Comparative Research on the Relationship between Investor Sentiment and Stock Price during COVID-19 Pandemic and Russian-Ukrainian War

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Abstract. The current world is significantly influenced by the Russia-Ukraine war and the Covid-19 epidemic. This paper explores the relationship between investor sentiment and stock price during the Russian-Ukrainian war and the COVID-19 pandemic, which is currently a research hotspot in the academic field. First, we choose the data of Shanghai and Shenzhen 300 index and use the principal component analysis (PCA) methodology to determine the investor sentiment index; Second, this paper uses the commonly time series model, i.e., VAR model to conduct the empirical research to make a comprehensively investigation regarding the lead-lag relationship between investor sentiment and related stock returns. The research results show that the stock price has a significant positive effect on investor sentiment in these two periods. The rise of stock price will make investor sentiment rise in several time period lags. However, investor sentiment's impact on stock price is insignificant, which is contrary with the previous case. Compared with the Russian Ukrainian war period, the estimation of the epidemic period has a larger impact on investor sentiment, and the long-term impact is more significant. The results in this paper may benefit certain investors in the financial management.

Keywords: Investor sentiment; VAR model; COVID-19; Russian-Ukrainian war

1. Introduction

In December 2019, the global outbreak of COVID-19 began, and so far, the COVID-19 has repeatedly occurred without effective containment. Many cities implemented static management during this period, not only industries were negatively affected, but also some people lost their jobs. In this situation, investors' confidence was dented, and the stock market was thrown into turmoil. In addition, North Atlantic Treaty Organization continues to expand eastward, squeezing Russia's living space. Therefore, Putin announced military measures against Ukraine on Feb. 27. His decision is undoubtedly to bring a short-term risk to global equity markets, as well as an impact on investor sentiment. There may be a logic here that the war between Russia and Ukraine in the context of COVID-19 affects investor sentiment, which will further impact the stock market. We have studied the previous literature and found that the COVID-19 pandemic and the Russia-Ukraine war affected investor sentiment, which in turn affected the stock market. This paper will compare the two things and analyze the correlation between investor sentiment and the stock market under different black swan events.

China's economy has an important position in the world. According to the purchasing power parity calculation, the Chinese economy has accounted for about 13% of the global economy. If its stock market fluctuates, it also affects the world stock markets. Therefore, we choose the research object of the Chinese stock market. The empirical investigations are summarized as follows. First, we establish investor sentiment through principal component analysis with 5 components related to investor sentiment. Second, we construct VAR model and analyze economic meanings of coefficients. Third, we apply external impulse to each factor to better understand the dynamic behavior of the model.

The rest of this paper is structured as follows. Part two briefly reviews some related investigations. Part three refers to the empirical analysis and part four concludes the paper.

2. Literature Review

Black and Kyle first proposed the concept of "noise trader", which was defined as an investor who erroneously regards the noise as insider information to trade, and such behavior would cause the market price of stocks to deviate from the intrinsic value [1]. On this basis, Lee, Shleifer, and Thaler proposed the investor sentiment hypothesis [2]. They empirically analyzed the relationship between sentiment fluctuation and the monthly discount rate of 68 closed-end funds from 1956 to 1985. The results show that the net value premium occurs when noise traders are optimistic, and the net value discount appears when noise traders are pessimistic. Stein described investor sentiment as a systematic deviation from investors' expectations for the future [3].

This topic is also widely discussed in the Chinese A share market. For example, Wang and Wang selected six indicators: turnover rate, institutional shareholding ratio, PE, number of shareholders, trading volume and transaction amount to construct the sentiment index through the principal component analysis method [4]. KMO result and Bartlett spherical test results were significant using the data of Quoted Companies in China's stock market from January 1, 2015, to December 31, 2020. Yang selected five indicators: PE, historical PE relative profit growth ratio, turnover rate, market trading volume and rise and fall range to construct the sentiment index by principal component analysis [5].

Wu and Chi represented the cross-sectional mean and variance of investor sentiment respectively as the overall investor sentiment and investor sentiment divergence and introduced their interaction terms to establish a model with stock returns [6]. Based on data from publicly traded companies in Shanghai and Shenzhen from 2007 to 2020, the bootstrap test was performed. The results showed that the overall investor sentiment, investor sentiment divergence and interaction were significantly positive for stock returns.

