Relationship between Investor Emotion Change and Stock Market Volatility

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Abstract. Since the establishment of Shanghai Stock Exchange in 1990, China's stock market has made great achievements in the nearly 30 years of reform and development. However, compared with the stock market in the west, China's stock market is not mature enough either in the stock market system or in investor behavior. From the perspective of behavioral finance, this paper analyzes and studies the relationship between investor sentiment and stock market volatility. By establishing the VAR quantity model of investor sentiment index and Shanghai Composite Index, we use regression analysis to test the causal relationship between them.

Introduction

In view of the "abnormal" phenomena in traditional financial theory, behavioral finance theory breaks through the theoretical framework of traditional finance by drawing lessons from behavioral science such as psychology, and studies the "abnormal" phenomena often occurring in financial market from the psychological factors behind individual behavior. Compared with the traditional financial descriptions of how market individuals "should" conduct market behavior, behavioral finance focuses more on the analysis of how market individuals "actually" conduct market behavior.

With the in-depth study of behavioral finance in the two theoretical cornerstones of investors' Psychological Analysis and limited arbitrage, behavioral finance integrates more research into affective psychology, cognitive psychology and social psychology into the analysis of individual behaviors in financial markets. Investor sentiment in financial market, as an important psychological feature of investors in investment decision-making, is one of the important factors affecting the change of financial asset prices and the volatility of financial market. This paper will empirically analyze the relationship between investor sentiment change and stock market volatility from the perspective of behavioral finance.

Empirical Analysis

Descriptive statistics

Three sample data of investor sentiment index, Shanghai Composite Index and Shanghai Composite Index from January 2003 to December 2017 were collected from Tai'an database. The three sample data are plotted to show the investor sentiment index ISI in Figure 1, the Shanghai composite index Clsidx in Figure 2 and the return rate Idxrtn in Figure 3 respectively.

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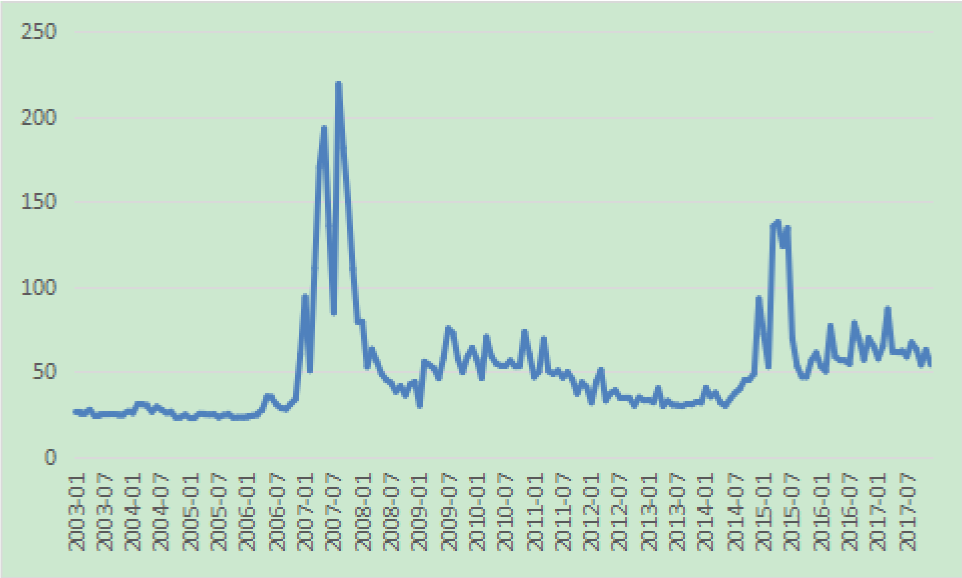

