International Journal of Database Theory and Application
Vol.9, No.8 (2016), pp.371-380
http://dx.doi.org/10.14257/ijdta.2016.9.8.33

Influence of Chinese Stock Index Futures on Investor Sentiment Volatility based on EGARCH Model and Big Data Mining

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Abstract

The introduction of stock index futures (Hereinafter referred to as SIF) marks an important measure of China's stock financial reform and imposes a profound impact on the development of the stock market. From the perspective of behavioral finance, this study employs the EGARCH model and its message–response curve (Hereinafter referred to as MRC) to conduct an empirical study on the long-term effects and influence of the introduction of SIF on investor sentiment. The results show that the introduction of SIF has first increased the volatility of investor sentiment and, second, demonstrate the asymmetric reactions of 'good news' and 'bad news' as per the variations of MRC flatting degrees. Therefore, this indicates an escalated sensitivity of investor sentiment to "bad news".

Keywords: *Stock index futures, Investor sentiment, EGARCH model, Empirical analysis*

1. Introduction

On 16 April 2010, China officially launched the first stock market-linked index futures, the Shanghai-Shenzhen (CSI) 300 SIF (stock index futures), with an initial vision of stabilising stock market fluctuations and avoiding systemic risks; however, the actual performance has been far from satisfactory. The Everbright Securities' 'Fat Finger' incident and the recent drastic market fluctuations show that SIF failed to stabilise the market in irrational exuberance and panic crash, whereas Chinese the stock market is characteristic of 'emerging and transitional' features and drastically susceptible to investor sentiments compared with more mature stock markets; therefore, this study focuses on the systemic impact of the introduction of SIF on investor sentiment.

Currently, academic discussions on SIF focus on three aspects. The first is the SIF's price discovery role on the spot market. Hua and Liu studied this role with high-frequency data. Their results showed the SIF market's strong price discovery capacity and predominance [1] in the transmission of information. Xiao (2006) used the general factorisation model and impulse response function to test multiple futures markets' price discovery effects on the spot markets. Their study showed that the futures market plays the role of an information (pricing) centre [2] in the price discovery process. Yang and Wan (2010) showed that the initial SIF market amplifies the market volatility, which will be reduced along with constantly improved market investment mechanisms [3]. Second, there are two opposing views in relation to SIF's impact over spot market volatility and its significance: one view holds that SIF will affect spot market volatility, whereas the other view is quite the opposite: Tu and Guo (2008) conducted a theoretical analysis of the impact of SIF on the spot market price, deeming that the introduction of index futures may reduce the volatility of the market [4]. Third is the volatility of SIF returns. Chaboud (2010), Patton and Sheppard (2009), Martens and Dijk (2007) and other studies realised

ISSN: 2005-4270 IJDTA

the description of SIF volatility characteristics via double power, range and other methods [5-7]. Domestic scholars like You Rui, Xie Chi, Zeng Zhijian, *et al.*, (2011) and others, used three classic approaches: realised volatility, realised range volatility and realised double power volatility under intra-day high-frequency information environment to measure the income fluctuations of the CSI 300 index futures [8]. Wang Peng and Wei Yu (2014) compared several measurement methods of SIF volatility [9]. However, most studies depend on the traditional CAPM asset pricing paradigm. Chen Junhua and Zinoviev (2014) found that the Shanghai and Shenzhen 300 SIF market has a lot of noise investors, with higher market volatility and who are subject to great risk exposure [10]. Xie Jun, Yang Chunpeng, *et al.*, (2012) found that in high-frequency environments, SIF market investor sentiment is an important systemic factor for index futures pricing and has significant positive influence on SIF earnings. It has also manifested an obvious intra-day impact on SIF contracts [11].

In sum, on the basis of the modelling of the volatility of Chinese stock market investor sentiment, this study explored the potential influence of the introduction of SIF over investor sentiment fluctuations. This will not only enrich the SIF risk management academic literature but provide empirical reference for the further deepening of China's securities industry reform to prevent SIF market risk.

