Research on risk transmission mechanism of Chinese A-share industry under COVID-19 based on VAR model

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Abstract. This article uses Python to implement the VAR model to construct the volatility spillover effect of industry sub-index merged by Shenwan's first-class classification. The systemic financial risk transmission relationship among different industries of Chinese A-share listed companies under the background of public health emergencies was observed, and the driving mechanism behind it was studied in depth. The empirical results show that the spillover impact of COVID-19 risk on industry volatility is significant in 2 days prediction period, but part of the risk impact can be absorbed by the market as the prediction period is extended to 5 days. The external market risk impact on non-financial service and financial industry has the most significant positive correlation with COVID-19 indicators, while the external impact of comprehensive industry on A-share market has the most significant positive correlation with COVID-19 indicators. On this basis, considering the difference in time between economic variables and COVID-19 variables and weekend effect, this paper innovatively constructed intermediate-term indicators and short-term indicators, this paper concluded that the impact of intermediate-term indicators on industry risk impact is greater than that of short-term indicators. To sum up, from the perspective of public health emergencies and industries, this paper puts forward relevant opinions on how to effectively prevent the impact of epidemic, which provides an effective reference for improving the systemic risk supervision mechanism of Chinese A-share market.

Keywords: Systemic risk transmission, Chinese Stock Market Volatility, Public Health Emergency, Sector Index, The VAR model， Python

1 Introduction

Since the outbreak of COVID-19 in 2020, Chinese macroeconomic uncertainties have increased significantly. With the rapid spread of COVID-19, Chinese epidemic prevention and control efforts have been intensified, and the real economy is facing a series of business difficulties, such as production shutdown, supply chain disruption and falling market demand. In the capital market, the stock volatility of Chinese A-share market has increased. As the bilateral risks faced by investors have been increased by

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COVID-19, investors have reduced their investment to reduce the risks, resulting in shrinking market trading volume and increasing systemic financial risks in the overall market. Under the background of economic turbulence caused by public health emergencies, how to effectively restrain the expansion of systemic financial risks in the market has become an important challenge for the government. In this paper, from the perspective of different industries, VAR model is used to construct the volatility portfolio of different industries to measure the impact of different industries on external market risks and their own impact on external market risks. On this basis, the study on the risk driving mechanism between different industries in the context of public health emergencies and insight into the transmission path of systemic risk in the Chinese market not only has important academic value, but also provides a brand-new policy reference for the government. This paper effectively quantifies the risk impact of COVID-19 on Chinese capital market by analyzing the transmission routes of systemic risks in the context of public health emergencies from an industry perspective, and accurately captures the risk sources (different indicators of COVID-19) and positions (different industries) most severely affected by COVID-19 in the market. This paper observes the degree of impact on different industries through the transmission path and analyze the impact on the whole macro economy. At the same time, the study results of this paper also provide an effective policy reference for the government to guarantee the development of the industry from the perspective of industrial policies, block the transmission path of systemic risks, and then effectively control systemic financial risks. At the same time, the study results also provide an effective policy reference for the government to guarantee the development of the industry from the perspective of industrial policies, block the transmission path of systemic risks, and then effectively control systemic financial risks. Finally, the intermediate-term indicators created in this paper have a significant impact on financial market risks, proving that there is a hysteresis effect in market risk transmission due to irrational factors of investors, and effectively utilizing the gap period generated by the hysteresis effect to prevent the spread of financial risks has become an effective solution.

Many scholars have conducted comprehensive and multi-angle studies on systemic financial risks by using VAR model. At present, the mainstream analysis method is to quantify systemic financial risks based on indicators such as Earnings linkage of financial assets [1], Volatility spillover [2] and Tail risk resonance [3]. However, most studies are based on the macroeconomic market. For example, VAR model is used to measure the macro-economy and monetary policy [4] and observe the interaction between monetary policy and systemic financial risks. This study explores the transmission mechanism of international systemic financial risks from the risk impact of the single market to the risk resonance of international financial markets [5]. Or take a country's stock market as a whole to explore the mutual risk impact mechanism between the development of COVID-19 and EPU (an indicator of economic uncertainty) and stock market volatility [6]. The above research is to explore the transmission mechanism between systemic financial risk and external variables in the financial market as a whole, but there is still a lack of research on the transmission mechanism of systemic risk in the financial market. Some scholars proposed to observe the transmission mechanism of systemic financial risks in the financial market from the perspective of industry. A large number of studies analyzed from the perspective of inter-industry entity operation and found that inter-industry trade linkage is an important channel for the internal transmission of systemic financial risks [7]. On this basis, it is found that the performance of upstream and downstream industry chains that are most related to trade linkage are most closely linked, so the spillover effect of financial risks is stronger [8, 9, 10]. Although the above literature has analyzed the transmission mechanism of systemic financial risks in the financial market from a micro perspective, it does not consider the risk transmission mechanism of different industries in the capital market. Therefore, this paper analyzes the risk linkage relationship in capital markets of different industries from the perspective of industry, explores the impact of COVID-19 risk on systemic financial risk and the transmission mechanism of systemic financial risk among different industries from the perspective of the major external risk impact of the latest public health emergency.

