Irrational Exuberance in Financial Markets: Empirical Evidence from Investor Sentiment in the Shanghai Stock Exchange

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Abstract

Nowadays, one of the biggest contemporary financial issue exists in the financial markets is irrational exuberance, which is also known as bubble. It can be defined as periodic episodes where assets are unduly over-valued than their fundamentals by irrational investor. Since the noise trader risk model was proposed by De long et al. (1990), a promising topic in behavioral finance, namely investor sentiment, has been developed to reveal the impact of investors irrationality on financial markets. This paper firstly identifies six reasons for the crash in the Chinese stock market in 2015, and secondly, conducts principle components analysis to construct sentiment index in the Shanghai Stock Exchange. By carrying out Johansen cointegration test, this paper finds the sentiment index and the Shanghai Stock Exchange price index exist in long-run relationship, and market returns on the Shanghai Stock Exchange Index Granger cause sentiment index. In addition, this paper examines the mean-variance relation between monthly excess return and conditional variance in different sentiment regimes. However, I find mean-variance relation is significantly negative, and the presence of sentiment weakens this negative mean-variance relation, which seems to be consistent with theoretical implication from the noise trader risk model (De long et al. 1990).

Preliminary draft

Key words: Irrational Exuberance, Investor Sentiment, Volatility, Mean-Variance relation, Sentiment regimes

Introduction

Irrational exuberance was firstly used by Alan Greenspan, Chairman of the American Federal Reserve, in the speech on Dec 5 1996, to express his worry about the unduly escalated asset values in financial markets. Three years later, Nobel laureate Robert J. Shiller (2000), wrote a book called "Irrational Exuberance" just before the Internet Bubble broke. In his book, he revealed the irrational exuberance behind the Internet market, which was inconsistent with the fundamental economic growth. In other words, it was a bubble. However, under the traditional finance paradigm, where investors are assumed to be rational utility maximizers, theoretical frameworks such as CAPM and Efficient Market Hypothesis cannot explain the existence of irrational exuberance in the financial markets. Fortunately, behavioral finance, which takes investor psychology into account, has emerged in response to difficulties faced by the traditional finance paradigm (Barberis and Thaler 2003).

Indeed, the issue of irrational exuberance exists in financial markets and has led to numbers of markets crash since the tulip bubble happened in the 17th century. More recently, the bubble in Chinese stock market resulted in the market crash in June 2015. Unfortunately, few empirical test has been done to examine impacts of investor sentiment on this market crash. The aim of this paper, is first, to reveal factors that boosted irrational exuberance in Chinese stock markets. Second, sentiment-based empirical findings will be presented, which enable us to take insight of the role of investor sentiment that played in this market crash.

The paper is organized as follows: Section I briefly describes the reasons for Shanghai stock market crash and reveals six factors that contributed to it. Section II chooses six sentiment proxies to construct the investor sentiment index in Shanghai Stock Exchange from January 2009 to March 2016 by conducting the principle components analysis. Section III examines the cointegrating relationship between the Shanghai Stock Exchange price index and sentiment index, and the Granger causality between market returns and the change of investor sentiment. Section IV identifies the relationship between market excess return and its volatility in high- and low sentiment regimes based on two volatility model, namely GARCH(1,1) model and Rolling window model. The last section concludes our main findings and their theoretical implications.

Section I: The crash of Shanghai Stock Market

Shanghai Stock Exchange, the largest stock market in China, crashed in June 2015.

However, before the market crash, the market price index soared from 2038 in 9/07/2014 and peaked at 5166 in 12/06/2015. Only two and a half months later, almost a half of market value was wiped out. As a result, market participants, especially individual investors, suffered a big loss.

Unfortunately, there is few academic paper that identify the reasons for the market crash. Drawing on Shiller' book (2000), this paper examines six factors that give rise to the bubble in the Chinese stock market in 2015.

Economy revived after the global financial crisis but the real interest rates is low

Although the global financial crisis happened in 2008, China' economy revived very quickly and GDP soared from around ¥27 trillion in 2008 to ¥68 trillion in 2015. In the meantime, the GDP per capita rocketed from ¥20,000 to ¥50,000. As Chinese people were wealthier than before, it was understandable that they invested more savings into the stock market. (Appendix 1)

The question is why Chinese investors did not save their money into banks? Since 2012, the basic one-year interest rate in China has declined by 8 times to 1.5% in 2015. However, the inflation rate in China kept high. As illustrated in the graph (Appendix 2), the inflation rate was higher than the interest rate in 2012, and kept close to the interest rate after 2012. Hence, if people put their savings into the bank, the real interest rate was negligible. As a result, investing into the stock market seemed to be a better choice.

Multiple channels to trade stocks

Nowadays, more and more stock trading computer softwares and mobile applications have been invented, so it is more convenient to trade stocks than ever before. Traders do not need to go to the security exchange and ask the dealers to help them with their transactions any more. Instead, they can easily use their computers or mobiles to do real-time transactions. The technology development in stock trading is a strong incentive that simulates an increasing number of investors to engage in stock markets, which in turn boosting the prosperity in the stock market.

The growth of securities companies and new stock trading accounts

Just as Shiller (2000) identified the growth of mutual funds as one of the reasons for the Internet Bubble, this paper attributes the stock market bubble to the fast increase of securities companies, which mainly serve individual investors as dealers in China that help them to open stock trading accounts as well as to trade stocks. The number of securities companies soared from 704 in 2010 to 2723 in 2015. More surprisingly, as illustrated by the panel, the number of new stock trading accounts was 26.16 million in 2015 while it was merely 5.26 million in 2012 (Appendix 3)

Less trading cost with high stock turnover rate

Trading cost cannot be neglected in the stock market, and generally, lower trading cost encourages more frequent transactions. In China, the main stock trading cost is called the trading stamp tax. According to Deng, Liu and Wei (2014), the trading stamp tax reduced from 6‰ to 2‰ on 24 August, 2008. In addition, trading stamp tax for buyer was abolished On 19 Sep, 2008, and stamp tax for seller was reduced to 1‰ at the same date. Deng, Liu and Wei (2014) point out in an immature stock market, higher transaction costs will discourage the noise traders but lower transaction costs make stock prices more volatile.

Analysts' increasingly optimistic forecast in TV programs

According to Shiller (2000), analysts' increasingly optimistic forecast in TV programs contributes to the Internet Bubble. As the stock market becomes a hot topic, there are plenty of TV programs about stocks investment, and commentators of these TV programs are often notable experts in economic and finance area. These experts always give an optimistic forecast when the market is bull. For instance, one of the most famous economist, Xianping Lang, advised people to keep investing in the stock market in his TV show. However, it was very ridiculous as bubble crashed in the following week after his TV show. Moreover, Truemen (1994) suggests herd behavior exists among the analysts, so they tend to release a forecast that is closer to or even more optimistic than prior return expectations announced by other analysts. Hence, an increasingly optimistic forecast that experts instilled into naïve investors contributed to the bubble.

