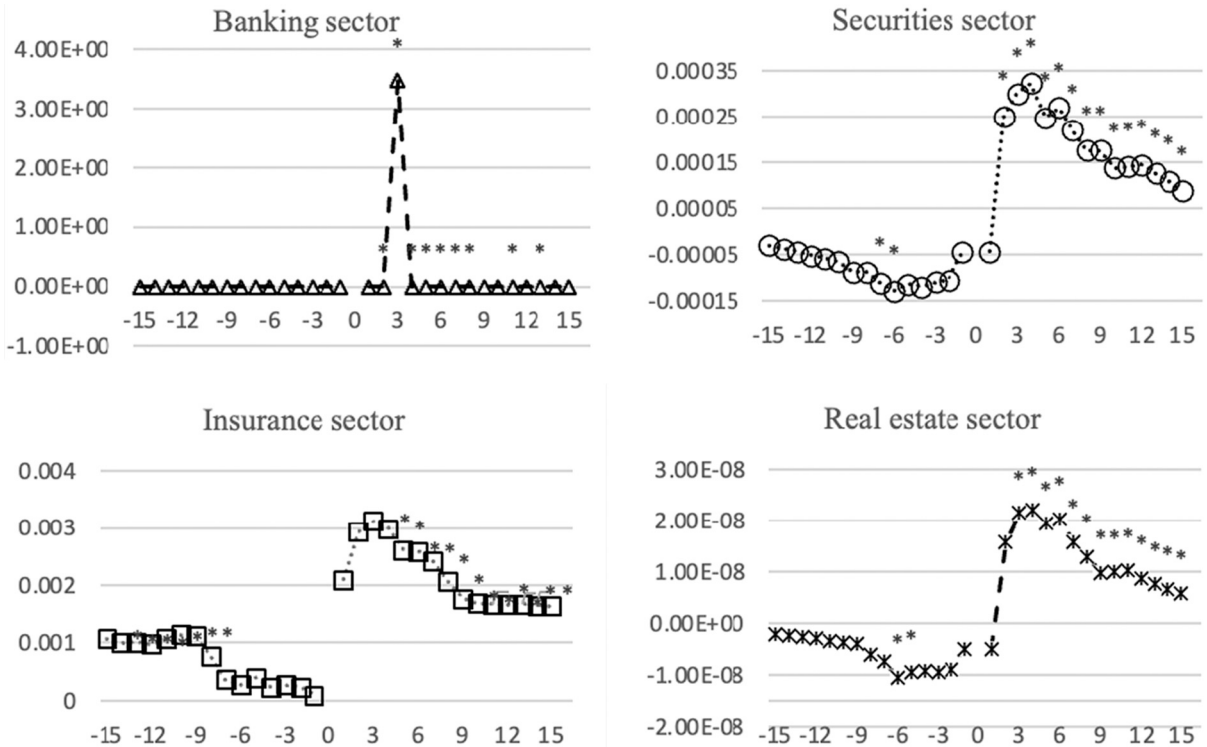
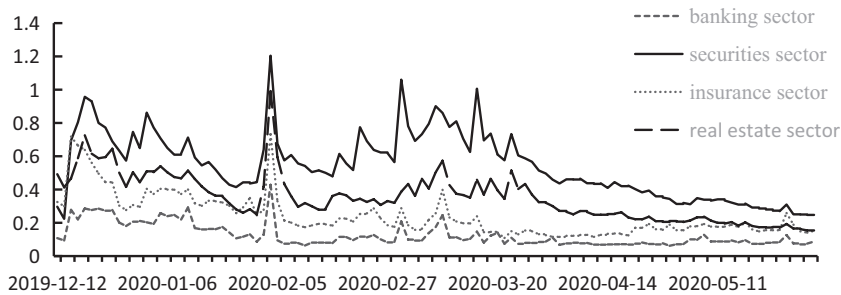**Fig. 8.** Level effect of the COVID-19 pandemic on EDF.

Fig. 9. Trends of systemic risk by the MES model in financial sectors.

19 significantly impacts the systemic risk of China's financial sectors and real estate—is robust.

8. Conclusions and policy implications

8.1. Conclusions

Based on an improved event study methodology, this study quantifies the impact of external shocks from the COVID-19 outbreak in late 2019 on systemic risk in the banking, securities, insurance, and real estate sectors and branch sectors of real estate. This method can simultaneously describe the level and trend effects of COVID-19's impact on systemic risk. It provides a relatively accurate quantitative method for studying similar external shocks' impact on systemic risks in the financial sector. Through relevant empirical analysis, this study draws the following conclusions:

First, COVID-19's impact on systemic financial risks in banking, insurance, securities, and real estate sectors and its branch sectors exhibit both level and trend effects. Furthermore, compared with the securities and real estate sectors, the banking and insurance sectors exhibit a stronger ability to withstand external shocks. Additionally, during COVID-19, the systemic financial risks in the securities and real estate sectors have increased more significantly, and the impact duration is expected to be longer.

