國 立 交 通 大 學

經營管理研究所

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波動成分情緒指標與雜訊交易者風險
Volatility Components Sentiment Indices and Noise Trader Risk

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摘　要

我們使用 GJR-GARCH 和七種情緒指標來檢驗 De Long 等(1990a)所提出雜訊交易者風險在條件波動和超額報酬上的影響。我們發現情緒是一個解釋股票超額報酬和條件波動很顯著的因子。情緒的變化量對於條件波動和超額報酬有很顯著的影響。PCO、AAII、II 和 IPON 可以用來預測未來的報酬，而 ARMS、PCO、PCV、AAII 和 IPON 可以預測報酬波動。看漲的情緒會使得條件波動向下修正，而看跌的情緒則會使波動向上爬升。此外，我們使用 Component GARCH 檢測雜訊交易者風險在長期和短期的情形。我們發現情緒在短期波動的影響比長期波動來的大且顯著。

關鍵詞：情緒、雜訊交易者風險、GJR-GARCH、Component GARCH

Volatility components sentiment indices and noise trader risk

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ABSTRACT

Using seven sentiment indices, we employ a GJR-GARCH specification to test the impact of noise trader risk on both the formation of conditional volatility and expected return as suggested by De Long et al. (1990a). Our main findings suggest that sentiment is a significant factor in explaining equity excess returns and conditional volatility. We find that the magnitude of shifts in sentiment has a significant impact on the formation of conditional volatility of returns and expected returns. PCO, AAII, II, and IPON can be used to forecast the future returns and ARMS, PCO, PCV, AAII, and IPON are good proxy to forecast the volatility of returns. Bullish (bearish) shifts in sentiment lead to downward (upward) revisions in the volatility of returns. In addition, we try to use the component GARCH to divide the noise trader risk into two components which are the transitory component and the permanent component. We find that effect of sentiment in the transitory component is larger and more significant than in the permanent component.

Keywords: Sentiment, Noise trader risk, GJR-GARCH, Component GARCH

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1. Introduction

For decades, the success and popularity of the efficient market hypothesis (EMH) lies in its ability to explain the lack of predictability in liquid asset returns, meanwhile traditional “search for value” is clashed by many finance practitioners. More recent analysis has discussed how such traders acting sentiment might induce systematic risk and affect asset prices in equilibrium. For example, as the noise trader models of De Long, Shleifer, Summers, and Waldmann (1990a; 1990b) suggest that if informed arbitrageurs know that prices may diverge further away from fundamentals before they converge closer, they may take smaller positions when betting against mispricing. If these uninformed noise traders base their trading decisions on sentiment, sentiment may have predictive power for asset price behavior. The noise trader model of De Long, Shleifer, Summers, and Waldmann (1990a) has motivated empirical attempts to substantiate the proposition that noise trader risks influence price formation.

Most papers test whether sentiment can predict returns or volatility. They attempt to explain this correlative relationship through the role of noise traders whose changes in sentiment can influence subsequent returns and volatility. If it is true, we can use sentiment as an indicator to forecast not only the returns but volatility as well. Many papers in the past have used sentiment to forecast return or volatility, but rarely both at the same time.

The model of De Long, Shleifer, Summers, and Waldmann (1990a) predicts that the direction and magnitude if changes in noise trader sentiment are relevant in asset pricing, the subsequent empirical testing focused on the impact of sentiment either on the mean or variance in asset returns alone, such testing are mispecified and at best can only be considered as incomplete. The “price-pressure” and “hold-more” effects capture the impact of noise trading on excess returns resulting from lagged changes in investor sentiment. The

“Friedman” and “create-space” effects reflect the impact of noise trading on excess returns associated with the influence of the magnitude of sentiment changes on the future volatility of returns.

The “hold-more” effect implies that noise traders’ increased holdings of risky assets when their sentiment becomes more bullish raises market risk and thereby increases expected returns; and vice versa, when they are bearish. However, noise traders overreact to good and bad news. Asset prices are either too high or too low depending on where noise traders are on average optimistic or pessimistic. Such overreaction lowers expected returns. This “price-pressure” effects and market returns will correlate with changes in investor sentiment and the direction of the correlation depends on which effect dominates.

In addition, the magnitude of the changes in perceptions about the asset’s risk by noise traders associated with their shifts in sentiment also impact expected returns. Noise traders usually have poor market timing because of their tendency to trade together with other noise traders. Their capital losses are larger due to poor market timing and the magnitude of losses regards the magnitude of the change in their misperceptions. The Friedman effect implies that this changes result in higher market risk and lower expected returns. There is an adverse impact that the Friedman effect has on expected returns depending on the “space” the noise trading creates. A rise in noise traders’ misperceptions increases price uncertainty and crowds out risk-averse informed investors. Therefore, the greater is the proportion of noise trading, the higher will be expected returns.

Lee, Jiang, and Indro (2002) employ a generalized autoregressive conditional heteroscedasticity (GARCH) in-mean model (Engle, 1982; Bollerslev, 1986; Engle, Lilien, and Robins, 1987) to show that both the conditional volatility and excess returns are affected by investor sentiment. In this paper, we also use a GJR-GARCH in-mean (Glosten, Jagannathan, and Thaler, 1993) to show such a relationship. It is different with Lee et al.’s model which includes contemporaneous shifts in investor sentiment within the mean equation, while our model includes lagged shifts in investor sentiment in the mean equation.

We examine the relationship between volatility of market excess returns, excess returns, and investor sentiment for three different market indices, the DOW Jones Industrial Average (DJIA), the Standard and Poor's 500 (S&P500) and the NASDAQ. In this paper, we use a lot of sentiment indices to proxy the noise traders' sentiment. For the daily data, we use the OEX put-call trading volume ratio (PCV), the OEX put-call open interest ratio (PCO), and the ARMS index for NYSE as the sentiment indices. For weekly data, we use the bullish percentage of sentiment indices of Investors' Intelligence (II) and the American Association of Individual Investors (AAII). And for monthly data, we use the initial public offering first day returns (IPORET) and the number of offerings (IPON).

Our main findings suggest that sentiment is a significant factor in explaining equity excess returns and conditional volatility of the excess return. In addition, we find that the magnitude of shifts in sentiment has a significant impact on the formation of conditional volatility of excess returns and excess returns. Bullish (bearish) shifts in sentiment lead to downward (upward) revisions in the volatility of returns.

Furthermore, we find that PCO, AAII, II, and IPON can be used to forecast the future returns and ARMS, PCO, PCV, AAII, and IPON are good proxy to forecast the volatility of returns. Some of the indices are useful in forecasting the one of the large and small capitalization stocks.

Since we find the sentiment of noise trader has an impact on the conditional volatility of the excess return. And few researches discuss that noise trader risk whether is only a transitory phenomenon. We try to use the component GARCH (Engle and Lee, 1999) to divide the noise trader risk into two components which are the transitory component and the permanent component. We find that effect of sentiment in the transitory component is larger and more significant than in the permanent component. That is to say noise trader risk should be a transitory phenomenon in the conditional volatility, and the stock market will recover in the future (long-term).

The remainder of the paper proceeds as follows. Section 2 of the paper discusses the noise trader risk and the relationship among the sentiment, return, and volatility and introduces the literatures of GARCH models. Section 3 of the paper presents the data source. Section 4 presents the empirical model. Section 5 discusses the empirical results. The last section provides some conclusions.

2. Literature Review

Over the past years, there has been ample research on the noise trader risk and the relationship between stock returns and the noise traders' sentiment. In this section we provide a review of literature related to our perspective and motivation for further empirical investigation.

Economists have been debating the effect, if any, of uninformed investors—so-called noise traders—have on the price of finance for decades. Early papers (Friedman, 1953; Fama, 1965) argue noise traders are unimportant in the financial asset price formation process because trades of the rational arbitrageurs drive prices close to their fundamental values. However, some evidences of the market anomalies challenge this efficient markets theory.

Black (1986) considers the noise of a large number of small events is often a causal factor that is much more powerful than a small number of large events can be. Noise not only causes markets to be inefficient, but also prevents us from taking advantage of inefficiencies within the markets.

De Long, Shleifer, Summers, and Waldmann (1990a) suggest, if some investors trade on a "noisy" signal that is unrelated to fundamental values, then asset prices will deviate from their intrinsic value. Noise traders can introduce a systematic risk that is priced. In their model, changing investor sentiment can create deviations in price from fundamental value that are unpredictable. In the short run, arbitrageurs betting against mispricing run the risk, and investor sentiment becomes more extreme and prices move even further away from fundamental values. The potential loss and the arbitrageurs' risk aversion reduce the positions which they are willing to take. In the long run, the prices will revert to their fundamental values. This process may not be very smooth, and may take a long time. Finally, arbitrage cannot completely eliminate mispricing and investor sentiment ultimately affects security prices in equilibrium.

Lee, Shleifer, and Thaler (1991) suggest closed-end fund discounts are a measure of the sentiment of individual investors. This sentiment is widespread to affect the small stocks prices in the same way that it influences the closed-end funds. Smaller stocks must also be underpriced relative to their fundamentals, since the same investor sentiment affects small stocks and so makes them riskier. That the small firms appear to earn excess returns is well-known as the small firm effect.

A number of researchers, such as Black (1986), De Long, Shleifer, Summers, and Waldmann (1990a; 1990b), and Barberis, Shleifer, and Vishny (1998) have more formally modeled the role of investor sentiment. But their models are difficult to test directly, because they usually involve sources of noise which are difficult to measure.

Many papers' findings show sentiment as having a predictive capability for returns. Neal and Wheatley (1998) find the discounts on closed-end funds and the redemptions of mutual funds predict equity returns.

Fisher and Statman (2000) studied three groups of investors, Wall Street strategists, writer of investment newsletters, and individual investors, which denote large, medium, and small investors respectively. They found the sentiment of small and large investors are reliable contrary indicators for future S&P 500 returns.

Simon and Wiggins (2001) find sentiment indicators such as the VIX, the put-call ratio, and the ARMS had significant predictive power for subsequent S&P futures over the sample periods January 1989 through June 1999.

Lee, Jiang, and Indro (2002) estimate a GARCH-in-mean model which includes contemporaneous shifts in investor sentiment in the mean equation and lagged shifts in sentiment in the conditional volatility equation. They use the sentiment survey indicator provided by Investor's Intelligence to examine the impact of changes in investor sentiment on the conditional volatilities of the DJIA, S&P 500, and NASDAQ indices, which are estimated from the GJR-GARCH model. They find sentiment can affect returns through volatility.

Many papers also investigated the relationship between sentiment and volatility. Brown (1999) examines whether investors' sentiments relate to the volatility of closed-end fund returns. He uses both direct investor survey (the American Association of Individual Investors Sentiment Survey) and closed-end fund discounts as measures of sentiment and finds individual investor sentiment is related to increased volatility in closed-end fund discounts. He also finds that deviations from the average level of sentiment are associated with increases in fund volatility only during trading hours. Lee, Jiang, and Indro (2002) find that bullish (bearish) changes in sentiment result in downward (upward) adjustments in volatility. Wang, Keswani, and Taylor (2006) find ARMS has predictive power for future realized volatility but that this is limited when returns are included.

However, many researchers find that sentiment indicators might be caused by returns or volatility. Fisher and Statman (2000) found high S&P 500 returns during one month can make individual investors and newsletter writers bullish on their sentiments.

Brown and Cliff (2004) use a large number of sentiment indicators to investigate investor sentiment and its relationship to near-term stock market returns. They find that past market returns are also an important determinant of sentiment and sentiment has little predictive power for future stock returns. And Wang, Keswani, and Taylor (2006) also find most sentiment measures are caused by returns and volatility.

In summary, the literature tells us that sentiment may be useful for forecasting return and volatility. It also tells us that this relationship may be influenced by the behavior of returns.

Engle (1982) proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model which has become the most famous model in processing the conditional volatility. The ARCH model which would be possibly the most important innovation in modeling markets volatility changes adopts the effect of past residuals and helps explain the volatility clustering phenomenon. In traditional econometrics models, the one period forecast variance is assumed to be constant. But the ARCH model assumes that variance of residuals to be time varying and conditional on past sample. And Bollerslev (1986) proposed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model which brings the previous volatility term into the ARCH model. The GARCH model is widely applied in research of financial and economic time series. Engle's (1982) ARCH model extended to allow the conditional variance to be a determinant of the mean and is called ARCH-M.

Some latest researches are interested in the asymmetry effect of the volatility. Nelson (1991) gave different weights to different sign of residuals. Glosten, Jagannathan and Runkle (1993) used a dummy variable to catch the additional impact of the negative return.

Engle and Lee (1999) propose the component GARCH model. In their model, the conditional variance of stock returns has been decomposed in a statistical unobserved component model to describe the long-run (trend) and the short-run (transitory) movement of stock market volatility.

The GARCH model can let us consider excess return and conditional volatility of excess return contemporaneously, therefore we use a GJR-GARCH model to model the noise trader risk. In addition, we estimate a component GARCH to find whether effect of sentiment in the transitory component is larger and more significant than in the permanent component.

3 Data

3.1. Direct sentiment measures

There are two indices that directly measure the sentiment of market participants. The first is a survey conducted by the American Association of Individual Investors (AAII). AAII has conducted a sentiment survey by polling a random sample of its members each week, beginning in July 1987. The association asks each participant whether they are bearish, bullish, or neutral about the stock market in 6 months. Only subscribers to AAII can vote. Since this sentiment survey is targeted towards individuals, this can be interpreted as an individual sentiment measure. We use the bullish percentage as a measure of investor sentiment in this paper.

The second survey is conducted by Investors Intelligence (II). Since 1964, Investors Intelligence compiles its sentiment data weekly by categorizing approximately 150 market newsletters. Newsletters are read and marked as bullish, bearish, or neutral starting on Friday each week. The results are reported on the following Wednesday. We interpret the bullish percentage compiled by Investors Intelligence as a proxy for institutional sentiment, because a lot of the writers of those newsletters are past or current market professionals.

Fisher and Statman (2000) use II and AAII index as medium and small investors' sentiment respectively. They found the relationship between II and AAII sentiment index is strong and the AAII bullish percentage index is reliable contrary indicators for future S&P 500 returns.

< Figure 1 is inserted about here >

< Table 1 is inserted about here >

We find AAII and II have some similarities that they have the same long run trend and their correlation coefficient is 0.513088. AAII and II have strong correlation. But we can see that AAII fluctuates stronger than II, because AAII represent the small investors' sentiment and small investors are influenced by information of market easier than other investors.