Herd behavior among individual investors and its epidemics

Herd behavior is defined as individuals altering their opinions to be consistent with the publicly expressed views from others (Cote and Sanders 1997). Shiller (2000) points out herd behavior is epidemic and even completely rational people can participate in herd behavior, thereby leading an irrational group behavior. In addition, Spyros (2013) thinks herd behavior that is widespread among institutional and individual investors is the primary reason for the stock price volatility. Moreover, Chang (2014) suggests when social interactions among the investors get stronger, the herd behavior rises and a small bubble may become bigger as more investors are engaged in herd behavior.

Therefore, it is reasonable to argue herd behavior among investors gives rise to irrational exuberance in the stock market since the majority of investors in Chinese stock markets are individual and lack experience. More specifically, when the stock price in Chinese stock market was pushed up by some irrational investors, other investors followed their steps and pushed the price to an extremely high level where the bubble formed.

Section II: Construction of investor sentiment

Sir Issac Newton has stated "I can calculate the motions of heavenly bodies, but not the madness of people", after he suffered a big loss in the South Sea Company bubble in 1720s.

Nowadays, academic papers suggest the madness of people is measurable, namely investor sentiment. The most widely used approach to measure investor sentiment by using market and macroeconomic variables is introduced by Baker and Wurgler (2006, 2007). By choosing six objective indices including discount of closed-end fund, NYSE turnover, the number of IPOs and the mean 1st-day IPO return, the premium for dividend-paying stocks and equity share in new issues, Baker and Wurgler (2006, 2007) use the first principle component analysis to pick up common components of aforementioned indices as the proxy of sentiment index, namely BW index. They also construct long-short portfolios based on different firm characteristics such as size, age and book-to-market value, and run the regression between long-short portfolios return (R_t) and the beginning-of-period sentiment ($Sentiment_{t-1}$) to test predictability of sentiment on future cross-section stocks return. The test result demonstrates that when sentiment is high, stocks with speculative characteristics such as younger and small earn a low subsequent return. In addition, Baker, Wurgler, and Yuan (2012) provide further evidence to prove investor sentiment is essential to volatility in international markets. However, instead of BW index, they choose the number of IPOs and the mean 1st-day IPO return, volatility premium and share turnover as proxies of investor sentiment. In addition, they use the first principle component analysis to pick up the global sentiment index from total sentiment indices in six countries. The test result shows when both global and local sentiment are high, local stocks earn low returns. Instead of first principle component analysis, Huang et al. (2015) use the same proxies as BW index does but adopt the partial least squares method to present a better predictive regression for aggregate market return and cross-section stocks return than the principle component analysis.

Another approach to measure investor sentiment is text based. For example, Tetlock (2007) obtains pessimistic media factor by conducting the principle component analysis to capture the maximum variation from 77 predetermined GI categories, in which daily variation in the Wall Street Journal "Abreast of the Market" column has been analyzed. Then he constructs a Vector Autoregression with five lags, in which the endogenous variables are Dow Jones Industrial Average, the pessimistic media factor and the detrended log of daily volume, while the exogenous variables are detrended squared Dow Jones Industrial Average residuals, dummy variables for weekdays and January and another dummy variable for the market crash on October 19, 1987.

Methodology and Data

This paper adopts the following six sentiment proxies to construct monthly sentiment index:

1) Consumer Confidence Index (CCI). Prior works suggest CCI can be reviewed as a sentiment proxy. For instance, Fisher and Statman (2003) argue there is strong positive relationship between changes in consumer confidence and changes in investor sentiment. Lemmon and Portniaguina (2006) use consumer confidence to measure investor optimism. This paper uses the monthly CCI as a proxy of investor sentiment.

2) Closed-end fund discount, CEFD. Closed-end fund discount is the difference between market prices of closed-end fund shares and their net asset values. Prior published papers indicate CEFD is correlated with investor sentiment. De long et al. (1990) are first to argue the noise trader risk can explain the fluctuation of CEFD. Lee, Shleifer and Thaler (1991) point out CEFD can be a good sentiment proxy. This paper uses the monthly value-weighted closed-end fund discount rates as a sentiment proxy:

$$CEFD_t=\sum_{i=1}^{n}\{[(Pit - NAVit)/NAVit]*CF_{it}\}/M_t$$

P_{it} is the market price of shares of closed-end fund i on the last transaction day of every month. NAV_{it} is the corresponding net asset value for per share. CF_{it} is the value of the closed-end fund i, calculated by multiplying NAV_{it} with number of shares in closed-end fund i. M_t is the total value of all close-end funds in month t. Since this paper uses the above formula to calculate the CEFD, the sign of CEFD is different from that in Baker and Wulger (2006). That is when CEFD is less than 0, it is discount, otherwise it is a premium. Therefore, we expect a positive relationship between our CEFD and sentiment index.

3) Share Turnover, ST. It is the ratio of traded shares to the market listed shares. As suggested by Baker and Stein (2004), the more optimistic investors are, the higher turnover rates will be. This paper uses the Shanghai Stock Exchange monthly share turnover as sentiment proxies, and SI is expected to be positively correlated with sentiment index.

4) The number of IPO, NIPO and the first day returns on IPO, RIPO. According to Baker and Wurgler (2006), the IPO market is often viewed as sensitive to investor sentiment. Hence, NIPO and RIPO can be both cited to reflect sentiment. The sample of NIPO and RIPO is from Shanghai Stock Exchange. The NIPO is the number of IPOs in month t. The monthly RIPO is value-weighted rate of return of IPOs in month t:

$$RIPO_t = \sum_{i=1}^{n} [(Pit - P'it) / P'it * Vit] / Mit$$

Where Pit is the closed price of stock i at the end of first day of IPO in month t, P'_{it} is its issued price, V_{it} is the market value of stock i at its IPO date, and M_t is the total market value of IPO stocks issued in month t.

5) Our last proxy is the number of new investor accounts opened, NIA. As the markets in developed countries are more mature, there are few papers has used this proxy to measure investor sentiment. However, Yi and Mao (2007) point out it is indeed a good sentiment proxy that can be applied into immature stock markets such as in China where the market history is less than 30 years. In addition, as discussed in the last section, the soar of NIA over last few years manifest the irrationality behind the market exuberance. Therefore, our prediction is sentiment index and the number of new account opened are positively correlated. The sample of NIA is monthly new trading accounts opened in

Shanghai Stock Exchange.

However, as suggested by Baker and Wulger (2006), sentiment proxies not only have the common investor sentiment component but also common business cycle components. Hence, they should be regressed on common business cycle components firstly, and orthogonalized sentiment proxies obtained from residuals in these regression will be better sentiment proxies. To remove the impact from business cycle components, this paper chooses two widely used economical index, namely the industrial production index (IPI) and the consumer price index (CPI). Baker and Wulger (2006) suggests INF is one of the common business cycle components that should be removed from sentiment proxies. As for CPI, it is a common business component that have impacts on our sentiment proxies. For instance, the first Section in this paper has concluded that inflation, generated from CPI, is one of reasons for more and investors to participate in the stock markets, thereby leading more investor accounts opened, which suggests CPI might be correlated with NIA. Hence, it is reasonable to remove CPI from our sentiment proxies.

