Does Investor Sentiment affect Cross-Sectional Stock Returns on the Chinese A-Share Market?

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Attestation of Authorship:

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been accepted for the qualification of any other degree or diploma of a University or other institution of higher learning.

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Abstract:

Modern finance theory suggests investor sentiment should not be priced as the mispricing induced by sentiment can be removed by trades of rational investors and arbitraging. However, research in recent decades illustrates that if investor sentiment induces uninformed demand shock, and the cost of arbitrage is high, the influence of investor sentiment cannot be ignored. This research continues the investigation of the role of investor sentiment in the asset pricing mechanism by focusing on two exchanges in China. By using multiple factors to construct a sentiment index, this study provides some evidence to show that if the sentiment at the beginning of a period is low, large stocks (growth stocks) tend to have relatively lower return than small stocks (value stocks), and vice versa. By splitting the entire period into bull and bear periods, the regression outcomes suggest that the impact of investor sentiment in the bear periods is much more influential than in bull periods. Furthermore, this study suggests investors in the Chinese markets exhibit a significant learning effect. As the regression analyses show that the influence of the sentiment index is rarely significant since 2006, it implies that investor sentiment may not be one of the major risk factors that should be accounted for in recent.

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1. Introduction:

For decades the traditional asset pricing models which assume the market is highly efficient have been unable to explain some of the most striking events in the history of stock markets, such as the Nifty Fifty bubble, the Black Monday crash, and the internet or Dot.Com bubble. Since the 1980s, there have been several attempts to carry out asset pricing studies by assuming the efficient market hypothesis may be violated, at least in the short-run. A body of research has emerged from this (Delong et al., 1990; Black, 1986; Brown & Cliff, 2004; Baker & Wurgler, 2006; Lee et al., 1991) which argues that some of the anomalies observed in the stock market can be attributed to noise created through trades which are motivated by sentiment.

Investor sentiment refers to the general feeling, mood, belief or expectation of market performance. It is an emotional factor which may have a direct influence on investors' decision making. Sentiment can be irrational. It may be induced by noisy information (information that does not reflect the fundamental characteristics of stocks), limited trading experience, knowledge or skills, and it may stimulate investors to trade at illogical times and either over or underestimate the stock performance. Based on this logic, investors affected by irrational emotion may impose additional risk on the stocks they trade.

Classical finance theory posits that only systematic risk factors which can affect the entire market should be priced. The risk imposed by the sentiment of investors on the stocks they trade is recognised as an idiosyncratic type of risk which should only affect certain individual stocks, and not the whole market. For this reason, it is assumed the sentiment risk can be eliminated through portfolio diversification (which will be discussed further in the literature review). Thus, it should play no role in the asset pricing process. In contrast, Delong et al. (1990), Lee et al. (1991) and Baker and Wurgler (2006) suggest that if the sentiment of investors is stimulated or impacted by a common noisy signal of the market, such as rumours or noisy information, investors may simultaneously over or under react to the future performance of the majority of stocks in the market. In this case, a sentiment factor may serve as a systematic factor which can lead asset prices to deviate from their equilibrium levels, when arbitrage is limited or restricted.

The literature explaining the impact of investor sentiment on the stock market has generally focused on developed markets, such as in the U.S. and U.K. (Barberis, Shleifer & Vishny, 1998; Lemmon & Portniaguina, 2006; Delong et al., 1990; Lee et al., 1991; Baker & Wurgler, 2006, 2007). However, whether the effect of investor sentiment in emerging stock markets plays the same role as it does in developed markets is a matter for further research. Because emerging stock markets are constantly developing, the stocks in these markets are recognised to be influenced by frequent changes in regulatory framework, as well as financial and country-specific events. Therefore, the effect of investor sentiment in emerging markets is assumed to be different from that of developed markets and should not be constant (Canbas & Kandir, 2009; Sehgal, Sood & Rajput, 2010).

In this study, I intend to provide further empirical contributions to this field. To be more specific, I will focus on the two stock markets in China – the Shanghai and Shenzhen stock exchange markets. These markets were established on December 19^{th}, 1990 and July 3^{rd}, 1991, respectively. Listed companies in these markets can issue two kinds of shares: A-shares, which can only be traded by domestic investors, and B-shares, which were only supplied to foreign investors until 2001. Both of these markets follow the same regulatory framework administrated by China Securities Regulatory Commission. They have a relatively short trading history (only 20 years) compared with other developed markets. Short selling was forbidden on these exchanges until April 2010.