Second, among branch sectors under real estate, the systemic risk of residential property and park comprehensive industry is more
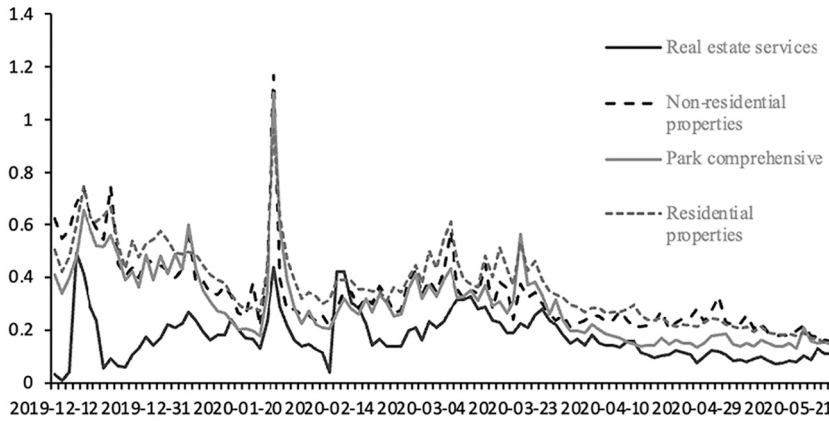
Fig. 10. Trends of systemic risk by the MES model in branch sectors of real estate.
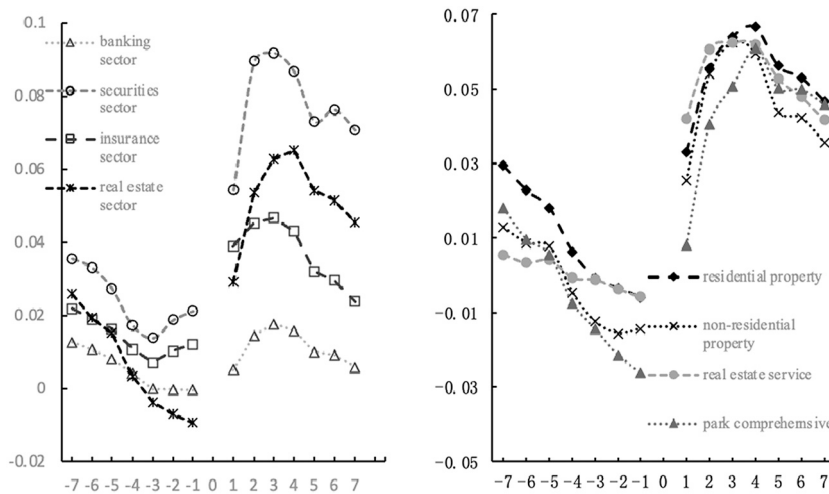

Fig. 11. Level effect of the COVID-19 pandemic on systemic risks by the MES model.

serious. Furthermore, these two sectors exhibit the highest financial attributes, which further confirms the rationality of considering real estate along with the financial sector.

Third, COVID-19's impact on the systemic financial risks of the banking, insurance, securities, real estate, and branch sectors was reflected quickly after the event. Specifically, a single event's impact reached its peak within 2–3 days, and an inflection point occurred within 3–4 days, indicating that the impact was slowly being digested. Successive events' impact precipitated an overall increase in systemic risk.

Fourth, from the perspective of transmission mechanism, the increase in systemic risk in the real estate industry and securities industry mainly came from market liquidity and financing liquidity channels. In contrast, the insurance industry's impact is mainly reflected by the higher probability of default. Moreover, the increase in the systemic risk of banks mainly comes from financing liquidity, but it is still the most stable and least volatile sector among all sectors.

8.2. Policy implication

To improve the ability to counter public safety incidents' impact, this empirical study can result in proposing a new governance strategy from four different perspectives, detailed as follows.

First, under COVID-19's impact, the systemic financial risks of the securities sector increased significantly, and the impact duration is expected to be longer. It is suggested that the securities sector should be rationally planned and guided to invest capital and appropriately increase its loss reserves to increase its stability and improve its ability to cope with external shocks.

Second, compared with traditional financial sectors, the real estate sector was less capable of withstanding COVID-19's impact. It is suggested to strictly supervise the crossover financial business and product launch, and reasonably regulate the comprehensive operation of the financial *sec*tor to reduce the excessive correlation between *sec*tors and prevent the increase of systemic financial risks

caused by the cross-infection and overlapping resonance of risks.

Third, the policy support for the real estate sector should be appropriately tilted toward the housing development service and comprehensive real estate enterprises in the park. The suggestion is reduce the credit risk contagion to banks and other financial sectors by asset securitization and broadening the sources of capital of the real estate industry.

Fourth, from the perspective of the transmission mechanism of the epidemic on systemic financial risks, the systemic risks of the securities and real estate sectors are mainly derived from liquidity, while the insurance sector is mainly affected by default probability. Therefore, in the face of public health emergencies, it is recommended to expand financing channels for the securities industry and real estate sectors or provide short-term policy loans to reduce the uncertainty caused by risks and cope with a liquidity crisis. For the insurance industry, the supervision should be strengthened and appropriate payment policy support should be provided to reduce insurance companies' default risk.

CRediT authorship contribution statement

Wenli Huang: Supervision, Conceptualization, Methodology, Funding acquisition, Writing – original draft. **Cheng Lan:** Data curation, Software, Writing – original draft. **Yueling Xu:** Investigation, Writing – review & editing, The transmission mechanism research. **Zhaonan Zhang:** Supervision, Conceptualization, Methodology, Investigation, Writing – review & editing. **Haijian Zeng:** Conceptualization, Methodology.

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