Xiao, Peng, Ke selected the daily yield, three-day cumulative turnover and snowball sentiment indicators of Suning Yunshang securities from May 26, 2014, to November 17, 2014, and explored the relationship between shareholders' sentiment and stock investment return from the qualitative and quantitative perspectives based on effective market theory and behavioral finance theory and VAR model [7]. Finally, the authors get the following conclusion: first, the fluctuation of turnover rate can explain 35% of the fluctuation of yield; second, Performance and investor sentiment are positively correlated, and between turnover and investor sentiment in the short term, while there is a long-term relationship between yield and turnover; third, whether it is investor sentiment or yield or turnover, in the case of great fluctuations, it is accompanied by greater risks; fourth, the short-term turnover rate and the fluctuation of investors' mood cannot predict the fluctuation of yield very well.

3. Empirical Analysis

3.1 Data

The sample period covers January 21, 2020, to July 6, 2022, consisting of 594 observations of CSI 300. In order to differentiate investor sentiment between the period of COVID-19 pandemic and the period of Russia-Ukraine war, we choose February 24, 2022, as a separation date to make comparisons. Some basic descriptive statistics are shown in the following Table 1 and 2, respectively.

Table 1. Descriptive Statistics in the Period of Pandemic

	Stock Price	Rate of Return	Trading Volume (Million)	Trading Amount (Million)	PE	Turnover Rate
Mean	4747.26	0.02	15930.66	299964.86	13.95	0.0088
Variance	233559	1.7061	2.32E+9	8.44E+11	2.11	5E-6
Max	5807.72	5.67	40600.85	635254.74	17.45	0.018
Min	3530.31	-7.88	7744.80	119874.30	10.71	0.0043

Table 2. Descriptive Statistics in the Period of War

	Stock Price	Rate of Return	Trading Volume (Million)	Trading Amount (Million)	PE	Turnover Rate
Mean	4190.90	-7.47	14413.45	272906.44	12.47	0.0070
Variance	36818.99	17.949	7.86E+8	3.59E+11	0.24	1E-6
Max	4619.69	2.00	25704.65	459766.82	13.36	0.009
Min	3784.12	-16.45	9293.66	171756.50	11.21	0.0053

Through visualizing the data, we can discover that the average stock price, rate of return, trading volume, trading amount, PE and turnover rate in the period of pandemic are higher than those in the period of war. When it comes to max and min, the data presents the same result. The variance of stock price, rate of return, PE and turnover rate in the period of pandemic are also higher, while the variance of trading volume and amount shows an opposite result.

3.2 Investor Sentiment Index

In this paper, we select five indicators to reflect the investor's sentiment: the rise and fall rate, Trading volume, trading amount, the turnover, and the P / E ratio. The turnover rate, trading volume and trading amount can reflect the trading frequency of investors during this period, which is positively related to the investor's mood. The P / E ratio reflects the investment opportunities of stocks. The high rise and fall range will make investors trade more frequently, which is positively related to investor sentiment. The correlation between these variables may be relatively strong, so the principal component analysis is used to convert these variables into linear unrelated variables, which can reflect the investor's sentiment to the greatest extent. Given the temporal lag in investor sentiment’s impact on stock prices, each index is treated with a first-order lag.

$$Sent = \beta_1 RFrate + \beta_2 TrdV + \beta_3 TrdS + \beta_4 PE + \beta_5 Torate \tag{1}$$

Kmo is used to test whether the matrix is an identity matrix. Kmo value and Bartlett spherical test are often used to test whether the variables are appropriate for principal component analysis. It is commonly believed that when the kmo value and the kmo in Bartlett's spherical test are greater than 0.6, each variable can be subject to principal component analysis. In this paper, kmo value is 0.602, which indicates an acceptable degree of information overlap between variables. The estimated statistical value of chi square in the Bartlett spherical test is 2216.258, the degree of freedom is 10, and the level of significance is 0.000. The assumption that each variable is independent is rejected. Each variable has strong correlation, and a relatively satisfactory factor analysis model should be available. The related outcomes are shown in Table 3.