Figure 1. Stock index futures trend

2. Literature Review

2.1. Investor sentiment

The concept of investor sentiment first appeared in the bear market sentiment index of the American investor intelligence magazine in 1963. Foreign scholars have carried out researches on investor sentiment, the domestic scholars because of the development of China's capital market relatively late, so the investor sentiment of late, most still use Chinese and foreign scholars on the definition, but in foreign definitions related to investors the mood in the definition is still not formed a unified standard, this is because the investor sentiment belongs to the research category of behavioral finance, psychology and finance and behavioral finance cross category, learn so far has not formed a complete theoretical system, one reason is because the behavioral finance research started late on the other hand, reason is that behavioral finance will combine the finance and psychology of people, joined the psychological characteristics of people is difficult to quantify, with science and technology The development of people's ability to accept information and process information with great changes over time, which makes more difficult and difficult to grasp the behavior of financial research, and thus the definition of investor sentiment is difficult to unify. At present, most of the domestic and foreign scholars on the definition of investor sentiment is basically from the combination of Finance and psychology to elaborate and illustrate.

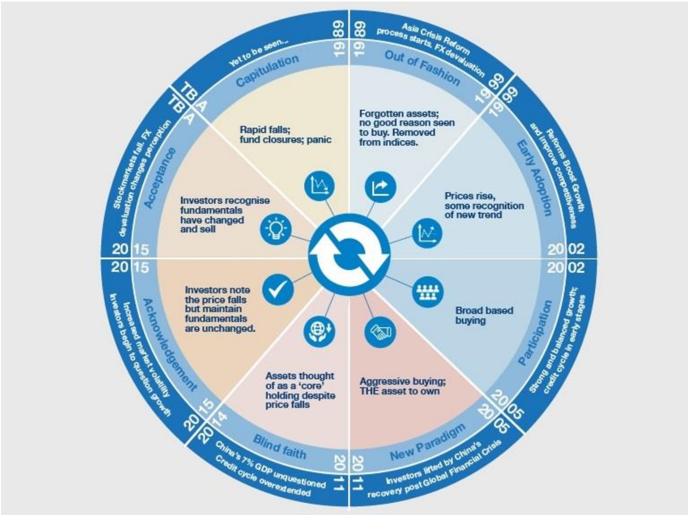

Figure 2. The Chinese investor sentiment

The direct investor sentiment index, the index can reflect different groups of investors on the market in the future trend of attitude, generally divided into bullish, bearish or look flat, the index is through a questionnaire to reflect, one is the use of alternative economic index. Domestic and foreign scholars use more such indicators have the following:

- ***Smart investors index (II index):*** by Chartcmft system, surveyed more than 130 newspapers in the stock market review specialist view of the market, divided into the call and put three and look at the expected market, the index is defined as the percentage of bullish and bearish percentage difference, is considered to be representative of medium-sized investor sentiment the.
- ***Morgan investor confidence index:*** the investor confidence index survey of investors in response to investor sentiment index based on first announced in early 1990s the British market investor confidence index, through the survey of investors on the market expectations, investment risk and other aspects of the attitude and the index system. This kind of index market organization's research and development personnel use is quite many, mostly is based on this index to construct the investment strategy.
- ***The American Association of individual investors index (AAII index):*** a monthly survey by the American Association of individual investors and investors from the beginning of July 1987 judgment for the next six months in the market, based on the proportion of bullish or bearish compiled, mainly reflects the change of individual investor sentiment.
- ***Friendly index:*** Hadadi based on the national main press, the fund and the investor's weekly trading proposal, through the scoring to assess their optimism or pessimism.
- ***Alternative indicators of economic index:*** the index of economic indicators in the domestic academic research is more consumer confidence index. Consumer confidence index from the National Bureau of statistics Economic

Prosperity Monitoring Center from 1997 to prepare, reflecting the strength of consumer confidence index. The index is composed of the consumer expectation index, the consumer satisfaction index and the consumer's main industry, and provides detailed statistical data according to the age, income level and regional division.