As for the impact of public health emergencies on stocks in the capital market, academic studies generally believe that the epidemic risk has a negative effect on the stock market [11, 12], and many scholars believe that the main reason is that the risk of COVID-19 increases the volatility shock in the stock market [13]. To confirm the robustness of this finding, existing studies have used the simplest ordinary least squares to analyze the impact of COVID-19 on stock market volatility [14] in addition to the GARCH model to explore the co-influence between stock market volatility due to COVID-19 [15]. However, given that stock market volatility is asymmetric, the use of GARCH model measurements may lead to erroneous measurements, and later studies using EGARCH model regressions found that COVID-19 has a significant positive effect on stock market volatility [16]. In conjunction with the research objectives of this paper, in order to study the interaction mechanism of systemic financial risk, the VAR model was finally used to calculate the risk shock impact of COVID-19 on the capital market by substituting different volatilities between industries as variables into the VAR model to calculate industry risk shock indicators.

Considering that the economic variable is trading day data, while the COVID-19 index is natural day data, the difference between the two calendars will lead to the weekend effect [17, 18], which may lead to endogeneity problems such as measurement error. The official Chinese COVID-19 data is released in the evening, while the Chinese A-share market trades between 9AM and 3PM. There is also intra-day variability, and this variability due to measurement error may have serious endogenous consequences, so this paper draws on existing methods to run regressions using t-1 natural day COVID-19 data [19]. In the context of public health emergencies, investors' irrational emotions will lead to the increase of stock market volatility [20, 21, 22], We can analyze the different importance that investors attach to indicators of COVID-19 at different times in a market dominated by irrational sentiment, therefore, different influences may exist for COVID-19 indicators at different times. This Paper innovatively constructed intermediate-term indicators and short-term indicator. A comparative analysis was also applied to observe the extent to which intermediate-term indicators and short-term indicator affect risk shocks in different sectors. To sum up, the second part will describe data sources and model construction, the third part will conduct empirical analysis, and the fourth part will carry out conclusions and policy suggestions.

2 Data sources and model construction

2.1 Data sources

This paper collects data through the following means: downloading 31 Shenwan's first-class sector indices (2021) from the Wind, the sector indices include 658 trading days of highest price, lowest price and market capitalization data. The time range of the sector index is from 2019/8/23 to 2022/5/16. From 2020/1/20 to 2022/5/16, new confirmed cases every day, new suspect case every day and new death case every day of COVID-19 were downloaded from Wind, the total of 848 data were collected. Downloaded 559 trading days of Chinese A-share market FAMA five-factor data from CSMAR Factor Database, including Riskpremium, HML, SMB, RMW, CMA, time range from 2020/1/21 to 2022/5/16.

Table 1. Combination of industries description analysis

National industries classification	Industries classification of this paper	Shenwan's first-class sector indices	Variable symbol
Primary Industry	Agriculture	Shenwan's Agriculture, Forestry, Animal Husbandry, Fishery	5
Secondary Industry	Light Industry	Shenwan's Pharmaceutical and Biological Industry, Shenwan's Household Appliances Industry, Shenwan's Electronics Industry, Shenwan's Textile and Clothing Industry, Shenwan's Computer industry, Shenwan's Light Industry Shenwan's Manufacturing Industry, Shenwan's Food and Beverage Industry	6
	Heavy Industry	Shenwan's Utility Industry, Shenwan's Defense Industry, Shenwan's Basic Chemical Industry, Shenwan's Non-ferrous Metal Industry, Shenwan's Machinery and Equipment Industry, Shenwan's Automobile Industry, Shenwan's Coal Industry, Shenwan's Power Equipment Industry, Shenwan's Petroleum and Petrochemical Industry, Shenwan's Iron and Steel Industry	3
	Construction Industry	Shenwan's Building Materials Industry,Shenwan's Building Decoration Industry	4
Tertiary Industry	Non-Financial Services Industry	Shenwan's Transportation Industry, Shenwan's Media Industry, Shenwan's Real Estate Industry, Shenwan's Social Services Industry, Shenwan's Beauty Care Industry, Shenwan's Communications Industry, Shenwan's Commercial Retailing Industry	2
	Financial Industry	Shenwan's Bank Industry, Shenwan's Non-bank Financial Industry	7
Other Industries	Comprehensive Industry	Shenwan's Comprehensive Industry,Shenwan's Environmental Protection Industry	1

As shown in table 1, In this paper, based on the existing Shenwan's first- classification industry, 31 Shenwan first- classification industries are reintegrated into first-level industries, second-level industries and third-level industries and other industries by referring to the standard of China's "National Economic Industry Classification". The secondary industry was subdivided into light industry, heavy industry and construction industry, and the tertiary industry was subdivided into non-financial service industry and financial industry. Finally, the industries covering the secondary and tertiary industries were integrated into comprehensive industries, and the seven secondary industries were classified as the seven regression research objects. In the process of industry consolidation, the paper adopts the method of weighting the market capitalization to integrate the daily highest price and lowest price of each industry index to obtain the daily highest price and lowest price of agriculture, light industry, heavy industry, construction industry, non-financial service industry, financial industry and comprehensive industry index.

2.2 Construction of FROM and TO indicators

Based on the research [22] and sector indices data of all industries, daily volatility V is calculated in this paper:

$$\boldsymbol{V_{it}} = \mathbf{0.361} * \left(\ln\left(\boldsymbol{P_{it}^{high}}\right) - \ln\left(\boldsymbol{P_{it}^{low}}\right)\right)\text{\textasciicircum}\mathbf{2} \tag{1}$$

$$\mathbf{X^H_{i\to j}} = \frac{\boldsymbol{\theta^H_{i\to j}}}{\sum_{j=1}^{n}\boldsymbol{\theta^H_{i\to j}}} \tag{2}$$

In (1), P_{it}^{high} represents the daily highest price of the combined sector index i on the day t, P_{it}^{low} represents the daily lowest price of the combined sector index i on the day t. Based on the calculated daily volatility indicators (for a total of seven industries) brought into the VAR model, the risk spillover indicators were constructed based on the Cholesky decomposition method (Impulse Response Function) by referring to and extending the research methods of [23], [24] and [25].