3.2. Indirect sentiment measures

Brown et al. (2004) find that many commonly used indirect measures of sentiment are related to direct surveys of investor sentiment. They examine many financial indicators, which they categorize into a number of main groups. We use the three categories here, and we choose some of these indicators as our indirect sentiment measures. In addition, we also add some market measures in this paper.

3.2.1. Market performance

The ARMS (or TRIN) index is developed by Richard Arms in 1967 and first introduced by Barron's in the same year. One of the first to adopt this indicator in his market analysis was Richard Russell, the last living Dow Theorist and writer of the Dow Theory Letters. The ARMS Index is a market breadth and strength indicator, which attempts to analyze the relationship between the number of advancing and declining issues and the advancing and declining volume.

The ARMS index is the ratio of the number of advances to declines standardized by their respective volumes. It is calculated as:

$$ARMS_t = \frac{\#Adv_t / AdvVol_t}{\#Dec_t / DecVol_t} = \frac{DecVol_t / \#Dec_t}{AdvVol_t / \#Adv_t}$$

where $\# Adv_t$, $\# Dec_t$, $AdvVol_t$, and $DecVol_t$, respectively, denote the number of advancing issues, the number of declining issues, the trading volume of advancing issues, and the trading volume of declining issues. An ARMS Index reading of one implies that the market is in balance, while a reading above one implies more volume is moving into declining stocks (bearish) and vice versa. When the market is more bearish, the trading volume of declining issues will rise and the ARMS Index will greater. When the market is more bullish, the trading volume of advancing issues will rise and the ARMS Index will go down. The ARMS Index can also be used as an oversold/overbought indicator when smoothed by a simple moving average – such as using a 10-day or a 21-day moving average. Wang et al. (2006) find that ARMS has predictive power for future realized volatility. Our ARMS daily data is obtained form Bloomberg.

< Figure 2 is inserted about here >

3.2.2. Derivatives variables

The put-call trading volume ratio (PCV) and the put-call open interest ratio (PCO) are also the measures of market participants' sentiment. The PCV equals the trading volume of put options divided by the trading volume of call options. The market participants buy put to hedge their spot positions, when their sentiment is bearish. The PCV then goes up, because the trading volume of put options increases in relation to the trading volume of call options, and vice versa.

We also can calculate the ratio by using the open interest of options instead of trading volume. The PCO is a good measure of sentiment, because it can reflect the sentiment at the end of the day or the week. Option open interest is used to proxy for heterogeneous beliefs as the put/call open interest ratio is widely used in behavioral finance as a measure of investor sentiments (e.g. Dennis and Mayhew, 2002). We use the OEX put-call trading volume ratio and the OEX put-call open interest ration here. The daily data is obtained from Bloomberg.

< Figure 3 is inserted about here >

3.2.3. Other sentiment proxies

Many other variables don't fall neatly within one of the aforementioned categories. IPO activity is often considered a measure of sentiment because of the information asymmetries between managers and investors. We include monthly data on initial public offering first day returns (IPORET) and the number of offerings (IPON) in this paper. The number of initial public offering and the first day return of initial public offering are both a bullish market indicator. These IPO monthly data are reported by Ritter (http://bear.cba.ufl.edu/ritter).

< Figure 4 is inserted about here >

3.3. Sample period and stock return proxies

Our daily, weekly, and monthly samples cover the period from August 22, 1996 to December 31, 2007, July 24, 1987 to December 28, 2007, and February 01, 1971 to December 31, 2006, respectively. Three different market indices which are the DJIA, S&P500, and NASDAQ are used to characterize the overall performance of the market. The DJIA is a price-weighted average of 30 large "blue-chip" stocks. Although the limitations in the composition and construction of the index are well known, yet, it is the most widely followed and reported stock index. The S&P500 and NASDAQ are both value-weighted indices that reflect the return of large and small capitalization stocks respectively. The data of DJIA, S&P500, and NASDAQ are obtained from yahoo finance.

< Figure 5 is inserted about here >

< Figure 6 is inserted about here >

< Figure 7 is inserted about here >

As reported in Panel B of Figure 5, the volatility of excess return of NASDAQ is greater than DJIA and S&P500, because NASDAQ index is composed of many small high tech companies where many of their investors are small investor and they tend to be easily influenced by noise information.

Panel A of Figure 5 shows the daily close prices of DJIA, S&P500, and NASDAQ from August 22, 1996 to December 31, 2007. As reported in Panel A of Figure 5, we find the close prices are unusual from March 29, 2000 to April 27, 2000, especially in NASDAQ. During this period, the close price of NASDAQ drops off substantially from 4958.56 to 3774.03. The excess returns of stock index are an abnormal negative. It appears commonly in all three indices and obviously in NASDAQ index. This phenomenon is commonly known as the bursting of the dot-com bubble.

The average three-month T-Bill yield is used as a proxy for the risk-free rate of interest in computing the excess returns for each stock index. The daily and weekly three-month T-Bill yield is obtained from Bloomberg and the monthly three- month T-Bill yield is obtained from Taiwan Economic Journal (TEJ).

< Figure 8 is inserted about here >

4. Empirical design

4.1. Hypotheses

In De Long et al.'s (DSSW (1990a) hereafter) model, if informed investors have shorter horizons than noise traders and are concerned with resale prices, arbitrage is limited. Noise traders' optimism or pessimism results in transitory divergences between price and fundamental value. Moreover, the extent sentiment induced takes place contemporaneously across many assets in the markets, and the additional variability in returns is a systematic risk. In DSSW, there are four effects of sentiment on returns and volatility shown in Figure 1. We test two hypotheses that used by Lee et al. (2002). The two hypotheses result from the interaction of the four effects.

< Figure 9 is inserted about here >

HYPOTHESIS 1 (Direct sentiment effect): *The "hold-more" effect dominates the "price-pressure" effect. When noise traders' sentiment becomes more bullish, the excess returns will be higher. If their sentiment becomes more bearish, the excess returns will be lower.*

In DSSW, investor sentiment can influence mean returns directly through two effects, they are "price-pressure" and "hold-more" effects. The trading of noise traders creates "price pressure" which results in a purchase (sale) price higher than fundamental value and lowers expected returns, when the average sentiment of noise traders is bullish (bearish). This is the "price-pressure" effect.

On the other hand, when noise traders' sentiment become more bullish (bearish), they will increase (decrease) demand for the risky assets. This results in a higher (lower) expected return, which is the "hold-more" effect. As a result, only if the "hold-more" effect dominates (does not dominate) the “price-pressure” effect, the mean return is higher (lower) while noise traders’ sentiment becomes more bullish. But when the sentiment of noise traders becomes more bearish, the net result on mean return is always negative because both effects are intensifying. Lee, Jiang, and Indro (2002) use the sentiment index which is AAII to examine these effects, and they find the “hold-more” effect dominates the “price-pressure”.

HYPOTHESIS 2 (Indirect sentiment effect): *The “Friedman” effect dominates the “create-space” effect. A rise in noise traders’ misperceptions about the asset’s risk incurs lower expected returns.*

In DSSW, prices are also affected by changing in the noise traders’ misperceptions about the asset’s risk. There are two different ways. One of these is the “Friedman” effect. When many other noise traders are buying (selling), noise traders will buy (sell) most of the risky asset. Then they will likely suffer a capital loss because of their poor market timing. The more variable noise traders' misperceptions are, the more damage their poor market timing does to their returns. The changes in the noise traders’ misperceptions about the risk of the asset incur lower expected returns.

Another way is the create-space effect. A rise in noise traders’ misperceptions about the asset’s risk increases price uncertainty and reduces sophisticated investors’ desire to hold risky assets. Because noise traders’ momentum crowds out risk-averse sophisticated investors, noise traders benefit more from their trading. Overall, when the “create-space” effect is more (less) important than the “Friedman” effect, the mean returns are higher (lower).

4.2. The generalized autoregressive conditional heteroscedasticity model

The interaction of four effects results in the impact of noise trading on the risky assets’ price. The “hold-more” and “price-pressure” effects are related to the direction of movement in noise traders' sentiment, so they influence mean returns directly. The "Friedman" and "create-space" effects influence mean returns indirectly through changes in noise traders' misperceptions of the asset's risk. Therefore the two effects are related to the magnitude of the movements in noise traders' sentiment.

4.2.1. The GJR-GARCH model

Here we use a GARCH-in-mean model which Lee et al. (2002) propose, which includes lagged shifts in investors' sentiment in the conditional volatility (variance) equation. It is different from Lee et al.'s model which includes contemporaneous shifts in investor sentiment in the mean equation, and it includes lagged shifts in investor sentiment in the mean equation.

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 Dot + \alpha_5 \Delta S_{t-1} + \varepsilon_{it} \qquad (1)$$

where R_{it} is the return on a market index, R_{ft} is the risk-free rate, Jan_t is a dummy variable for January effect, Oct_t is a dummy variable for October effect, Dot is a dummy variable for dot-com bubble of period, and ΔS_{t-1} is a measure of noise trader risk associated with the shifts in sentiment.[1] $\Delta S_{t-1} = \Delta SI_{t-1} \equiv (SI_{t-1} - SI_{t-2}) / SI_{t-2}$. Moreover, in equation (1), $\varepsilon_{it} \sim N(0, h_{it})$ and

$$\begin{aligned} h_{it} = {} & \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{t-1} + \beta_3 h_{it-1} + \beta_4 R_{ft} + \beta_5 (\Delta S_{t-1})^2 D_{t-1} \\ & + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1}) \end{aligned} \qquad (2)$$

where (i) $I_{t-1} = 1$ if $\varepsilon_{it-1} < 0$ and $I_{t-1} = 0$ if $\varepsilon_{it-1} \geq 0$; and (ii) $D_{t-1} = 0$ if $\Delta S_{t-1} \leq 0$ and $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$.

Bollerslev, Chou, and Kroner (1992) suggest that GARCH (1,1) is a parsimonious yet

[1] We already examined the autocorrelation functions and the partial autocorrelation functions.

appropriate specification is most applications, therefore we specify only one lag in our GJR-GARCH model in this paper. Because equity market volatility is found to be higher in high inflation periods, we include the risk-free interest rate in the variance equation. The dummy variables, January and October, specify the well-documented seasonal effect in equity excess returns. Glosten, Jagannathan, and Runkle (1993) specify the dummy variables of the two seasonal effects and the risk-free interest rate in their GARCH-M model. In addition, we find the shock of dot-com bubble on stock market caused the close prices to be unusual from March 29, 2000 to April 27, 2000, especially in NASDAQ. During this period close price of NASDAQ drop off substantially from 4958.56 to 3774.03 and the excess returns of stock index are abnormally negative. Then we use a dummy variable to capture the abnormal return in the period.

We recognize through the dummy variable I_{t-1} that investors in forming their expectations of conditional volatility may perceive positive and negative shocks differently in Equation (2). In particular, we expect β_2 to be positive, because a negative shock is more likely to cause a larger upward revision of volatility than a positive shock of same magnitude. This is the leverage effect that is different for negative than for positive shocks. A surprisingly bad stock market performance causes the debt ratio of the firm to be higher, and investors perceive the company to be more risky and later revise their expectation of conditional volatility upward, vice versa. A good stock market performance induces the debt ratio of the firm to be lower, and investors perceive the company to be less risky and subsequently revise their expectation of conditional volatility downward.

Many scholars find this asymmetric effect for volatility by empirical researches. For example, Nelson (1991) finds that news arriving in the market tends to affect volatility in an asymmetric way, depending on the nature of the news. Glosten, Jagannathan, and Runkle (1993) also find that the magnitude of the change in market volatility is greater for bad news than for good news.

Moreover, we recognize in Equation (2) through the dummy variables D_{t-1} and $(1-D_{t-1})$ that the magnitude as well as direction of shifts in investor sentiment can have an asymmetric impact on conditional volatility. Individual investors may react differently to the magnitudes of the shifts in bullish and bearish sentiment in forming expectations of conditional volatility.

Lee, Jiang, and Indro (2002) find that shifts in sentiment of investor are negatively correlated with the market volatility. Volatility increases when investors become more bearish and volatility decreases when they become more bullish,

The coefficients (α_5) reflects the net impact of hold-more and price-pressure effects on excess returns in the mean equation. The coefficients (β_5, β_6) in the variance equation capture the effect of the magnitude of shifts in sentiment on volatility formation. The net impact of the Friedman and the create-space effects on excess returns is reflected through the sign and the significance of the coefficient(α_1).

4.2.2. The component GARCH

Engle and Lee (1999) propose the component GARCH model, can separate the conditional volatility as the permanent and transitory volatility components, and reflect the long-term and short-term effect. Engle and Lee (1999) also consider the leverage effect and propose the component GARCH including threshold term. To capture the components of volatility of noise trader, we estimate a components GARCH model including threshold term.

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 Dot + \varepsilon_{it} \tag{3}$$

where R_{it} is the return on a market index, R_{ft} is the risk-free rate, and Dot is a dummy variable for dot-com bubble of period.[2] Moreover, in equation (3), $\varepsilon_{it} \sim N(0, h_{it})$ and

$$h_{it} = q_t + [\beta_5 + \beta_6(\varepsilon_{it-1}^2 - q_{t-1})I_{t-1}] + \beta_7(h_{it-1} - q_{t-1}) + \beta_8(\Delta S_{t-1})^2 D_{t-1} + \beta_9(\Delta S_{t-1})^2(1 - D_{t-1}) \quad (4)$$

$$q_t = \beta_0 + \beta_1(q_{t-1} - \beta_0) + \beta_2(\varepsilon_{it-1}^2 - h_{it-1}) + \beta_3(\Delta S_{t-1})^2 D_{t-1} + \beta_4(\Delta S_{t-1})^2(1 - D_{t-1}) \quad (5)$$

where (i) $I_{t-1} = 1$ if $\varepsilon_{it-1} < 0$ and $I_{t-1} = 0$ if $\varepsilon_{it-1} \geq 0$; and (ii) $D_{t-1} = 0$ if $\Delta S_{t-1} \leq 0$ and $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$. ΔS_{t-1} is a measure of noise trader risk associated with the shifts in sentiment. $\Delta S_{t-1} = \Delta SI_{t-1} \equiv (SI_{t-1} - SI_{t-2}) / SI_{t-2}$.

We recognize in Equation (4) and (5) through the dummy variables D_{t-1} and $(1 - D_{t-1})$ that the magnitude as well as direction of shifts in investor sentiment can have an asymmetric impact on conditional volatility. Individual investors may react differently to the magnitudes of the shifts in bullish and bearish sentiment in forming expectations of conditional volatility.

