How does Investor Sentiment have Impacts on Stock Returns and Volatility in the Growth Enterprise Market in China?

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Thesis submitted to the University of Ottawa
in partial Fulfillment of the requirements for the
Master of Science in Management (Finance)

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ABSTRACT

This dissertation mainly explores the effect of investor sentiment on stock returns and volatility on Growth Enterprise in China using monthly data from Shenzhen Stock Exchange of China from June 2010 to November 2019. Using five explicit and market-related implicit indicators an investor sentiment has been measured and constructed with the help of principal component analysis. The analysis has been done by employing a vector autoregression(VAR) model and impulse response functions (IRFs) generated from a VAR model to examine the relationship between the unanticipated changes in investor sentiment and stock returns and volatility. We also establish EGARCH model to test the validity of previous results and if the asymmetric impact of positive and negative news on market returns volatility. The results show a significant impact of investor sentiment on stock return and volatility. We also document that there is a positive leverage effect between investor sentiment and the volatility of returns. The findings of this paper can help both individual and institutional investors have a better understanding of GEM market and improve their investment returns by incorporating investor sentiment into their asset forecasting model. This paper also provides policymakers guidance on reducing volatility on stock markets from the perspective of investor sentiment. Additionally, this paper has important contributions to behavioral finance and adds to the limited number of studies on investor sentiment and stock return in not only the Chinese market but emerging markets.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude and appreciation to my supervisor, Dr. Yuri Khoroshilov, for his support, valuable suggestions, and encouragement during the writing of this dissertation. He has served as guidance throughout my entire master's study. I am also grateful to my committee members, Dr. Fabio Moneta and Dr. Anna Dodonova for their invaluable assistance and constructive suggestions for my thesis.

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1. Introduction

This paper focuses on studying the impacts of investor sentiment on stock returns and volatility in the growth enterprise market in China by developing unique indicators of investor sentiment for China. The topic on the relationship of investor sentiment and stock returns has been widely discussed by behavioral finance researchers. De Long et al. (1990) proposed an asset pricing model (DSSW model) for noise traders to study how volatile investor sentiment affects asset pricing and volatility. After that, many researchers started to research the impact of investor sentiment on stock market returns.

However, there is no consensus on the relationship between investor sentiment and stock returns because of different measurements, methodologies, locations, and periods. Some researchers suggest that there is a strong correlation between investor sentiment and stock returns. Charoenrook (2005) finds that the change of investor sentiment is positively correlated with the excess return of the stock market in the same period, but negatively correlated with the return of the stock market after a month and a year. Baker and Wurgler (2007) study the effect of individual investor sentiment on the whole stock market and find that the returns of small and high volatile stocks are negatively correlated with investor sentiment in the U.S stock market. However, not all studies show the same results. Baker and Wurgler (2007) conclude that investor sentiment tends to be conversely sensitive to young, small, and unprofitable stocks of growth companies as they are too difficult to value to arbitrage. Verma and Verma (2007) divide investor sentiment into two types: rational and irrational. They study the relationship between the two emotions and the volatility of stock returns. The results show that irrational emotions have a significant positive impact on the volatility of stock returns, whereas rational emotions show an opposite result.

The Growth Enterprise Market (GEM) in China has some characteristics that may lead to a similar result of the research of Baker and Wurgler (2007), which is that investor sentiment has a significant impact on the stock returns in the growth enterprise market in China. Compared to developed markets, the stock market in China tends to have a majority of irrational individual investors (Long, 2017). Also, the relatively high risk caused by short history, and low listing threshold are likely to lead GEM to be sensitive to investor sentiment because hard-to-arbitrage stocks are more likely to be affected by investor sentiment for irrational investors (Baker and Wurgler, 2007).

The VAR models are established to explore the effects of investor sentiment on GEM stock returns and volatility. The results generated from impulse response functions provide the following empirical results: First, the effect of a one time increase in investor sentiment on GEM returns is positive and significant but in a declining trend of the increase during the first two periods. Also, major investors in China are irrational investors. Thus, this finding provides potential support that investor sentiment from irrational investors have a significant positive impact on stock market returns on GEM. Second, the investor sentiment tends to significantly increase the GEM market volatility with a delayed response at the time of the second month. This indicates that irrational sentiment significantly leads to market volatility. Third, there is a positive leverage effect between investor sentiment and the volatility of returns. These findings are robust to model specifications.

The results of this study have important implications for investors, policy makers, and academia. For individual investors, this paper will provide a new perspective for investors to gain an understanding of the stock market and can potentially improve their portfolio performance by taking into consideration investor sentiment as a determinant of stock market returns in addition to technical analysis and fundamental analysis. It is also beneficial for asset managers to manage portfolios. Mutual funds are more likely to

experience inflows in periods of positive sentiment and outflows in periods of negative sentiment (Indro, 2004). This means that managers can adjust the portfolios by buying or selling stocks in GEM according to positive or negative sentiment. This research is also useful for policy makers to formulate regulation to maintain market stability. If investor sentiment can sensitively affect stock returns, policy makers can, for example, improve the transparency and avoid investors from being misled and then making irrational decisions. Additionally, this paper has important contributions to behavioral finance and adds to the limited number of studies on investor sentiment and stock return in not only the Chinese market but also emerging markets. The findings of this study are valuable especially for those stock markets that are similar to GEM such as GTSM in Taiwan, MOTHERS in Japan, and KOSDAQ in Korea.