Figure 1. Investor sentiment index

Figure 2. Shanghai composite index

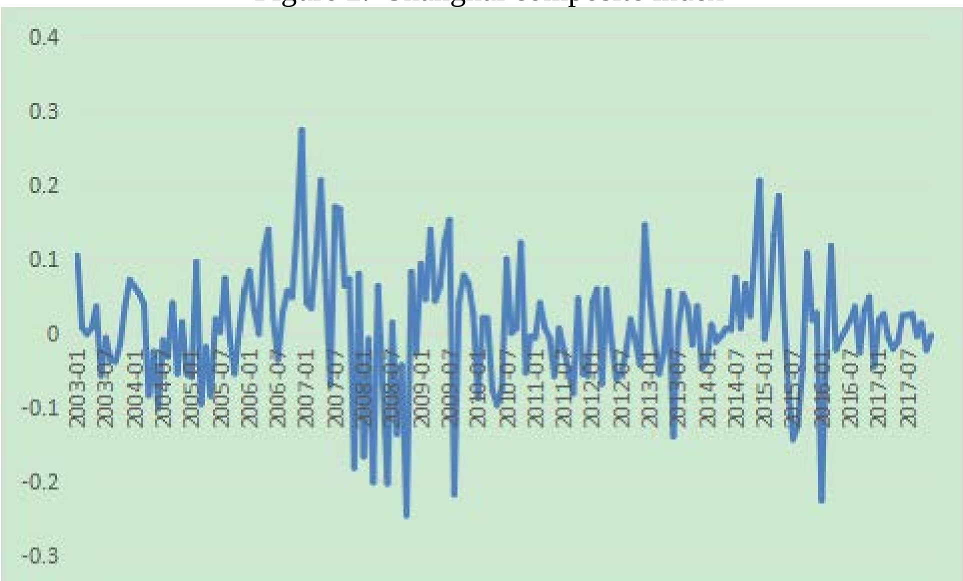

Figure 3. Shanghai Composite Index Return Rate

Table 1 Sample statistical analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
isi	180	51.45344	32.19432	22.78	218.96
clsidx	180	2516.521	948.8559	1060.74	5954.77
idxrtn	180	.0082443	.0806543	-.246314	.274464

In Figure 1, the sample mean of the investor sentiment index is 51.45 higher than 50, which shows that investor sentiment in China is in a positive state as a whole during the sample period. This should be attributed to the better economic situation in which China is developing rapidly throughout the sample period. Combining Figures 1 and 2, it is not difficult to see that the corresponding investor sentiment index is in the two stages of rising and falling respectively in the period of stock market rising and falling. The return rate of Shanghai Stock Exchange Index in Figure 3 fluctuates greatly during the sample period. The return rate is influenced by the stock market.

Relevant Analysis.

Table 2 Coefficient of correlation

	isi	clsidx	idxrtn
isi	1.0000		
clsidx	0.8259	1.0000	
idxrtn	0.2111	0.1220	1.0000

ISI is the investor sentiment index, clsidx is the Shanghai composite index, idxrtn is the return of the Shanghai composite index. From the results of calculation and analysis, the correlation coefficient between investor sentiment index and Shanghai Composite Index is 0.8259, which is larger than that between investor sentiment index and Shanghai Composite Index, which is 0.2111, and also larger than that between Shanghai Composite Index and Shanghai Composite Index, which is 0.1220. It shows that the stock market may affect the level of investor sentiment index, and the change of investor sentiment index may further react to the stock market. Next, the empirical analysis is focused on the relationship between investor sentiment index and Shanghai Composite Index.

Stationarity Test.

Table 3 ADF test of ISI

Augmented Dickey-Fuller test for unit root   Number of obs = 176

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.893	-3.485	-2.885	-2.575

MacKinnon approximate p-value for Z(t) = 0.0461

From the test analysis of Table 3, we can see that the ADF test of investor sentiment index has a P value of 0.0461, and the test results are significant at the level of 5%. Therefore, the original assumption of unit root can be rejected at the level of 5%. It can be judged that the investor sentiment index is a stationary sequence.

Table 4 ADF test of clsidx

Augmented Dickey-Fuller test for unit root Number of obs = 171

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.132	-3.486	-2.885	-2.575

MacKinnon approximate p-value for Z(t) = 0.0242

From the test analysis of Table 4, we can see that the P value of ADF test of Shanghai Composite Index is 0.0242, and the test results are significant at the level of 5%. It can be judged that the sample data is a stationary sequence.

VAR Model Test. A binary VAR model is constructed by investor sentiment index and Shanghai composite index.

$$\mathrm{ISI_t} = \beta_{10} + \beta_{11}\mathrm{ISI_{t-1}} + ... + \beta_{1p}\mathrm{ISI_{t-p}} + \gamma_{11} CLSIDX_{\mathrm{t-1}} + ... + \gamma_{1p} CLSIDX_{t-p} + \varepsilon_{1t} \qquad (1)$$

$$CLSIDX_t = \beta_{20} + \beta_{21}\mathrm{ISI_{t-1}} + ... + \beta_{2p}\mathrm{ISI_{t-p}} + \gamma_{21} CLSIDX_{\mathrm{t-1}} + ... + \gamma_{2p} CLSIDX_{\mathrm{t-p}} + \varepsilon_{2t} \qquad (2)$$

Firstly, the residuals of VAR model need to satisfy the condition that there is no autocorrelation, and then they are tested from lower to higher order. Finally, table 5 is obtained. When the lag order of variables of VAR model is 6, the residuals of the model no longer have autocorrelation.