Compared with developed markets, Chinese markets are recognised as less efficient in pricing stocks due to limited trading experience, knowledge and an incomplete regulatory framework (Ng & Wu, 2007, Kling & Gao, 2008). The individual investors in these markets are influenced by noisy information, and they rarely carry out valuation research based on the fundamentals of stock before they make investment decisions (Wang, Shi & Fan, 2006). For this reason, and consistent with the evidence from developed markets, it is reasonable to believe that investor sentiment should impact pricing in the Chinese markets. However, another body of literature (Li, Malone & Zhang, 2004; Ng & Wu, 2007, Kling & Gao, 2008) employs a series of proxies to measure investor sentiment, such as closed-end fund discounts, survey, liquidity, and trades of institutional and individual investors; and provides no support for investor sentiment affecting asset pricing in the Chinese markets.

There are any number of reasons why they may have reached this unexpected conclusion, including poor proxies for sentiment and short trading history. First, due to country-specific characteristics, development of the regulatory framework and the market, some of the proxies employed by previous studies to measure investor sentiment in the Chinese markets have been argued as being inappropriate and insufficient. For example, Chen, Rui, and Xu (2004) and Li, Malone and Zhang (2004) use closed-end fund discounts to measure sentiment. Zweig (1973), Baker and Wurgler (2006), and Lee et al (1991) suggest that individual investors are the main force which drive the fluctuations of sentiment. Closed-end fund discounts may directly measure the expectations of individual investors if these funds are at least partly held by individual investors. Hence, closed-end fund discounts may reflect the variation of investor sentiment, if these funds are not held by institutional investors. However, since February 2000, the major owners of closed-end funds have been insurance companies and financial institutions in the Chinese markets (Chen, Rui & Xu, 2004). This holding structure suggests using closed-end fund discounts alone is not sufficient to capture the influence of individual investors.

Wang, Shi and Fan (2006) and Kling and Gao (2008), as an alternative, conducted a survey to directly measure how investors react to fluctuations in the stock market. However, both studies, along with another conducted by Kang, Liu and Ni (2002), state that the quality of data derived from surveys in the Chinese market is low. The data collected is highly likely to be biased by factors such as the types of questions, individual emotion, and how and when investors are surveyed. Kang, Liu and Ni (2002) further indicate that as only institutional investors and some large or wealthy individual investors may receive the survey, a sentiment index built from the data may not fully reflect the true features of the whole population.

Secondly, previous studies of the Chinese stock markets are tightly restricted due to the short trading history. The vast majority (Chen, Rui & Xu, 2004; Wang, Shi & Fan, 2006; Li, Malone & Zhang, 2004; Kang, Liu & Ni, 2002) only cover 3-5 years worth of monthly data, which is relatively short in comparison to the sample periods of studies from developed markets. For example, the sample period used by Baker and Wurgler (2006) is 38 years, and that of Lee et al. (1991) is 26 years. For this reason, the correlation coefficients derived from the short sample period may not fully reflect the true features of each relevant variable and may not be long enough to allow the effect of sentiment to be accurately reflected in the stock prices. As a consequence, a longer period should be employed to nullify the influence of specific events.

Over time, due to the rapid development of the host country and its regulation framework, and accumulation of trading skills and knowledge, there is no reason to assume that the impact of a sentiment factor remains (Kang, Ni & Liu, 2002), and it is reasonable to assume that investors may become more rational due to a learning effect. Consequently, appropriate sub-periods should be constructed. Kang, Ni & Liu (2002) suggest that normally, each sub-period should include 3-5 years of data to allow for the possible influence of the learning effect. Furthermore, Kling and Gao (2007) suggest that the sensitivity of investor sentiment during bull periods differs from that of bear periods. For this reason, it is also reasonable to construct sub-sample periods based on bull and bear periods, when the effect of investor sentiment in pricing is expected to be distinct.