2. Literature review

2.1 Investor Sentiment and Stock Returns

It was found by certain research that there is a significant relationship between investor sentiment and stock returns in both developed and developing countries. Bhaskaran (1996) examines the relation between closed-end fund discounts and small firm returns. He discovers that discounts forecast future small firm returns, which also provide independent information about the conditional expected returns of small firms. Brown and Cliff (2004) investigates the relationship between investor sentiment and market returns and considers that investor sentiment can be regarded as an important determinant for the stock returns in long term but not in the case of the near-term stock market. Baker and Wurgler (2007) point out that in the case of young firms, extreme growth firms, small firms, and non-dividend-paying firms the chance of subjective evaluation increases, which leads to susceptibility to market sentiment. Thus, if the market itself is young, there should be an even higher probability of the presence of sentiment. Sayim and Rahman (2015) suggest that in the Turkish market, positive investor sentiment tends to increase stock returns and has a negative significant effect on ISE volatility. Zhu (2013) uses a Fama-French three-factor model and regression model and concludes that investor sentiment is an important factor affecting SME market returns in China. Zeng (2015) uses the Haodan index as the proxy index of investor sentiment and concludes that the changes of investor sentiment index and Shanghai Composite Index return are both affected by their lag term, and there is a two-way causal relationship between them.

However, some research shows different results. Brown and Cliff(2004) find that investor sentiment cannot effectively predict market returns, but market returns have a significant impact on investor sentiment. Although investor sentiment fluctuations are significantly correlated with stock returns, their tests reveal that investor sentiment has little explanatory power on near-term future stock returns. Lastly, their evidence does not support the theory that investor sentiment mostly has an impact on individual investors and small

stocks. Güner & Önder(2009) examine the impact of investors on the Turkish Stock Market returns. They show that stock portfolio returns do not have effects on investor sentiment. Philipp, Alexandra and Stefan (2012) illustrate that sentiment does still play a role in explaining contemporaneous stock returns but they do not find much predictive power of sentiment for future stock returns. Wu, Yang and Gong(2012) analyze the impact of investor sentiment on the aggregate stock returns in the main board market and the GEM respectively and conclude that there is no significant impact on GEM.

2.2 Investor Sentiment Measures

Based on previous research, the measurement of investor sentiment can be divided into two categories: explicit and implicit proxies. Explicit proxies are based on a survey, which means that sentiment can be measured directly. Bram and Ludvigson(1998), Otoo (1999), and Qiu and Welch (2004) all measure sentiment using Consumer Confidence Index (CCI) extracted from consumer confidence surveys conducted by Michigan University**.** Brown and Cliff(2004) divide investor sentiment indicators into two parts: direct investor sentiment indicators and indirect investor sentiment indicators. Direct indicators are based on data collected by surveying the expectation of investors in future market returns including indicators American Association of Individual Investors (AAII) and Investor Intelligence(II). American Association of Individual Investors (AAII) is also used by other researchers (Calafiore, Soydemir, & Verma, 2010; Verma, Baklaci, & Soydemir, 2008; Verma & Soydemir, 2006). In China, the Haodan index conducted by a TV channel, Consumer Confidence Index, CCTVBSI, Friendship Index, which are national indexes, have been widely used in this area (Ho & Hung, 2009; Lixu & Xintian, 2011; Yin, 2015).

Investor sentiment can also be measured implicitly based on market variables that indicate the patterns of sentiment. Implicit sentiment proxies have been commonly used by researchers in this area. Neal and

Wheatley (1998) use three indicators to measure individual investor sentiment: the level of discounts on closed-end funds, the ratio of odd-lot sales to purchases, and net mutual fund redemption and finds that fund discount and mutual fund redemption can be used to predict future market returns. Brown and Cliff (2004) divide investor sentiment indicators into two parts: direct investor sentiment indicators and indirect investor sentiment indicators. Indirect indicators are based on theoretical analysis including variables related to market performance, trading activities, and derivatives. Baker and Wurgler (2007) conduct top-bottom approach to propose a composite index for investor sentiment including surveys; mood proxies; retail investor trades; mutual fund flows; trading volume; premia on dividend-paying stocks; closed-end fund discounts; option implied volatility; first-day returns on initial public offerings (IPOs); the volume of initial public offerings; new equity issues; and insider trading. In China, in addition to the proxies shown above, the turnover rate is also used to measure sentiment indirectly (Ho & Hung, 2009; Lixu & Xintian, 2011; Yin, 2015).

2.3 Growth Enterprise Market (GEM)

The establishment of GEM has great impact on the stock market in China because of its unique characteristic. Compared with the main board market, which is designed for the listing of large-scale companies, the GEM has higher uncertainty and risk for companies listed in GEM are high-tech small and medium enterprises. Although the establishment of the GEM has improved the structure of the stock market, it also increases the complexity of the securities market (Bai, 2019). GEM only has an approximately 10-year history for it was established in June 2009, and most companies in GEM have an uncertainty of sustainable growth with relatively low history and scale (Gong & Yao, 2018). The characteristics lead Chinese researchers to research GEM.

Little research is focused on investor sentiment and stock returns. Wu, Yang and Gong(2012) analyze the impact of investor sentiment on the aggregate stock returns on the main board market and the GEM respectively using a multi-regression model and conclude that there is no significant impact on the GEM. Xia and Guo (2015) conclude that there is no long-term correlation between the sentiment of investors in GEM and stock returns and investor sentiment would affect the level of market fluctuations.

Most research related to GEM is associated with IPO pricing. Cao and Dong(2009) conclude that in terms of the intrinsic value of the listed companies in GEM, the market price of stocks does not perform as well as the issue price. It can be inferred that over-priced enterprises in the stock market are an important factor causing the high underpricing rate of IPO. Based on information asymmetry theory, Guo, Wan, and Wu (2011) empirically studies the pricing efficiency of underwriters in the process of IPO in GEM in China. They believe that the opportunistic behavior of underwriters could not be restrained by the imperfect reputation mechanism, which causes the stock price to deviate from the intrinsic value. Zhang, Huang, and Wen (2012) studies the relationships among the reputation of investment in GEM, long-term performance of IPO, and initial return and states that the reputation of investment is positively correlated with the long-term performance of listed companies, while it does not affect the initial return.

Therefore, research on investor sentiment and stock returns has been mainly focusing on developed countries, especially the U.S. stock market, and there is still no consensus on the relationship between investor sentiment and stock returns. Also, investor sentiment is hard to measure and can be different under certain circumstances, and different methods to measure can reach various conclusions. As for the previous research on GEM, they are still not mature enough because of a limited period and insufficient data.