In (2) $\mathrm{X}^{\mathrm{H}}_{\mathrm{i}\to\mathrm{j}}$ denotes the error variance contribution of volatility in forecast period H due to the transmission of risk volatility in market i to the market j. $\theta^{\mathrm{H}}_{\mathrm{i}\to\mathrm{j}}$ is the error variance of market j in the prediction period H caused by the impact of market i, $\sum_{j=1}^{n}\theta^{\mathrm{H}}_{\mathrm{i}\to\mathrm{j}}$ represents the population prediction variance of H in the prediction period. The economic significance of $\mathrm{X}^{\mathrm{H}}_{\mathrm{i}\to\mathrm{j}}$ is that all the daily volatility indicators of the seven sector indexes in the VAR model are taken as endogenous variables. When the variance of market i increases due to the change of volatility, it will surely be transmitted to the volatility of the remaining six industries and produce a chain reaction, which will increase the volatility variance of the remaining six industries and then affect other industries. Thus, the volatility variance of all variables in the VAR model increases. The change in market j volatility directly caused by the change in market i volatility is used as the numerator and the change in volatility of the whole industry caused by the change in market i volatility is used as the denominator, and the contribution degree of the change in market j volatility directly caused by the change in market i volatility to the change in population prediction variance is used to express the risk impact of market i on market j.

Finally, as described in (3), the risk spillover indicators of different industries to industry i (except the industry i) are summed with reference to [26] to obtain industry i's FROM indicator, which indicates that industry i is impacted by the volatility of the A-share market; and the risk spillover indicators of industry i to different industries (except industry i) are summed to obtain industry i's TO indicator, which represents the volatility impact of industry i on the A-share market.

$$\mathbf{X}_{\mathrm{if}}^{\mathrm{H}} = \sum_{j=1}^{n} \mathbf{X}_{\mathrm{j\to i}}^{\mathrm{H}}, \mathbf{X}_{\mathrm{it}}^{\mathrm{H}} = \sum_{j=1}^{n} \mathbf{X}_{\mathrm{i\to j}}^{\mathrm{H}}, \boldsymbol{i} \neq \boldsymbol{j} \tag{3}$$

2.3 New indicators of COVID-19 in China

$$\mathbf{ANew\_Diag_t} = \frac{1}{5} * \left(\mathbf{New_{Diag_{t-1}}} + \mathbf{New_{Diag_{t-2}}} + \mathbf{New_{Diag_{t-3}}} + \mathbf{New_{Diag_{t-4}}} + \mathbf{New_{Diag_{t-5}}}\right) \tag{4}$$

Considering that the COVID-19 indicators may have different influences on timeliness and weekend effects, the average value of COVID-19 indicators (new confirmed cases, new suspect case and new death case of COVID-19) of the past five natural days was used as the intermediate-term COVID-19 indicators on t days: $ANew\_Diag_t$, $ANew\_Diag_t$ is a weekly variable for COVID-19 indicators.

2.4 Stability test of time series

In order to build the VAR model of sector index volatility, we conducted DF test on the sample spacing of sector index volatility from 2019/8/26 to 2022/5/16, and the test results are shown in Table 2[1]:

Table 2. Unit Root Test of volatility spillover indicator (DF test)

Varible	T-statistic	1%	5%	10%	Obs
V_1	-12.909	-3.960	-3.410	-3.120	657
V_2	-14.126	-3.960	-3.410	-3.120	657
V_3	-16.626	-3.960	-3.410	-3.120	657
V_4	-15.789	-3.960	-3.410	-3.120	657
V_5	-15.789	-3.960	-3.410	-3.120	657
V_6	-16.371	-3.960	-3.410	-3.120	657
V_7	-16.547	-3.960	-3.410	-3.120	657

By observing the data in table 2, it can be concluded that the DF test results of the volatility data of V1 -- V7 industries are less than -3.960, that is, significant at the level

[1]In order to ensure the robustness of the results, this paper also took the 100-day rolling window as the sample interval to conduct the DF test, and the test results showed that the null hypothesis was significantly rejected, which was not shown in the text due to space limitation.

of 1%. Therefore, the null hypothesis that this time series has unit root is rejected, that is, the volatility indicators are all Stationary sequence.

This paper have tested the stationarity test of VAR model, as shown in Figure 1:

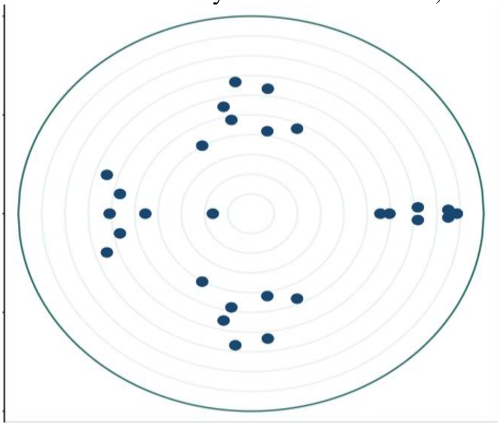

Fig. 1. Stationarity test of VAR

It can be seen from the test results that all the characteristic value are within the unit circle, so it can be concluded that the VAR model is stable in statistical significance.