Table 5 VAR Model Residual Autocorrelation Test

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	5.1826	4	0.26907
2	4.8586	4	0.30212

H0: no autocorrelation at lag order

In Table 5, the original assumption is that the model residuals no longer have autocorrelation, because the P values are 0.26907 and 0.30212, so the original assumption is accepted and the model residuals no longer have autocorrelation. Then the sixth-order vector autoregressive model is estimated to get Table 6.

Table 6 Vector Autoregressive Model Estimation

Vector autoregression

Sample:	2003m7 - 2017m12	No. of obs =	174
Log likelihood =	-1873.528	AIC =	21.83366
FPE =	1.04e+07	HQIC =	22.02515
Det(Sigma_ml) =	7717889	SBIC =	22.3057

Equation	Parms	RMSE	R-sq	chi2	P>chi2
isi	13	15.4891	0.7871	643.323	0.0000
clsidx	13	231	0.9446	2964.491	0.0000

Continue

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
isi						
isi						
L1.	.4359296	.087736	4.97	0.000	.2639702	.607889
L2.	-.0196748	.0955074	-0.21	0.837	-.2068659	.1675162
L3.	.2564509	.0960283	2.67	0.008	.0682389	.4446629
L4.	.0754231	.0950617	0.79	0.428	-.1108943	.2617405
L5.	-.0844863	.0903599	-0.93	0.350	-.2615885	.0926159
L6.	-.1845921	.0830234	-2.22	0.026	-.347315	-.0218692
clsidx						
L1.	.0424053	.0059468	7.13	0.000	.0307497	.0540609
L2.	-.0307437	.0079208	-3.88	0.000	-.0462682	-.0152192
L3.	-.0052132	.0078895	-0.66	0.509	-.0206763	.0102499
L4.	.003714	.0078254	0.47	0.635	-.0116235	.0190516
L5.	.0015605	.0077004	0.20	0.839	-.013532	.016653
L6.	-.0009454	.0055071	-0.17	0.864	-.0117391	.0098484
_cons	-.4393328	4.141523	-0.11	0.916	-8.556569	7.677903
clsidx						
isi						
L1.	.3346508	1.308474	0.26	0.798	-2.229911	2.899212
L2.	2.448179	1.424375	1.72	0.086	-.3435436	5.239902
L3.	-2.479046	1.432143	-1.73	0.083	-5.285996	.3279032
L4.	6.355409	1.417727	4.48	0.000	3.576715	9.134102
L5.	-4.851778	1.347607	-3.60	0.000	-7.493039	-2.210518
L6.	1.12848	1.238191	0.91	0.362	-1.29833	3.55529
clsidx						
L1.	1.080036	.0886897	12.18	0.000	.9062071	1.253864
L2.	-.0795476	.118129	-0.67	0.501	-.3110762	.151981
L3.	-.2412281	.1176618	-2.05	0.040	-.471841	-.0106151
L4.	.24637	.1167066	2.11	0.035	.0176294	.4751107
L5.	-.1256214	.1148417	-1.09	0.274	-.350707	.0994642
L6.	-.0147089	.0821315	-0.18	0.858	-.1756837	.146266
_cons	195.8597	61.76569	3.17	0.002	74.80118	316.9182

From the results of the table above, we can see that the estimated coefficients increase and the accuracy decreases due to the large lag order, and some of the coefficients are not significant. Next, the joint significance of each order coefficients is tested.

Table 7 Joint Significance Test of Coefficients of Each Order

Equation: isi

lag	chi2	df	Prob > chi2
1	155.3951	2	0.000
2	17.41585	2	0.000
3	7.131975	2	0.028
4	.9812306	2	0.612
5	.8993873	2	0.638
6	5.383104	2	0.068

Equation: clsidx

lag	chi2	df	Prob > chi2
1	209.0985	2	0.000
2	2.970678	2	0.226
3	9.542331	2	0.008
4	27.79333	2	0.000
5	14.56343	2	0.001
6	.830909	2	0.660

Equation: All

lag	chi2	df	Prob > chi2
1	260.3101	4	0.000
2	28.67181	4	0.000
3	30.8236	4	0.000
4	32.82721	4	0.000
5	17.06905	4	0.002
6	11.97209	4	0.018

From Table 7, we can see that most coefficients in ISI and clsidx of single equation are significant, and all coefficients of all equation as a whole are highly significant. Next, we further test whether the estimated VAR system is a stationary process.