CCI, IPI and CPI are obtained from Datastream, and CEFD is collected from CCER Database. ST, NIPO, RIPO and NIA are collected from the RESSET Database. All of above indices are monthly data from January 2009 to March 2016. In total, each sentiment proxy has 87 observations.

First of all, considering lagged effects of these proxies on sentiment, this paper runs principle component analysis for the standardized current and lagged values of aforementioned six proxies. The result suggests the lagged values of CCI, NIPO and RIPO are more correlated with the generated sentiment index.

Secondly, raw data of current values of CEFD, ST and NIA, and lagged value of CCI, NIPO and RIPO have been regressed on INF and IPI. The residuals generated from these regressions are saved, standardized and labeled with a subscript _.

Thirdly, principle components analysis has been conducted to pick up the common components from the above residuals as sentiment index. The test introduces six principle components, where only eigenvalues of first two principle components are more than 1, so the sentiment index should be generated from the first two principle components scores. The calculation procedures are:

$$PC1=\frac{0.327}{\sqrt{2.830}}CCI_{t-1}\_ + \frac{0.261}{\sqrt{2.830}}CEFD_{t}\_ +\frac{0.402}{\sqrt{2.830}}ST_{t}\_+ \frac{0.507}{\sqrt{2.830}}NIPO_{t-1}\_+\frac{0.337}{\sqrt{2.830}}RIPO_{t-1}\_ + \frac{0.510}{\sqrt{2.830}}NIA_{t}\_$$

$$PC2=\frac{0.165}{\sqrt{1.183}}CCI_{t-1}\_ + \frac{0.735}{\sqrt{1.183}}CEFD_{t}\_ - \frac{0.610}{\sqrt{1.183}}ST_{t}\_ - \frac{0.00321}{\sqrt{1.183}}NIPO_{t-1}\_+\frac{0.194}{\sqrt{1.183}}RIPO_{t-1}\_ - \frac{0.141}{\sqrt{1.183}}NIA_{t}\_$$

2.830 and 1.183 are eigenvalues of first and second principle components respectively, and numerators are factor loadings, namely eigenvectors. The sentiment index should be weighted average of the first two principle components scores, based on their eigenvalues, which is also the proportion of sample variance that they can explain. Thus, sentiments index scores are calculated as:

$$Sentiment\ Index = 0.472/0.669\ PC1 + 0.197/0.669\ PC2$$

Table 1 and 2 summarize our sentiment measures. PC1 account for 47.2% of total explanation of sample variance, while PC2 account for 19.7% of total explanation of sample variance. In total, they can explain 66.9% of variance, capturing the majority of information in the model. Lastly, we standardized the sentiment index scores obtained from the above equation.

The factor loadings in sentiment model is also be weighted average of factor loadings of first two principle components, based on their eigenvalues. Therefore, the parsimonious model of sentiment index is:

$$SENTIMENT_t = 0.201CCI_{t-1}\_ + 0.308CEFD_{t}\_ + 0.004\ ST_{t}\_ + 0.212NIPO_{t-1}\_ + 0.194\ RIPO_{t-1}\_ + 0.176NIA_{t}\_$$

The model is appealing, since all of the parameters on sentiment proxies are positive, which is consistent with existing empirical findings. The sentiment index leveled at around 0 from 2009 to 2013, but experienced a significant fluctuation in the pre- and post-market crash, suggesting a high sentiment regime during the bubble period (Appendix 4).

Table 1

Descriptive statistics about the monthly sentiment proxies and their correlations with sentiment index. The sample period is from January 2009 to March 2016. Raw data of current values of CEFD, ST and NIA, and lagged value of CCI, NIPO and RIPO are regressed agianst industrial production index and consumer price index firstly. The residuals obtained from regressions are orthogonalized sentiment proxies, labeled with a subscript _. Sentiment index has been generated from the first and second principle components of the orthogonalized sentiment proxies, namely SENTIMENT_.

	Mean	SD	Min	Max	Correlation with SENTIMENT_	Factor loadings on SENTIMENT_
$CCI_{(t-1)}$_	0	2.98	-6.8	6.37	0.63	0.201
$CEFD_{t}$_	0	4.12	-14.13	9.97	0.44	0.308
ST_{t}_	0	12.70	-20.25	35.08	0.68	0.004
$NIPO_{(t-1)}$_	0	3.48	-4.29	16.40	0.85	0.212
$RIPO_{(t-1)}$_	0	0.22	-0.38	0.58	0.57	0.194
NIA_{t}_	0	127.32	-116.36	558.93	0.86	0.176

Table 2

This table summarizes the eigenvalues of different order principle components and and eigenvectors of first and second order principle components

	PC1	PC2	PC3	PC4	PC5	PC6
Eigenvalues	2.83	1.18	0.88	0.63	0.30	0.16
$CCI_{(t-1)}$_	0.37	0.16	-	-	-	-
$CEFD_{t}$_	0.26	0.73	-	-	-	-
ST_{t}_	0.40	-0.61	-	-	-	-
$NIPO_{(t-1)}$_	0.51	-0.00	-	-	-	-
$RIPO_{(t-1)}$_	0.38	0.19	-	-	-	-
NIA_{t}_	0.51	-0.14	-	-	-	-

Section III: Cointegration and Granger causality

In the modern finance, it is very common that financial time series have same stochastic trends. Therefore, cointegration tests have been applied to capture their long-run relationships. Surprisingly, the trend of monthly price index in Shanghai Stock Exchange and of investor sentiment index are almost identical (Appendix 5). Since they may exhibit the same stochastic trend, this paper employees the Johansen cointegration test (Johansen and Katarina 1991) can to identify whether they have relationship in long-run. (This paper uses the market price index at the last trading day in a month to represent the monthly market index, because the first difference of natural logarithm is approximately monthly market return)

First of all, the natural logarithm of market price index has been taken (lgSI), as the natural logarithm does not change the properties and trend of data but can overcome the problem of heteroscedasticity. Secondly, the Augmented Dickey-Fuller test has been conducted, and the test result suggests both natural logarithm of market price index and sentiment index have one unit root, so the Johansen cointegrating test between two variables is applicable.

Table 3 presents the result for the Johansen test. Both the trace test and the maximum eigenvalue test suggest two variables are strongly cointegrated, indicating they exist in long-run relationship. According to Granger Representation Theorem (Granger and Lee 1989), cointegration and error correction model are necessary conditions on each other, and any cointegration relationship can be expressed as error correction models, so this papar generates error correction models by the Johansen test result:

$$\Delta(lgSI)t=0.026*(lgSI_{(t-1)}-0.258\ SENTIMENT\_{}_{(t-1)})+0.103\Delta(lgSI)_{t-1}-0.006\Delta SENTIMENT\_{}_{(t-1)}$$

$$\Delta(SENTMENT\_)t=1.888*(lgSI_{(t-1)}-0.258\ SENTIMENT\_{}_{(t-1)})+2.84\Delta(lgSI)_{t-1}-0.115\Delta SENTIMENT\_{}_{(t-1)}$$

In the vector error correction system, only the adjustment parameter of Δ(SENTIMENT_), the first difference of sentiment, is significant at 1% level of significance. It suggests all of the discrepancy from long-run equilibrium in the last month has been adjusted rapidly by Δ(SENTIMENT_) in the current month. In addition, $\Delta(lgSI)_{t-1}$, which is equivalent to the stock return in the last month, has a significantly positive short-term impact on the current change of sentiment

Δ(SENTIMENT_). Likewise, the Granger causality tests also suggests a significant causality relationship from Δ(lgSI), the stock market return, to Δ(SENTIMENT_), the change of sentiment, but not the other way round. Furthermore, impulse response function of the responsiveness Δ(SENTIMENT_) to the innovation to Δ(lgSI) suggests when there is a positive shock to Δ(lgSI), Δ(SENTIMENT_) will increase significantly in the first two months, and this kind of responsiveness dies out after three months (Appendix 6). Thus the sentiment has been driven up by positive shocks on market returns, and this kind effect can last around three months.