2.5 Model construction and Regression analysis

In this paper, FAMA five-factor [27] was selected as the control variable, and 559 trading days from 2020/1/20 to 2022/5/16 were selected as the sample spacing to construct the following model:

$$\boldsymbol{X_{Ht} = ANew\_Diag_t + New_{Diag_{t-1}} + Control\_Variable_t + u_t} \tag{5}$$

In (5), the dependent variable $\boldsymbol{X_{Ht}}$ contains $\mathrm{X}_{\mathrm{if}}^{\mathrm{H}}and\mathrm{X}_{\mathrm{it}}^{\mathrm{H}}$, which respectively represent the FROM indicator and TO indicator of t trading day of industry i, and the estimation result of variance decomposition based on the 100-day rolling window (variance decomposition prediction period is H). In this paper, the volatility data from t-99 to t days are used as the sample spacing and substituted into the VAR model to calculate the FROM indicator and TO indicator of t trading day. $\boldsymbol{ANew\_Diag_t}$ represents the weekly variables of COVID-19 indicators on the t trading day, including average new confirmed cases (ANew_Case), average new suspect case (ANew_Suspect) and average new death case (ANew_Death). $\boldsymbol{New_{Diag_{t-1}}}$denotes new confirmed cases every day (New-Case), new suspect case every day (New-Suspect) and new death case every day (New-Death) of COVID-19 for t-1 natural day. $\boldsymbol{Control_Variable_t}$denotes the FAMA five-factor data at data of that time-of-day t.

3 Analysis of empirical results

3.1 Analysis of FROM indicators results based on 5days forecast period

Table 3. Estimation results of FROM indicators based on the 5days forecast period

VARIABLES	(1) X^5_{1f}	(2) X^5_{2f}	(3) X^5_{3f}	(4) X^5_{4f}	(5) X^5_{5f}	(6) X^5_{6f}	(7) X^5_{7f}
New_Case	1.57e-06	1.26e-05	-4.02e-06	1.78e-06	1.02e-05	4.29e-06	7.25e-06
	(3.89e-06)	(1.66e-05)	(3.87e-06)	(5.74e-06)	(8.95e-06)	(7.56e-06)	(1.93e-05)
New_Suspect	-1.06e-05	0.000306**	6.64e-05*	0.000120**	5.92e-05	8.13e-05	0.000272**
	(4.06e-05)	(0.000130)	(3.96e-05)	(5.42e-05)	(4.83e-05)	(5.13e-05)	(0.000115)
New_Death	-0.00101*	-0.00326**	0.00117	0.000150	-0.00230***	-0.00146**	-0.00162
	(0.000577)	(0.00133)	(0.000817)	(0.000541)	(0.000695)	(0.000593)	(0.00143)
ANew_Case	-1.54e-05***	8.10e-05***	1.28e-05**	2.15e-05***	2.95e-05**	4.40e-05***	0.000134***
	(5.60e-06)	(2.28e-05)	(6.25e-06)	(7.68e-06)	(1.29e-05)	(1.13e-05)	(2.55e-05)
ANew_Suspect	1.73e-05	-0.000360**	-5.94e-05	-0.000128**	-9.36e-05*	-0.000116**	-0.000339***
	(3.91e-05)	(0.000144)	(4.35e-05)	(5.86e-05)	(5.04e-05)	(5.46e-05)	(0.000121)
ANew_Death	0.00233***	0.00615***	0.000427	0.00148***	0.00296***	0.00231***	0.00200
	(0.000609)	(0.00112)	(0.000872)	(0.000524)	(0.000636)	(0.000543)	(0.00130)
Observations	558	558	558	558	558	558	558
Adjusted R-squared	0.060	0.175	0.050	0.043	0.036	0.059	0.143

Note: (1) the estimation results of FAMA five factors are omitted. ***, ** and * respectively indicate that the regression results are significant at the level of 1%, 5% and 10%. (2) In parentheses are Robust Standard Error, and the variance decomposition forecast period is 5 days.

Table 3 is the result of FROM indicators obtained by regression based on (5). By analyzing Table 3, it can be found that X^5_{2f} (non-financial service industry) and X^5_{7f} (financial industry) FROM indicator are most significantly and positively correlated with the impact of COVID-19 indicators, while X^5_{3f} (heavy industry) FROM indicators is least significantly affected by COVID-19 indicators. The intermediate-term indicators were significantly higher than the short-term indicators, and the ANew_Suspect were significantly negatively correlated with the FROM indicators. We found that most of X^5_{2f} indicator were significant at the 1% level, indicating that COVID-19 had the most obvious impact on external risks in non-financial services industries and financial industries. This is consistent with the literature on the economic phenomenon that aviation industry [28], hotel industry [29], tourism industry [30] and catering industry [31] are faced with performance decline and stock price decline due to the decline of supply and demand under COVID-19. The above specific industries are all in the non-financial service industry in this paper. Therefore, we conclude that due to the outbreak of public health emergency, the service industry generally faces the decline of supply and demand, which leads to the decline of performance and stock price. In Table 3, X^5_{7f} indicator is significantly positively correlated with the COVID-19 indicators, which verifies the existing research conclusions that the financial industry has witnessed a dramatic increase in systemic risk and market uncertainty under the background of COVID-19 [32]. By analyzing the index coefficients, it can be seen that when all COVID-19 indicators increase by 10,000 people, the sum of the coefficients of non-financial services is 292, that is, when all COVID-19 indicators increase by 10,000 people, the FROM indicator of non-financial service industry increases by 292 units, the sum of the financial industry coefficients is 45, and the financial industry FROM indicator increases by 45 units for 10,000 people increase in all COVID-19 indicators. The impact of COVID-19 on the non-financial service industry and the financial industry shows that the increased risk of COVID-19 will lead to the reduction of the anti-risk ability of the two industries, and increase the uncertainty and volatility. On the contrary, the FROM indicator of X_{3f}^{5} (heavy industry) is the least affected by the COVID-19, indicators. New_Suspect indicator and ANew_Case indicator are significant at the level of 10% and 5% respectively, which means that the external risk impact intensity of heavy industry is the weakest. The economic explanation given in this paper is that heavy industry and its demand side are least affected by other industries, and heavy industry and construction industry have stable resistance to external risk shocks under the background of public health emergencies. By comparing the intermediate-term indicators with the short-term indicators, we found that the significance of the intermediate-term indicators was generally higher than short-term indicators, and most of the ANew_Case indicator, ANew_Suspect indicator and ANew_Death indicator were significant at the 1% level. However, New_Case indicator, New_Suspect indicator and New_Death indicator were mostly significant at the 5% level, and the number of X_{1f}^{5} to X_{7f}^{5} was significantly affected by the average new COVID-19 indicators, which was more than the daily new COVID-19 indicators. The reason is that investors' irrational expectations lead them to pay more attention to the changes in the number of new cases in intermediate-term rather than the changes in the number of new cases in short-term. They are skeptical of the information with strong timeliness and do not believe that it will last, which leads to different influences of information. In addition, we observe that the average new suspected cases (Anew-Suspect) have a significant negative correlation with X_{2f}^{5}, X_{4f}^{5}, X_{5f}^{5}, X_{6f}^{5}, X_{7f}^{5}. We do not rule out the possibility that the index could reduce the industry's exposure to external market risks.