Table 8 Stability test of VAR system

Eigenvalue stability condition

Eigenvalue	Modulus
.8583372 + .1095278*i*	.865297
.8583372 - .1095278*i*	.865297
.06327287 + .8233996*i*	.825827
.06327287 - .8233996*i*	.825827
-.6368805 + .4431425*i*	.775882
-.6368805 - .4431425*i*	.775882
.7248676 + .2506519*i*	.766981
.7248676 - .2506519*i*	.766981
.06875398 + .510434*i*	.515044
.06875398 - .510434*i*	.515044
-.4746194	.474619
-.1661174	.166117

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

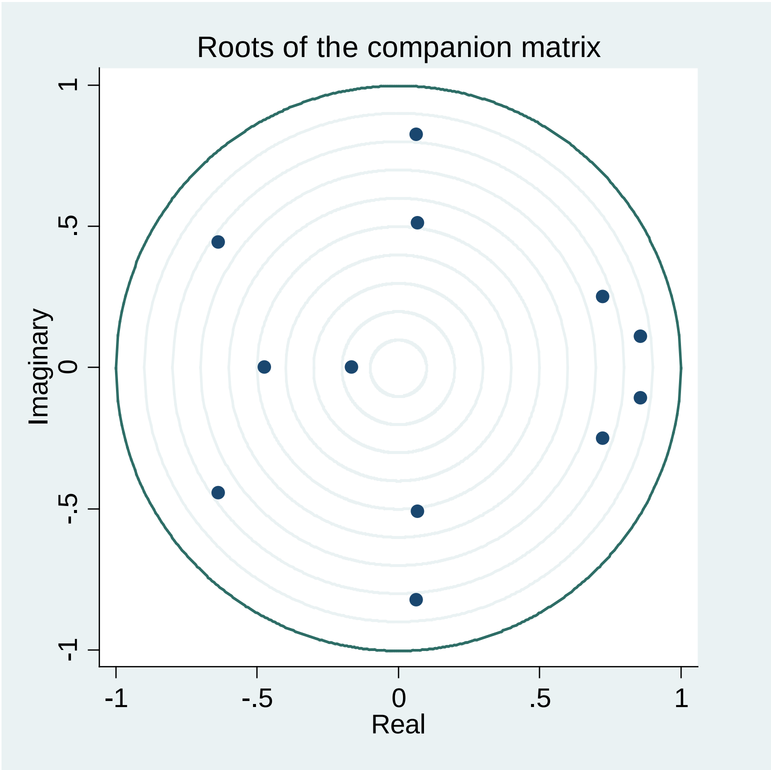

Figure 4. Eigenvalues and unit circles

Combining Table 8 and Figure 4, it can be judged that all eigenvalues are within the unit circle, so the VAR model satisfies the stationarity condition. Next, we will analyze the causal relationship between ISI and clsidx.

Table 9 Granger causality Wald test

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
isi	clsidx	54.081	6	0.000
isi	ALL	54.081	6	0.000
clsidx	isi	27.806	6	0.000
clsidx	ALL	27.806	6	0.000

As can be drawn from table nine, whether ISI or clsidx is the interpreted variable, the P value is less than 0.001, so there is a Granger Causal Relationship between them.. It shows that the stock market may affect the level of investor sentiment index, and the change of investor sentiment index may further react to the stock market.