Table 3. KMO and Bartlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.602
Bartlett's Test of Sphericity	Approx. Chi-Square	2216.258
	df	10
	Sig.	0

Select the effective contribution factor. Principal component analysis (PCA) is a methodology to transform multiple disordered and related variables into a group of unrelated new indicators through dimension reduction. When using PCA, it is necessary to make a scientific selection of the original indicators to avoid generating multiple new variables. The specific method is to measure the standard deviation of the new variable, that is, the contribution rate of the variable. The larger the variance, the higher the contribution rate. The initial eigenvalues of the first two factors are 2.792 and 1.181 respectively, both of which are greater than 1, and the cumulative contribution rate of the first two factors is 79.472%, which indicates that the two factors can describe much of the information in the initial index after removing the overlapping information. Therefore, it is appropriate to select the first two factors, as shown in Table 4.

Table 4. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% Of Variance	Cumulative %	Total	% of Variance
1	2.792	55.849	55.849	2.792	55.849
2	1.181	23.623	79.472	1.181	23.623
3	0.838	16.751	96.223		
4	0.115	2.302	98.526		
5	0.074	1.474	100		

Build investor sentiment indicators (sent). The linear relationship between the two components and each index is shown in Table 5.

Table 5. Component score coefficient matrix

	Component	
	1	2
TrdV	0.348	-0.012
TrdS	0.335	0.198
PE-TTM	0.105	0.771
TurnoverRate1	0.304	-0.299
Rfrate	0.148	-0.351

Then the sent used in this paper can be calculated by the following process,

$$F1=-0.148*Rfrate+0.348*Trdv+0.335*Trds+0.105*Torate-0.304*PE\text{-}TTM \quad (2)$$

$$F2=-0.351*Rfrate+(-0.012)*Trdv+0.198*Trds+(-0.299)*Torate+0.771*PE\text{-}TTM \quad (3)$$

Then, the variance contribution degree of the two factors is used to allocate the weights of the three principal components to obtain the equation.

$$Sent=(0.55856*F1+0.23621*F2)/79.475\% \quad (4)$$

Taking (2), (3) into (4), we can get that:

$$Sent=0.302939*Rfrate+0.241006*Trdv+0.294283*Trds+0.124785*Torate+(-0.00031)*PE \quad (5)$$

3.3 VAR Model Construction and Result Analysis

Since there has a mutual impact between investor sentiment and stock price, the bivariate VAR model is used to describe the relationship between investor sentiment and stock price.

3.3.1 Stationary test

For the establishment of the time series model, to avert spurious regression phenomenon, it is necessary to test the stationarity of the time series, so the unit root test is conducted for price and sent. The first step is to conduct ADF test, and the null hypothesis is that the unit root exists, and the series is non-stationary [8-10]. The test results are shown in Table 6.

Table 6. ADF test results

Variable	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value
price	-1.684	-3.430	-2.860	-2.570	0.4392
Sent	-6.080	-3.430	-2.860	-2.570	0.0000

Table 6 shows that the investor sentiment index sent cannot accept the null hypothesis at the 1% significant level, which is a stable time series. However, the price cannot reject the null hypothesis at a significance level of 10%. The price accepts the null hypothesis that there is a unit root, which indicates that the series is not stable. KPSS test is used to verify the non-stationarity of prices. The null hypothesis of KPSS test is opposite to ADF test, which is a stable time series. The experimental results are provided in Table 7.

Table 7. price KPSS test results

Lag Order	Test Statistic
0	12.5
1	6.28
2	4.2
3	3.16
4	2.54
5	2.12
6	1.83
Critical Values:10%: 0.119 5%: 0.146 2.5%: 0.176 1%: 0.216	

As indicated in Table 7, the test statistics of price lag from zero rank to the sixth rank are all larger than statistics at 1% significance level; therefore, the null hypothesis of the stationary series is rejected, and the price is considered a non-stationary series, the difference of first-order treatment of price is used to carry out ADF test and KPSS test for dprice. The test results are presented in Table 8.