3.2 Analysis of TO indicators results based on 5days forecast period

Table 4. TO index estimation results based on 5 days forecast period

VARIABLES	(1) X_{1t}^{5}	(2) X_{2t}^{5}	(3) X_{3t}^{5}	(4) X_{4t}^{5}	(5) X_{5t}^{5}	(6) X_{6t}^{5}	(7) X_{7t}^{5}
New -Case	2.20e-05	-7.35e-06	2.13e-05	1.49e-05*	-9.55e-06	-1.10e-06	-6.46e-06
	(8.44e-05)	(1.89e-05)	(1.39e-05)	(8.12e-06)	(1.12e-05)	(1.15e-05)	(4.68e-06)
New _Suspect	0.00134**	-0.000384**	-8.43e-05	3.42e-05	0.000139*	-0.000134	-1.93e-05
	(0.000609)	(0.000186)	(8.98e-05)	(8.19e-05)	(8.04e-05)	(8.54e-05)	(5.97e-05)
New	-0.00636	0.00257	-0.00544*	-0.00496***	0.00312**	0.00208**	0.000667

_Death	(0.00685)	(0.00214)	(0.00327)	(0.00125)	(0.00124)	(0.000952)	(0.000614)
Anew _Case	0.000600***	-7.39e-05***	-0.00015***	-4.36e-05***	4.32e-05***	-7.94e-05***	1.33e-05
	(0.000115)	(2.84e-05)	(2.17e-05)	(1.24e-05)	(1.41e-05)	(1.72e-05)	(8.47e-06)
Anew _Suspect	-0.00167**	0.000479**	0.000154*	-2.07e-05	-0.000198**	0.000156*	2.27e-05
	(0.000664)	(0.000204)	(8.96e-05)	(8.50e-05)	(9.17e-05)	(9.13e-05)	(5.81e-05)
Anew _Death	0.0138**	-0.00263	0.00739**	0.00656***	-0.00280***	-0.00299***	-0.00163***
	(0.00620)	(0.00185)	(0.00364)	(0.00129)	(0.00103)	(0.000806)	(0.000569)
Observa-tions	558	558	558	558	558	558	558
Adjusted R-squared	0.152	0.071	0.208	0.045	0.061	0.066	0.004

Note: (1) the estimation results of FAMA five factors are omitted. ***, ** and * respectively indicate that the regression results are significant at the level of 1%, 5% and 10%. (2) In parentheses are Robust Standard Error, and the variance decomposition forecast period is 5 days.

Table 4 shows the TO indicators results obtained by regression based on (5). The current research on the impact of COVID-19 on the industry is only on the analysis of industrial entities and financial indicators, and the capital market analysis of the industry is still on the receiving end of market risks. This paper provides a new TO indicators analysis to analyze the impact of different industries on the capital market risk from the supply side of market systemic risk, and clarify the transmission mechanism of market risk. By analyzing the results in Table 4, the TO index of X_{1t}^{5} (comprehensive industry) and X_{3t}^{5} (heavy industry) are most significantly and positively correlated with the impact of COVID-19 indicators, indicating that increasing the risk of COVID-19, the impact of comprehensive industry and heavy industry on the system is strengthened, and each COVID-19 indicators increases by 10,000 people, the total shock to the system of the comprehensive industry increased by an average of 771 units, and the total shock to the system of heavy industry increased by an average of 189 units. It strengthens the risk impact intensity of the market, which is in sharp contrast to the analysis of the above FROM indicators, and verifies that heavy industry and comprehensive industry are the main risk exposure of systemic market risk impact. By observing COVID-19 indicators coefficients of industries in the regression results, we found that unlike the FROM indicators, which proved that the COVID-19 indicators acted in different directions on the TO indicators. The reason is that most industries are more strongly impacted by external market risks and their impact on the market is relatively reduced. We can find that the significant influence of intermediate-term indicators is greater than the short-term indicators, which verifies the conclusions of preamble.

3.3 Robustness test

In order to ensure the robustness of the empirical results, this paper conducts two robustness tests. Firstly, the non-financial service industry was selected, with FAMA five factors and daily new confirmed cases as the starting variables, and the FROM indicators calculated in the 5 days forecast period as the dependent variable. Stepwise regression was used to substitute COVID-19 indicators into the regression to observe the regression changes of the FROM indicators. The regression results are shown in Table 5.