The coefficients (β_3) and (β_4) reflects the long-run effect of noise traders' sentiment in the variance equation. The coefficients (β_8) and (β_9) in the variance equation capture the short-run effect of the magnitude of shifts in sentiment on volatility formation. If noise trader risk affects the volatility is a transitory phenomenon, it will be reflected on the coefficients (β_8, β_9), and we expect the absolute value of the coefficients (β_8, β_9) to be greater than (β_3, β_4) and the transitory component of sentiment effect is more significant than the permanent component.

[2] Because the dummy variables of season effect in the mean equation are not significant and our main purpose is to examine the sentiment effect in the volatility, we only put the dummy of Dot-Com Burble in the mean equation. Although we do not put them in the mean equation, our result does not change.

5. Results

5.1. Summary statistics

< Table 2 is inserted about here >

As reported in Panel A of Table 2, the overall daily returns over the entire sample period are 0.0326% for the DJIA (8.215% annually), 0.0304% (7.661% annually) for the S&P500, and 0.0327% (8.240% annually) for the NASDAQ. The standard deviations of the weekly data are 1.1364 for DJIA, 1.1675 for S&P500, 1.7988 for NASDAQ, and NASDAQ has the largest standard deviation. The maximum daily return of NASDAQ is 12.6454%, and the minimum return is -13.9222%. NASDAQ has the largest maximum daily return and lowest minimum daily return, because NASDAQ index is composed of many small companies.

The excess returns of the three stock indices showed in Panel B are 0.0225% for DJIA, 0.0203% for S&P500, and 0.0226% for NASDAQ and all of excess returns are greater than zero. It means that there is a positive excess return in the overall stock market in the period from August 22, 1996 to December 31, 2007. NASDAQ has the highest mean excess return in the period.

As shown in Panel C, the daily average sentiment indices are 1.0878 for the ARMS, 1.2281 for the put-call open interest ratio, and 1.2106 for the put-call trading volumes ratio, respectively. The standard deviation of the ARMS, the put-call open interest ratio, and the put-call trading volume ratio are 0.6166, 0.2796, and 0.3825, respectively. That the means of the three daily sentiment indices are greater than one means the investors' sentiments in the period are more bearish.

Panel D shows that over the entire sample period, the average percentage change in

ARMS, PCO, and PCV of 0.2456, 0.0038, and 0.0670 respectively, are relatively small. The means of the three average percentage changes also greater than zero also shows the investors' sentiments are bearish in the period.

< Table 3 is inserted about here >

For the weekly data, as reported in Panel A of Table 3, the overall weekly returns over the entire sample period are 0.1580% for the DJIA (8.216% annually), 0.1469% (7.639% annually) for the S&P500, and 0.1718% (8.834% annually) for the NASDAQ. The standard deviations of the daily data are 2.1987 for the DJIA, 2.1355 for the S&P500, 3.1345 for the NASDAQ. We also see that the NASDAQ has the largest standard deviation and Maximum weekly return (17.3770%) and the lowest minimum weekly return (-29.1753%).

All of excess returns of stock indices are also greater than zero, so there is positive excess return in the period from July 22, 1987 to December 31, 2007. The same with the daily data, NASDAQ has the largest mean excess return in the period of our weekly data.

As shown in Panel C, the AAII has a mean of 39.3827% and a standard deviation of 11.0046, respectively. And the II has a mean of 45.8603% and a standard deviation of 7.8361. Between the two direct sentiment indices, AAII has the larger standard deviation. Fisher and Statman (2000) consider AAII represents the small investors' sentiment and II represents the medium investors' sentiment. In average, the medium investors are more bullish than the small investors. Maybe the small investors are more bullish than medium investors when the market is bullish and more bearish when the market is bullish, because AAII has the higher the maximum proportion of bullish and the lower the minimum proportion of bearish.

Panel D shows that over the entire sample period, the average percentage change in AAII and II of 0.0267 and 0.0029 respectively, are relatively small and the mean of the investor sentiment in the market are bullish. We also see the average percentage change of AAII has also larger standard deviation.

< Table 4 is inserted about here >

The period of our monthly data is from February 1, 1971 to December 31, 2006. As reported in Panel A of Table 4, the overall monthly returns over the entire sample period are 0.6484% for DJIA (7.781% annually), 0.6565% (7.878% annually) for S&P500, and 0.7753% (9.304% annually) for NASDAQ. The standard deviations of the monthly data are 4.4606 for DJIA, 4.3905 for S&P500, 6.4486 for NASDAQ, and NASDAQ has the largest standard deviation. The maximum monthly return of NASDAQ is 19.8653%, and the minimum return is -31.7919%. NASDAQ has the largest maximum monthly return and lowest minimum monthly return too. In Panel B, all of excess returns of the three stock indices are also greater than zero in the period from February 1, 1971 to December 31. 2006 and NASDAQ has the largest excess return among them.

As shown in Panel C, the monthly average sentiment indices are 17.8290% for the initial public offering first day return (IPORET) and 30.4171 for the number of offering (IPON). The number of initial public offering and the first day return of initial public offering are both a bullish market indicator. More the number of IPO and the first day return of IPO, the market are more bullish. The standard deviation of the initial public offering first day return and the number of offering are 17.8290 and 30.4171, respectively. The means of the three daily sentiment indices are greater than one implies the investors' sentiments in the period are more bearish.

In Panel D, the changes in the two sentiment index are greater than zero implies that the mean of the investor sentiment in the overall market are bullish in the period from February 1, 1971 to December 31. 2006. The means of the changes in the number of IPO and the return of IPO are 0.1830 and 0.5924, respectively.

5.2. Estimated GJR-GARCH results

For each of the three stock indices, we estimate a base model that excludes sentiment as an explanatory variable in the mean and conditional volatility equations. We estimate GJR-GARCH in the period from August 22, 1996 to December 31, 2007, July 22, 1987 to December 31, 2007, and February 1, 1971 to December 31, 2006 for daily, weekly, and monthly data, respectively. The period of our daily data is approximately ten years and the period of our weekly data which is approximately twenty years is relatively longer. The period of our monthly data which is the longest across the three periods is approximately thirty-five years. The estimated coefficients of the base models for the three stock indices for daily, weekly, and monthly data are reported in Table 5.

< Table 5 is inserted about here >

First, in the base model, the time-invariant portion of excess returns is not significant; and the time-varying portion of excess returns in the base model is not significant with conditional volatility too. The results are not consistent with previous findings of a negative price for time-varying risk (Glosten, Jagannathan, and Runkle, 1993; De Santis and Gerard, 1997; Lee, Jiang, and Indro, 2002).

Second, across the three stock indices, not all of the estimated GARCH coefficients in the base models are significant. We confirm that surprises have an asymmetric effect on conditional volatility and this result is consistent with our forecast, because most of coefficients of the asymmetric effect which is β_2 are significant and positive except the model of monthly NASDAQ return. Negative shocks cause higher upward revisions in volatility.

In addition, as Glosten, Jagannathan, and Runkle (1993) find, volatility is generally greater when inflation rates are projected to be higher in the future. Except the NASDAQ, the coefficients for the risk-free rate are positive and significant for both the DJIA and S&P500. This result is the same with Lee, Jiang, and Indro (2002). Despite the coefficients for the risk-free rate of the daily and weekly NASDAQ are not significant and significantly negative, respectively, it is significant and positive for the monthly NASDAQ.

In our base models, the seasonal effects which are January and October effect are not significant that only the dummy variables of October effect of monthly DJIA and S&P500 are significance at 10% level and negative. The season effect is very weak in our data period. The coefficients of the dummy variables for dot-com bubble in the mean equation are negative and are significant in the daily models of S&P500 and NASDAQ and weekly models of DJIA and NASDAQ, especially in NASDAQ (significant at 1% level). But all of dummy variables for dot-com bubble in the monthly base models are not significant. The impact from the crash of dot-com bubble to NASDAQ is the largest and the most obvious, because NASDAQ index is composed of many small high tech companies where many of their investors are small investor.

To the base model in Table 5, we then add measures of noise trader risk associated with shifts in sentiment in the mean and volatility equations. The percentage changes in sentiment for daily, weekly, and, monthly data are utilized in Table 6, 7, and 8, respectively. The major findings are summarized below.

< Table 6 is inserted about here >

< Table 7 is inserted about here >

< Table 8 is inserted about here >

As shown in Table 6, the time-invariant portion of excess returns and the coefficient of GARCH in mean equation are not significant. January and October effect is the same as in its insignificance. The dummy variable for dot-com bubble is not only significant and great, it is negative only in NASDAQ. The dot-com bubble variable is not significant, except S&P500 of PCO.

The three sentiment indices which are ARMS, the OEX put-call open interest ratio (PCO), and the OEX put-call trading volume ratio (PCV) in our daily data are bearish indicators. In daily model, only the coefficient of lagged shifts in PCO in mean equation for excess returns of all stock indices are very significant (significance at 1% level) and negative, but PCV and ARMS are not. We find that PCO can be used to forecast the excess return of a particular stock index. When the markets are more bearish, PCO goes up. This will affect stock market in that the excess return of stock market will go down in the future.

In the variance equation of the daily model, after adding the shifts of sentiment, the phenomenon that volatility is greater when inflation rates are projected to be higher in the future is no longer clear. In addition, it is the same with base model that surprises have an asymmetric effect on conditional volatility. This is the leverage effect that is different for negative than for positive shocks and the magnitude of the change in market volatility is greater for bad news than for good news.

For the models of ARMS, we find bullish shifts in sentiment in the current period result in statistically significant downward revisions in the volatility of future returns, and the coefficient of bearish shifts in ARMS in variance equation are very small. For PCO and PCV, bearish shifts in sentiment in the current period lead to upward revisions in volatility of future returns. Bullish shifts in PCO and PCV in the current period also lead to upward revisions, but it is less significance (only NASDAQ p-value is less than 5%). We find the three daily sentiment indices are good indicators to forecast the volatility of excess return of stock index.

As reported in Table 7, we use two direct sentiment indices AAII and II as the bullish sentiment indicator in our weekly models. The season effects are very weak. The dummy variable of dot-com bubble for each indices and sentiment are significant and great negative other than DJIA for AAII.

First for AAII, in mean equation, the time-invariant portion and the time-invariant portion of excess returns of DJIA and NASDAQ are not significant. But the time-invariant portion of excess return of S&P500 is significant and negative (-0.908) and its coefficient of GARCH in mean equation is significant and positive (0.159). We find AAII in the current period can be used to forecast the excess return of S&P500 in the future, because the coefficient of the shift of AAII is significant at 5% level and positive (0.771). When AAII rises, it will affect stock market in that the excess return of stock market will go up in the future. In variance equation, we don’t find the surprises having an asymmetric effect on conditional volatility and it is surprising that the coefficients of the risk-free rate are negative. We find that bullish shifts in AAII sentiment index in the current period result in statistically significant downward revisions in the volatility of future returns of DJIA and S&P500, and the coefficient of bearish shifts in AAII in the variance equation are not significant.

Second in the models of II, in the mean equation, each time-invariant portions and coefficient of GARCH-in-mean are not significant. In the mean equation for DJIA and S&P500, a shift in sentiment has a significant positive impact on excess return and the coefficients of DJIA and S&P500 are -1.576 and -1.559, respectively. It means the II is a good contrary indicator for the excess returns of DJIA and S&P500, especially for S&P500. In the variance equation, there is the leverage effect that is different for negative than for positive shocks, but II in the current period can’t affect the volatility in the future.

As shown in Table 8, we use IPON and IPORET as bullish sentiment index in our monthly data. In Table 8, we don’t find IPORET in the current period can affect the excess return in the future and each of coefficients of October effect is significant. Although IPORET in the current period can affect the volatility of the excess return of DJIA in the future, the coefficient is very small. So we can say with confidence that IPORET has poor forecasting power.

In addition, we find that when IPON rises, the excess returns of S&P500 and NASDAQ will go up in the future. However, IPON also has forecast power for the volatility of NASDAQ, bullish shifts in sentiment in the current period result in statistically significant downward revisions in the volatility of future returns.

Overall, we find that investor sentiment is an important factor in explaining equity excess returns and changes in conditional volatility. PCO can be used to forecast the excess returns of all stock indices. As PCO goes up, the excess returns will go down. AAII can be used to forecast the return S&P500 and II can be used to DJIA and S&P500. There is positive correlation between excess returns and shifts of AAII, but there is negative correlation between excess returns and II. When the bullish percentage of II rises up, the excess return will go down. We confirm II is a contrary indicator for excess returns of large capitalization stocks, because II represents the newsletters' sentiment and they are medium investors. Their opinion will affect other investor especially with the small investors and AAII represents the small investors' sentiment. Although there is great positive correlation (0.513) between AAII and II in Table 1, their results are very different. We consider that AAII might be close to noise traders' sentiment. We also find that there is a positive relationship between change in IPON in the current period and excess return of S&P500 or NASDAQ.

Our results show that shifts in sentiment have an asymmetric impact on conditional volatility. As the magnitude of shifts in bullish sentiment increases, there is a downward (upward) revision in the volatility of future returns. First, PCO and PCV can be used to estimate the effect of change of bearish sentiment to excess return of volatility, and ARMS can be used to estimate the effect of change of bullish sentiment. Second, when change of bullish sentiment percentage of AAII goes up in the current period, the volatility of excess return of DJIA and S&P500 which are large stock will go down in the future. But the effect of the change of bearish sentiment within AAII is not as clear. IPON also has the same effect, but there is some difference in that it is for volatility of NASDAQ.

However, only AAII used as a sentiment indicator to estimate the excess return of S&P500 fits in with our empirical hypothesis which is the noise trader model of De Long et al (1990a), so we use this result to explain the economical reasoning. In the mean equation, a shift in sentiment has a statistically significant positive impact in excess return. The hold-more effect tends to dominate the price-pressure effect and leads to an increase in excess returns when noise traders are more bullish in their sentiments. In particular, when sentiment becomes more bullish, optimism induces noise traders to hold more of the risky assets than fundamentals would indicate, this secures the compensation for bearing the increase in risk associated with sentiment. Nevertheless, the higher risk premium due to increased demand is partially offset by the unfavorable price at which noise traders transact.

If sentiment becomes more bearish, there is a reduction in excess returns. Noise traders choose to hold less of the risky assets when they are more pessimistic, and consequently, are unable to capture the risk premium related to sentiment. Moreover, there is a negative price impact caused by sentiment-induced sale of securities.

In the volatility equation, we also find that bullish shifts in sentiment in the current period result in significant downward revisions in the volatility of future excess returns. And bearish shifts in sentiment in the current period lead to upward revisions in volatility of future excess returns. As the magnitude of shifts in bullish (bearish) sentiment increases, there is a downward (upward) revision in the volatility of future excess returns resulting in lower (higher) future excess returns.