Table 3

Johansen cointegration tests between monthly price index of Shanghai Stock Exchange and investor sentiment index. The null pothesis is the number of cointegration.

Number of Cointegration	Trace stastistic	5% Critical value	p-values	Max-eigenvalue statistic	5% critical value	P-values
None	20.73	15.49	0.0074	16.32	14.26	0.0233
At most one	4.40	4.84	0.0358	4.40	3.84	0.0358

The intuition behind above empirical findings is simple. That is when the stock market generates high returns, more and more investors will be attracted and involved into the market, leading higher sentiment. This impact is particularly significant and persistent in bull markets, as bull markets generate returns more frequently than loss. Indeed, since middle of 2014, the price index of Shanghai Stock Exchange soared until June 2015, when it peaked at its highest point. During such a mania, sentiment traders became active in the stock market, giving rises of sentiment index, and the sentiment index also reached its highest point in June 2015.

However, when negative shocks came after June 2015, the responsiveness of change of sentiment became negative. It implicates sentiment traders became less active and dropped out from the markets gradually, thereby leading a decline in sentiment index. The market crash did not lead to the sentiment index to plummet to a very low level, where we call a panic. One possible explanation is that although the market crashed in June 2015, majority of investors were still very confident about financial markets, since the fundamental of the Chinese economy was still very good. The crash was just a temporary adjustment to the previous unduly escalated over-valuation by investors, namely irrational exuberance. Another possible explanation is that the market crash did result in a panic among the investors, as suggested by the significant drop after June 2015 in the sentiment index diagram. However, in August 2015, the Chinese Government input around 600 ¥billion pensions from pension funds into the stock market to prevent its further collapse and to avoid the same market tragedy as in 2007, when the Shanghai Stock Exchange Index plummeted from around 6100 to 1664 within just one year. With the bailout from the government, the panic did not keep long. Investor sentiment rose again after around September 2016, so the market was still in the high sentiment regime.

Section IV: Mean-variance relation

Yu and Yuan (2011) has published a remarkable paper to examine mean-variance relation in different sentiment regimes. They use the BW index as proxy of investor sentiment and identify the mean-variance relationship between high- and low sentiment. To test the tradeoff between expected return and volatility of market returns in high- and low sentiment regimes, they set up the following regression:

$$R_t = \alpha_1 + \beta_1 Var(R_t) + \alpha_2 D_t + \beta_2 D_t Var(R_t) + \varepsilon_t$$

in which, R_t is the monthly excess return (equal-weighted and value-weighted), $Var(R_t)$ is the conditional variance, using different volatility model, and D_t is the dummy variable to represent the high-sentiment regime. The test result is robust across four different volatility models. Additionally, the negative coefficient β_2 suggests mean-variance relation is weakened during the high-sentiment period, while a positive coefficient $\boldsymbol{\beta_1}$ shows there is positive mean-variance relation in the low-sentiment regime. Yu and Yuan (2012) point out sentiment traders have greater impacts on markets in the high-sentiment regime and their poor understanding of how to measure the tradeoff between the risk and return are the main reasons for a weaken mean-variance relation during high sentiment periods. In contrast, during low sentiment periods, there is a strong mean-variance relation as rational investors require more compensation for bearing more volatilities.

However, prior published papers suggest the relationship between the market access return and its volatility does not necessarily to be positive. Examples of negative mean-variance relation can be found from Campbell and Hentschel (1987), Nelson (1991), Glosten, Jogannathan and Runkle (1993), and Brant and Kang (2004). Campbell and Hentschel (1987) argue negative mean-variance relation does not violate the mean-variance framework under CAPM, since volatility is often higher when stock market falls than it rises in the same magnitude.

On the on other hand, even if mean-variance relation is positive, prior theoretical models in behavioral finance suggest this positive relation does not necessarily to be weakened by sentiment traders. For instance, De long et al. (1990) propose a noise trader risk model, in which noise traders, also known as sentiment traders, introduce a non-fundamental systematic risk that is priced. Thus noise traders can achieve abnormal returns over the expected return required by sophisticated traders. The abnormal return is subject to four effects, namely “hold more” effect, “price pressure” effect, “Friedman” effect, and “create space” effect. “Hold more” effect is known as that noise traders earn more returns as they are prone to hold more of the risky assets than sophisticated traders. “Price pressure” effect is when noise traders demand more of risky assets, the price of these assets will be driven up, thereby decreasing returns. “Friedman” Effect is known as noise traders’ misspecification may lead lower returns as they have poor market timing. “Create space” effect point outs that sophisticated investors are less likely to take advantage of noise trader misspecification, since they are risk averse and less likely to bet against the noise trader risk. The last effect is also known as the limitation of arbitrage, which is an important building block in the behavior finance. The evidence of limitation of arbitrage can be found from the case of Royal Dutch and Shell Transport (Froot and Dabora 1999).

De long et al. (1990) further argue a large “create space” effect will drive down the “price pressure” effect and the Friedman” effect. Therefore, if the “holding more” effect is significant, noise traders are more likely to achieve higher returns than sophisticated investors. Indeed, Lee, Jiang and Indro (2002) find there is a positive relationship between sentiment and market excess return across DJIA, S&P500, and NASDAQ indices, as the “holding more” effect is relatively more important than the other two negative effects on the expected return required by sentiment traders. Therefore, since sentiment traders are more likely to gain higher returns over expected returns required by non-sentiment investors, positive mean-variance relation dose not necessary to be weakened by the presence of sentiment traders in high sentiment regimes.

Drawing on Yu and Yuan (2011), this paper examines the relation between the monthly market excess returns of Shanghai Stock Exchange index and its conditional variance in low and high sentiment regimes. However, our findings are totally contradictory to those from Yuan and Yuan. Details will be discussed in following sub-sections.

Identifying sentiment regimes

Yu and Yuan (2012) rely on the value of the BW sentiment index to divide high and low sentiment regimes. More specifically, if the BW index is bigger than 0, it is a high sentiment regime, otherwise it is a low sentiment regime. However, our sample is from Jan 2009 to March 2016, where the sentiment index from 2009 to 2014 fluctuated around zero but was very close to zero. If we apply the same method by Yu and Yuan, it will be very hard to distinguish between low and high sentiment regimes for sentiment index that fluctuates around zero. In addition, this method is not satisfied since it does not manifest the magnitude of sentiment in bull markets. For instance, if the value of sentiment index is 0.5 it cannot be regarded as a high sentiment comparing with the value of sentiment index which is more than one. Therefore, a different method should be proposed to identify sentiment regimes in this paper.