Table 5. Estimation results of FROM indicators based on 5 days forecast period

VARIABLES	(1) X_{2f}^5	(2) X_{2f}^5	(3) X_{2f}^5	(4) X_{2f}^5	(5) X_{2f}^5	(6) X_{2f}^5
New_Case	5.72e-05***	5.53e-05**	4.07e-05*	-1.29e-05	-1.00e-05	1.26e-05
	(1.95e-05)	(2.28e-05)	(2.35e-05)	(2.00e-05)	(1.63e-05)	(1.66e-05)
New_Suspect		5.41e-06	-3.58e-05**	-4.64e-05***	0.000227*	0.000306**
		(1.17e-05)	(1.56e-05)	(1.20e-05)	(0.000117)	(0.000130)
New_Death			0.00232***	0.00161***	0.00271***	-0.00326**
			(0.000425)	(0.000454)	(0.000754)	(0.00133)
ANew_Case				9.83e-05***	9.91e-05***	8.10e-05***
				(2.66e-05)	(2.15e-05)	(2.28e-05)
ANew_Sus-pect					-0.000287**	-0.000360**
					(0.000128)	(0.000144)
ANew_Death						0.00615***
						(0.00112)
Adjusted R-squared	0.089	0.088	0.113	0.144	0.153	0.175

Note :(1) the estimation results of FAMA five factors are omitted. ***, ** and * respectively indicate that the regression results are significant at the level of 1%, 5% and 10%. (2) In parentheses are Robust Standard Error, and the variance decomposition forecast period is 5 days.

As shown in table 5, we found that the Observations Adjusted R-squared coefficient increased with the increase of COVID-19 indicators, indicating that the new COVID-19 indicators increased the explanatory power of the model and the fitting degree was higher. By observing the regression results of new confirmed cases every day and new death case every day, it can be seen that the significant influence of the original daily new COVID-19 indicators continues to weaken and disappear as the average new COVID-19 indicators is gradually substituted into the regression. Which verified the intermediate-term indicators was much greater than the short-term indicators. Similarly, by observing the regression results of the average new suspected cases (ANew_Suspect), it can be seen that it is always significantly negatively correlated. This indicates that the conclusion that the indicator has the potential to weaken the industry's exposure to external risk shocks is robust.

Table 6. Estimation results of FROM indicators based on the 2days forecast period

VARIA BLES	(1) X_{1f}^2	(2) X_{2f}^2	(3) X_{3f}^2	(4) X_{4f}^2	(5) X_{5f}^2	(6) X_{6f}^2	(7) X_{7f}^2
New _Case	3.97e-06	1.43e-05	6.43e-07	2.59e-06	6.03e-06	5.63e-06	5.87e-06
	(2.69e-06)	(2.15e-05)	(7.79e-06)	(8.07e-06)	(1.12e-05)	(7.69e-06)	(2.13e-05)
New _Suspect	-1.18e-06	0.000381**	0.000136**	0.000156**	0.000113*	0.000101**	0.000314**
	(3.02e-05)	(0.000154)	(6.70e-05)	(6.26e-05)	(5.86e-05)	(5.14e-05)	(0.000123)
New _Death	-0.00147***	-0.00362**	-0.00105	-7.22e-05	-0.00155*	-0.00155**	-0.00131
	(0.000532)	(0.00167)	(0.000710)	(0.000613)	(0.000934)	(0.000655)	(0.00162)
Anew _Case	-2.52e-05***	0.000110***	2.54e-05**	6.16e-05***	6.06e-05***	5.34e-05***	0.000169***
	(4.06e-06)	(2.91e-05)	(1.15e-05)	(1.13e-05)	(1.54e-05)	(1.18e-05)	(2.87e-05)

Anew _Suspect	1.40e-05	-0.000442***	-0.000126*	-0.000185***	-0.000153**	-0.000148***	-0.000393***
	(2.96e-05)	(0.000169)	(7.49e-05)	(6.63e-05)	(6.29e-05)	(5.45e-05)	(0.000129)
Anew _Death	0.00198***	0.00687***	0.00392***	0.00112**	0.00139*	0.00192***	0.00139
	(0.000574)	(0.00142)	(0.000658)	(0.000564)	(0.0008140	(0.000613)	(0.00142)
Adjusted R-squared	0.041	0.174	0.079	0.053	0.033	0.036	0.255

Note :(1) the estimation results of FAMA five factors are omitted. ***, ** and * respectively indicate that the regression results are significant at the level of 1%, 5% and 10%. (2) In parentheses are Robust Standard Error, and the variance decomposition forecast period is 2 days.

Second, by changing the forecast period to 2 days, as shown in table 6, the significance of the financial industry and non-financial service industry FROM indicators affected by the COVID-19 indicators does not change much, indicating that the above findings of this paper are robust. With the shortening of the forecast period, the significance of $\mathbf{X_{3f}^2}$ (heavy industry) is effectively improved, indicating that the risk exposure of heavy industry to COVID-19 risk expands with the shortening of the forecast period and cannot be compensated in the short term. However, as the forecast period is extended its risk is gradually absorbed by the market, and the industry's exposure continues to shrink and returns to its original stability level. Comparing the regression results in Table 3, we find that the significant coefficient of COVID-19 indicators of all industries increases significantly, indicating that the market's risk exposure to COVID-19 risk expands as the forecast period is shortened, but that some of COVID-19 risk shock can be gradually absorbed by the market over time. Similarly, shortening the forecast period to 2 days does not change the conclusion that the intermediate-term indicators have a significantly greater impact on the sector index risk shocks than the short-term indicators.