2.4 Hypothesis

I formulate two main hypotheses shown below.

H_1: Investor sentiment has a significant positive impact on the stock returns and volatility of stocks in the growth enterprise market.

According to Baker and Wurgler (2006) and Philipp, Alexandra, and Stefan (2012), stocks of young and risky companies with high potential growth and volatility are more likely to be sensitive to fluctuations of sentiment. These stocks are not attractive to arbitrageurs because they are sentiment-driven by irrational investors and arbitrageurs cannot value the stocks properly. Misvaluations will lead to high transaction costs so it is hypothesized that limits of arbitrage occur in GEM and sentiment tends to have an impact on stock return. In addition, the German market is the opposite of China market in terms of the structure of institutional and individual investors to some extent. Relatively rational investors (institutional investors) are the major players in the German market and they are less likely to experience sentiment fluctuations (Philipp, Alexandra, and Stefan, 2012). However, most investors in China are individual so they are relatively irrational and sentiment can be prone to have a great impact on stock returns

H_2: The impact is positive in the short term and becomes negative later on within ten months with a positive sentiment given and vice versa.

People are easily affected by others around them so they tend to follow them at the beginning. However, after a while, they may realize their decisions are wrong or have concerns that the stock price would decrease in the future. Therefore, it is hypothesized that the impact would be different in different periods within ten months after a positive sentiment given.

3. Methodology

This research mainly uses Vector autoregressive (VAR) model proposed by Sims (1980) to analyze the relationship between investor sentiment and, stock return and volatility, which suggested by previous research for its capability to capture the dynamic relationship between investor sentiment and stock return. (Brown and Cliff, 2004; Zhang et al., 2010; Sayim et al., 2013) Thus, Vector autoregressive (VAR) model is useful for exploring the dynamic relationship between multiple endogenous variables. Additionally, much research showed that VAR model provided a better way to forecast time series data than other structural equation models. (Lupoletti & Webb, 1986; Nakajima, 2011; Huirong, 2014) Unlike certain traditional analyses such as a multi-regression model, which is used to analyze the structural relationships between measured variables based on certain economic theories, Vector autoregressive model can capture the linear interdependencies in an unstructured way for more than one endogenous variables. The VAR model is estimated as follows.

$$Y_t = c + Z_1 Y_{t-1} + Z_2 Y_{t-2} + \cdots + Z_p Y_{t-p} + e_t$$

Where Y_t is a k-dimensional column vector of endogenous variables included in the model, c is a k-dimensional vector of constants, Z_j is a $k \times k$ matrix of coefficients, where j can be $1,2,\ldots,p$, and e_t is a k-dimensional vector of error terms with mean zero and no serial correlation.

However, time delays can occur between variables. Therefore, before establishing the VAR model, time lags, or the number of p are needed. Lag lengths are chosen based on the Akaike information criterion (AIC) and Schwarz information criterion (SC). AIC is used to measure the relative distance between the fitted likelihood function of the model and the unknown likelihood function of the model. SC is also an

estimate of function to determine the goodness of fit for a model based on posterior probability under a certain Bayesian setup. Thus, lag lengths are determined by the leg with the lowest AIC and SC.

Although VAR model provides a superior forecast, it is hard for it to elaborate on the coefficients with no theoretical support and not based on a structural equation (Sayim & Rahman, 2015). Impulse Response Function (IRF) generated from VAR model can be used to analyze the response of a model's endogenous variable to a shock in one or more other endogenous variables, which is used to analyze the full impact of unanticipated changes of one variable to the another in a dynamic system.

Therefore, this study incorporates stock return, investor sentiment, and volatility as endogenous variables into the VAR model to analyze the relationship among them and use IRF to explore the unanticipated impact of investor sentiment on stock return and volatility on GEM in China.

4. Data

4.1 Stock Market Data and Investor Sentiment Proxies

The sample data period is from June 2010 to November 2019 in monthly intervals for Shenzhen Stock Exchange officially issued the GEM composite index on June 1, 2010. To proxy investor sentiment, following Baker and Wurgler (2006) and Brown and Cliff (2004), five variables are used to construct the investor sentiment proxy as follows:

Investor Confidence Index (ICI) measured the level of confidence institutional and individual investors have in current and future financial market performance (Ho & Hung, 2009; Lixu & Xintian, 2011; and Yin,2015);

Number of New Account measured as the incremental changes in the accounts on GEM;

P/E Ratio, which is the price per share divided by earnings per share, measure as the monthly average P/E ratio from daily P/E ratio (Jitmaneeroj, 2017; Sehgal et al., 2009; Zhu, 2012);

Turnover Rate, which is the total number of shares traded divided by the average number of shares outstanding, measured as the monthly average turnover rate from daily turnover rate (Ni et al., 2015; Gunathilaka & Jais, 2019);

Advance-Decline Line (ADL), which is the difference of daily advancing stocks and declining stocks, measured as the sum of monthly difference (Gilbert, 2018; Teng & Yang, 2018, Teng & Liu, 2013);

This research evaluates the effect of investor sentiment on stock market return. Following Hull (2007), The monthly stock return is evaluated using the following model, where u_t is the compounding stock return

between the end of month t and month $t-1$. R_t is the monthly stock return extracted from the GEM composite index.

$$u_t = \ln(R_t) - \ln(R_{t-1})$$

The volatility is estimated by calculating the standard deviation of the monthly continuously compounded returns based on daily volatility (Hull,2007). The volatility σ is calculated based on the most recent m observations within a month on the u_t.

$$\sigma_t = \sqrt{\frac{1}{m} {u_t}^2}$$

The data on the Number of New Accounts is obtained from China Securities Depository and Clearing Corporation Limited (CSDC); P/E Ratio, Turnover Rate, Advance-Decline Line (ADL) and GEM composite index are obtained from Wind Database. Investor Confidence Index (ICI) is from Bloomberg Database.