Table 8. dprice unit root test results

Type of Test	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value
ADF	-23.847	-3.430	-2.860	-2.570	0.0000
KPSS	0.0497	0.119	0.146	0.176	

According to the results in Table 8, dprice rejects the null hypothesis of the ADF test at the 1% significance level and accepts the null hypothesis of the KPSS test at the significance level of 10%; therefore, dprice is considered a stationary time series. To sum up, sent is a stationary sequence, and the price is an integer sequence of the first order.

3.3.2 Cointegration test

Since price is stationary only after the first order difference and describes the short-term dynamics, it is necessary to test whether there is a cointegration relationship between price and sent. It is also necessary to judge does it exists a long-term stable relationship between the two variables. In this paper, Johansen's trace cointegration test and maximum characteristic root cointegration test are used to test the cointegration relationship between sent and price. The final results of the tests are presented in Table 9.

Table 9. cointegration test results

Maximum rank	Eigenvalue	Trace Test			Maximum Eigenvalue Test		
		Trace Statistic	5% Critical Value	1% Critical Value	Max Statistic	5% Critical Value	1% Critical Value
0		50.1976	11.44	15.69	50.1976	11.44	15.69
1	0.03167	0.08129	3.84	6.51	0.9304	3.84	6.51
2	0.00157						

According to Table 9, the maximum rank of the cointegration relationship is 0, which is rejected. There is at least a one rank cointegration relationship between price and sent, so we can determine there is a long-term stable relation in between. Next, a VAR model is constructed for in-depth analysis.

3.3.3 The establishment of VAR model

Using the outbreak of the Russia-Ukraine war on February 24 as the separation point to divide two time periods data and construct VAR models to compare the similarities and differences between the data of the two periods. This paper used LR test, FPE, AIC, BIC, and HQ information criteria to determine the lag rank. Finally, the VAR during the Russo-Ukraine War was determined as the two-rank, and the VAR during the COVID-19 was determined as the fourth rank.

After the determination of the rank, the regression equation of binary VAR can be written as follows:

$$dprice_t = \theta_t^1 + \sum_{i=1}^{m} \Phi_i^1\, dprice_{t-i} + \sum_{j=1}^{m} \Theta_j^1\, Sent_{t-j} + \varepsilon_t^1 \tag{6}$$

$$Sent_t = \theta_t^2 + \sum_{i=1}^{m} \Phi_i^2\, Sent_{t-i} + \sum_{j=1}^{m} \Theta_j^2\, dprice_{t-j} + \varepsilon_t^2 \tag{7}$$

$m = 1/4, war/pandemic$

The regression results for the two periods of the Russia-Ukraine war and the COVID-19 pandemic are shown in Table 10.

Table 10. VAR regression results

PERIOD	VARIABLES	(6) dprice	(7) Sent
Pandemic			
	L.dprice	0.016	3,488.516***
		(0.36)	(3.89)
	L2.dprice	0.044	4,403.924***
		(0.99)	(5.01)
	L3.dprice	-0.025	548.279
		(-0.55)	(0.61)
	L4.dprice	-0.016	1,920.443**
		(-0.36)	(2.15)
	L.Sent	-0.000	0.643***
		(-1.17)	(14.54)
	L2.Sent	0.000*	0.212***
		(1.69)	(4.02)
	L3.Sent	-0.000	-0.040
		(-1.27)	(-0.76)
	L4.Sent	-0.000	0.119***
		(-0.15)	(2.72)
	Constant	17.791*	602,246.668***
		(1.86)	(3.14)
	Observations	501	501
		(6)	(7)
War			
	L.dprice	0.002	3,715.774*
		(0.02)	(1.83)
	L.Sent	0.000	0.733***
		(0.87)	(10.11)
	Constant	-30.162	2256742.198***
		(-0.91)	(3.65)
	Observations	86	86

z-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

By analyzing the results of VAR, it can be found that the one rank lag of stock prices during the Russo-Ukraine War positively impact the sentiment, which means that when the stock market presents a good market, that is, when stock prices increase, investor sentiment rises. This result is very similar to the results during the COVID-19 pandemic, where the one rank lag of stock prices has a significantly positive impact upon sentiment, and the values of the coefficients are very close. However, the one rank lag coefficient in the war period is only significant at the level of 10%, while the one rank lag and second rank lag in the COVID-19 epidemic period are both significant at the level of 1%, which indicates the effect of the stock price on sentiment in the war period is not as significant as that in the COVID-10 epidemic period.