Table 7. TO indicators estimation results based on the 2days forecast period

VARIABLES	(1) X_{1t}^2	(2) X_{2t}^2	(3) X_{3t}^2	(4) X_{4t}^2	(5) X_{5t}^2	(6) X_{6t}^2	(7) X_{7t}^2
New_Case	3.02e-05	-7.68e-06	8.90e-06	1.85e-05**	-3.57e-06	1.46e-07	-7.47e-06*
	(0.000105)	(1.81e-05)	(1.12e05)	(8.41e-06)	(3.68e-06)	(5.90e-06)	(3.81e-06)
New_Suspect	0.00171**	-0.000337**	-9.51e-05	6.40e-05	1.25e-05	-8.70e-05**	-6.65e-05**
	(0.000695)	(0.000159)	(6.53e-05)	(0.000113)	(2.72e-05)	(4.40e-05)	(3.31e-05)
New_Death	-0.00821	0.00201	-0.00101	-0.00522***	0.000713**	0.000941*	0.000151
	(0.00810)	(0.00149)	(0.00158)	(0.00162)	(0.000331)	(0.000494)	(0.000407)
ANew_Case	0.000755***	-6.71e-05**	-0.000108***	-9.82e-05***	-1.29e-06	-4.36e-05***	1.76e-05***
	(0.000144)	(2.79e-05)	(1.72e-05)	(1.29e-05)	(6.45e-06)	(9.09e-06)	(4.83e-06)
ANew_Suspect	-0.00211***	0.000392**	0.000128*	-1.57e-05	-2.47e-06	0.000113**	6.61e-05*
	(0.000746)	(0.000178)	(6.70e-05)	(0.000118)	(2.88e-05)	(4.72e-05)	(3.76e-05)
ANew_Death	0.0156**	-0.00379***	0.00100	0.00853***	-0.00125***	-0.00140***	-0.000105
	(0.00685)	(0.00125)	(0.00155)	(0.00170)	(0.000299)	(0.000446)	(0.000319)
Adjusted R-squared	0.164	0.023	0.113	0.260	0.022	0.054	0.046

Note:(1) the estimation results of FAMA five factors are omitted. ***, ** and * respectively indicate that the regression results are significant at the level of 1%, 5% and 10%. (2) In parentheses are Robust Standard Error, and the variance decomposition forecast period is 2 days.

This paper also conducts OLS in 2 days forecast period for the TO indicators of various industry indexes, as shown in table 7. The significance of heavy industry affected by COVID-19 indicators decreased, while the significance of construction industry increased significantly. This paper holds that with the decline of the forecast period, the heavy industry's exposure to external risk impact increases, and its own impact to external risk intensity decreases. The construction industry's exposure to market shocks exhibits short-term characteristics, with the forecast period is extended, the COVID-19 risk being absorbed within the industry, and the increased exposure to external risk shocks and is located in the transmitted part of the market's systemic risk transmission chain. However, the regression coefficient of the X_{1t}^2 (Comprehensive industry) indicator gets significantly higher with the shortening of the forecast period and the risk shock capacity to the market keeps increasing, proving that the Comprehensive industry has been exposed to the risk of COVID-19 and is the main source of risk to the Chinese A-share market. The influence of intermediate-term indicators is still significantly greater than the short-term indicators. It verifies the conclusion that in the context of the outbreak of COVID-19, the negative sentiment of investors leads to the intensification of irrational factors in the stock market, and people pay more attention to the intermediate-term indicators.

3.4 Granger Causality Test

To ensure the accuracy of the VAR model estimation, this paper needs to find the correct order of variable substitution to calculate the variance decomposition of the impulse response function in order to obtain the accurate FROM indicators and TO indicators. Granger causality tests can examine the transmission relationships inherent in economic variables and inform the choice of the correct order of variable substitution for this paper. In addition, this paper performs Granger causality tests on the volatility variables for each industry to see if there is an endogeneity problem, and the regression results are shown in table 8.

Table 8. Granger causality test

Equation	Excluded	chi2	df	Prob>Chi2
V1	V2	2.086	4	0.720
V1	V3	4.483	4	0.345
V1	V4	4.335	4	0.363
V1	V5	12.819	4	0.012
V1	V6	2.633	4	0.621
V1	V7	3.614	4	0.461
V1	ALL	28.190	24	0.252
V2	V1	5.727	4	0.220
V2	V3	2.678	4	0.613
V2	V4	7.894	4	0.096

V2	V5	8.919	4	0.063
V2	V6	4.271	4	0.371
V2	V7	1.312	4	0.859
V2	ALL	25.786	24	0.364
V3	V1	19.204	4	0.001
V3	V2	17.090	4	0.002
V3	V4	5.892	4	0.207
V3	V5	3.786	4	0.436
V3	V6	7.801	4	0.099
V3	V7	0.669	4	0.955
V3	ALL	59.231	24	0.000
V4	V1	22.615	4	0.000
V4	V2	4.295	4	0.368
V4	V3	8.395	4	0.078
V4	V5	10.506	4	0.033
V4	V6	8.667	4	0.070
V4	V7	1.272	4	0.866
V4	ALL	60.335	24	0.000
V5	V1	10.784	4	0.029
V5	V2	3.740	4	0.442
V5	V3	5.895	4	0.207
V5	V4	15.007	4	0.005
V5	V6	3.343	4	0.502
V5	V7	1.774	4	0.777
V5	ALL	38.810	24	0.029
V6	V1	7.916	4	0.095
V6	V2	17.547	4	0.002
V6	V3	3.372	4	0.498
V6	V4	5.310	4	0.257
V6	V5	9.252	4	0.055
V6	V7	1.756	4	0.781
V6	ALL	59.346	24	0.000
V7	V1	3.081	4	0.544
V7	V2	24.980	4	0.000
V7	V3	3.037	4	0.552
V7	V4	5.594	4	0.232
V7	V5	2.331	4	0.675
V7	V6	2.107	4	0.716
V7	ALL	42.444	24	0.012