4.2 Construction of Investor Sentiment Index

Principle Component Analysis (PCA) is used for developing a more accurate investor sentiment measurement (Verma and Soydemir, 2009; Baker & Wurgler, 2006; Naik & Padhi, 2016; Finter et al., 2012). Additionally, it is necessary to utilize Principle Component Analysis to reduce dimension to avoid multicollinearity in the process of constructing the proxy for sentiment for its high correlation with each other. The cross-correlation between ICI, Number of New Account, P/E Ratio, Turnover Rate, and ADL is reported in Table 4.2.1.

Before performing PCA, it is necessary to normalize those five variables to make sure all data have the same weight and standard deviation. Thus, z-score is used to transform the data in this study by simply subtracting the mean $\bar{x}$ from each data point and dividing the result by the standard deviation s.

$$Z_i = \frac{x_i - \bar{x}}{s}$$

Now PCA is employed to construct a composite investor sentiment index to represent the five variables that are highly related to investor sentiment. The PCA invented by Hotelling (1933) converts the original data set into a single series that accounts for the main variance of the original data. Thus, the factors loadings are needed to extract for the original five indicators to construct a composite sentiment index by the following formula, where a_j is the Eigenvectors (factor loadings) for *j*-th variable derived by the PCA, *k* is the number of sentiment proxies and Z_i is the normalized sentiment proxies.

$$Sent_t = \sum_{j}^{k} a_j Z_i$$

Considering that the essential five variables are affected less with their lags, variables without lags are selected to conduct the PCA as shown in Table 4.2.2. According to the results of PCA below, 86% of the total variance in the initial data can be explained by each eigenvector for the first three main components, which means that most relevant variables are selected to summarize and represent the initial five variables.

The first three principal components having 86% sample variance gives the following measure of sentiment index.

$$Sent_t = 0.368ADL_t + 0.193PE\_RATIO_t + 0.164NUMACC_t + 0.289TURNOVER_t + 0.226ICI_t$$

5. Empirical Results

5.1 Descriptive Statistics

Table 5.1.1 reports the descriptive statistics of all variables included in this paper. The table shows that the mean of SENT is -0.008, which is negative but very less in magnitude so it is not sufficient to justify a bearish sentiment. its standard deviation is 0.881 which is relatively higher compared to the stock market return and volatility. This indicates that investor sentiment has been highly volatile. Besides, the variables used to proxy sentiment index all have a high standard deviation, which suggests that those selected variables are decent proxies to construct the sentiment index.

The cross-correlation between investor sentiment, stock returns, and volatility on GEM are reported in Table 5.1.2. The table indicates that the sentiment index is highly positively correlated with the stock return. Thus, it can be hypothesized that with the increase in investor sentiment index, the stock market return will be positive and vice versa. Additionally, the sentiment also has a positive correlation with volatility, which suggests that sentiment might have a certain relationship with volatility. Moreover, there is a high correlation between sentiment index and the five sentiment proxies. It implies that the sentiment index can represent the sentiment proxies to a large extent.

Figure 1 depicts the trend of investor sentiment index and GEM composite index from June 2010 to November 2019. To better compare the relationship between investor sentiment and stock return using a line graph, both sentiment index and stock price are standardized. It is shown that those two variables have a similar trend with sentiment index fluctuating more widely. Therefore, further analysis can be conducted to explore the relationship between investor sentiment and stock return.

5.2 Empirical Results

5.2.1 Unit Root Test

Before establishing the VAR model, a stationary test needs to be. All three variables included in the future VAR model do not have unit root because the null hypothesis that unit root exists is rejected with low p-value, which means the time series are all stationary. Augmented Dickey-Fuller (ADF) Test (Dickey and Fuller, 1979, 1981) is used in this study to test if each variable is stationary or has a unit root. Table 5.2.1 reports the results of unit root tests using the ADF test, which indicates that the null hypothesis of non-stationarity is rejected at levels of the time series for each variable. The lag length is chosen based on Akaike Information Criterion (AIC) and Schwarz information criterion (SC) criteria shown in table 5.2.2.

5.2.2 VAR Model Results

As mentioned in Figure 1 above, there is a consistent trend between investor sentiment and market index, but it is not intuitive to justify whether they change contemporaneously. To explore this relationship, we use a VAR model to test the dynamic interaction between them. Table 5.2.2 reports the results of the VAR model with two lags selected based on AIC and SC criteria, which indicates that the lagged levels of investor sentiment, stock return, and volatility can explain about 46% of the variation in sentiment. Both sentiment and volatility show a powerful forecast of themselves. The sentiment is positive and significant at its first lag but significantly negative in its second lag in influencing the return.

However, some previous research points out the difficulties in explaining the coefficients from regression equations in the VAR model (Sims, 1980; Fischer, 1981; Genberg, Salemi, and Swoboba, 1987). Sims (1980) illustrates that Impulse Response Functions (IRF) is more reliable and easy to analyze the results by

looking at the response of a random shock for the VAR model is quite complicated to describe the results succinctly. Therefore, we focus on IRF to estimate the final results.

Var Granger causality test is conducted to explore a deeper insight into the direction of causality as is reported in table 5.2.4. The null hypothesis ‘ Investor sentiment does not Granger cause return’ has been rejected at 1% level of significance, but a bidirectional causality between them is not expected. This is not consistent with some previous findings such as Brown and Cliff (2004) and Wang et al. (2006), who obtain empirical results for sentiment caused by return but not vice versa. Similarly, the null hypothesis ‘Investor sentiment does not Granger cause volatility’ has been rejected at 5% level of significance. Hence, it can be concluded that investor sentiment causes stock return and volatility and not vice versa.

Before performing IRFs, the VAR model needs to be tested to see if it is stationary by looking at the AR roots graph. Inverse AR roots graph is to test if the estimated VAR is stationary visually. If the roots of its characteristic polynomial lie outside the unit circle, it means that the VAR model has no unit root so the time series is stationary and vise versa. Eviews shows inverse roots for better visualization. Figure 2 shows that all roots lie inside the unit circle, which means the process is stationary.