3.3.4 Granger causality test

To confirm if there is a causality between investor sentiment and stock price rather than a correlation without economic significance, the Granger causality test is utilized to judge the causal relationship between investor sentiment and stock price. The data in the Table 11 is the final result.

Table 11. Granger-Engle Test

Period	Equation	Excluded	chi2	df	Prob>chi2
War					
	dprice	Sent	0.76077	1	0.383
	dprice	All	0.76077	1	0.383
	Sent	dprice	3.3627	1	0.067
	Sent	All	3.3627	1	0.067
Pandemic					
	dprice	Sent	6.793	4	0.147
	dprice	All	6.793	4	0.147
	Sent	dprice	45.249	4	0.000
	Sent	All	45.249	4	0.000

According to the results in Table 11, it can be found that the null hypothesis that stock price is not Granger cause of investor sentiment changes can be rejected at 1% significance level during the epidemic period, while the null hypothesis that stock price is not Granger cause of investor sentiment changes cannot be accepted at 10% significance level during the Russia-Ukraine War. However, the null hypothesis that investor sentiment is not a Granger cause of stock price changes cannot be rejected in both periods. The result indicates that in these two periods, the one-way impact of stock price on investor sentiment is far more than the one-way impact of investor sentiment on stock price.

3.3.5 Impulse response analysis and variance decomposition analysis

VAR model results of single factor estimation can only provide limited information, to further analyze the interdependence between stock prices and investor sentiment and better understand the dynamic behavior of the model, so using the impulse response analysis and variance decomposition analysis, by applying external shocks to one of the variables respectively, observe the change of another variable and the degree of influence each other between the stock price and investor sentiment. Before the impulse response, the stationarity of the VAR model needs to be verified, and the unit root test results are shown in the Figure 1.