Given the fact that the role of investor sentiment in China is still an open question, I propose to construct a more complete model to observe the influence of investor sentiment on the two Chinese stock exchange markets across a longer time frame. To achieve this, a multi-factor sentiment index was used, including closed-end fund discounts; market turnover; average first-day return of IPOs; number of IPOs; consumer confidence index; and the number of trading accounts opened. These proxies are combined into a single sentiment index by using Principle Component Analysis (PCA). The sample period covers the monthly trading data of all active trading stocks which were alive between January 1st, 1998 and August 31st, 2010. To investigate the learning effects of investors and the evolution of the impact of sentiment, the entire sample period is further split into 3 sub-samples, each containing 4 years' data. Furthermore, in order to determine whether the influence of sentiment factor in pricing stocks is constant across bull and bear periods, eight sub-samples based on the bull and bear periods determined by the China Securities Regulatory Commission are constructed.

From the results, this study provides some evidence to support the proposition that sentiment plays an important role in the short run asset pricing of Chinese stocks. When the consumer confidence index and number of trading accounts opened are excluded from the proxies, the sentiment index is significantly priced for the whole sample period. It is inversely related to the market performance of stock portfolios which implies that high sentiment may drive returns down from their equilibrium level. Consistent with the findings of Baker and Wurgler (2006), Lee et al. (1991), and Delong et al. (1990), I find small stocks are more likely to be affected by the fluctuation of investor sentiment, and on average, these stocks can earn higher returns than large stocks, if the sentiment at the beginning of a period is low. However, conflicting with Baker and Wurgler (2006), I find that in the Chinese markets value stocks are more sensitive to the fluctuation of sentiment. the returns of value stocks are relatively higher than the returns of growth stocks when the sentiment at the beginning of a period is low.

Furthermore, this study indicates that sentiment is more influential during periods of recession, especially during 2004 – 2005. The explanatory power of sentiment displays a rough diminishing trend across time, and it has become increasingly insignificant since 2006. This may be due to the learning effect of investors and market regulation.

The rest of this study is organised as follows: Section 2 covers a literature review on asset pricing models and investor sentiment. Section 3 describes the data and methodology employed in this study. Section 4 presents the empirical results, and section 5 concludes this study.

2. Literature Review:

2.1. Classical Asset Pricing Models:

Classical finance theory suggests that investor sentiment should not be priced. In an efficient market, all information which relates to the growth and development of firms is already reflected in their stock prices once it is created or published (DeLong et al, 1990; Lee et al, 1991). Investors analyse the fundamental characteristics of firms to measure their growth potential before they make investment decisions. Their trades reflect their perceptions of the current stock prices. They purchase under-valued stocks and sell over-valued stocks. As a consequence, the trades of these investors will adjust the trading prices of stocks back to their fair levels. Hence, they can motivate the efficiency of the market's pricing mechanism. In contrast, the trades of some less rational investors may be highly influenced by their sentiment factor, rather than information which is related to the fundamentals of stocks. For this reason, these trades may induce stock prices to deviate from their equilibrium levels in the short-term. But this will be adjusted by rational investors immediately, as they are always actively looking for mis-priced stocks (Baker & Wurgler, 2006, 2007; Lee et al, 1991).

Given that the majority of market participants are risk averse, the returns they require depend on the level of risk they are exposed to. Risky assets are assumed to have higher returns than other assets as compensation for the risk borne by investors. The risk associated with any given asset is comprised of two parts – systematic risk and idiosyncratic risk. Systematic risks are induced by risk factors which affect the entire market. Idiosyncratic risks, which are incurred by a firm's specific characteristics, can only influence the firm itself. Based on finance theory, investors are always able to reduce their overall risk by forming portfolios of stocks. As long as the stocks are not perfectly correlated, the introduction of different stocks or assets results in diversification which can effectively reduce or remove idiosyncratic risks. Therefore, in an efficient market, investors are only rewarded for bearing systematic risks, as idiosyncratic risks can be diversified away.

Following the efficient market hypothesis, one of the leading models was developed by Sharpe (1964), Lintner (1965a), and Black (1972). This model, the Capital Asset Pricing Model (CAPM), proposes that the expected return of a given security or well-diversified portfolio is comprised of the risk-free expected return (the minimum return can be achieved from investing in risk-less assets, such as government bonds) and the market risk premium (the compensation of investors for bearing systematic risk) multiplied by the degree of risk exposure. It assumes in an efficient market, investors only face a single systematic risk imposed by the performance of the market, which contains all investable assets in the market. The market risk exposure of an asset or portfolio is measured by the sensitivity (market beta) of its expected return to the fluctuation of the return of the market portfolio. As the CAPM model is simple to apply and understand, it is still widely employed in practice. Nevertheless, the possible shortcomings of CAPM have been well documented. The market portfolio proposed by the CAPM is un-measurable in real life. Proxies, such as a broad market index, have been chosen to mimic the performance of the market portfolio, but may not fully reflect the true features of the market portfolio (Ross, 1976; Ross & Roll, 1980). CAPM also assumes investors only face market risk. In other words, CAPM assumes that the market risk factor captures all systematic risk. A number of studies have challenged the explanatory power of market beta (Banz, 1981; Ross & Roll, 1980; Fama & French, 1992, 1993, 1996; Carhart, 1997), and they argue that using the market beta alone as the risk measurement of a given asset or portfolio is inadequate.