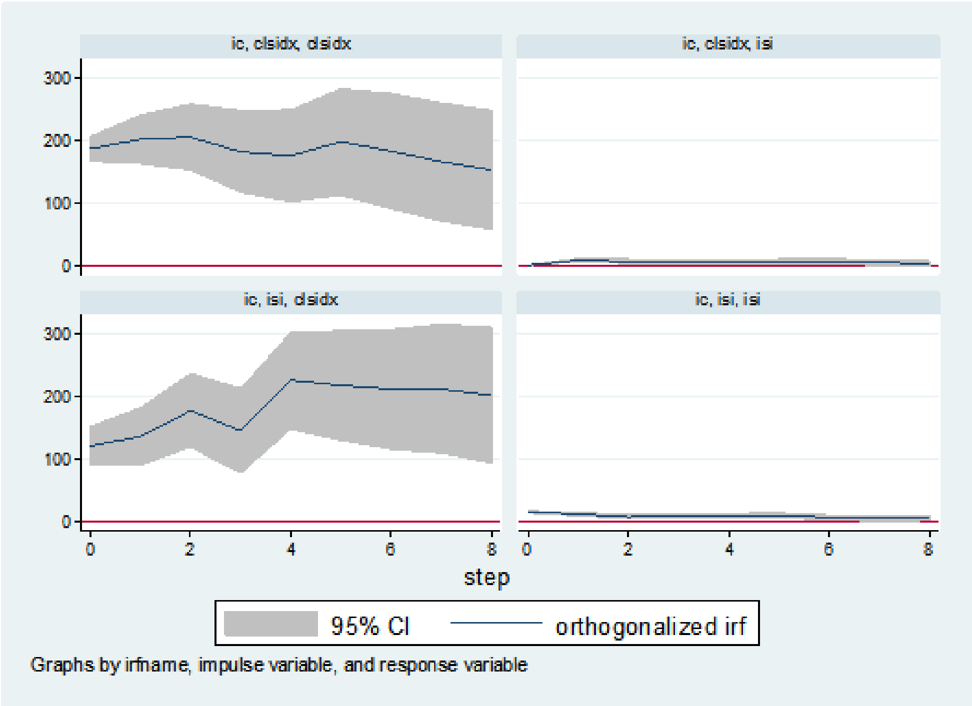

Figure 5. Orthogonalization impulse response graph

The titles of the four sub-graphs in Fig. 5 are named in the order of "impulse name, impulse variable and response variable". For example, the lower left plot represents the impulse response diagram based on the impulse result ic, impulse variable ISI and response variable clsidx. The chart shows the positive impact of a standard deviation of the investor sentiment index isi, which will lead to the rise of the Shanghai Composite Index clsidx in the future. This also proves to some extent that the rise of investor sentiment index has a positive impact on the Shanghai Composite Index.

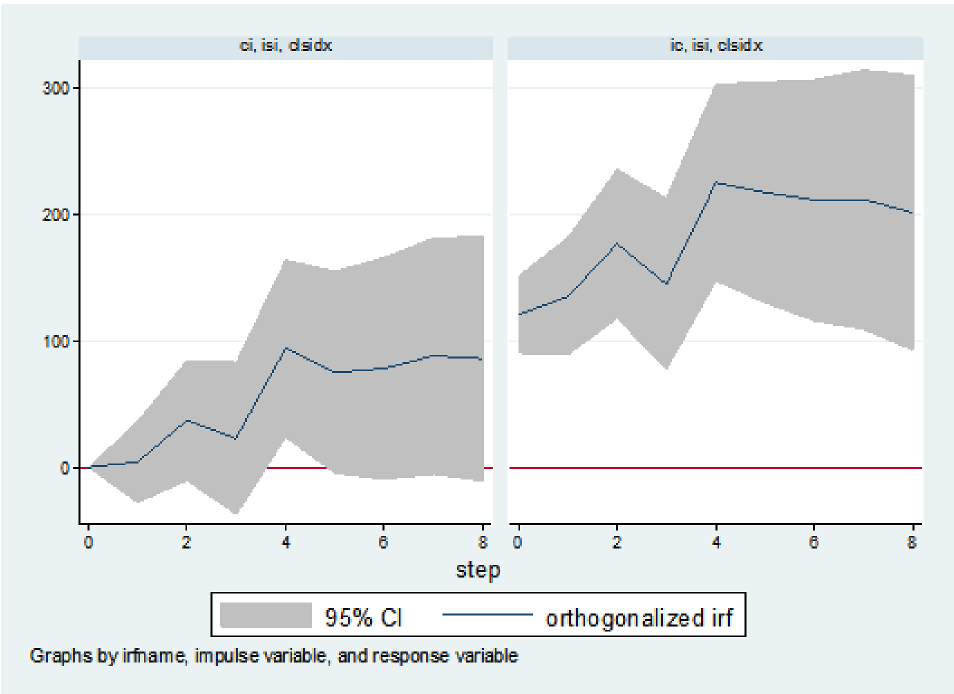

Figure 6. Comparing impulse response graphs under two kinds of variable ordering（isi→clsidx）

The order of variables is transformed to investigate the robustness of orthogonalized impulse response function.

Fig.6 shows that the absolute value of impulse response of variable ISI to clsidx shocks varies with the ranking of variables, but the trend of change is similar. On the whole, the positive impact of investor sentiment index ISI will lead to the upward change of Shanghai Composite Index, and this influence ability will increase first and then weaken with the increase of lag period in the short term. The potential reached its strongest in the fourth lag period. This shows that the impact of investor sentiment changes on the Shanghai Composite Index may not be fully reflected in the current period, there is a time lag. This can be explained by the fact that for a new market sentiment to emerge, herd-like investors' herding mentality needs some time to develop in order to have a greater impact on the stock market.