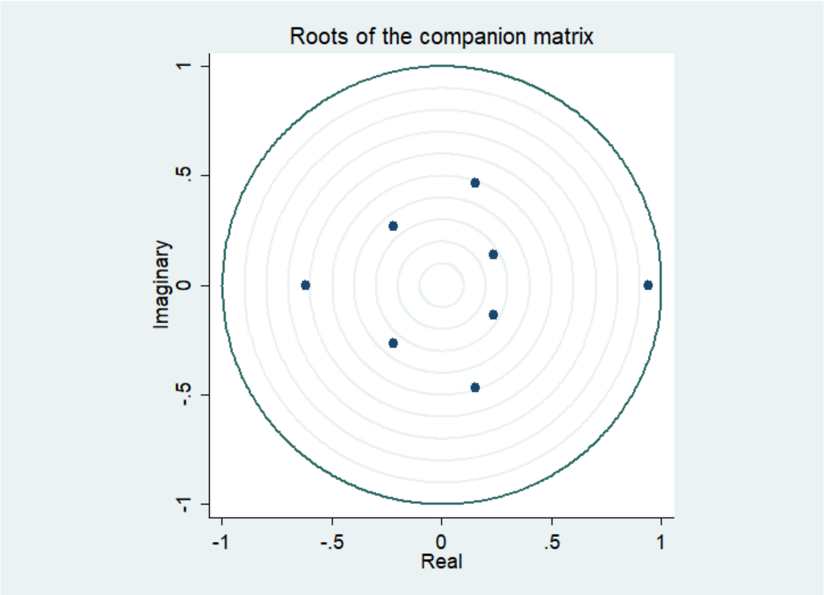

Fig. 1 Unit root test of pandemic's VAR model

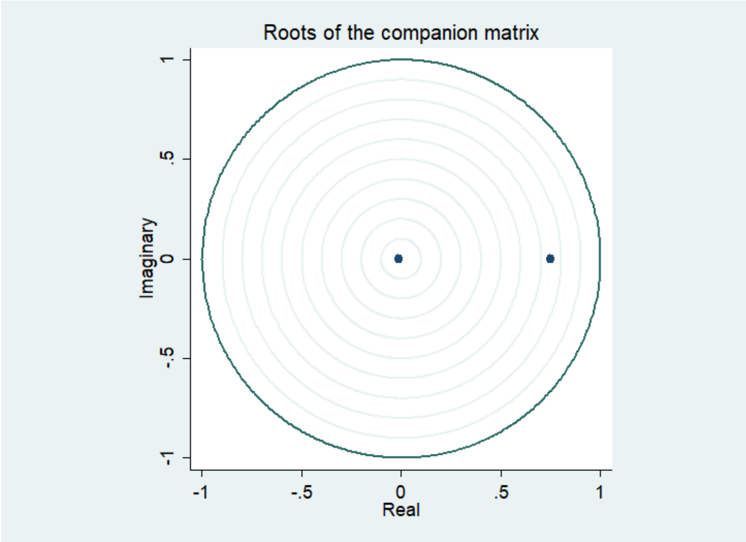

Fig. 2 Unit root test of war's VAR model

The results in Figure 1 and Figure 2 show that the unit roots all exist within the unit circle, indicating that the VAR model is stationary; therefore, impulse response analysis can be performed, and the results are presented in Figure 3 and Figure 4.

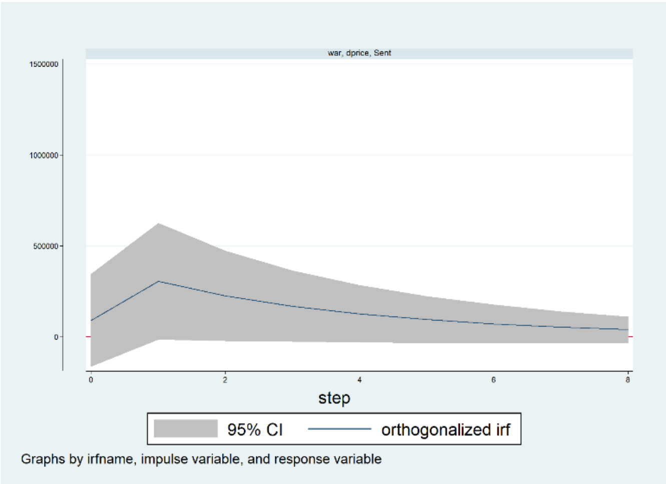

Fig. 3 War's impulse response diagram

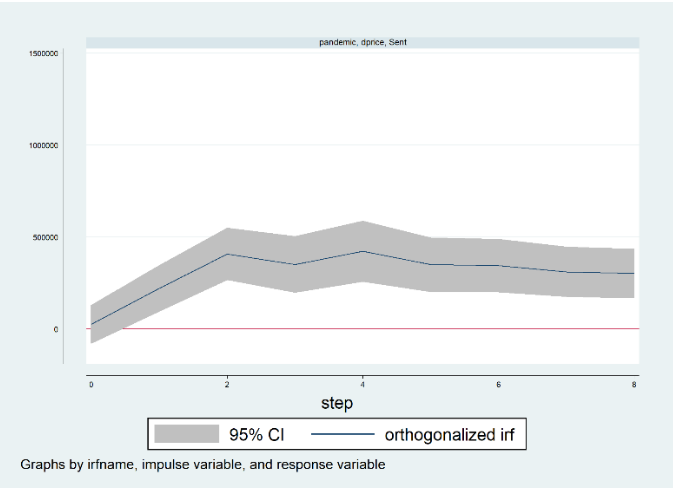

Fig. 4 Pandemic's impulse response diagram

Figure 3 shows that when imposing an external positive shock on the stock price, the sentiment also changes positively, and the shock fluctuates from the second period to the fourth period, peaks in the fourth period, and slowly declines from the fourth period. This shows that when the stock price changes, investor sentiment will change in same direction in the long run, and the change will be the largest in the fourth period. Figure 4 shows imposed external shock to sentiment during the Russia-Ukraine war, and stock prices do not change at all. In the right figure, a positive external shock is applied to the stock price, and after reaching a peak in the first period, it tends to stabilize and fall in the long run. Next, the variance decomposition analysis after the impact is carried out can explain the degree of mutual influence between stock price and investor sentiment. The results are shown in Figure 5 and Figure 6.