Because of their tendency to trade together, noise traders usually have poor market timing where they end up buying high and selling low. The Friedman effect implies that asset prices tend to be negatively affected when noise traders' misperceptions are more severe. But the extent that asset prices are adversely influenced by the Friedman effect depends on the space which noise trading creates. The lower excess return associated with volatility revisions due to bullish sentiment shifts indicates that the positive effect on price of the space created by sentiment-induced noise trading is not large enough to offset the negative effect on price of poor market timing. In contrast, there is a higher excess return associated with volatility revisions due to bearish sentiment shifts. In this case, the positive effect on price associated with noise trader created space is sufficient to offset the negative effect on price associated with poorly timed sales of securities triggered by bearish shifts in sentiment.

5.3. Estimated Component GARCH results

Here we find some sentiment indices can affect the volatility of excess return of stock index, so we try to use the component GARCH to find whether the noise trader risk is only a transitory phenomenon. The estimated component GARCH results for daily, weekly, and, monthly data are utilized in Table 9, 10, and 11, respectively. The major findings are summarized below.

< Table 9 is inserted about here >

As reported in Table 9, the coefficients of dummy variable of dot-com bubble are significant for NASDAQ in the daily data, and most of the time-invariant portion of excess returns is positive and significant. First, in the transitory component, all the coefficients of threshold term (β_6) are positive and most of them are significant, hence the leverage effect still exist. We also find that the magnitude of the percentage change in sentiment has a significant impact on the formation of transitory component of conditional volatility. Bullish shifts in sentiment in the current period result in statistically significant downward revisions in the volatility of future returns, but bearish are not obvious except S&P500 for PCO (1.102) and PCV (8.541) and NASDAQ for PCV (-0.011). Although -0.011 is positive and significant, the value is very small.

Second, we also find some results in the permanent component. For ARMS, we also find the same result that Bullish shifts in sentiment in the current period result in statistically significant downward revisions in the volatility of future returns and the shifting of bearish is not statistically significant.

In addition, we find that the absolute value of the coefficient of sentiment shift in the transitory component is greater than in the permanent, but it seems not very clear for NASDAQ.

< Table 10 is inserted about here >

For weekly data, shown in Table 10, the coefficient of the magnitude of the change in the AAII sentiment is not significant. But it is not the same with II sentiment. The coefficients of (β_6) are 88.170, 95.093, and 130.1932 for DJIA, S&P500, and NASDAQ, respectively which are positive and statistically significant. For NASDAQ, both that bullish shifts in sentiment in the current period result in statistically significant downward revisions in the volatility of future returns and bearish shifts in sentiment in the current period result in significant upward revisions in the volatility of future returns. Especially, we find that the short-run effect of noise traders' sentiment is greater than the long-run effect.

< Table 11 is inserted about here >

But in our monthly data, the coefficient of the magnitude of the change in sentiment does not have a significant impact on the conditional volatility, no matter in the permanent or transitory component.

6. Conclusion

The model of De Long, Shleifer, Summers, and Waldmann (1990a) predicts that the direction and magnitude of changes in noise trader sentiment are relevant in asset pricing. It is mispecified and at best incomplete because the empirical tests focused on the impact of sentiment either on the mean or variance in asset excess returns alone. Lee, Jiang, and Indro (2002) use a GARCH framework to jointly test the four behavioral effects delineated in the noise trader model of De Long, Shleifer, Summers, and Waldmann (1990a). Their specification allows us to explicitly test the impact of noise trader risk on both the formation of conditional volatility and expected return as suggested by De Long, Shleifer, Summers, and Waldmann (1990a). They only use a direct measure of investor sentiment compiled by Investors' Intelligence to proxy noise trader risk. We also use a GJR-GARCH framework to test the four effects in the noise trader model, but we use more sentiment indices to proxy this kind of risk and include lagged shifts in investor sentiment in the mean equation. There are seven sentiment indices which are use in this paper. For example there are ARMS, OEX put-call trading volume ratio (PCV), OEX put-call open interest ratio (PCO), AAII, II, the number of initial public offering (IPON), and the initial public offering first day returns (IPORET). We try to find whether the sentiment can affect the excess return and volatility.

First, we find that PCO can be used to forecast the excess return of stock index. When the market are more bearish that PCO goes up, it will affect stock market that the excess return of stock market will go down in the future. AAII and IPON have the same effect on S&P500 and NASDAQ, respectively. However, II is a good contrary indicator for excess returns of DJIA and S&P500.

Second, we find that the three daily sentiment indices (ARMS, PCO, and PCV) are good indicators to forecast the volatility of excess return of stock index. AAII and IPON are also good indicators to forecast the volatility of excess return of large and small capitalization stock, respectively. We find that shifts in sentiment are negatively correlated with the market volatility; that is, as volatility increases (decreases) investors become more bearish (bullish). The significance of sentiment on conditional volatility implies that conventional measures of temporal variation in risk omit an important factor. Moreover, Lee, Shleifer, and Thaler (1991) find that closed-end fund discounts which proxy for investor sentiments have the highest correlation with the smallest stocks. But we examine among the three indices, sentiment does not have the most profound impact on NASDAQ. This is not consistent with the finding of Lee, Shleifer, and Thaler (1991) and Lee Jiang, and Indro (2002). Sentiment and noise trading not only affect the volatility of the small capitalization stocks, but also large capitalization stocks. In this paper, we use NASDAQ index as the proxy of small capitalization stocks. But NASDAQ index is composed of many small high technology company, we can not exclude the conclusion that traders' sentiments affect the stocks of high technology industry, not small capitalization stock.

In addition, although only one of our models which use AAII as sentiment on excess return of S&P500 fits for the four effects of De Long et al. (1990a) and the inclusion of sentiment changes the negative relation between the equity excess return and conditional volatility documented in prior studies (Nelson, 1991; Glosten et al., 1993; Lee et al., 2002), we find that lower excess returns are associated with a decrease in conditional volatility resulting from larger bullish shifts in sentiment. These results are consistent with the market reaction to noise trading as suggested by Friedman and create-space effects of De Long et al. (1990a). In this model, there is a positive relation between shifts in sentiment (AAII) and excess returns (S&P500) which indicate that the increase in risk premium associated with the hold-more effect is relatively more important than the negative impact of the price-pressure effect on expected return.

Many technical analysts use the ARMS index to forecast the trend of the stock market, they think the ARMS index are a good index to be used to find the sentiment of investors. Though Wang, Keswani, and Taylor (2006) do not find that ARMS can be used to forecast the return of stock, they find the ARMS index may affect the following volatility. In this paper, we have similar result with them. NYSE ARMS is an index which is the ratio of the number of advances to declines standardized by their respective volumes in NYSE, and we find bullish sentiment of investor is more significant than bearish sentiment. It might about that ARMS is a performance of whole stocks in NYSE.

The put-call trading volume ratio and the put-call open interest ratio stand for the sentiment of derivatives market. We find bearish sentiment of investor is more significant than bullish sentiment in the two indices. As everyone knows, most of the participators of derivatives market are not small investors, and they are medium or institutional investors. The functions of derivatives market are not only the speculation but also hedge. Hedgers usually have spot stocks. If they worry about the loss because of their stocks dropping, they will buy a put to hedge this kind of risk. This phenomenon might be one of the important reasons of the significant response of bearish sentiment. The put-call open interest ratio might be a better index to represent the investors' sentiment, because it not only affects the volatility but also excess return.

Fisher and Statman (2000) use II and AAII index as medium and small investors' sentiment respectively. II is a good contrary indicator for excess returns of DJIA and S&P500. Investors Intelligence compiles its sentiment data weekly by categorizing approximately 150 market newsletters. Market newsletters can affect the other investors' sentiment, and the other investors often trade later than them. AAII might is a proxy of small investors, because AAII has conducted a sentiment survey by polling a random sample of its members each week. And we do not find the tow direct sentiment measures affect significantly the following excess return of small stock.

IPO activity is often considered a measure of sentiment because of the information asymmetries between managers and investors. In this paper, we include monthly data on initial public offering first day returns and the number of offerings. Lee et al. (1991) show that the annual number of IPOs is negatively related to the discount on closed-end mutual funds, which they argue is a measure of the sentiment of retail investors. Ljungqvist , Nanda, and Singh (2006) suggest that as investor sentiment grows, IPO offer size increases and lower-quality companies are taken public, resulting in a decrease in average issuer quality. As the optimism of sentiment investors increases, more companies have an incentive to go public (to take advantage of the optimistic investors) and offer sizes increase. Loughran, Ritter, and Rydqvist (1994) find that there is a positive correlation between the annual volume of IPOs and the level of the stock market, and annual IPO volume is negatively related to the market return during the following year. We find the IPON can be used to forecast following return and volatility of NASDAQ. It might be the reason that it is true that IPO activity is close to small and high technology stock during decades. In addition, in our paper, the IPORET affect the following excess return and conditional volatility is not significant. Because the more number of IPO might result from the greater market return or IPO return.

Lastly, we estimate an asymmetric component GARCH to find whether the effect of noise trader sentiment on the volatility has larger and more significant effect in the short-term than in the long-term. It would be better to say that whether noise trader risk is a transitory effect and is not significant in the permanent component. In our component GARCH results, we find sentiment effect is greater and more obvious in the transitory component than in the permanent component in our most models. It may be that noise trader's sentiment effect on the conditional volatility is a transitory effect. Namely, in the short-run, the shifts of noise trader's sentiment make the volatility of excess return up and down, but in the long-run the sentiment just make a little effect and the market will recover form the abnormal condition.

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Table 1

Correlation matrix for the weekly American Association of Individual Investors sentiment index (bullish percentage) and Investors' Intelligence sentiment index (bullish percentage) from July 24, 1987 to December 28, 2007.

	AAII	II
AAII	1.000000	0.513088
II	0.513088	1.000000

Table 2

Summary statistics of return, excess return, and sentiment index, for daily data, 8/22/1996-12/31/2007.

This table provides summary statistics for daily return, excess return, and sentiment index over the period from August 22, 1996 to December 31, 2007. Daily return (Panel A) and excess return (Panel B) are reported for three indices: the DJIA, S&P500, and NASDAQ. The three sentiment indices, ARMS index (ARMS), the OEX put-call open interest ratio (PCO), and the OEX put-call trading volume ratio (PCV), are reported in Panel C. The measure of changes in investor sentiment is used in Panel D: $\Delta S_t = \Delta SI_t \equiv (SI_t - SI_{t-1}) / SI_{t-1}$.

	Mean	Std. Dev	Max	Min	Skewness	Kurtosis
Panel A: daily returns (%)						
DJIA	0.0326	1.1364	6.6453	-7.5903	-0.1836	7.4289
S&P500	0.0304	1.1675	5.5744	-7.1127	-0.1176	6.1476
NASDAQ	0.0327	1.7988	12.6454	-13.9222	-0.2644	9.0261
Panel B: Excess returns (%)						
DJIA	0.0225	1.1363	6.6290	-7.5974	-0.1839	7.4327
S&P500	0.0203	1.1675	5.5698	-7.1267	-0.1181	6.1510
NASDAQ	0.0226	1.7988	12.6308	-13.9383	-0.2662	9.0297
Panel C: Sentiment index						
ARMS	1.0878	0.6166	14.2600	0.0400	6.8315	109.2862
PCO	1.2281	0.2796	2.6980	0.5222	0.4478	3.0076
PCV	1.2106	0.3825	5.2000	0.2950	1.6767	11.0833
Panel D: Change in sentiment index (ΔS)						
ΔARMS	0.2456	1.4280	30.1429	-0.9783	12.1370	217.2361
ΔPCO	0.0038	0.0886	0.8593	-0.5560	1.5371	21.8023
ΔPCV	0.0670	0.4692	12.3676	-0.8094	8.3529	191.6624

Table 3

Summary statistics of return, excess return, and sentiment index, for weekly data, 7/24/1987-12/31/2007

This table provides summary statistics for weekly return, excess return, and sentiment index over the period from July 22, 1987 to December 31, 2007. Weekly return (Panel A) and excess return (Panel B) are reported for three indices: the DJIA, S&P500, and NASDAQ. The two direct sentiment indices, American Association of Individual Investors (AAII) and Investor's Intelligence (II), are reported in Panel C. The measure of changes in investor sentiment is used in Panel D: $\Delta S_t = \Delta SI_t \equiv (SI_t - SI_{t-1}) / SI_{t-1}$.

	Mean	Std. Dev	Max	Min	Skewmess	Kurtosis
Panel A: Weekly returns (%)						
DJIA	0.1580	2.1987	8.0898	-15.3880	-0.8909	7.8655
S&P500	0.1469	2.1355	7.4923	-13.0071	-0.6938	6.7209
NASDAQ	0.1718	3.1345	17.3770	-29.1753	-1.2937	14.2312
Panel B: Excess returns (%)						
DJIA	0.0700	2.1984	8.0673	-15.4406	-0.8941	7.8714
S&P500	0.0589	2.1352	7.4467	-13.1111	-0.6963	6.7367
NASDAQ	0.0838	3.1351	17.2642	-29.2864	-1.2929	14.2483
Panel C: Sentiment index (bullish %)						
AAII	39.3827	11.0046	75.0000	12.0000	0.2034	2.7523
II	45.8603	7.8361	67.3000	21.1000	-0.2403	2.6294
Panel D: Change in sentiment index (ΔS)						
ΔAAII	0.0267	0.2406	1.7000	-0.6667	1.0103	6.7052
ΔII	0.0029	0.0754	1.0000	-0.5010	2.1235	34.8906

Table 4

Summary statistics of return, excess return, and sentiment index, for monthly data, 2/01/1971-12/31/2006

This table provides summary statistics for monthly return, excess return, and sentiment index over the period from February 1, 1971 to December 31, 2006. Monthly return (Panel A) and excess return (Panel B) are reported for three indices: the DJIA, S&P500, and NASDAQ. The two monthly sentiment indices, the number of initial public offering (IPON) and the initial public offering first day returns (IPORET), are reported in Panel C. The measure of changes in investor sentiment is used in Panel D: $\Delta S_t = \Delta SI_t \equiv (SI_t - SI_{t-1}) / SI_{t-1}$.