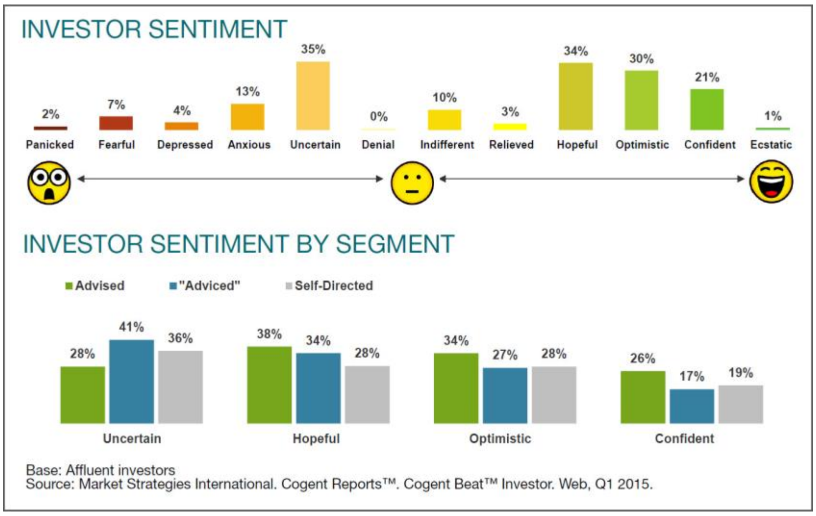

Figure 3. Investor sentiment

2.2. The relationship between investor sentiment and market

A foreign investor sentiment and market returns more research, Wheatley (1998) to the closed-end fund discount rate as investor sentiment, the investor sentiment cross-section of different scale stock portfolio yield effect, the index of different sizes in different scale of company stock, and can predict the future income of small companies stock; Baker, Wurgler (2006) BW was constructed on the sentiment index of investor sentiment on stock portfolio effects of different types of cross section, found that investor sentiment volatility of speculative arbitrage to stock a greater impact, the sensitivity of other types of stock portfolio of investor sentiment are different; Baker (2009) based on BW index research the Anglo American Ridefajia six stock market index of investor sentiment, and the six indexes of synthesis of global sentiment index, the study also found that investor sentiment Cross section effect of different types of stock portfolio

Statman (1988) studied the relationship between investor sentiment and market index returns that sentiment on the market in short three yields were not significantly affected by tatman; (2000) opposite views, they think of strategic investors and individual investors and market future earnings were negatively correlated, but this relationship in large and small investors significantly. But in the investors is not significant, and that the mood of a reverse indicator of big and small investors the relationship between investor sentiment and market index returns that sentiment on the market in short three yields were not significantly affected; Fisher, Statman (2000) opposite views, they think of strategic investors and individual investors and the market future returns are negatively related, but the relationship between the large and small investors significantly, but in the investors is not significant, and that the mood for large and small investors a reverse indicator. Schmeling (2009) believes that the consumer confidence index to characterize individual investor sentiment, and found that it has a negative relationship with the market earnings, sentiment is a reverse indicator.