Taffler and Tuckett (2005) point out unconscious investor psychology is the main driver of the dot.com bubble. They provide a psychoanalytic theory to profile different stages of investors’ emotion in different stages of bubbles. By the inspiration from Taffler and Tuckett, this paper proposes to use the multiple breakpoint tests, which have been widely used to find structural breakpoints in time-series, to identify investor sentiment regimes in the pre- and post- stock market crash. Comparing with simply identifying sentiment regimes by the value of sentiment index, the breakpoint tests can help to find the structural breakpoints in sentiment index, giving different sentiment regimes.

This paper conducts two structural break points tests. One is the information criterion method (Liu, Wu, and Zidek 1997), where the number of breaks has been identified by minimizing modified Schwarz criterion. The other is the Bai-Perron global maximizer test (Bai and Perron 1998), where the minimized sums of squared residuals determines the number of breaks in the regression model.

Firstly, the ordinary least square method has been applied to run the sentiment index against a constant:

$$SENTIMENT_t = \mu + \varepsilon_t$$

where ε_t is an error term. The information criterion method suggests the breakpoints happened in April 2012 and September 2014. Likewise, when defining two structural break points in the Bai-Perron global maximizer test, it also suggests April 2012 and September 2014 are breakpoints. In addition, both multiple breakpoint tests do not indicate a break point happened between June 2015 and March 2016, when the sentiment index decreased dramatically. It is consistent with the previous conclusion that the crash of market did not lead to a persistent sentiment decline. By contrast, the sentiment rebounded after August 2015, and the market was still in a high sentiment regime.

Since two tests generate the identical structural breakpoints, the pre- market crash can be traced from April 2012 to August 2014, when the market was not in a mania, namely the low sentiment regime. As for the period from September 2014 to March 2016, the trend of sentiment index suggests an obvious higher level. Hence, this period can be defined as the high sentiment regime.

Volatility models

This paper adopts two volatility models to generate the conditional variance of daily return of Shanghai Stock Exchange index, namely the GARCH(1,1) model and the Rolling window model. The daily return is obtained from RESSET database.

GARCH(1,1)

The GARCH model is a popular non-linear model that can used to model non-constant and conditional volatility in financial data. More specifically, it allows conditional variance in current period to be dependent upon on the volatility and fitted variance in previous period. The GARCH model was developed by Bollerslev (1986), based on the

ARCH model by Engle (1982). Generally, the GARCH (1,1) model is sufficient to capture the important features in volatility such as volatility clustering.

In this paper, the GARCH(1,1) model has been used to get the daily volatility of value-weighted market return on the Shanghai Stock Exchange Index:

$$r_t = \mu + U_t$$

$$h_t = \alpha + \beta_1 h_{(t-1)} + \beta_2 U_t^2$$

r_t is daily stock market return. h_t isconditional variance of daily return. $h_{(t-1)}$ is the conditional variance of daily return in previous period, and U_t^2 is squared residual. The monthly volatility of market excess returns can be generated as:

$$Var(R_t) = \sum_{t=1}^{n} h_t$$

where h_t is the daily volatility within month t, and n is the number of trading days.

Rolling window model

French, Schwert and Stambaugh (1987) firstly use the rolling window model to estimate conditional variance of market returns. Yu and Yuan (2012) also use it to estimate the volatility in stock markets. In this paper, monthly conditional variance of returns in Shanghai Stock Exchange can be generated as:

$$Var(R_t) = \frac{22}{n} \sum_{d=1}^{n} (r_d - r_m)^2$$

r_d is daily market return, and r_m is the mean return of month t. n is the number of trading days within month t and 22 is approximately number of trading days in one month.

Market access return

This paper uses monthly value-weighted returns on the Shanghai Stock Exchange index over risk free rates as the proxy of monthly market excess returns. Both monthly value-weighted returns and risk free rates are collected from RESSET database for the period from April 2012 to March 2016. The table 4 summarizes the statistic of market excess returns.

Table 4

Descriptive statistic of the market returns, computed from monthly value-weighted returns on the Shanghai Stock Exchange Index and risk free rates. The whole sample period is from from April 2012 to March 2016. The low sentiment regime is from April 2012 to August 2014, and the high sentiment regime from September 2014 to March 2016.

Period	Mean	Max	Min	SD	Skewness	Kurtosis
Whole sample	0.567%	20.181%	-22.904%	0.081	-0.109	3.969
High sentiment	1.905%	20.181%	-22.904%	0.112	-0.420	2.734
Low sentiment	-0.309%	14.278%	-14.394	0.053	0.140	4.424

Te mean of monthly market excess returns is negative (-0.309%) in the low sentiment regime but positive (1.905%) in the high sentiment regime. It is contradictory to the empirical findings from Yu and Yuan (2011) that mean returns in high sentiment regimes should be lower than that in low sentiment regimes, since high sentiment drives up prices, which in turn depresses returns. However, the empirical findings in this paper is consistent with noise trader model proposed by De long et al. (1990), and the empirical findings from Lee, Jiang and Indro (2002). That is the sentiment traders can get higher returns than non-sentiment traders due to "hold more" effect and "create space" effect". The first effect increases the return required by sentiment traders since they hold more of risky assets than non-sentiment traders. The second effect is known as limitation of arbitrage, as non-sentiment traders have short horizon, and they are less likely to bet against stocks mispricing generated by noise trader. For instance, noise traders push up a stock's price to a level that deviates above its fundamental. Non-sentiment traders know the stock has been overvalued, but few of them choose to arbitrage, because arbitrage might incur a big loss as the price will be overvalued further by sentiment traders.

In addition, the standard deviation in the high sentiment regime is also higher than that in the low sentiment regime, indicating market returns are more volatile in the high sentiment regime. This pattern is consistent with the economic intuition that the presence of sentiment traders results in a more volatile market return, which has been well documented by the existing literature

Mean-variance relation in different sentiment regimes

Yu and Yuan (2011) incorporate an intercept sentiment dummy variable and a slope sentiment dummy variable into the mean-variance regression, where the slope sentiment dummy variable on the volatility represents the impact of high sentiment regime on the mean-variance relation. They find the coefficient on the slope sentiment dummy variable is negative, and conclude the presence of sentiment traders weakens mean-variance relation.