The unpredicted changes are captured by Impulse Response Functions (IRFs) generated from the VAR model. Figure 3 shows the response of each endogenous variables to shocks with one standard deviation in the dynamic system. Following Doan and Litterman (1986) and Sims (1980), Monte Carlo methods are used to build confidence bands around the mean response. 95% confidence intervals are selected for the statistical significance of impulse responses derived from VAR coefficients when the upper and lower bands carry the same sign.

The impulse response in Figure 4a and b plot the time path of stock return to a one-standard-deviation shock of investor sentiment and the response of sentiment to return respectively. Figure 4a shows that there is a positive and statistically significant impact of sentiment on return in the first two months but the impact disappears quickly since the third month. The response to sentiment also increases at first and then decreases quickly after the first two months. This result indicates that sentiment does not have a long-term effect on the stock return and in short term, the investors tend to impulsively buy the stocks when the market performs well, but quickly they start to suffer a capital loss with the declining stock price. Similarly, the response of sentiment index to shocks of stock return is positively significant in the first two months but insignificant afterward. Also, in the first period, a one-standard-deviation shock of return results in an approximate 40 percent increase in stock return, which shows that investor sentiment tends to be very sensitive to market performance. This result is consistent with some research on the Chinses stock market (Wu et al., 2012; Zhu, 2013; Zeng, 2015; Gong & Yao, 2018).

Figure 4c plots the impulse responses of volatility to a one-time standard deviation increase in investor sentiment. The results turn out to be consistently statistically significant from the second period to the ninth period. This indicates that unexpected changes in sentiment tend to have a positive impact on volatility in a relatively long term. Thus, it can be concluded that the increase in sentiment changes after two months leads investors to consistently buy or sell risky stocks to deal with those large volumes of stocks they own. Figure 4d presents the relative impact of volatility on investor sentiment, which shows that a one-standard-deviation shock increases market volatility in only the first two periods. This result further strengthens the evidence that most investors are irrational in GEM, so the increase in positive sentiment tends to make the market more volatile.

The variance decomposition determines the amount of information or variability each independent variable can explain including themselves in the autoregression. Table 5.2.5 shows the results of variance

decomposition. The results show that around 13 percent of the forecast error variance of return can be explained by sentiment and most are contributed by themselves (86%). In addition, return explains around 42 percent on sentiment, and around 58 percent is accounted for by its shocks. Similarly, around 27 percent of the forecast error variance of volatility is contributed by investor sentiment and around 68 percent explained by its shocks. Therefore, this indicates that investor sentiment has a certain ability to effectively explain the stock return and volatility.

5.2.6 Robustness test

EGARCH model developed by Nelson(1991) is used to evaluate the robustness of the results generated from the previous specific model, and test if there is an asymmetric impact of sentiments on the volatility of returns. Many previous studies show that the responses of volatility to positive and negative news are different. (Ezzat, 2012; Guo et al., 2014; Su, 2010) For exploring the relationship, investor sentiment is introduced as independent in the model. The mean equation is:

$$R_t = C + \alpha R_{t-1} + e_t$$

R_t is the return on GEM; α is the coefficient of the previous return; e_t is the residual term while the other two parameters are estimated.

The variance equation in this model is indicated by:

$$\ln(\sigma_t^2) = \gamma + \delta(|z_{t-1}| - E[|z_{t-1}|]) + \theta z_{t-1} + \varepsilon \ln(\sigma_{t-1}^2) + \beta Sent_{t-1}$$

Where γ, δ, θ, ε and β are parameters to be estimated, which stands for constant, last period volatility, the leverage effect, impact of long term volatility and impact of a change in sentiment on the return's variance. Specifically, θ is the parameter used to test asymmetries. The model is symmetric while $\theta = 0$.

When $\theta < 0$, then the positive shocks have less effect on the conditional variance compared to the negative shocks, which means that good news generates less volatility than bad news for returns, and vice versa ; z_t is standard Gaussian.

The results show that the relationship between sentiment and the volatility of returns is positive for the coefficient β of the impact of a change in sentiment on the return's conditional variance in the variance equation is significantly positive, which is consistent with the results from the VAR model. Also, the coefficient of θ is positive and significant at the 5% level, which indicates that positive changes in sentiment have a larger impact on the volatility of returns than negative changes. This is opposite to previous studies in the U.S stock market. It can be explained by that there are a certain large amount of institutional investors and they tend to be relatively rational and risk-averse, so they are likely to be more cautious even in bullish markets. While in China, especially on the GEM, most investors are individual investors and irrational, they tend to rush to the market when they hear the good news and be risk-averse in bearish markets. Therefore, then the positive shocks have a larger effect on the volatility of stock returns compared to the negative shocks.

6. Conclusion

The present study investigates the effect of investor sentiment on the GEM returns and volatility using vector autoregression (VAR) model. Principle component analysis (PCA) has been used to construct the indicator of investor sentiment by employing five market-related sentiment proxies including Investor Confidence Index(ICI), Number of New Account, P/E Ratio, Turnover Rate, and ADL. After that, the analysis has been done by incorporating investor sentiment, stock returns, and volatility into the VAR model. There are several findings as follows: First, the effect of a one time increase in investor sentiment on the GEM returns is positive and significant but in a declining trend of the increase during the first two months. Also, major investors in China are irrational investors. Thus, this finding provides potential support that investor sentiment from irrational investors have a significant positive impact on stock market returns on the GEM. Second, the investor sentiment tends to significantly increase the GEM market volatility with a delayed response at the time of the second month. This indicates that irrational sentiment significantly leads to market volatility. Third, there is a positive leverage effect between investor sentiment and the volatility of returns.