This paper selects a sample spacing of 658 trading days from 2019/8/23 to 2022/5/16 for Granger causality testing[2], it was found that V1 and V5, V4 and V5 were Granger-Causes for each other at 5% confidence level. V2 (non-financial services industry) is the Granger-Causes for V7 (financial industry), while V1 (Comprehensive industry) and V2 (non-financial services industry) are Granger-Causes for several industries. The regression results of the Granger causality test demonstrate that the Comprehensive

[2]To ensure the robustness of the results, Granger causality tests were conducted for each 100-day rolling regression window in this paper, and the significance of the results was found to be unchanged and not addressed in the main text due to space constraints.

industry and non-financial services are the main sources of risk for systemic risk transmission, while the financial industry is at the tail of the systemic risk transmission chain. This finding not only validates the conclusion that the non-financial services industry is the most exposed to market risk shocks in the event of COVID-19 outbreak, but also finds that the impact on the non-financial services industry is transmitted to other related industries. Leaving the rest of the industry exposed to COVID-19 risks, ultimately creating a systemic market risk affecting the financial industry. The reasons are as follows: the government's need to reduce cross-regional human activity for the purpose of epidemic control has reduced the demand for travel and tourism, so COVID-19 has first hit the Comprehensive industry and the non-financial services industry with risk. As the financial industry is the upper tier of the real economy, it is in a tail position to be affected by fluctuations in other industry. In summary, the final order of the VAR model variables used in this paper is V1-V2-V3-V4-V5-V6-V7. For the robustness of the conclusions, this paper also selected other variable orders for VAR model construction and analysed the Granger causality test results, and finally found the best results for this variable order.

4 Conclusions and policy recommendations

To sum up, this paper believes that the impact of COVID-19 risk on industry indicators is very significant in 2 days forecast period, but with the extension of the forecast period to 5 days, part of the risk impact can be absorbed by the market, which is manifested by the smaller regression coefficient of the FROM indicators. The most significant positive correlation between external risks to the financial industry and non-financial service industry shocks from COVID-19 suggests that the spread of COVID-19 has increased uncertainty in the service industry and amplified the market's industrial shocks to the service industry. The external risk shock to the heavy industry is significantly positively correlated with COVID-19 in the short term. COVID-19 strengthens the market risk shock to the heavy industry, but as the forecast period is extended, the market risk shock to the heavy industry is gradually absorbed within the industry and the performance of the external risk shock to the heavy industry from COVID-19 turns Not Significant, while conversely its shock to the market risk becomes significantly positive. Most COVID-19 indicators have a positive correlation with the external risk impact on the industry, that is, COVID-19 strengthen the market's risk impact on the industry, but the average new suspect cases reduce the market's external risk impact on the industry, and the result is robustness. The risk impact of the comprehensive industry on the market is significantly positive correlated with the impact of COVID-19, which is the main risk source of the market exposed to COVID-19 risk. In the short term, the impact of the construction industry on the market risk is significantly positively correlated with COVID-19, which expands the systemic financial risk. However, with the extension of the forecast period, the risk impact of the construction industry on the market is absorbed by the industry itself, and the risk exposure of the COVID-19 is constantly expanded. The intermediate-term indicators constructed in this paper generally have a more significant impact on both external risk shocks to the industry and their own response to external risk shocks than the short-term indicators, demonstrating that investors' irrational factors are reinforced in the public health emergencies and that investors are more concerned about trends in COVID-19 risk over the intermediate-term.

This paper presents a detailed study of the transmission mechanism of systemic financial risk in the context of public health emergencies from an industry perspective, and based on the results, the paper draws the following three insights.

First, when maintaining the stability of financial markets after the outbreak of public health emergency, the government should prioritize the order of protection of various industries, and prioritize the industries most affected by COVID-19 risk. The financial industry and non-financial services industry are the most relevant to the performance of the macroeconomic development. The financial industry and non-financial services industry were most significantly impacted by market risks in the context of the macroeconomic downturn caused by the epidemic control, In the public health emergency, the government should focus on ensuring the risk-resilience of financial industry and non-financial services industry, thereby maintaining capital market stability and avoiding a " Herd Behavior ".

Secondly, since the outbreak of COVID-19, uncertainty in the financial markets has increased dramatically and systemic risk has increased significantly. In order to prevent the market from further harming the real economy in financial crisis, the government should implement relevant policy measures to effectively mitigate systemic financial risk in the market. This paper analyses the industry perspective, selecting the main sources of risk in the market for risk aversion and reducing the intensity of market risk shocks from the comprehensive industry, while also taking into account the intensity of market risk shocks from the construction industry in the short-term and from the heavy industry in the intermediate-term.

Third, in the context of the outbreak of COVID-19, the negative sentiment of investors in the market has increased, and the impact of irrational factors on the market has increased significantly. Investors are more concerned about the intermediate-term of COVID-19. Therefore, the government should strengthen the epidemic control to shorten the duration of COVID-19 and boost investors' confidence in capital market investment, thereby further maintaining financial market stability.

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