Instead of using both intercept and slope sentiment dummy variables, this paper only chooses a slope sentiment dummy variable on the volatility to represent the impact of high sentiment regime on the mean-variance relation, since an intercept sentiment dummy does not serve any meaning in the model. As discussed in the Section III, only the market return Granger causes the change of sentiment but not the other way round. Therefore, the dummy variable for sentiment cannot be an explanatory variable in a regression where the market access return is the dependent variable, since changes in sentiment does not cause changes in market returns. If we use the intercept dummy variable wrongly, it might introduce undesirable properties, such as multicollinearity between explanatory variables, leading inaccurate standard errors for parameters. Hence, a better and more parsimonious model to examine the Mean-variance relation in different sentiment regimes should be:

$$R_t = \alpha_0 + \beta_0 Var(R_t) + \varepsilon_t$$

$$R_t = \alpha_1 + \beta_1 Var(R_t) + \beta_2 D_t Var(R_t) + \varepsilon_t$$

where R_t is value-weighted monthly excess returns on the Shanghai Stock Exchange Index. $Var(R_t)$ is monthly conditional variance calculated by the GARCH(1,1) model and the Rolling window model respectively. D_t is the sentiment dummy variable. It takes value one from September 2014 to March 2016 (high sentiment regime), and zero from March 2012 to August 2014 (low sentiment regime). In this paper, parameter β_2 is expected to be positive as higher return are compensated for extras risk that sentiment traders bear. In the meantime, β_0 and β_1 are not expected to be positive, since negative mean-variance relationships have been documented in existing literature (Nelson 1991; Campbell and Hentschel 1992; Glosten, Jogannathan and Runkle 1993; and Brant and Kang 2004).

Table 5

Monthly excess returns against conditional variance in the GARCH(1,1) model and the Rolling window model.

$$R_t = \alpha_0 + \beta_0 Var(R_t) + \varepsilon_t$$

$$R_t = \alpha_1 + \beta_1 Var(R_t) + \beta_1 D_t Var(R_t) + \varepsilon_t$$

where R_t is value-weighted monthly excess returns on the Shanghai Stock Exchange Index. $Var(R_t)$ is monthly conditional variance calculated by the GARCH(1,1) and the Rolling window model. D_t is a sentiment dummy variable.

Model	α_0	β_0	α_1	β_1	β_2
GARCH(1,1)	0.031	−4.678	0.082	−30.431	22.908
t-statistic	(2.056)	(−2.447)	(4.493)	(−3.030)	(2.606)
Rolling window	0.034	−5.149	0.075	−29.577	22.704
t-statistic	(2.567)	(−3.469)	(4.082)	(−3.569)	(2.989)

In the mean-variance regression in the GARCH(1,1) model, the coefficient on conditional variance β_0 is -4.68 (significant at 5% level of significance), suggesting a negative mean-variance relation. When adding a slope sentiment dummy variable into the mean-variance regression, the coefficient on conditional variance β_1 is still significantly negative at 1% level of significance, and the coefficient on slope sentiment dummy variable is 22.908 (significant at around 1% level of significance), indicating the negative mean-variance relation has been weakened by sentiment traders.

As for the mean-variance regression in the Rolling window model, the parameter β_0 is -5.149 (significant at 5% level of significance), confirming the negative mean-variance relation in the Shanghai Stock Exchange. After adding a slope sentiment variable, the parameter β_1 is still significantly negative at 1% level of significance, and the parameter on slope sentiment dummy variable is 22.704 (significant at around 1% level of significance), confirming the presence of sentiment traders strengthens the mean-variance relation.

The test results have several appealing properties. First of all, all of parameters in the man-variance regressions in two different volatility models are significant at least 5% significance level, indicating a strong relation between market excess returns and conditional variance. Secondly, both volatility models yield almost the same implication. That is market excess returns is negatively correlated with conditional variance, and the presence of sentiment traders weakens this negative correlation. In other words, sentiment traders strengthen mean-variance efficiency. Thirdly, R^2 in all mean-variance regressions are more than10%, which means these models have modest explanatory power. Lastly, after adding a sentiment dummy variable, the R^2 in the mean-variance regression based GARCH(1,1) model has been improved from 11.52% to 23.12%, while the R^2 in the mean-variance regression based on Rolling window model has been improved from 20.73% to 33.86%, suggesting the sentiment dummy variable has a strong impact on the mean-variance relation.

Unfortunately, there is few existing framework that can enable us to find the intuition behind these empirical findings. This paper starts from the Non-Expected Utility theory to give a preliminary explanation for them.

A preliminary explanation

In modern finance, mean-variance efficiency is developed under the framework of CAPM. According to Mossin (1969) and Rubinstein (1973), CAPM is derived from a negative quadratic utility function. In the expected utility theory, investors with negative quadratic utility function are known as risk averse. Thus positive mean-variance relation is based on the assumption that investors are risk averse.

The contradictory to the expected utility theory and risk averse investors is non-EU theories, which argues that investor psychology biases are involved into decisions making process. One of the most important non-EU theories, namely prospect theory, was firstly proposed by Kahneman and Tversky (1979). The core argument from the prospect theory is that investors are loss-aversion. More specifically, investors are very sensitive to losses, and risk-seeking over losses. Therefore, when stock market generates more returns than losses, investors will not behave very actively in the market, so market is less volatile, leading less volatile market returns. However, when market falls, which in turn generate more losses, investors are risk-seeking, leading a more volatile markets. As a result, since high volatility accompanies with losses while low volatility accompanies with returns, the mean-variance presents a negative relation. The intuition behind above argument is consistent with the explanation for negative mean-variance relation from Campbell and Hentschel (1987). That is falls of stock market cause volatility to rise more than after it rises in the same magnitude.

Hence, it is reasonable to argue that investors, excluding sentiment investors in Chinese stock markets are loss averse rather than risk averse. However, Loss averse investors are different from sentiment traders, because the latter is easily driven by sentiment or emotion. Sentiment traders regard the stock market as a fantasy, where they can get considerable returns. They weaken the negative mean-variance relationship as they require higher returns to compensate for bearing more volatilities in the high sentiment regime. One strong evidence that can support this argument is from the noise trader risk model (De long et al. 1990). Another strong evidence is the Granger causality from the stock market return to the change of sentiment index, which has been identified in Section III. That is when positive shocks on stock market returns came, sentiment would be driven up in the following a few periods. Particularly, when the market was bull, a plenty of sentiment traders, who expected high returns from stock market, engaged into stock market in August 2014, and their presence led to a high sentiment regime since August 2014. Comparing with the existing loss averse investors in the market, if sentiment traders cannot get higher returns, they would not be involved or become active in the stock market, as the market was too volatile. Therefore, the previous negative mean-variance relationship has been weakened by these sentiment traders.

Conclusion

The majority of investors in Chinese stock markets are individuals, who are easily effected by their sentiment. The market crash in June 2015 is a vivid example that manifests the existence of investor sentiment in financial markets. To take insight of how sentiment played in the market crash, this paper firstly reveals the six factors that boosted market exuberance, and secondly, conducts principle components analysis to construct sentiment index, based on six sentiment proxies, including consumer confidence index, close-end fund discount rate, share turnover, net investor account opened and the number of IPO and its first-day return. Since sentiment index and the Shanghai Stock Exchange Index has similar stochastic trends, Johansen cointegration test has been carried out to examine their interactions. The test result suggests sentiment index and the market index exist in long-run relationship, and stock market returns Granger cause changes in sentiment.