Few previous studies focusing on the effects of investor sentiments on stock returns and volatility on the GEM in China do not have consistent findings with this paper. Previous studies conclude that there is no significant impact of investor sentiment on stock returns. (Wu & Yang & Gong(2012); Xia & Guo, 2015)However, a study (Xia & Guo, 2015) shows that investor sentiment would affect the level of market fluctuations using the same methodology and similar proxies for investor sentiment as this research, which is consistent with this present study. Thus, different results are mainly due to the sufficiency of samples. In conclusion, the results support the conclusion that investor sentiment, especially irrational investor sentiment has a strong ability to affect the stock market returns and volatility.

Appendix

Table 4.2 1 Cross-Correlation among Sentiment Proxies

	ADL	ICI	NUMACC	PE_RATIO	TURNOVER
ADL	1.00				
ICI	0.42	1.00			
NUMACC	0.21	0.31	1.00		
PE_RATIO	0.22	0.33	0.78	1.00	
TURNOVER	0.31	0.27	0.48	0.58	1.00

Notes: The table reports the results of coefficients of correlation among sentiment variables. The variables are Advance-Decline Line (ADL), Investor Confidence Index (ICI), Number of New Account(NUMACC), P/E Ratio (PE_RATIO), Turnover Rate(TURNOVER).

Table 4.2 2 Principle Component Analysis

Principle Component Factor Loadings	I	II	III	Total
ADL	0.32	0.68	0.44	
ICI	0.37	0.54	-0.64	
NUMACC	0.51	-0.35	-0.24	
PE_RATIO	0.53	-0.34	-0.11	
TURNOVER	0.47	-0.13	0.58	
Variance explained	52.34%	21.13%	12.65%	86%
Eigenvalue	2.62	1.56	0.63	4.3

Notes: The table reports the results of three Principle Component Analysis. The variables are Advance-Decline Line (ADL), Investor Confidence Index (ICI), Number of New Account(NUMACC), P/E Ratio (PE_RATIO), Turnover Rate(TURNOVER).

Table 5.1 1 Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
SENT	-0.008	-0.154	3.080	-1.506	0.881	0.830	3.906
RETURN	0.005	0.002	0.229	-0.291	0.084	-0.183	4.247
VOLATILITY	0.018	0.017	0.045	0.007	0.008	1.549	5.913
ADL	0.002	-0.158	4.228	-2.371	1.004	0.627	4.963
ICI	0.006	-0.074	2.452	-1.951	1.004	0.498	2.925
NUMACC	0.003	-0.237	5.768	-0.785	1.008	3.602	18.169
PE_RATIO	-0.007	-0.138	3.715	-1.348	1.004	1.026	4.155
TURNOVER	-0.033	-0.195	3.116	-1.270	0.937	1.219	4.355

Notes：*The table reports the results of descriptive statistics of sentiment proxies and stock market variables. The variables are Investor Sentiment Index (SENT), Monthly Stock Return on the GEM (RETURN), Monthly Volatility on the GEM (VOLATILITY), Advance-Decline Line (ADL), Investor Confidence Index (ICI), Number of New Account(NUMACC), P/E Ratio (PE_RATIO), Turnover Rate(TURNOVER).*

Table 5.1 2 Cross-Correlation

	SENT	RETURN	VOLATILITY	ADL	ICI	NUMACC	PE_RATIO	TURNOVER
SENT	1.00							
RETURN	0.56	1.00						
VOLATILITY	0.36	-0.09	1.00					
ADL	0.72	0.55	0.06	1.00				
ICI	0.67	0.42	-0.08	0.42	1.00			
NUMACC	0.69	0.32	0.43	0.21	0.32	1.00		
PE_RATIO	0.73	0.20	0.51	0.23	0.34	0.78	1.00	
TURNOVER	0.76	0.39	0.54	0.34	0.33	0.51	0.59	1.00

Notes：The table reports the results of cross-correlation among all sentiment variables and stock market variables. The variables are Investor Sentiment Index (SENT), Monthly Stock Return on the GEM (RETURN), Monthly Volatility on the GEM (VOLATILITY), Advance-Decline Line (ADL), Investor Confidence Index (ICI), Number of New Account(NUMACC), P/E Ratio (PE_RATIO), Turnover Rate(TURNOVER).

Table 5.2 1 Unit Root Test

	ADF test statistic	p-value	Lag length
Levels			
SENT	-3.165**	0.025	2
RETURN	-6.366***	0.000	2
VOLATILITY	-2.922**	0.046	2

Notes: The table reports the results of the ADF test for three variables that will be included in the VAR model. The variables are Investor Sentiment Index (SENT), Monthly Stock Return on the GEM (RETURN), Monthly Volatility on the GEM (VOLATILITY).

****, ** and * denote rejection of the null hypothesis of unit roots for the Augmented Dickey-Fuller(ADF) tests at the 1%, 5%, and 10% significance levels respectively.*

Unit root tests were run with the linear trend and intercept at levels. Lag lengths were chosen using the Akaike Information Criterion (AIC) and Schwarz information criterion (SC).

Table 5.2 2 VAR lag length selection criteria

Lags	AIC	SC
0	-7.111	-7.034
1	-8.103	-7.756
2	-8.296*	7.795*
3	-8.285	-7.513
4	-8.200	-7.197
5	-8.101	-6.865
6	-8.076	-6.609
7	-7.975	-6.276
8	-7.867	-5.937

Notes：AIC: Akaike information criterion; SC: Schwarz information criterion

** indicates lag order selected by the criterion.*

Table 5.2 3 VAR Model Results

	SENT	RETURN	VOLATILITY
SENT(-1)	0.698***	0.056***	0.002**
	(0.125)	(0.014)	(0.001)
SENT(-2)	0.002	-0.059***	0.001
	(0.13)	(0.01)	(0.00)
RETURN(-1)	-1.332*	0.046	-0.013
	(1.03)	(0.12)	(0.01)
RETURN(-2)	-0.318	0.145	0.008
	(1.03)	(0.12)	(0.01)
VOLATILITY(-1)	23.628*	1.718	0.356***
	(12.10)	(1.37)	(0.10)
VOLATILITY(-2)	-15.270	-1.501	0.250***
	(11.61)	(1.31)	(0.09)
C	-0.158	0.001	0.007
	(0.23)	(0.03)	(0.00)
R-squared	0.461	0.239	0.542
Adj. R-squared	0.429	0.194	0.514
Sum sq. resids	44.729	0.572	0.003
S.E. equation	0.665	0.075	0.005
F-statistic	14.389	5.280	19.887
Log likelihood	-105.644	129.712	415.377
Akaike AIC	2.086	-2.272	-7.563
Schwarz SC	2.260	-2.099	-7.389
Mean dependent	-0.024	0.005	0.018
S.D. dependent	0.881	0.084	0.008

Notes: The table reports the results of the VAR model. The variables are Investor Sentiment Index (SENT), Monthly Stock Return on the GEM (RETURN), Monthly Volatility on the GEM (VOLATILITY).