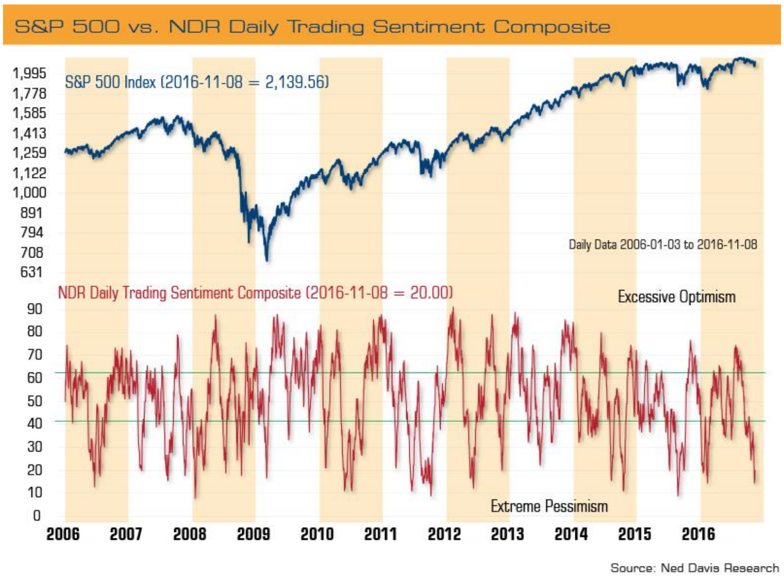

Figure 4. The relationship between investor sentiment and S&P 500

3. Research Methods

3.1. Introduction of research model

The volatility of financial time-series often shows a clustering phenomenon, namely, most series exhibit drastic time-phased fluctuations after relatively stable periods. Bollerslev (1986) proposed a GARCH model to provide better tail characteristics descriptions of the financial time–series. This model added an autoregressive lag item in its variance equation, which can predict the fluctuation variance, whereas the conditional variance is subject to the co-influence of new information and previous conditional variances. The GARCH variance equation is expressed as:

$$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots a_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \cdots \beta_q \sigma_{t-q}^2 \quad (1)$$

Let I_t express investor sentiment from time t-1 to t in a market and investors' information set at time t-1 for next stage decision-making is L_{t-1} ; then, investors' sentiment volatility and risks are conditional mean and conditional variance:

$$y_t = E(I_t|L_{t-1}),\ \ h_t = Var(I_t|L_{t-1}) \quad (2)$$

Deviation in investor sentiment volatility at time t is:

$$\varepsilon_t = I_t - y_t \quad (3)$$

Random variable ε_t can be used to measure the 'market news', $\varepsilon_t < 0$ indicates the market has 'bad news', $\varepsilon_t > 0$ indicates 'good news', $|\varepsilon_t|$ expresses the 'strength' of the news and the square embodies corresponding volatility.

In sum, the GARCH (1,1) model can be expressed as:

$$I_t = \mu + \sigma I_{t-1} + \varepsilon_t$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad (4)$$

Wherein the conditional variance h_t is expressed as a function of the average level of volatility ω, pre-disturbance item information ε_{t-1}^2 and early prediction variance h_{t-1} . α + β can measure the volatility persistence under a given impact. We can see from the above equation that the GARCH model assumes that the external impact of ε_t upon conditional method is symmetric, which is not applicable to the description of investor sentiment volatility, which is asymmetric; hence, this study adopts the Nelson (1991) EGARCH model, which no longer requires non-negativity of parameters. Conditional variance of the EGARCH (1,1) model is:

$$\log(h_t) = \omega + \alpha\left|\varepsilon_{t-1}/\sqrt{h_{t-1}}\right| + \beta\log(h_{t-1}) + \delta(\varepsilon_{t-1})/\sqrt{h_{t-1}} \quad (5)$$

As the EGARCH model adopts logarithmic transformation without parameter constraints and the conditional variance is dependent on the absolute level of information shocks, it can reflect the impact and its direction. If $\delta \neq 0$, then the information impact is asymmetric; if $\delta < 0$, then the leverage effect is significant.

This study chooses the EGARCH model as an analytical tool for an empirical analysis of the long-term effect of the introduction of SIF on investor sentiment fluctuations in the Chinese stock market. The EGARCH model is used in the analysis for separate modelling of volatility changes of investor sentiment before and after the introduction of SIF.

3.2. Data selection

According to the research contents, this study first measures China's securities market's investor sentiment. The current literature has direct and indirect methods to measure investor sentiment. Baker and Wurgle (2006) selected 6 indices closed-end fund discount, IPO numbers, IPO rate of return, trading volume, and stock and securities issuance proportion to construct a composite sentiment index, namely, the BW index [12] via principal component analysis. Based on the BW index, domestic scholars Yi Zhigao, Mao Ning (2006), Huang Delong and Wen Fenghua et al. (2009), separately established a new investor sentiment index commensurate with the situation of China [13]. Taking into account data availability and related studies at home and abroad, this study selects turnover (TURN), price/book value ratio (PB), price-earnings ratio (PE), number of new accounts (NA), money for IPO (MIPO), rise and drop level (RADL) and average share price (ASP) as index components for a sentiment measurement model. The data time span in this empirical analysis is weeks-based and the sample period for main board is from January 1997 to June 2015. In the analysis, to exclude the short-term impact of SIF introduction on investor sentiment volatility, we take the SIF Launch Day of 16 April 2011 as a reference. Fifty observations of the dates before and after that date are excluded, respectively, and the remaining data are taken as research samples. All data is from the Wind database.