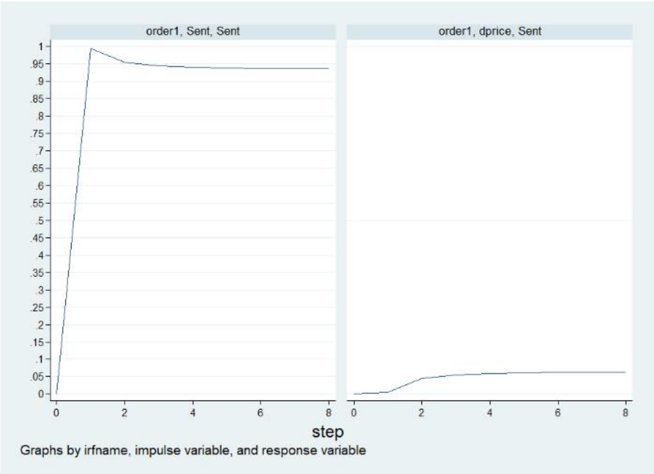

Fig. 5 War's variance decomposition diagram

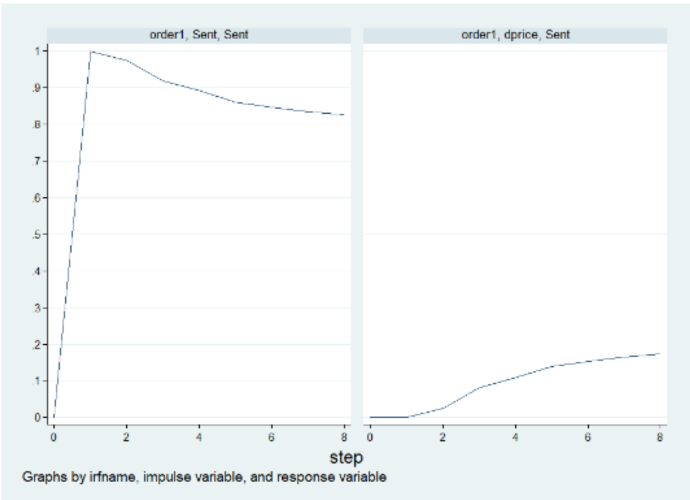

Fig. 6 Pandemic's variance decomposition diagram

The first graph of Figure 5 is imposing shock to sentiment during the Russia-Ukraine war, the explanatory power of sentiment changes caused by their fluctuations gradually decreases from 100% to about 95%, and the right graph illustrates that the influence of stock price on sentiment changes gradually increases in the long run, and can explain about 5% of sentiment changes stably in the later stage. The second figure shows that after the first phase of the COVID-19 epidemic period, the explanatory power of the changes in sentiment gradually decreased from 100% to about 80% in the long run, while the influence power of stock price on sentiment gradually increased, which could explain about 20% of the changes in sentiment in the later period. This result is the same as the Granger causality test. The impact of stock prices on sentiment during the epidemic period is more significant than that during the Russo-Ukraine War.

4. Conclusion

This paper refers to the construction method of investor sentiment index in previous literature, using principal component analysis to establish an investor sentiment index. Besides, this paper adopts stationarity test, cointegration test, VAR model, Granger causality test, impulse response analysis, and variance decomposition analysis to further explain the mutual influence between stock price and investor sentiment during the Russia-Ukraine war and the COVID-19 epidemic, the empirical results can be summarized as follows.

During the Russia-Ukraine war and the COVID-19 epidemic, stock prices had a unilateral impact on investor sentiment, that is, when stock prices changed, investor sentiment would have a significant impact and show a trend of change in the same direction as stock prices. Therefore, stock prices increase will drive up investor sentiment, and the change in stock prices has a stronger ability to explain the change of sentiment in the long run, especially during the COVID-19 pandemic than during the Russia-Ukraine war. Conversely, the effect of investor sentiment on stock price is not significant, and the explanatory power of investor sentiment on stock price changes is almost zero. Compared with the period of COVID-19, the influence of stock price on sentiment is stronger in the period COVID-19, and the influence of stock price on sentiment is significant in the short-term during the Russia-Ukraine war, while the influence of stock price on sentiment during COVID-19 pandemic is significant in the long term.

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