Ross (1976) filled the gap left by the CAPM model by introducing a multi-factor model, named the Arbitrage Pricing Theory (APT). They assume that all investors hold a well-diversified portfolio, and any arbitrage opportunity cannot exist indefinitely. Given these assumptions, they argue that the expected return of a well-diversified portfolio should equal the risk-free interest rate plus the risk premium multiplied by the corresponding risk exposure of each relevant systematic risk factor. In contrast with the CAPM model, the APT model proposes that all relevant un-diversifiable risk factors which can affect the asset or portfolio returns should be included in the asset pricing equation. Furthermore, APT does not require the assumption of a market portfolio which may avoid the bias introduced by using a broad market index to mimic the performance of a market portfolio. Nevertheless, as it assumes investors hold well-diversified portfolios, it may not be able to assess the actual returns of some individual stock or portfolios which only contain a few assets.

Although the APT model is recognised as more efficient than the CAPM model because it considers all systematic risk exposures, it still fails to explain some pricing anomalies (some observations display significant deviation from the forecasted levels of the model). These pricing anomalies include: firm-specific characteristics puzzle – stock returns seem to relate to their firm-specific characteristics (Banz, 1981; Stattman, 1980; Basu, 1983; Rosenberg et al., 1985; Lakonishok et al., 1994); mean reversion – stocks with lower average returns in the past tend to have higher average returns in the future (DeBondt & Thaler,1985); and momentum – stocks with higher average returns in the past 3-12 months tend to continue to earn higher returns in the following short-term (Jegadeesh & Titman, 1993).

To complement CAPM and APT, and attempt to capture these anomalies, a further body of work focuses on the risks imposed by firm-specific characteristics (Banz, 1981; Stattman, 1980; Rosenberg et al., 1985; Lakonishok et al., 1994; Basu, 1983; Ball, 1978; Bhandari, 1988). In the 1990s, Fama and French (1992 and1993) analysed and summarised the previous studies on asset pricing models under the efficient market hypothesis, and highlighted two extra risk factors, firm size (ME) and the book-to-market ratio (BE/ME), to complement the explanatory power of the market factor as proposed by the CAPM model. They argued that ME and BE/ME are negatively and positively related to the stock average returns, respectively. Their three-factor model (FF-3 model), comprised of market beta, ME and BE/ME, was sufficient to explain the fluctuations of stock returns as the outcomes of their regression analysis displayed highly significant coefficients and much higher R^2 than other studies. They made the case that the market beta and ME of a firm may significantly capture the influence of market fluctuations and size effect on its stock performance, and that BE/ME is a catch-all proxy for other unnamed risks that relate to expected return. Furthermore, they stated that the superior explanatory power of their FF-3 model was due to the components of their models which captured the characteristics of factors employed by other models. Essentially, the explanatory power realised from other models can be explained as their employed risk proxies (such as leverage ratio and earnings – price ratio) are related to the three factors introduced by Fama and French.

Fama and French (1996) tested the explanatory power of their three-factor model on the pricing anomalies mentioned in the last paragraph. The empirical results suggested that the FF-3 model can efficiently explain the effect of firm-specific characteristics and the long-term return reversal. The effect of firm-specific characteristics can be sufficiently captured by ME and BE/ME (ME captures the size effect, while BE/ME accounts for all other unnamed risks induced by firm-specific characteristics). The long-term return reversal can be explained as follows: stocks with lower returns in the past tend to be smaller and have a high BE/ME. These stocks will offer higher returns to investors as compensation for bearing higher risk, and vice versa; stocks with higher past returns tend to be large in size and have a low BE/ME. These stocks are normally issued by mature firms which face lower risk exposure. Therefore, they are more likely to offer lower returns in the future. However, disappointingly, the FF-3 model failed to explain short-term return persistence. This outcome may imply that further control variables should be taken into account.