	Mean	Std. Dev	Max	Min	Skewmess	Kurtosis
Panel A: monthly returns (%)						
DJIA	0.6484	4.4606	17.3408	-26.4173	-0.7460	7.4714
S&P500	0.6565	4.3905	15.4168	-24.5428	-0.7621	6.9005
NASDAQ	0.7753	6.4486	19.8653	-31.7919	-1.0000	6.7886
Panel B: Excess returns (%)						
DJIA	0.1486	4.4802	16.9083	-26.9506	-0.7485	7.4224
S&P500	0.1567	4.4075	14.9843	-25.0761	-0.7738	6.8756
NASDAQ	0.2755	6.4665	19.4295	-32.3253	-0.9947	6.7802
Panel C: Sentiment index						
IPON	30.4171	24.5907	122.000	1.0000	0.9219	3.4020
IPORET (%)	17.8290	19.8418	119.100	-15.0000	2.3823	9.9934
Panel D: Change in sentiment index (ΔS)						
ΔIPON	0.1830	0.8324	7.0000	-0.8421	3.5684	22.2541
ΔIPORET	0.5924	7.8445	107.000	-47.8571	8.8855	123.9691

Table 5

Estimation of the GJR-GARCH base model without sentiment index for daily, weekly, and monthly excess return

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 Dot + \varepsilon_{it}$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{t-1} + \beta_3 h_{it-1} + \beta_4 R_{ft}$$

This table reports the GARCH-in-mean models, described by Eqs. (1) and (2), for the DJIA, S&P500, and NASDAQ indices over the period from August 22, 1996 to December 31, 2007 for daily data, from July 22, 1987 to December 31, 2007 for weekly data, and from February 1, 1971 to December 31, 2006 for monthly data. The base model does not include the effect of investor sentiment. Jan and Oct are dummy variables for seasonal effect. Dot is a dummy variable for dot-com bubble from March 29, 2000 to April 27, 2000. Dummy variable I_{t-1} is used to indicate that negative shocks by investors in forming their expectations of conditional volatility. $I_{t-1} = 1$ if $\varepsilon_{it-1} < 0$ and otherwise $I_{t-1} = 0$.

	Daily base model			Weekly base model			Monthly base model		
	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ
α_0	0.001	-0.012	0.017	0.002	0.008	0.127	0.278	0.494	0.353
h_{it}	0.017	0.018	0.003	0.019	0.019	0.006	-0.001	-0.010	0.006
Jan_t	-0.031	0.045	0.062	0.026	0.082	0.289	0.232	0.073	0.441
Oct_t	0.039	0.072	0.093	-0.135	-0.102	-0.168	-1.297*	-1.134*	-2.309
Dot	-0.450	-0.659**	-3.230***	-1.921**	-3.040	-13.375***	-2.554	-4.056	-19.197
β_0	0.006**	0.005*	0.005	0.164***	0.083**	0.739***	3.682***	4.294***	1.414
ε_{it-1}^2	0.003	-0.011*	0.026***	0.006	0.029	0.161***	-0.100***	-0.089*	0.103**
$\varepsilon_{it-1}^2 I_{t-1}$	0.110***	0.120***	0.073***	0.202***	0.136***	0.126***	0.318***	0.291**	0.060
h_{it-1}	0.934***	0.943***	0.934***	0.821***	0.864***	0.728***	0.536***	0.545***	0.755***
R_{ft}	0.533***	0.494***	0.635	1.643***	0.828**	-3.035**	9.137***	5.916**	6.367**
Log-likelihood	-3630.211	-3698.741	-4584.263	-2246.294	-2208.918	-2500.871	-1178.426	-1166.765	-1311.544

*Significance at 10% level. **Significance at 5% level. ***Significance at 1% level.

Table 6

Estimation of the GJR-GARCH model with sentiment index for daily excess returns from August 22, 1996 to December 31, 2007

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 Dot + \alpha_5 \Delta S_{t-1} + \varepsilon_{it}$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{t-1} + \beta_3 h_{it-1} + \beta_4 R_{ft} + \beta_5 (\Delta S_{t-1})^2 D_{t-1} + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1})$$

This table reports the GARCH-in-mean models, described by Eqs. (1) and (2), for the daily DJIA, S&P500, and NASDAQ indices over the period from August 22, 1996 to December 31, 2007. The daily sentiment indices are the ARMS, the OEX put-call open interest ratio, and the OEX trading volume ratio and the effect of change in investor sentiment as measured by $(SI_{t-1} - SI_{t-2}) / SI_{t-2}$. Jan and Oct are dummy variables for seasonal effect. Dot is a dummy variable for dot-com bubble from March 29, 2000 to April 27, 2000. Dummy variable I_{t-1} is equal to one if $\varepsilon_{it-1} < 0$ and I_{t-1} is equal to zero otherwise. Dummy variables D_{t-1} and $1 - D_{t-1}$ are used to indicate the direction of changes of sentiment. $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$ and otherwise $D_{t-1} = 0$

	ARMS			PCO			PCV		
	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ
α_0	0.008	0.000	0.026	0.008	0.002	0.024	-0.001	-0.009	0.017
h_{it}	0.015	0.010	-0.002	0.016	0.014	0.005	0.015	0.012	0.004
Jan_t	-0.047	0.033	0.061	-0.020	0.051	0.064	-0.026	0.051	0.058
Oct_t	0.027	0.046	0.079	0.120	0.035	0.053	0.034	0.050	0.060
Dot	-0.447	-0.579	-3.282***	-0.516	-0.682**	-3.198***	-0.505	-0.707	-3.170***
ΔS_{t-1}	-0.006	-0.005	0.027	-1.468***	-1.570***	-1.394***	0.061	0.052	0.037
β_0	0.016***	0.021***	0.020*	0.005**	0.005*	0.009	-0.006**	0.005*	0.010
ε_{it-1}^2	0.005	-0.006	0.031***	-0.006	-0.018***	0.023***	-0.002	-0.018***	0.023***
$\varepsilon_{it-1}^2 I_{t-1}$	0.111***	0.121***	0.073***	0.100***	0.105***	0.071***	0.106***	0.117***	0.075***
h_{it-1}	0.935***	0.946***	0.935***	0.945***	0.956***	0.937***	0.939***	0.950***	0.935***
R_{ft}	0.061	-0.235	0.129	0.112	-0.027	-0.247	0.185	0.001	-0.343
$(\Delta S_{t-1})^2 D_{t-1}$	0.001***	0.000	-0.002**	0.901***	0.890***	0.849***	0.858***	0.988***	0.984***
$(\Delta S_{t-1})^2 (1-D_{t-1})$	-0.159**	-0.251***	-0.261**	0.583	0.866*	1.598*	0.496	0.717*	1.614**
Log-likelihood	-3626.798	-3692.201	-4578.609	-3606.419	-3668.503	-4567.753	-3624.126	-3688.362	-4577.670

*Significance at 10% level. **Significance at 5% level. ***Significance at 1% level.

Table 7
Estimation of the GJR-GARCH model with sentiment index for weekly excess returns from July 22, 1987 to December 31, 2007

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 Dot + \alpha_5 \Delta S_{t-1} + \varepsilon_{it}$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{t-1} + \beta_3 h_{it-1} + \beta_4 R_{ft} + \beta_5 (\Delta S_{t-1})^2 D_{t-1} + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1})$$

This table reports the GARCH-in-mean models, described by Eqs. (1) and (2), for the weekly DJIA, S&P500, and NASDAQ indices over the period from July 22, 1987 to December 31, 2007. The weekly sentiment indices are the bullish percentage of American Association of Individual Investors (AAII) and Investors Intelligence (II) and the effect of change in investor sentiment as measured by $(SI_{t-1} - SI_{t-2}) / SI_{t-2}$. Jan and Oct are dummy variables for seasonal effect. Dot is a dummy variable for dot-com bubble from March 29, 2000 to April 27, 2000. Dummy variable I_{t-1} is equal to one if $\varepsilon_{it-1} < 0$ and I_{t-1} is equal to zero otherwise. Dummy variables D_{t-1} and $1 - D_{t-1}$ are used to indicate the direction of changes towards more bullish and more bearish sentiment, respectively. $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$ and otherwise $D_{t-1} = 0$

	AAII			II		
	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ
α_0	-0.675	-0.908***	-0.812	0.021	0.022	0.126
h_{it}	0.085	0.159***	0.045	0.014	0.015	0.005
Jan_t	-0.162	-0.533*	-0.149	0.034	0.097	0.301
Oct_t	-0.139	-0.210	0.195	-0.059	-0.030	-0.138
Dot com	-1.294	-3.008***	-8.124***	-1.900**	-3.137***	-13.321***
ΔS_{t-1}	0.382	0.771**	0.776	-1.576*	-1.559**	-0.585
β_0	4.321**	3.787***	8.078***	0.202***	0.114**	0.673***
ε_{it-1}^2	0.035	0.118*	0.135	0.004	0.033	0.161***
$\varepsilon_{it-1}^2 I_{t-1}$	0.051	0.033	0.036	0.222***	0.151***	0.113***
h_{it-1}	0.562***	0.499***	0.518***	0.807***	0.851***	0.737***
R_{ft}	-5.533	-11.162**	-15.503***	1.054	0.369	-3.192**
$(\Delta S_{t-1})^2 D_{t-1}$	-2.636***	-2.271***	-4.890	5.433	3.420	-2.912
$(\Delta S_{t-1})^2 (1 - D_{t-1})$	-6.218	-3.838	-12.172	7.693	3.161	29.040
Log-likelihood	-2410.978	-2317.708	-2710.747	-2235.523	-2199.269	-2496.535

*Significance at 10% level
**Significance at 5% level
***Significance at 1% level

Table 8

Estimation of the GJR-GARCH model with sentiment index for monthly excess returns from February 1, 1971 to December 31, 2006

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 h_{it} + \alpha_2 Jan_t + \alpha_3 Oct_t + \alpha_4 Dot + \alpha_5 \Delta S_{t-1} + \varepsilon_{it}$$

$$h_{it} = \beta_0 + \beta_1 \varepsilon_{it-1}^2 + \beta_2 \varepsilon_{it-1}^2 I_{t-1} + \beta_3 h_{it-1} + \beta_4 R_{ft} + \beta_5 (\Delta S_{t-1})^2 D_{t-1} + \beta_6 (\Delta S_{t-1})^2 (1 - D_{t-1})$$

This table reports the GARCH-in-mean models, described by Eqs. (1) and (2), for the monthly DJIA, S&P500, and NASDAQ indices over the period from February 1, 1971 to December 31, 2006. The monthly sentiment indices are the number of initial public offering (IPON) and the first day return of initial public offering (IPORET) and the effect of change in investor sentiment as measured by $(SI_{t-1} - SI_{t-2}) / SI_{t-2}$. Jan and Oct are dummy variables for seasonal effect. Dot is a dummy variable for dot-com bubble from March 29, 2000 to April 27, 2000. Dummy variable I_{t-1} is equal to one if $\varepsilon_{it-1} < 0$ and I_{t-1} is equal to zero otherwise. Dummy variables D_{t-1} and $1 - D_{t-1}$ are used to indicate the direction of changes towards more bullish and more bearish sentiment, respectively. $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$ and otherwise $D_{t-1} = 0$

	IPON			IPORET		
	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ
α_0	-1.087	-2.921*	-1.136	-1.296	-1.639	-0.306
h_{it}	0.065	0.086*	0.028	0.057	0.087	0.021
Jan_t	0.165	-0.033	0.629	0.022	-0.130	0.837
Oct_t	-1.683**	-1.277	-1.983	-1.654*	-1.542*	-2.608***
Dot com	-2.330	-4.709	-18.192	-2.505	-3.516	-14.359
ΔS_{t-1}	0.219	0.479**	0.729*	0.023	0.007	0.018
β_0	10.871**	13.542	30.618***	15.549	13.006*	18.392***
ε_{it-1}^2	-0.060	0.022	0.100	0.051	-0.063	0.073
$\varepsilon_{it-1}^2 I_{t-1}$	0.189	0.087	0.052	-0.008	0.163	0.200
h_{it-1}	0.436*	0.509	0.509***	0.508	0.474	0.444***
R_{ft}	-0.542	-5.840	-18.094***	-5.922	-4.448	-3.336
$(\Delta S_{t-1})^2 D_{t-1}$	-0.330	-0.556	-1.431***	-0.005	0.003	0.001
$(\Delta S_{t-1})^2 (1 - D_{t-1})$	0.107	-2.678	-3.861	-0.012***	-0.010	-0.014
Log-likelihood	-1179.478	-1179.584	-1326.893	-1193.249	-1173.580	-1314.325

*Significance at 10% level
**Significance at 5% level
***Significance at 1% level

Table 9

Estimation of the Components GARCH model with sentiment index for daily excess returns from August 22, 1996 to December 31, 2007

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 Dot + \varepsilon_{it}$$

$$h_{it} = q_t + [\beta_5 + \beta_6(\varepsilon_{it-1}^2 - q_{t-1})I_{t-1}] + \beta_7(h_{it-1} - q_{t-1}) + \beta_8(\Delta S_{t-1})^2 D_{t-1} + \beta_9(\Delta S_{t-1})^2(1 - D_{t-1})$$

$$q_t = \beta_0 + \beta_1(q_{t-1} - \beta_0) + \beta_2(\varepsilon_{it-1}^2 - h_{it-1}) + \beta_3(\Delta S_{t-1})^2 D_{t-1} + \beta_4(\Delta S_{t-1})^2(1 - D_{t-1})$$

This table reports the CGARCH models, described by Eqs. (3), (4), and (5), for the daily DJIA, S&P500, and NASDAQ indices over the period from August 22, 1996 to December 31, 2007. The daily sentiment indices are the ARMS, the OEX put-call open interest ratio, and the OEX trading volume ratio and the effect of change in investor sentiment as measured by $(SI_{t-1} - SI_{t-2})/SI_{t-2}$. Dot is a dummy variable for dot-com bubble from March 29, 2000 to April 27, 2000. Dummy variable I_{t-1} is equal to one if $\varepsilon_{it-1} < 0$ and I_{t-1} is equal to zero otherwise. Dummy variables D_{t-1} and $1 - D_{t-1}$ are used to indicate the direction of changes of sentiment. $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$ and otherwise $D_{t-1} = 0$

	ARMS			PCO			PCV		
	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ
α_0	0.043**	0.045***	0.072***	0.032*	0.038**	0.066***	0.045***	0.018	0.077**
Dot	-0.176	-0.518	-3.982***	-0.174	-0.575	-3.898***	-0.191	-0.239	-3.093***
β_0	5.897***	10.122***	34.965**	0.949***	0.941***	2.312	1.979*	2.021***	2.825***
β_1	0.997***	0.998***	0.999***	0.973***	0.990***	0.997***	0.995***	0.993***	0.805***
β_2	0.081***	0.073***	0.069***	0.070***	0.068***	0.055***	0.074***	0.032***	0.096**
β_3	-1.96E-05	-0.0002	0.002	0.274	-0.273	-0.815	0.003	0.008**	0.007
β_4	-0.116**	-0.165***	-0.238***	0.453	1.315	2.157**	-0.071	-0.419***	0.091
β_5	-0.119***	-0.131***	-0.045*	-0.032	-0.131***	-0.042	-0.112***	-0.051***	0.023
β_6	0.066***	0.100***	0.004	0.004	0.140***	0.040	0.135***	0.134***	0.042
β_7	-0.196	0.025	-0.729***	-0.095	0.522***	0.201	0.637***	0.952***	0.091
β_8	0.005	0.002	-0.001	0.443	1.102**	8.541***	-0.005	-0.011**	-0.020
β_9	-0.466***	-0.551***	0.020	-2.610***	-3.111***	-4.916***	0.836***	0.807***	-1.250
Log-likelihood	-3649.214	-3722.894	-4587.501	-3662.885	-3720.445	-4575.209	-3652.799	-3698.358	-4834.790

*Significance at 10% level. **Significance at 5% level. ***Significance at 1% level.