4. Empirical Results

4.1. Research design and methods

This study adopts principal component analysis to construct investor sentiment index for China's securities market. While building the sentiment index, we first analysed the lead–lag relationship between the indexes and the sentiment index to determine the lead–lag integration of indexes (see Table 1). Second, the orthogonal regression method is used to eliminate the impact of investor sentiment index on macroeconomic fluctuations. This study takes the value of the growth rate of industrial added value divided by producer price index as the orthogonal regression parameter. Third, the processed index data used principal component analysis to construct the corresponding index of investor sentiment.

Investor Sentiment Index of China's Securities Market:

$$ZISI_t = 0.412TURN_t + 0.256PB_{t-1} + 0.312PE_{t-1} + 0.398NA_{t-1} + 0.334MIPO_t + 0.641RADL_t + 0.362ASP_{t-1} \quad (6)$$

Table 1. Correlation Test of Sentiment Indexes

Correlation	NA_{t-1}	$TURN_t$	PB_{t-1}	PE_{t-1}	$MIPO_t$	$RADL_t$	ASP_{t-1}
NA_{t-1}	1						
$TURN_t$	0.601**	1					
PB_{t-1}	0.535**	0.235**	1				
PE_{t-1}	0.352**	0.303**	0.445**	1			
$MIPO_t$	0.272**	0.312**	0.511**	0.526**	1		
$RADL_t$	0.417**	0.497**	0.312**	0.231**	0.378**	1	
ASP_{t-1}	0.437**	0.461**	0.408**	0.205**	0.522**	0.402**	1

Note: ** indicates a significance level of 5%

According to the established Chinese stock market investor sentiment index, to reduce errors and the impact of volatility and facilitate empirical research, this study defines investor sentiment volatility as $I_t = \log ISI_t - \log ISI_{t-1}$. First, a stationary test is performed on investor sentiment index volatility series. These test results are shown in Table 2. The Jarque–Bera statistic is far greater than any reasonable threshold levels of significance; therefore, the normal distribution assumption of investor sentiment index volatility series is rejected.

Table 2. Normality Test of Investor Sentiment Volatility Series

	Skewness	Kurtosis	$Jarque-Bera\ Statistic$	P-value
I_t	2.14008	9.12471	996.341	0.00000

Further, the ARCH-LM test method is used to test stability of the investor sentiment index volatility series, namely, the existence or absence of ARCH effect. First, regression is made on the sentiment index volatility series to derive the residuals sequence and take 12 lag orders for verification. The results obtained are shown in Table 3. The investor sentiment index volatility series showed a typical volatility clustering phenomenon, indicating a certain degree of conditional heteroscedasticity in the volatility series; hence, the use of EGARCH model for volatility modelling is reasonable.

Table 3. ARCH Test Results of Investor Sentiment Volatility Series

I_t	F-statistic	9.938380	Prob. F(12,735)	0.0000
	Obs*R-squared	171.6839	Prob. Chi-Square(12)	0.0000

4.2. EGARCH (1,1) model

Based on the above test results and the EGARCH (1,1) model, this study performed the fitting of investor sentiment index volatility series before and after the introduction of SIF, respectively. The results are shown in Table 4.

Table 4. EGARCH (1,1) Estimation of Investor Sentiment Volatility Series Before and After the Introduction of SIF

	ω	β	γ	α	σ^2
Pre-launch of SIF	−0.178	0.811	−0.175	0.126	0.0002354
Post-launch of SIF	−0.121	0.996	−0.239	0.235	0.0046327

The message–response curve (MRC) can be deduced from the parameters of the EGARCH (1,1) model, as shown in Figures 1 and 2.