** ** and *** denote significance levels at the 10, 5, and 1% respectively. The standard errors is shown in ().*

Table 5.2 4 VAR Granger Causality

Dependent variable: RETURN			
Excluded	Chi-sq	df	Prob.
SENT	21.12136	2	0.0000
VOLATILITY	1.921301	2	0.3826

Dependent variable: SENT			
Excluded	Chi-sq	df	Prob.
RETURN	1.938277	2	0.1794
VOLATILITY	3.956498	2	0.1383

Dependent variable: VOLATILITY			
Excluded	Chi-sq	df	Prob.
RETURN	3.176662	2	0.2043
SENT	8.290570	2	0.0158

Notes：*The table reports the results of VAR Granger Causality. The variables are Investor Sentiment Index (SENT), Monthly Stock Return on the GEM (RETURN), Monthly Volatility on the GEM (VOLATILITY).*

Table 5.2 5 Variance decomposition

Variance Decomposition of RETURN:				
Period	*S.E.*	*RETURN*	*SENT*	*VOLATILITY*
1.000	0.075	100.000	0.000	0.000
2.000	0.086	87.010	11.875	1.115
3.000	0.086	86.420	12.375	1.205
4.000	0.086	86.153	12.532	1.315
5.000	0.086	85.986	12.700	1.314
6.000	0.086	85.897	12.776	1.327
7.000	0.086	85.811	12.857	1.331
8.000	0.086	85.761	12.903	1.336
9.000	0.086	85.723	12.938	1.339
10.000	0.086	85.698	12.961	1.341

Variance Decomposition of SENT:				
Period	*S.E.*	*RETURN*	*SENT*	*VOLATILITY*
1.000	0.665	42.161	57.839	0.000
2.000	0.792	35.141	62.402	2.458
3.000	0.831	32.669	64.879	2.452
4.000	0.854	31.568	65.871	2.561
5.000	0.871	30.773	66.610	2.617
6.000	0.881	30.293	67.019	2.687
7.000	0.888	29.972	67.298	2.730
8.000	0.893	29.762	67.471	2.767
9.000	0.896	29.618	67.589	2.793
10.000	0.899	29.521	67.666	2.813

Variance Decomposition of VOLATILITY:				
Period	*S.E.*	*RETURN*	*SENT*	*VOLATILITY*
1.000	0.005	1.891	1.376	96.733
2.000	0.006	2.213	5.345	92.441
3.000	0.006	2.897	8.879	88.224

4.000	0.007	3.480	15.349	81.171
5.000	0.007	3.871	18.833	77.296
6.000	0.007	4.173	21.855	73.972
7.000	0.008	4.402	23.918	71.680
8.000	0.008	4.563	25.483	69.954
9.000	0.008	4.679	26.587	68.734
10.000	0.008	4.762	27.391	67.847

Notes: *The table reports the results of Variance decomposition in the Var model. The variables are Investor Sentiment Index (SENT), Monthly Stock Return on the GEM (RETURN), Monthly Volatility on the GEM (VOLATILITY).*

Table 5.2 6 Testing sentiment impact asymmetry on GEM returns

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.010	0.007	-1.407	0.159
	Variance Equation			
γ	-2.363	0.806	-2.932	0.003
δ	0.169	0.241	0.702	0.483
θ	0.136	0.139	-0.981	0.027
ε	0.574	0.148	3.886	0.000
β	0.472	0.192	2.460	0.014
R-squared	-0.034	Mean dependent var		0.005
Adjusted Rsquared	-0.034	S.D. dependent var		0.084
S.E. of regression	0.085	Akaike info criterion		-2.312
resid	133.164	Schwarz criterion		-2.165
Log likelihood	1.476	Hannan-Quinn criter.		-2.252

Notes: The table reports the results of EGARCH model. The dependent variable is GEM Return(R). β *is the coefficient of sentiment.*

γ, δ, θ, ε *and* β *are parameters to be estimated, which stands for constant, last period volatility, the leverage effect, impact of long term volatility and impact of a change in sentiment on the return's variance.*

Figure 1 Trend of investor sentiment index and GEM composite index from June 2010 to November 2019