The last section in this paper examines the impact of sentiment on mean-variance relation. Instead of distinguishing sentiment regimes by comparing the value of sentiment index with zero, this paper uses the information criterion method (Liu, Wu, and Zidek 1997), and the Bai-Perron global maximizer test (Bai and Perron 1998), to identify the multiple structural breaking points in the time-series of sentiment index. Both tests suggest the breakpoints happened in April 2012 and September 2014, giving the low sentiment regime for the period from 2012 to August 2014 and the high sentiment regime for the period from September 2014 to March 2016. Thus, a slope sentiment dummy variable, which takes value one for the period September 2014 to March 2016 and zero otherwise, has been incorporated in the regression model of mean-variance relation. By using GARCH(1,1) model and Rolling window model, monthly conditional variance of value-weighted market return has been generated. Both mean-variance regressions in GARCH(1,1) model and Rolling window model suggest value-weighted market access returns and conditional variance are significantly negatively correlated, but the presence of sentiment traders weakens this negative relationship.

Unfortunately, few theoretical framework can be applied to explain these empirical findings. This paper provides a preliminary model based on the prospect theory (Kahneman and Tversky 1979) to present the intuition behind these findings. The model assumes the existing investors in the market are loss-averse rather than risk averse. Since they are more sensitive to losses than gains, market falls result in higher volatility than market rises, thereby leading a negative mean-variance relation. However, since August 2014, a plenty of sentiment traders turned up and became very active in the stock market. Their presence strengthened the mean-variance efficiency, as they required higher return than the existing loss averse investors to compensate for high volatility, namely extra risks they are bearing. In the meantime, their presence also boosted the market bubble, which in turn led to the market crash in June 2015.

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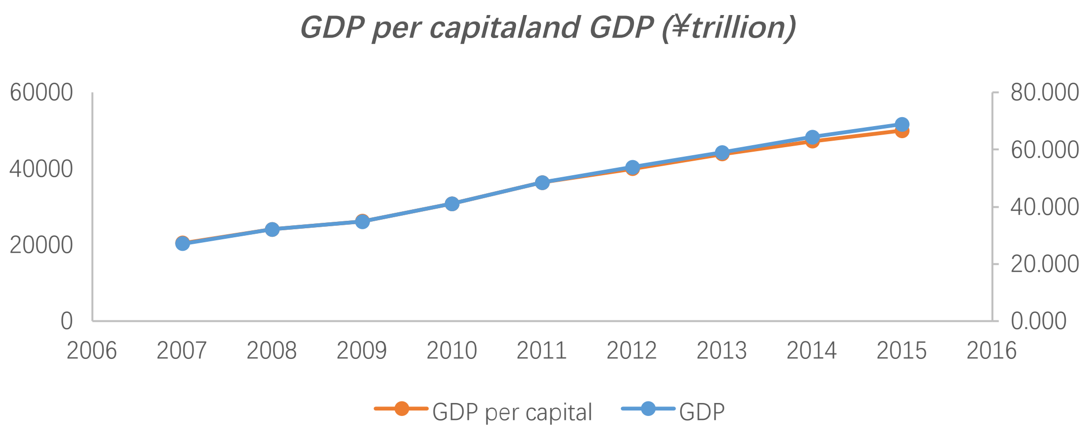
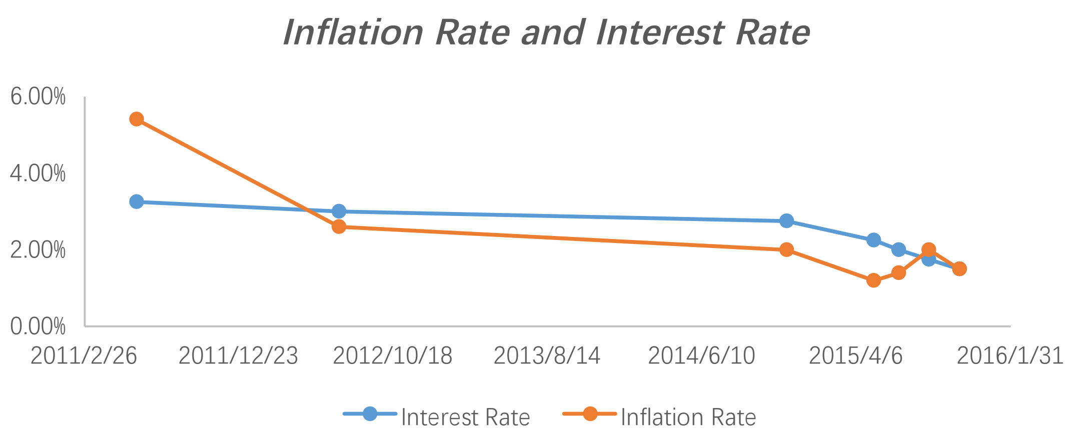
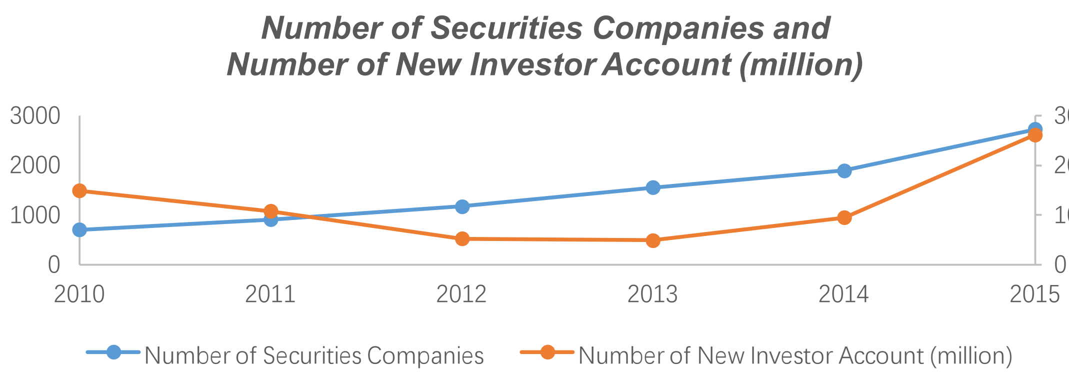
Appendix 1