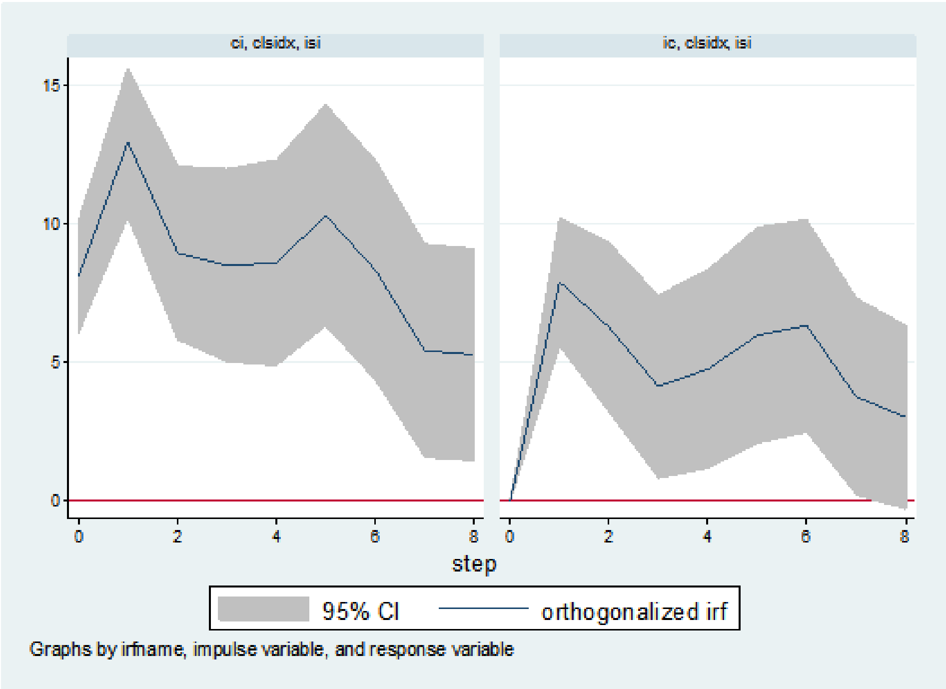

Figure 7. Comparing impulse response graphs under two kinds of variable ordering（clsidx→isi）

Fig. 7 shows that the absolute value of the impulse response of the variable clsidx to ISI shocks varies with the order of variables, but the trend of the two variations is similar. On the whole, a positive impact of the Shanghai Composite Index clsidx will have an upward impact on the investor sentiment index. Unlike Figure 6, the figure in Figure 7 shows a downward trend of fluctuation, which indicates that the impact of the current changes of the Shanghai Composite Index on investor sentiment shows a downward trend of fluctuation with the increase of lag order. It shows that investor sentiment is more affected by recent market changes, which to some extent reflects the existence of a certain proximity effect of investor sentiment.