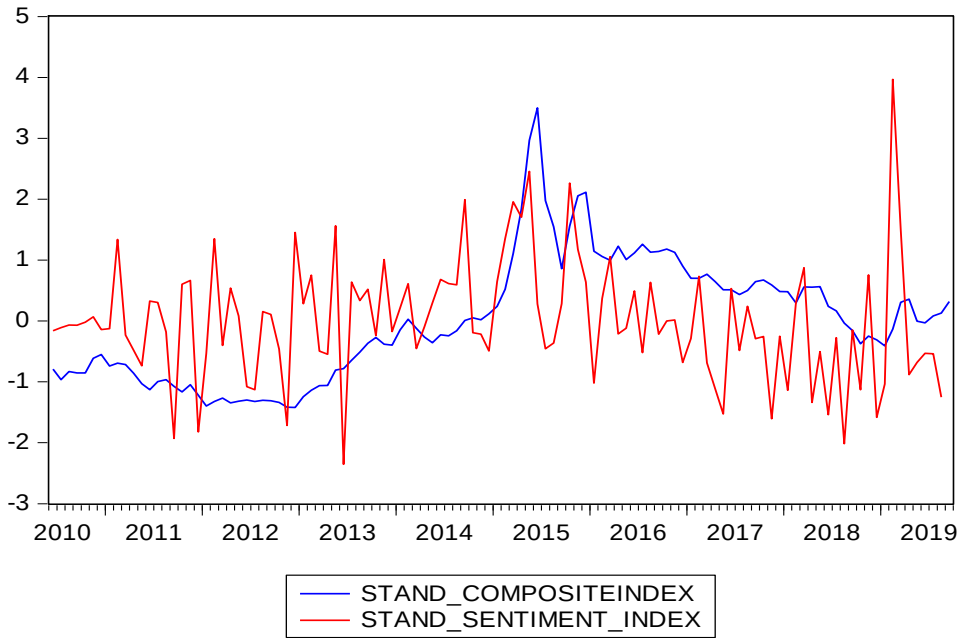


Figure 2 Inverse AR Roots Graph

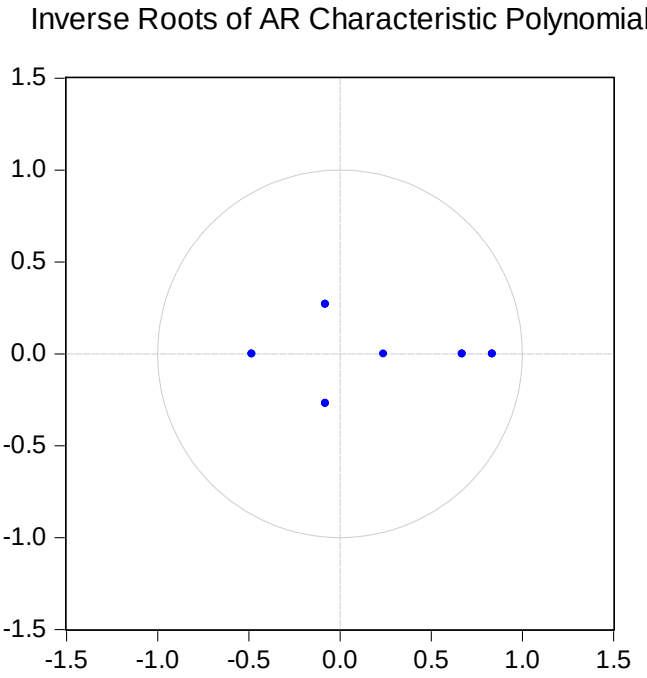
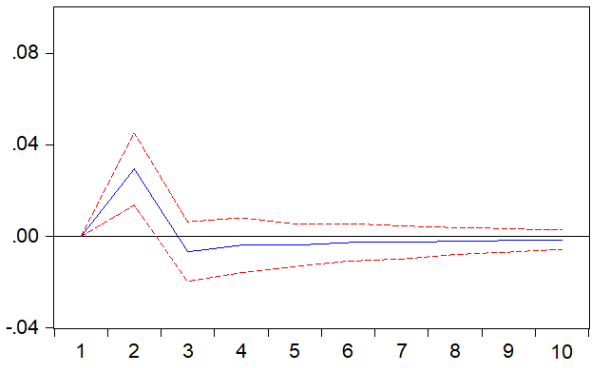
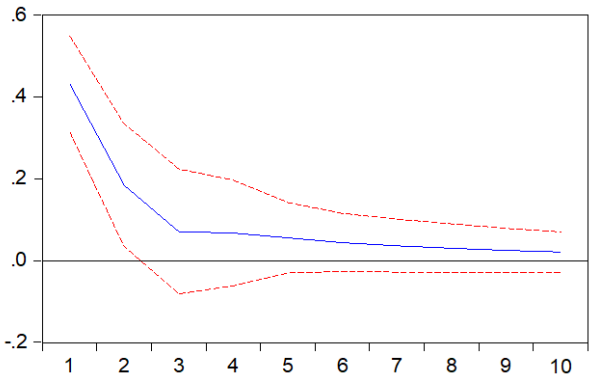


Figure 3 Impulse Response

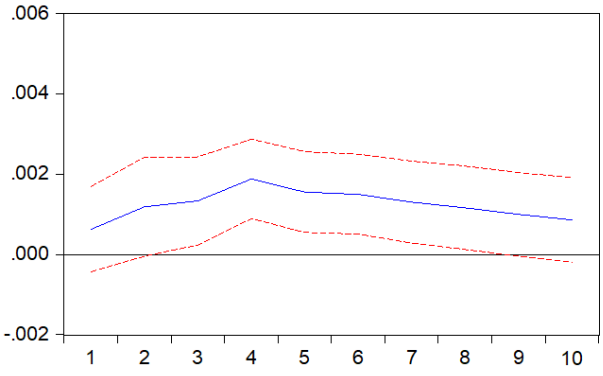
(a) Response of return to sentiment



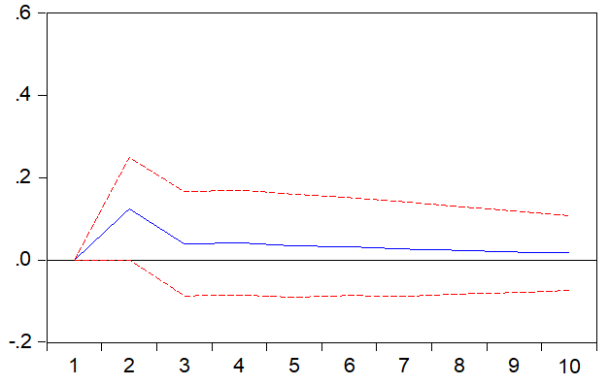
(b) Response of sentiment to return



(c) Response of volatility to sentiment



(d) Response of sentiment to volatility



Notes: *The table reports results of IRFs. The dash lines on each graph presents the upper and lower 95% confidence interval. The response is statistically significant when bands hold the same sign. The vertical axis represents the percentage returns and horizontal axis represents the time.*

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