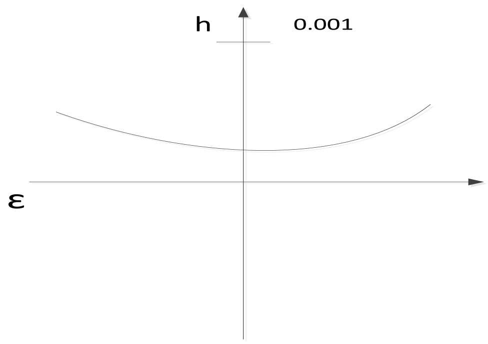

Figure 1. Message–response curve before the launch of SIF.

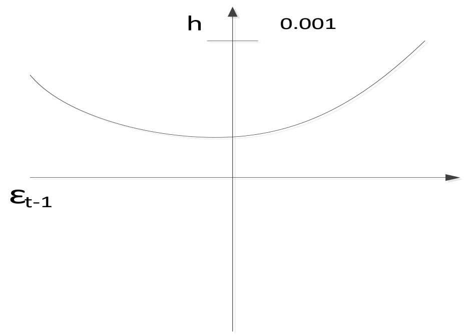

Figure 2. Message–response curves after the introduction of SIF

In sum, it can be seen from Table 4, that the EGARCH (1,1) model parameters of investor sentiment index volatility series changed from the pre-launch 0.0002354 to post-launch 0.0046327 before and after the introduction of SIF. Judging from the volatility measure of σ ^ 2, the introduction of SIF augmented investor sentiment volatility, which is significantly higher than before the pre-launch value. The γ-value, as a measurement of the asymmetric effect, is significantly negative either before or after the introduction of SIF, indicating that the shock effect of bad news on investor sentiment is greater than that of good news. The introduction of SIF did not change the asymmetric effect of volatility in investor sentiment. Judging from the α, the β value that measure the shock effect of historical messages and the previous message after the introduction of SIF, the α value increased from 0.235 to 0.126, indicating the impact of the previous message on investor sentiment volatility increased. The β value rose from 0.811 to 0.996, also indicating an increase of the impact of historical messages on the current investor sentiment volatility.

From Figures 1 and 2, it can also be seen that investor sentiment index volatility has significant asymmetric effect; that is, the same size of bad news can lead to greater volatility than good news. When ε_ (t-1) = 0, it indicates investor sentiment volatility without the impact of news. Judging from the MRC, after the introduction of SIF, investor sentiment volatility increased significantly. As a whole, the curve is relatively flatter before the introduction of SIF.

5. Conclusion

The results of this study show that the introduction of SIF has increased the volatility of investor sentiment. It also demonstrates the asymmetric reactions of good news and bad news as per the variations of MRC flatting degrees, indicating an escalated sensitivity of investor sentiment to bad news.

This fact contradicts with the original intention of SIF to stabilise the spot market as well as the futures market. This is probably due to the fact that China’s stock market, as a new and developing market, has a serious phenomenon of noise trading and significantly irrational behaviour. Market investors believe that SIF reflects a variety of stock index-related information, and the expectations of different buyers and sellers; they are over-confident upon the leading role of SIF. However, if SIF is manipulated, then the artificially distorted market prices and confused market expectations will exacerbate market volatility instead of stabilising the overall market sentiment. In extreme cases, drastic volatility of SIF is bound to result in dramatic changes in market sentiment, causing economic and financial systemic risks. Therefore, this study recommends the following: first, the SIF trading system should be modified to increase the cost of speculation and difficulty of manipulation; second, more comprehensive hedging transaction instruments should be introduced to reduce the impact of SIF hedge instruments; and third, supervision shall be strengthened to crack down on illegal manipulations.

Acknowledgments

The authors would like to thank the editor-in-chiefs, the area editors and the referee(s) for giving useful suggestions and comments for the improvement of this paper.

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