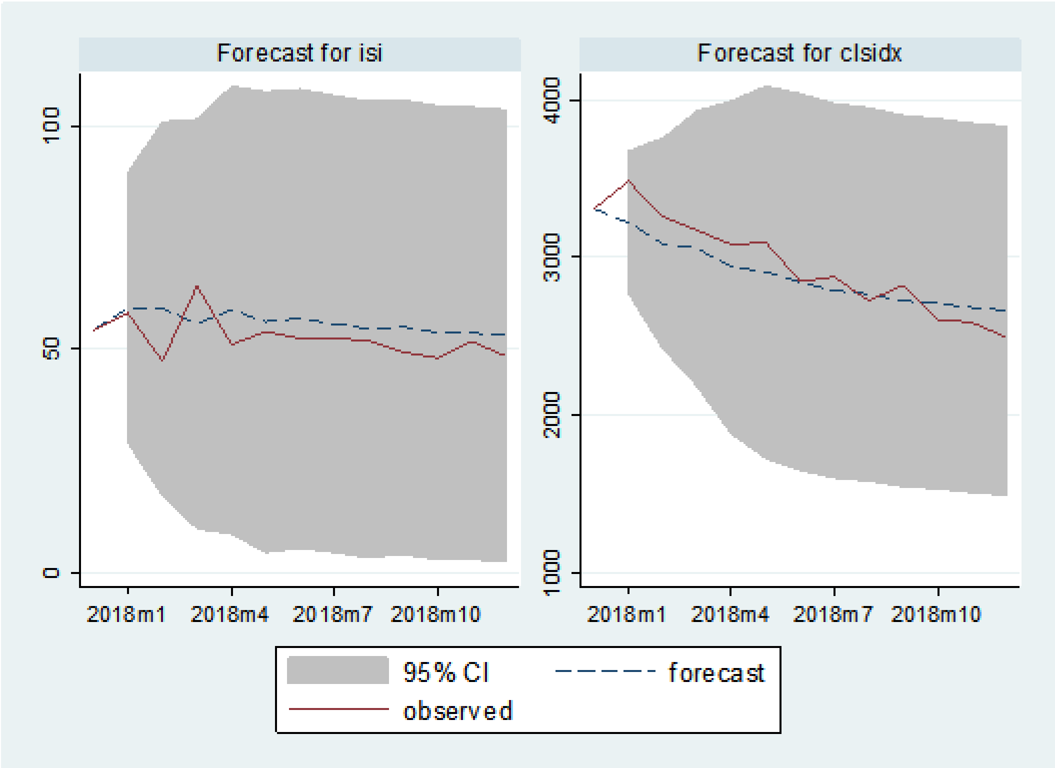

Figure 8. Data forecast for 12 months in 2018

Through the estimated VAR model, the dotted line trend of market sentiment index and Shanghai composite index in Figure 8 is predicted. The real line represents the object of prediction: the actual data observed in 2018. Although there are some errors between the predicted value and the actual value, the actual observation values of ISI and clsidx fall within 95% confidence interval, indicating that the model has certain predictive ability.

According to the data of market sentiment index and Shanghai Composite Index in 2018, the predicted value of the model is more stable than the observed data trend. In the forecasting chart of the market sentiment index on the left, the actual value of the market sentiment index fluctuates more than the forecasting value from January to April of 2018, which matches the sharp fluctuation of the market at the beginning of 2018.

In 2018, the Shanghai Composite Index rose rapidly from 3348 in early January to 3587 at the end of January, and rose by 7.14% in a month as a whole. After that, the Shanghai Composite Index began to decline rapidly in February. It dropped to 3129 in mid-February and 12.77% in half a month. Although the Shanghai Composite Index returned to 3326 in the following month, it dropped to around 3100 in late April. It also maintained the overall downward trend in the month after 2018. It is precisely because of the sharp decline of the Shanghai Composite Index in early 2018. Volatility makes investor sentiment in the stock market change greatly. The rapid rise of Shanghai Composite Index in January raised the optimistic expectations of market investors for the future stock market, while ignoring the objective market risks at that time, which further promoted the stock market to a high level. The cliff-like decline of the Shanghai Composite Index in February forced market investors to change their optimistic expectations about the future of the stock market, which led to a rapid decline in the market sentiment index. The market panic caused by the sharp decline of the Shanghai Composite Index further accelerated the selling of stock investors through herding effect, thus further expanding the decline of the Shanghai Composite Index.

In the forecasting chart of the Shanghai Composite Index on the right, the actual observation value of the Shanghai Composite Index in early 2018 is located above the forecasting line, but it falls below the forecasting line at the end of 2018. While maintaining the overall downward trend, the actual observation value and the forecast value of the Shanghai Composite Index have a larger decline than the forecast value. This phenomenon is related to the deteriorating international trade situation in 2018, together with other unpredictable new factors in 2018, which makes the estimated data of the original model have some errors with the actual observations. When forecasting the medium and long-term trend through the model, we need to pay attention to the new factors which will aggravate the uncertainty and volatility of the future trend.

In the forecasting chart of market sentiment index on the left, besides the fact that the observed value of market sentiment index fluctuates more than the forecasted value, the short-term trend of change between them still lags behind. From the two data trends of the left chart, it can be seen that the peak of the observed value in the trend line of market sentiment index corresponds to the trough of the predicted value of the model, and the observed trough corresponds to the peak of the predicted value of the model. The short-term trend changes of the two are not consistent. This shows that in the short term, there is a time lag between the forecast value of the model and the actual value of the market sentiment index. During the application of the model, the data used should be updated continuously to minimize the error between the predicted value and the actual value of the model.