Table 10

Estimation of the Components GARCH model with sentiment index for weekly excess returns from July 22, 1987 to December 31, 2007

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 Dot + \varepsilon_{it}$$

$$h_{it} = q_t + [\beta_5 + \beta_6(\varepsilon_{it-1}^2 - q_{t-1})I_{t-1}] + \beta_7(h_{it-1} - q_{t-1}) + \beta_8(\Delta S_{t-1})^2 D_{t-1} + \beta_9(\Delta S_{t-1})^2(1 - D_{t-1})$$

$$q_t = \beta_0 + \beta_1(q_{t-1} - \beta_0) + \beta_2(\varepsilon_{it-1}^2 - h_{it-1}) + \beta_3(\Delta S_{t-1})^2 D_{t-1} + \beta_4(\Delta S_{t-1})^2(1 - D_{t-1})$$

This table reports the CGARCH models, described by Eqs. (3), (4), and (5), for the weekly DJIA, S&P500, and NASDAQ indices over the period from July 22, 1987 to December 31, 2007. The weekly sentiment indices are the bullish percentage of American Association of Individual Investors (AAII) and Investors Intelligence (II) and the effect of change in investor sentiment as measured by $(SI_{t-1} - SI_{t-2})/SI_{t-2}$. Dot is a dummy variable for dot-com bubble from March 29, 2000 to April 27, 2000. Dummy variable I_{t-1} is equal to one if $\varepsilon_{it-1} < 0$ and I_{t-1} is equal to zero otherwise. Dummy variables D_{t-1} and $1 - D_{t-1}$ are used to indicate the direction of changes towards more bullish and more bearish sentiment, respectively. $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$ and otherwise $D_{t-1} = 0$

	AAII			II		
	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ
α_0	0.126**	0.118**	0.203***	0.074***	0.125***	0.229***
α_1	-1.515*	-2.334***	-10.704***	-1.334	-2.651***	-12.897***
β_0	3.774**	2.255**	10.896***	3.373***	3.599***	10.513***
β_1	0.986***	0.979***	0.980***	0.986***	0.988***	0.990***
β_2	0.037***	0.060***	0.067***	0.030**	0.037***	0.036***
β_3	-0.496	-0.759	0.028	3.394	4.371	18.307***
β_4	1.366	3.702*	-4.964	-8.534	-11.494	-45.641***
β_5	0.176***	0.195***	0.065	-0.002	0.015	0.109**
β_6	-0.004	-0.072	0.102*	0.157***	0.111*	0.129**
β_7	0.317	0.257	0.607***	0.691***	0.612***	0.609***
β_8	-0.220	-0.314	-0.952	-3.205	-6.381	-23.661***
β_9	-0.685	-4.361	5.542	88.170***	95.093***	130.1932***
Log-likelihood	-2246.549	-2205.047	-2494.534	-2236.252	-2195.785	-2487.852

*Significance at 10% level
**Significance at 5% level
***Significance at 1% level

Table 11

Estimation of the Components GARCH model with sentiment index for monthly excess returns from February 1, 1971 to December 31, 2006

$$R_{it} - R_{ft} = \alpha_0 + \alpha_1 Dot + \varepsilon_{it}$$

$$h_{it} = q_t + [\beta_5 + \beta_6(\varepsilon_{it-1}^2 - q_{t-1})I_{t-1}] + \beta_7(h_{it-1} - q_{t-1}) + \beta_8(\Delta S_{t-1})^2 D_{t-1} + \beta_9(\Delta S_{t-1})^2(1 - D_{t-1})$$

$$q_t = \beta_0 + \beta_1(q_{t-1} - \beta_0) + \beta_2(\varepsilon_{it-1}^2 - h_{it-1}) + \beta_3(\Delta S_{t-1})^2 D_{t-1} + \beta_4(\Delta S_{t-1})^2(1 - D_{t-1})$$

This table reports the CGARCH models, described by Eqs. (3), (4), and (5), for the monthly DJIA, S&P500, and NASDAQ indices over the period from February 1, 1971 to December 31, 2006. The monthly sentiment indices are the number of initial public offering (IPON) and the first day return of initial public offering (IPORET) and the effect of change in investor sentiment as measured by $(SI_{t-1} - SI_{t-2})/SI_{t-2}$. Dot is a dummy variable for dot-com bubble from March 29, 2000 to April 27, 2000. Dummy variable I_{t-1} is equal to one if $\varepsilon_{it-1} < 0$ and I_{t-1} is equal to zero otherwise. Dummy variables D_{t-1} and $1 - D_{t-1}$ are used to indicate the direction of changes towards more bullish and more bearish sentiment, respectively. $D_{t-1} = 1$ if $\Delta S_{t-1} > 0$ and otherwise $D_{t-1} = 0$

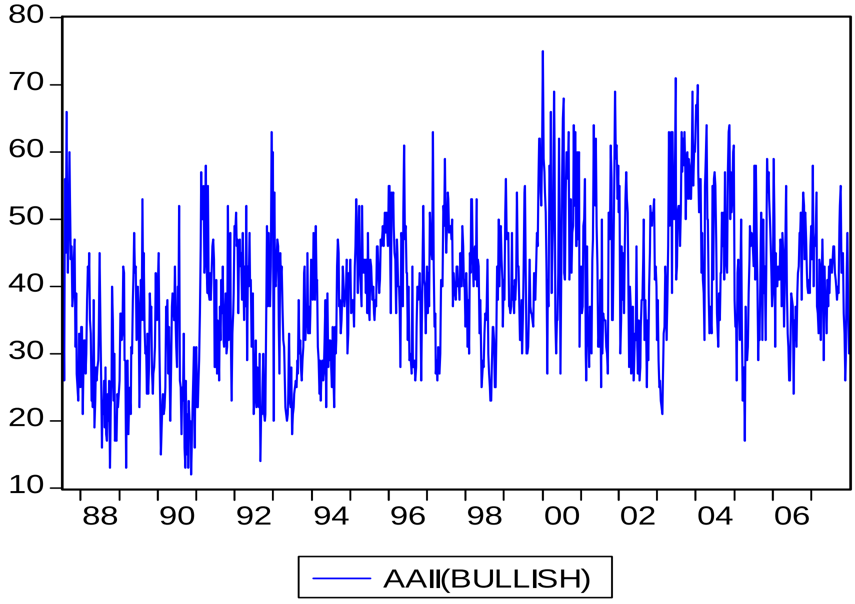
	IPON			IPORET		
	DJIA	S&P500	NASDAQ	DJIA	S&P500	NASDAQ
α_0	0.121	0.071	0.375***	0.081	0.204	0.307***
α_1	-2.178	-3.653	-18.156	-2.289	-3.808	-17.746
β_0	27.281***	26.040***	65.795***	19.073***	32.952***	42.665***
β_1	0.938***	0.959***	0.926***	0.672***	0.5444**	0.896***
β_2	0.121***	0.121***	0.144*	0.020	-0.056	0.072
β_3	0.543*	-0.006	-0.581	0.014	0.012	0.014
β_4	-13.699*	-4.588	-17.276	-0.003	0.004	-0.007
β_5	-0.276***	-0.270***	0.001	-0.038	0.197***	0.052
β_6	0.198***	0.166***	-0.092***	0.090	-0.128***	-0.067
β_7	0.573***	0.456*	1.036***	0.673	0.824***	0.896***
β_8	-0.142	-0.057	-0.209	-0.009	-0.002	-0.014
β_9	17.177	1.936	10.006	-0.003	-0.010	-0.004
Log-likelihood	-1172.773	-1168.473	-1294.830	-1183.385	-1166.476	-1308.102

*Significance at 10% level

**Significance at 5% level

***Significance at 1% level

Panel A. American Association of Individual Investors sentiment index



Panel B. Investors' Intelligence sentiment index

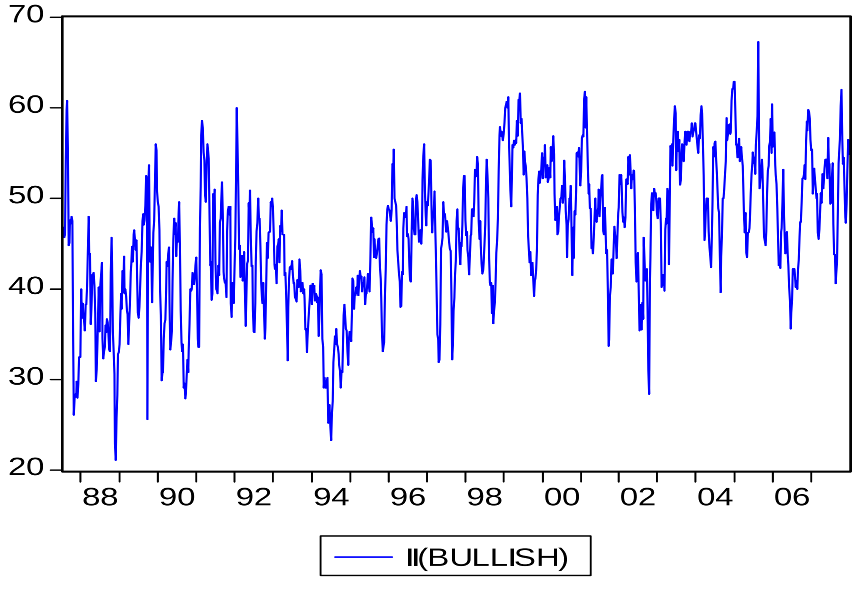


Figure 1. Direct sentiment measures

This figure shows the weekly American Association of Individual Investors sentiment index (bullish percentage) and Investors' Intelligence sentiment index (bullish percentage) from July 24, 1987 to December 28, 2007.

ARMS index

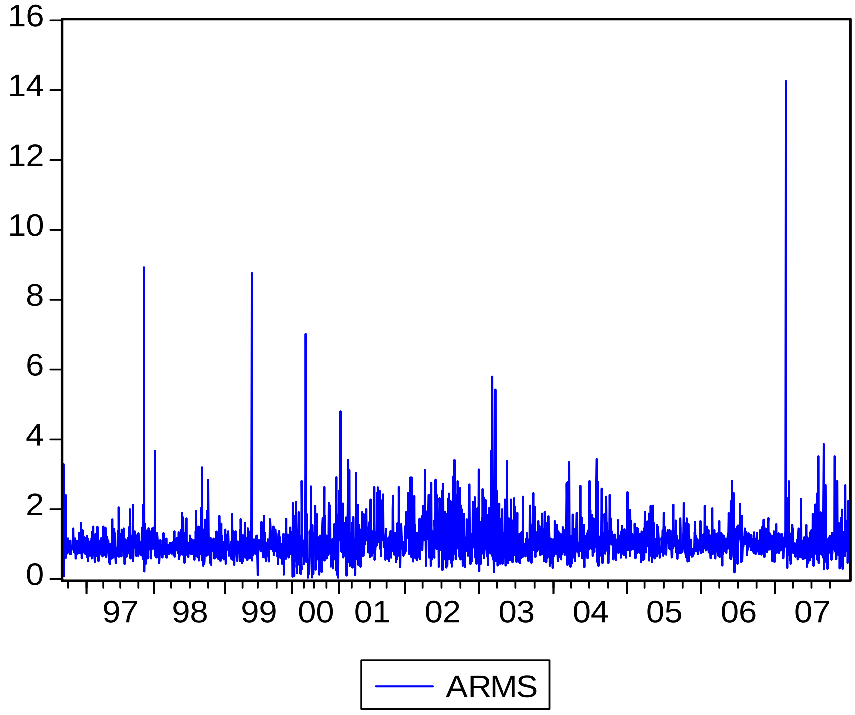
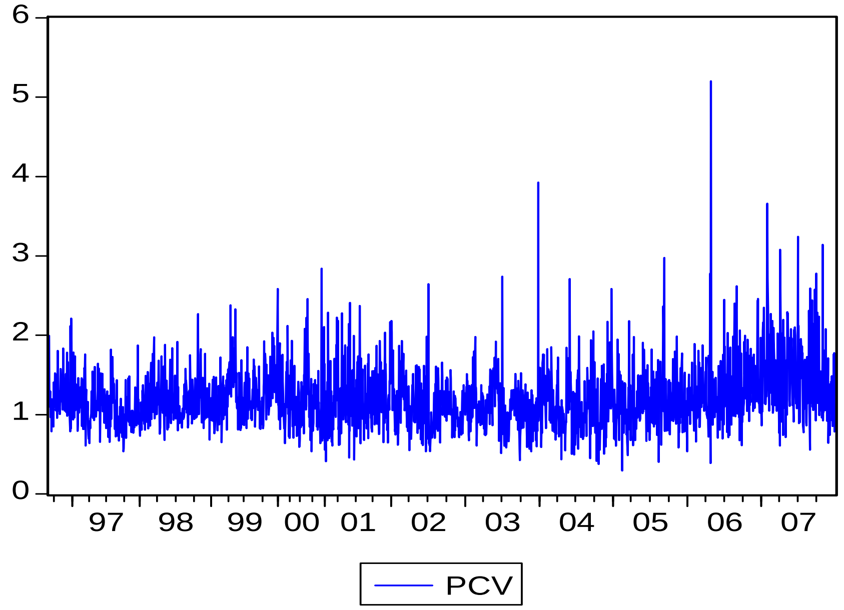


Figure 2. Market performance measures

This figure shows the daily ARMS index from August 22, 1996 to December 31, 2007.