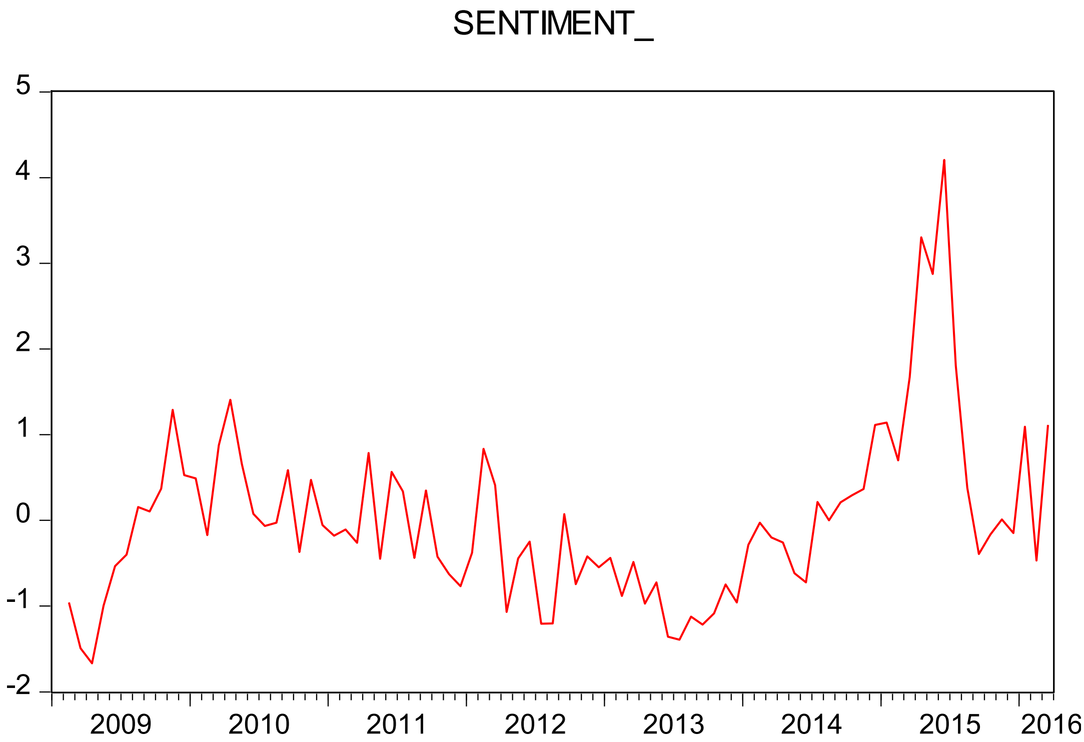
Appendix 2



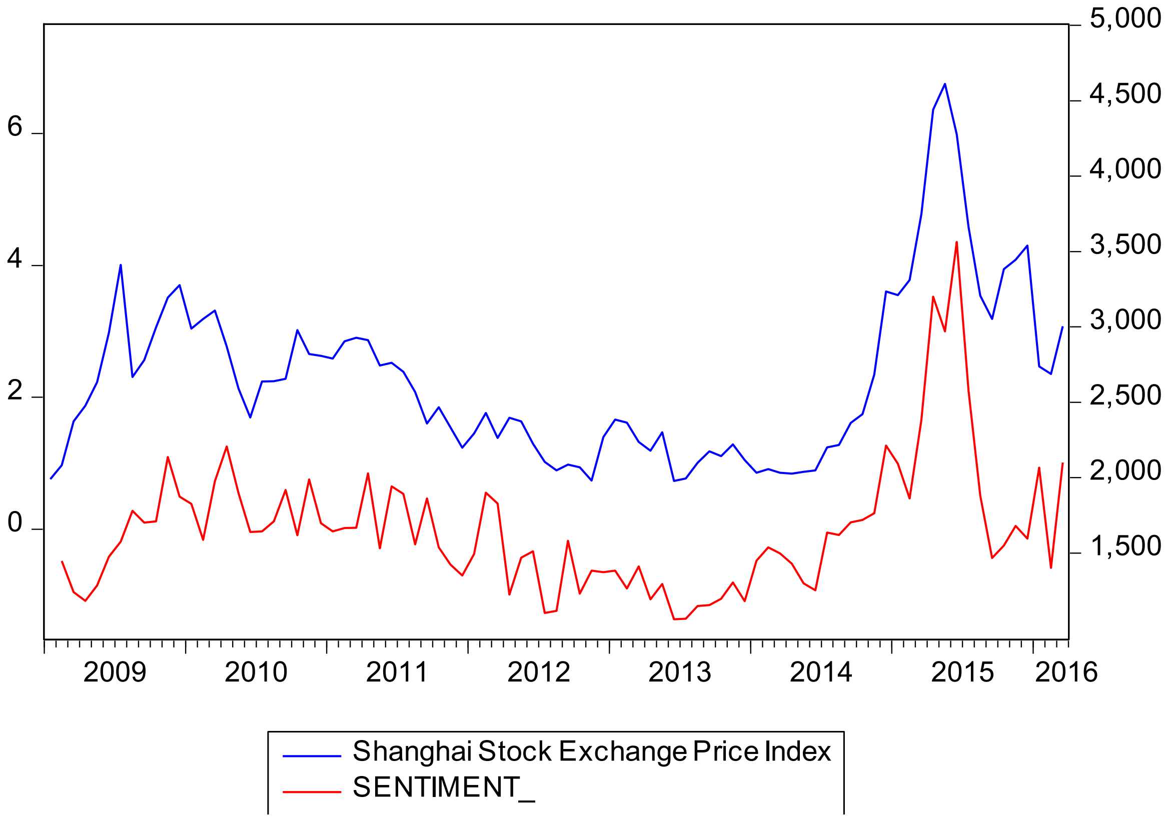
Appendix 3



Appendix 4

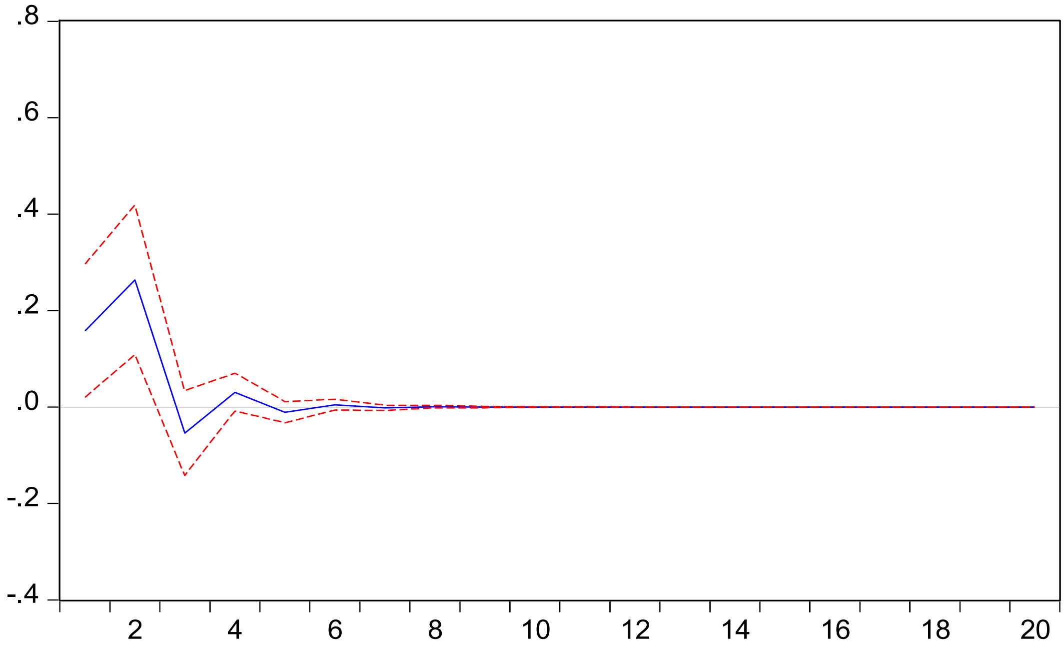


Appendix 5



Appendix 6

Responsiveness of Δ(SENTIMENT) to the innovation on monthly the stock market return



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