Literature References

Nicholas Barberis and Richard Thaler divide behavioral finance into two parts: one is arbitrage restriction, which holds that rational market participants can not completely eliminate the market value deviation caused by irrational traders; the other is psychology, which can be used to classify the observed irrational phenomena. The author carries out relevant research around these two parts, and summarizes some applications in the field of behavioral finance.[1]

According to Jay R. Ritter (2003), behavioral finance includes the study of the traditional assumption that rational investors abandon the maximization of expected utility in efficient markets. The two cornerstones of behavioral finance are cognitive psychology (how people think) and arbitrage restrictions (when markets are inefficient). The power of arbitrage is very effective for high-frequency incidents, but it is difficult for low-frequency incidents to play a role. [2]

RH Thaler believes that the abnormal phenomena in financial markets can be better explained by incorporating psychological theory into financial market models. In order to study the behavior of financial market more effectively, it is necessary to combine the relevant results of Finance with psychology and other social sciences. Researchers in financial market need to incorporate the "behavior" they actually observed in the market into the research model of financial market.[3]

D Hirshleifer and S Hong Teoh believe there are many patterns of capital market convergence and fluctuation, such as fixed bad projects, stock market plunge, rapid changes in investment and unemployment, bank runs and so on. Even in the face of negative external benefits, such behavioral convergence often occurs. Although other factors hinder inefficient behavior, the theory of rational social learning, especially cascades theory , is different, which means universal and vulnerable herding behavior.[4]

N Barberis, A Shleifer and R Vishny argue that empirical studies in finance reveal two common laws: the overreaction of stock markets to news such as earnings announcements, and the overreaction of stock markets to a series of good news or bad news. They proposed an investor sentiment model consistent with the empirical results. The model is based on psychological evidence and can be used to study how investors form beliefs and produce parameters of underreaction and overreaction.[5]

M Baker and J Wurgler studied the impact of investor sentiment on cross-sectional stock returns. They found that investor sentiment volatility has a greater impact on securities that are highly subjective in valuation and difficult to arbitrage. Traders were in low mood at the beginning of trading, and then returns were relatively high in small stocks, young stocks, highly volatile stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and bad stocks. On the other hand, when sentiment is high, the returns of these types of stocks are relatively low.[6]

Sushil Bikhchandani and Sunil Sharma made a partial summary of the theoretical and empirical research on Herding Behavior in financial markets. Starting from the meaning and causes of herding behavior, this paper expounds the influence of herding effect on financial market by using existing research results.[7]

WU Fu-long, ZENG Yong and TANG Xiao-wo think that herding effect can be divided into rational herding effect and irrational herding effect. Rational herding effect can accelerate the speed of securities price discovery and maintain market stability; irrational herding effect can slow down the speed of price discovery and aggravate market turbulence. [8]

Summary

From the results of this empirical analysis, the investor sentiment index in financial market is interrelated with the Shanghai Composite Index. From Figure 6, we can see that the positive impact of the Investor Emotion Index (isi) will lead to the upward change of the Shanghai Composite Index, which indicates that the investor sentiment in the financial market, as an important psychological feature of investors in investment decision-making, is one of the important factors affecting the change of financial asset prices and the volatility of financial markets. When market participants hold optimistic investment forecasts for the stock market as a whole, they will promote the upward development of stock market prices, and vice versa.

Changes and fluctuations in asset prices in financial markets will have an impact on investor sentiment. From Figure 7, we can see that a positive impact of the Shanghai Composite Index clsidx will have an upward impact on the investor sentiment index. This shows that the fluctuation of financial market prices will affect the financial market investors'prediction and judgment of future financial market prices, and then affect the overall investor sentiment in the financial market. When the stock market price rises as a whole, investors will hold more optimistic predictions and judgments about the future stock market. The positive changes of investors'investment sentiment will mainly be reflected in two aspects: one is to attract more investors to participate in the investment of the stock market; the other is to encourage traders who have already participated in the investment of the stock market to invest more funds.

Although investor sentiment and stock market interact, they interact in different ways. From the results of Figure 6, we can see that the impact of investor sentiment changes on the Shanghai Composite Index has not been fully realized in the current period, and there is a time lag. There are many factors behind this phenomenon. Firstly, for the off-the-counter investors, because they do not pay attention to the information of the stock market, they will not know the rising price of the stock market at the first time. Even if they know, there may be a period of continuous watching, which makes the change of the off-the-counter investors' mood not turn into the actual investment in the stock market at the first time. Second, for on-site investors, investor sentiment needs a certain time to change from the initial small-scale, shallow level to produce a wide range of deep-seated impact. The herding mentality of investors takes a certain time to produce in a larger range, thus exerting greater influence on the stock market after that.

From the results of Figure 7, it can be concluded that the impact of the current changes of the Shanghai Composite Index on investor sentiment fluctuates and decreases with the increase of lag time. It shows that investor sentiment is more affected by recent market changes, which proves that investor sentiment has a certain proximity effect.

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