Panel A. the OEX put-call trading volume ratio



Panel B. the OEX put-call open interest ratio

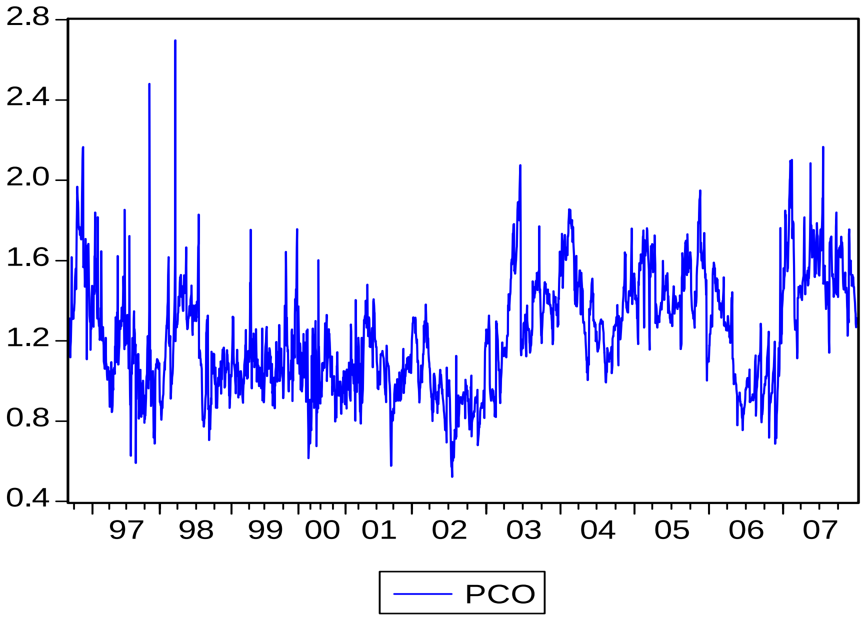
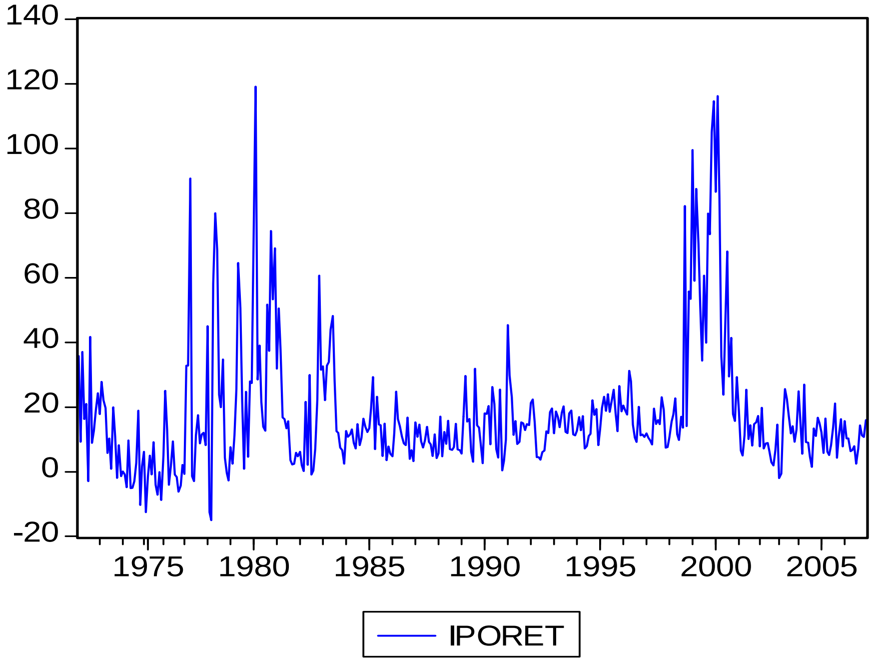


Figure 3. Derivatives variable measures

This figure shows the daily OEX put-call trading volume ratio (PCV) and the OEX put-call open interest ratio (PCO) from August 22, 1996 to December 31, 2007.

Panel A. the initial public offering first day returns



Panel B. the number of initial public offerings

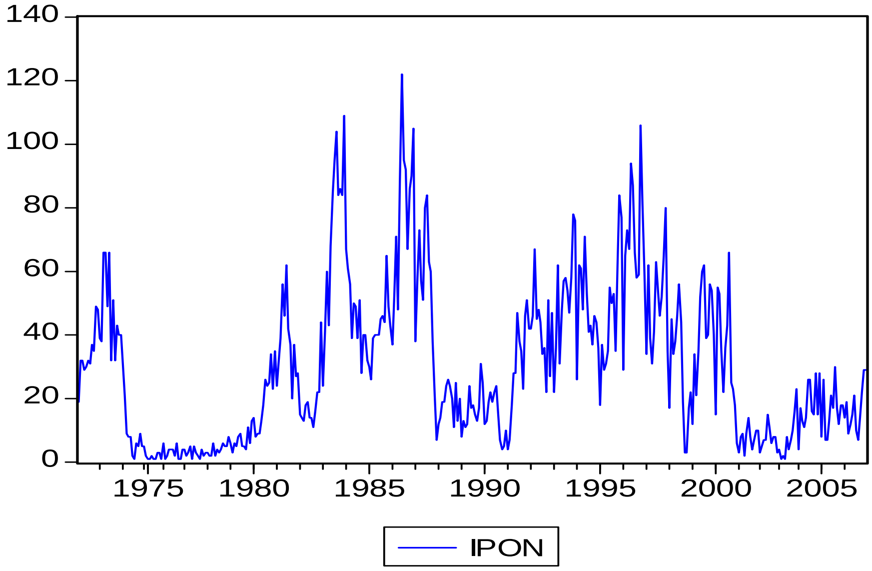


Figure 4. Other sentiment proxies

This figure shows the initial public offering first day returns (IPORET) and the number of offerings (IPON) from February 01, 1971 to December 31, 2006.

Panel A. Close Price

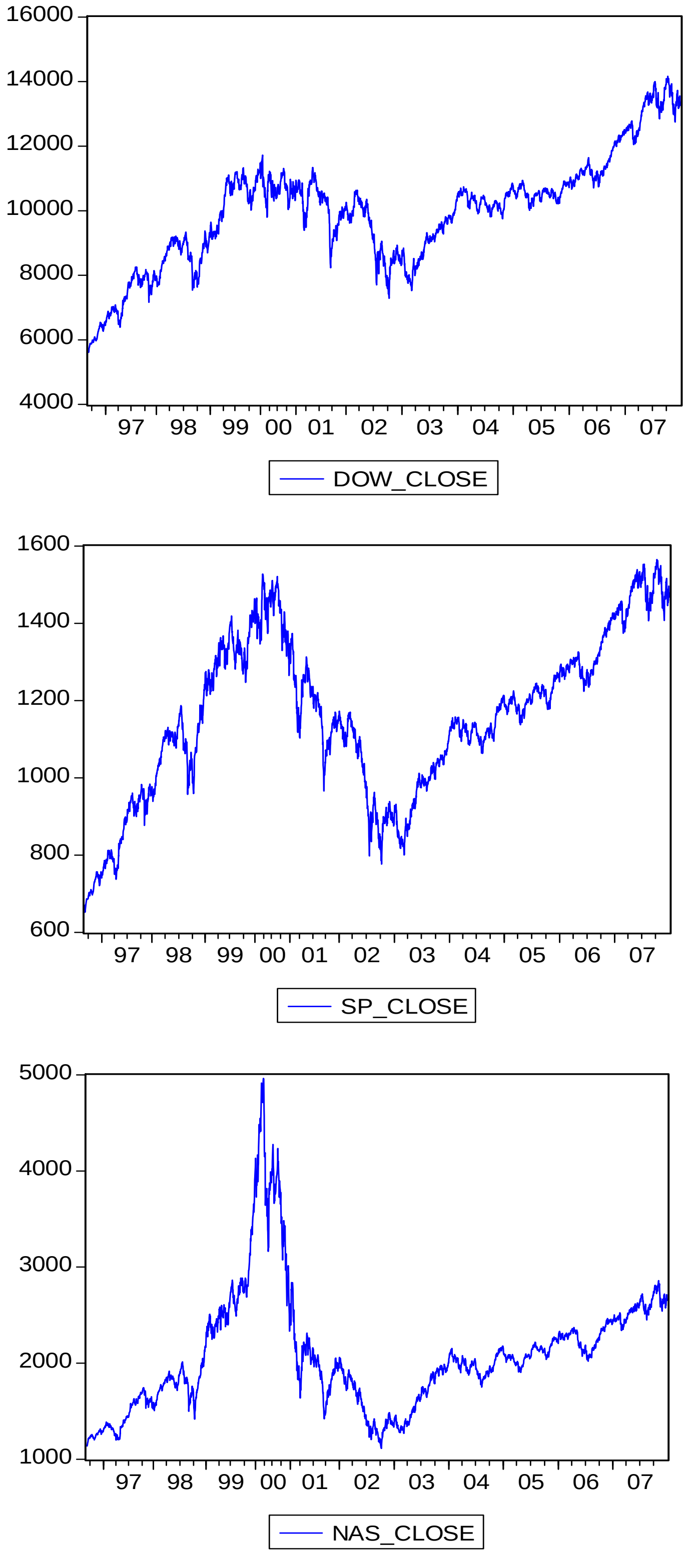


Figure 5. Daily stock indices

This figure shows the daily close prices and excess returns of DJIA, S&P500, and NASDAQ index from August 22, 1996 to December 31, 2007.

Panel B. Excess Return (%)

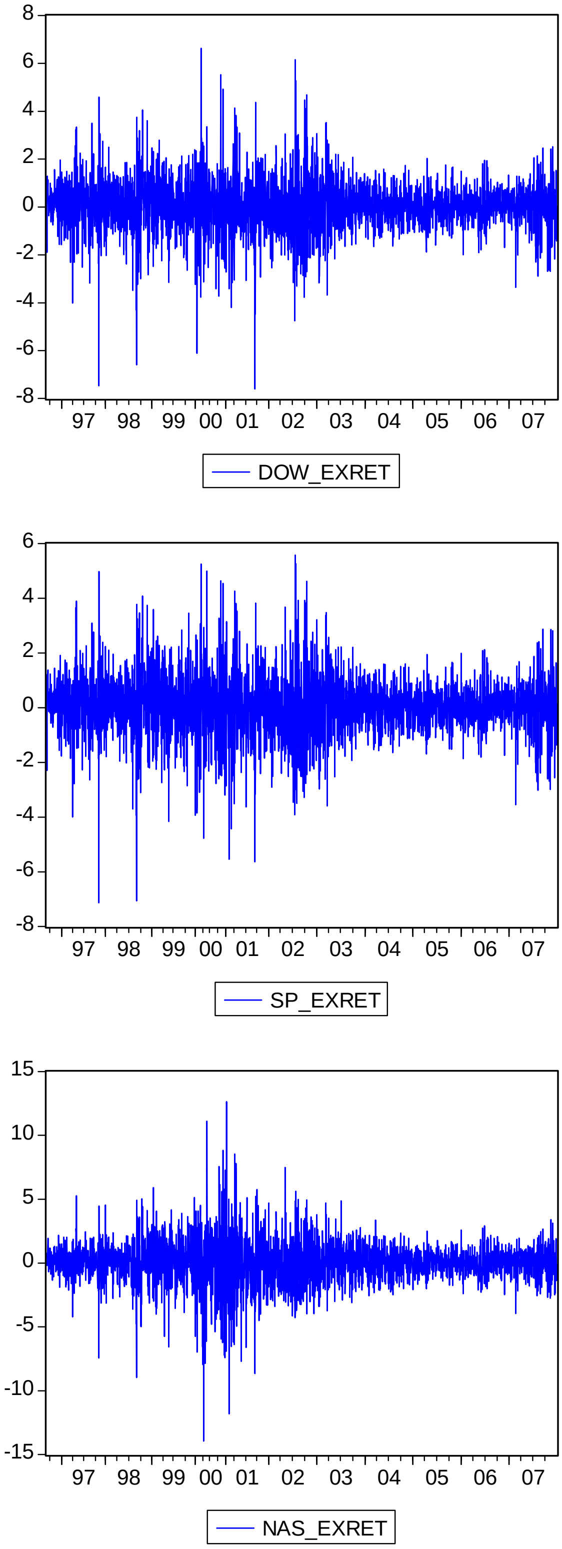


Figure 5. Daily stock indices (continued)

Panel A. Close Price

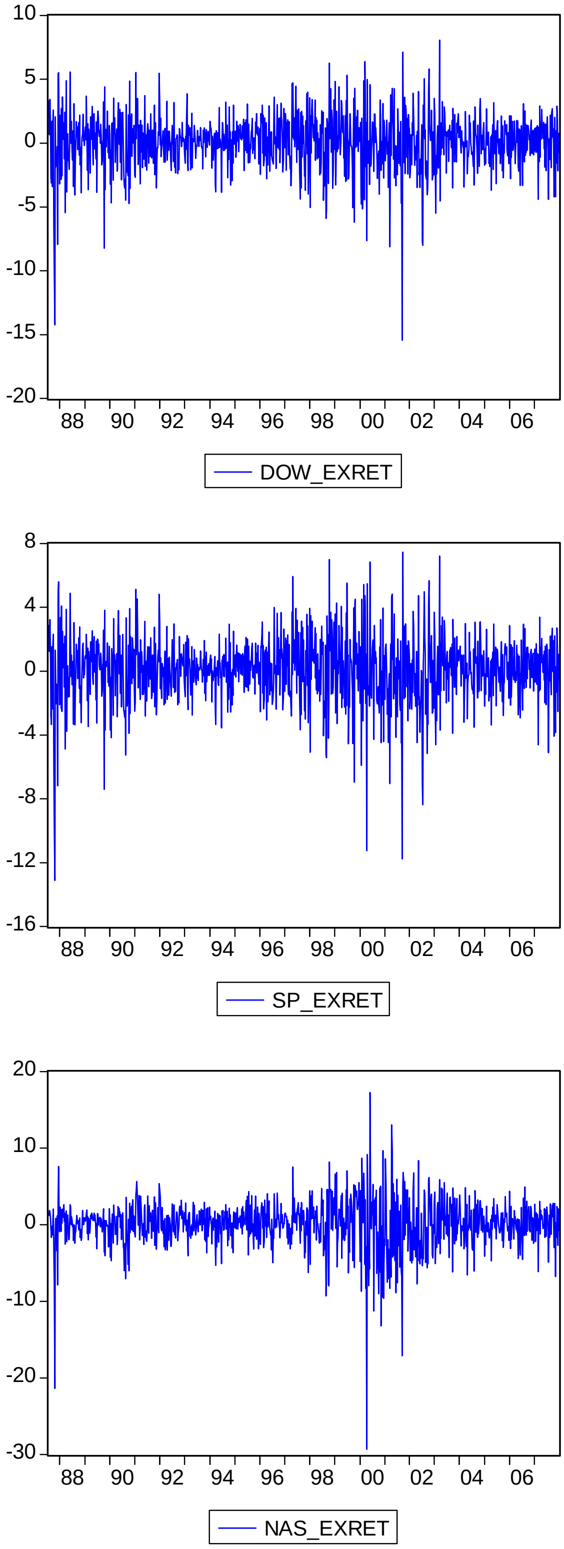
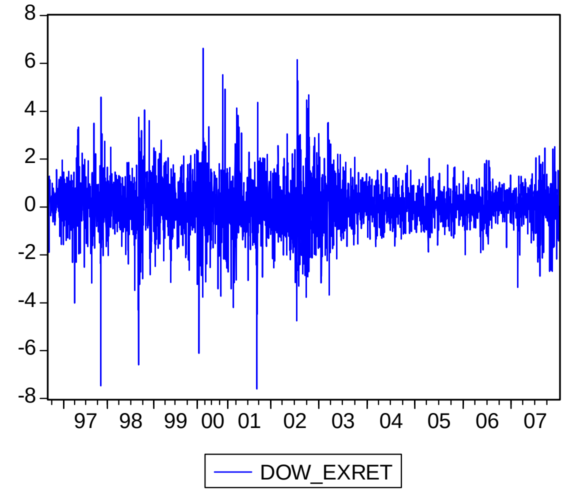
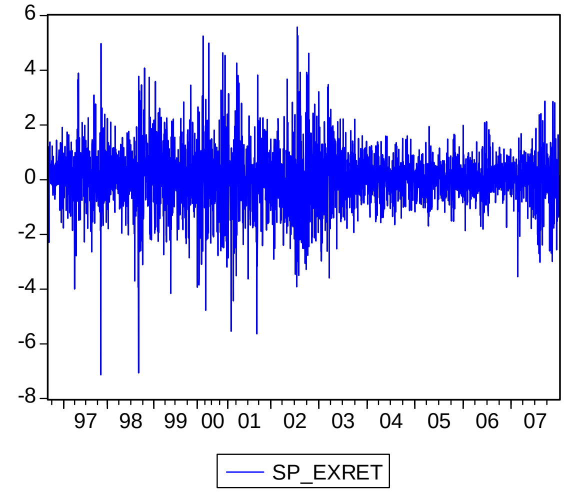


Figure 6. Weekly stock indices

This figure shows the weekly close prices and excess returns of DJIA, S&P500, and NASDAQ index from July 24, 1987 to December 28, 2007.

Panel B. Excess Return (%)





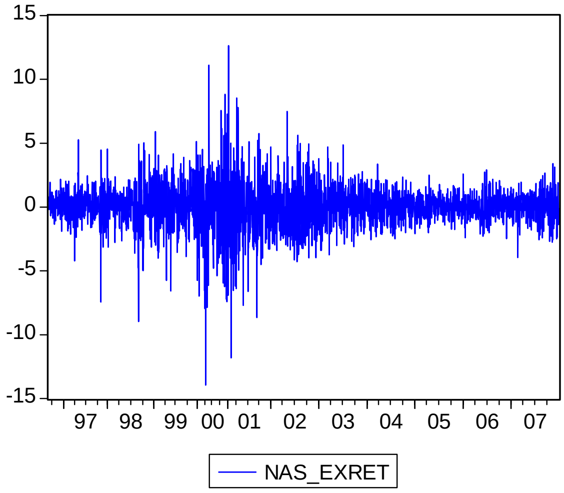


Figure 6. Weekly stock indices(continued)

Panel A. Close Price

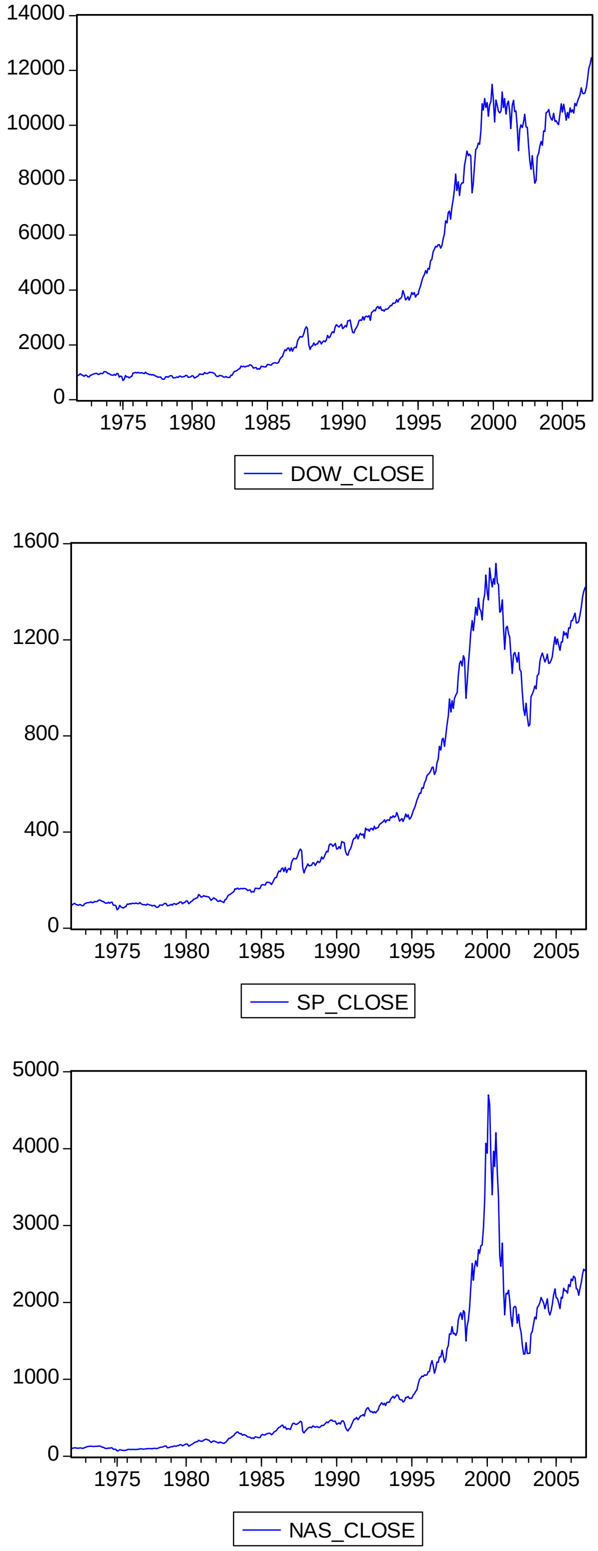


Figure 7. Monthly stock indices

This figure shows the monthly close prices and excess returns of DJIA, S&P500, and NASDAQ index from February 01, 1971 to December 31, 2006.

Panel B. Excess Return (%)

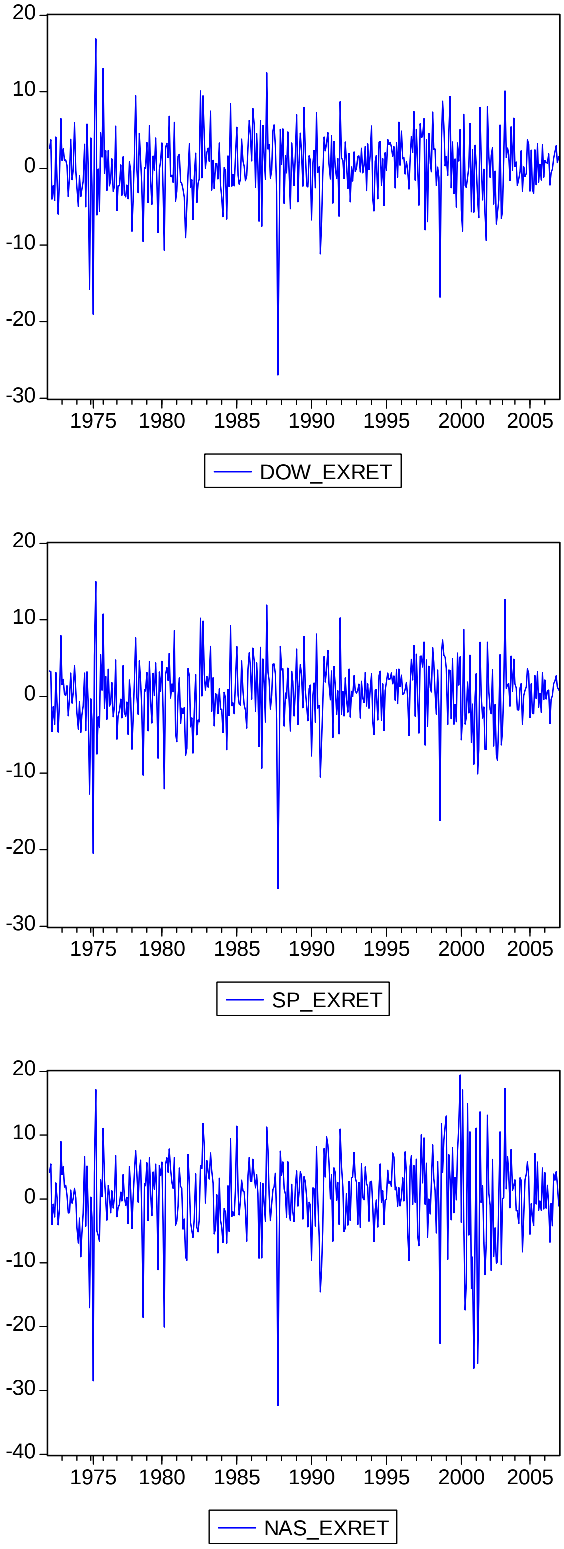
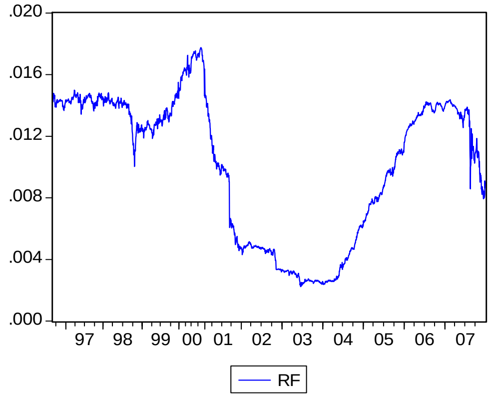
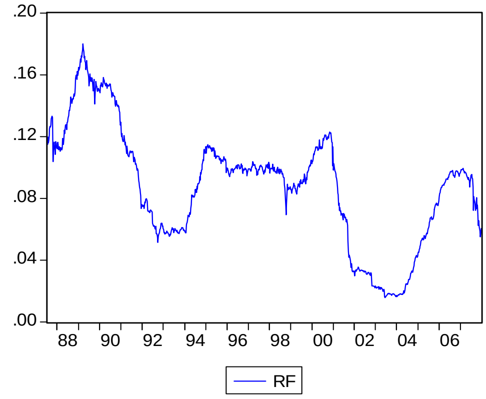


Figure 7. Monthly stock indices(continued)

Panel A. Daily three-month T-Bill yield (%)



Panel B. Weekly three-month T-Bill yield (%)



Panel C. Monthly three-month T-Bill yield (%)

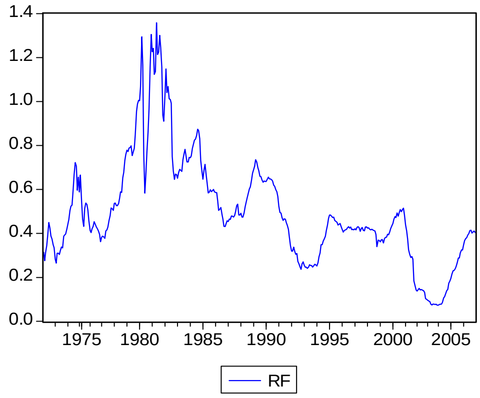


Figure 8. Average three-month T-Bill yield

This figure shows the daily, weekly, and monthly average three-month T-Bill yield. The daily data is from August 22, 1996 to December 31, 2007, the weekly data is from July 24, 1987 to December 28, 2007, and the monthly data is from February 01, 1971 to December 31, 2006.

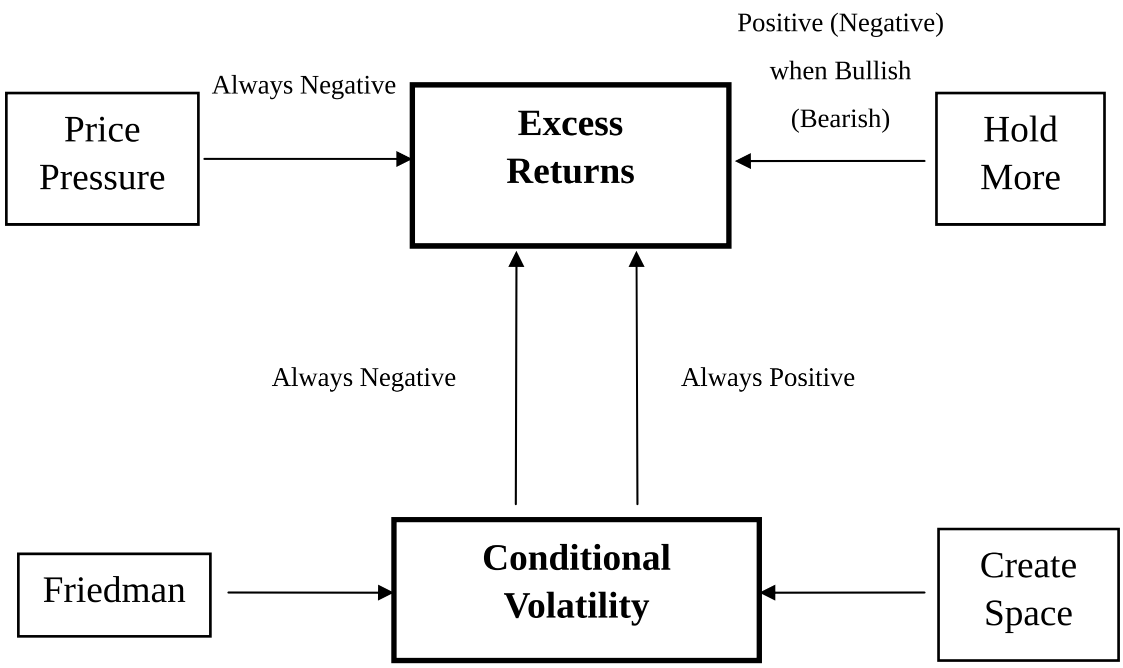


Figure 9. Impact of sentiment on volatility and returns