Indeed, an entire body of study exists which focuses on stock market persistence (Hendricks et al., 1993; Goetzmann & Ibbotson, 1994; Brown and Goetzmann, 1995; Wermers, 1996; Carhart, 1992). Jegadeesh and Titman (1993) suggested that investors who follow the momentum trading strategy (holding stocks with higher average returns in the past 3-12 months and selling stocks with lower average returns in the same period) may earn around 1% per month on average for the following 3-12 months. To efficiently account for this anomaly and enhance the asset pricing model under the assumption of efficient market theory, Carhart (1997) proposed a four-factor model which also included the three factors of the FF-3 model. He argued that, although the FF-3 model had already improved the explanatory power for cross-sectional stock returns, by introducing a fourth extra control variable – momentum (which is used to capture the influence of past returns of a stock on its future performance) – his four-factor model could significantly improve the explanatory power for stock returns with fewer errors. Empirical findings also show that the four-factor models can significantly account for short-term return persistence.

2.2. Challenges to Efficient Market Theory:

Before the 1980s, the asset pricing models which assumed the market's efficiency were strongly accepted and employed. Later on, to complement the FF-3 model and Carhart four-factor model, other scholars introduced additional control variables or methodologies to account for short-run violations or anomalies. Nevertheless, there are still key events which do not fit into any of the standard models under the efficient market hypothesis, such as the Black Monday crash and the Dot.com bubble.

In recent decades, scholars investigating these anomalies argue that some of these incidents may be induced by the over- or under-reaction of investors to information. Black (1986) suggests not all investors are rational when it comes to investment decision making. They trade on noisy information rather than quality information, they sell when the market declines and buy when the market rises, and most of them fail to diversify their position. These investors who trade on noisy information may explain the development of bubbles or even crashes. Hence, the behaviour of investors may have a significant influence on stock prices.

Fama (1998) argued in defence of the efficient market hypothesis. According to Fama, anomalies are normally created by chance. Although over- and under-reactions can be often observed, it is normally followed by post-event reversal in which the asset price returns to its equilibrium level. And arbitrage may accelerate this process further, ensuring the mispricing can be eliminated as soon as possible. Furthermore, he proposes that some of the anomalies are due to restrictions in the estimation methodologies. The evolution of asset pricing models may help the market to predict the stock returns more efficiently.

In stark contrast with the argument of Fama (1998), the key forces that maintain the efficiency of the market, such as arbitrage, are relatively weaker and more limited than proposed in theory (this will be discussed in detail in the following section). This reality implies that mis-pricing caused by over- or under-reaction of the activities of investors may not be adjusted by the market in a timely manner. Anomalies may tend to display a high persistence, and therefore, should be considered during the asset pricing process.

Accordingly, to study the irrational activities of investors and how they may affect stock prices, researchers in behavioural finance have begun working to challenge the standard asset pricing models (which assume the market is efficient) with alternative models that incorporate mental factors to capture the influence of the beliefs of investors that motivate their trades.

2.3. Behavioural Finance:

Behavioural finance is the study of how psychological factors affecting investors impact on the performance of the stock market. It examines how mental factors influence investors' choices, and attempts to explain whether financial participants may create systematic errors through their activities and so cause stock prices to deviate from their fundamental value (Swell, 2010).

Behavioural finance does not ascribe to the efficient market hypothesis. It states that the biases induced by irrational trades or responses from investors induce deviations in stock prices from their fundamental value. These biased trades or responses may be attributed to limited investor attention, over-pessimism or over-optimism, mimicking of trading strategies, or the impact of noise or rumour. Baker and Wurgler (2007) suggest that normally research on how behavioural finance challenges the standard efficient market asset pricing model is based on two assumptions. The first assumption focuses on the weakness of the forces which sustain market efficiency. It argues that the behaviour of rational investors and arbitragers may not be as aggressive as is proposed by the efficient market theory. To take the opposite trading positions of irrational investors can be costly and extremely risky. The second assumption focuses on how a wave of investor sentiment induces unpredictable speculating. The theoretical and empirical support for these two assumptions are summarised in the following sections.

2.4. The Limitation of Arbitrage:

Classical finance theory suggests that in an efficient market, asset prices are monitored by arbitragers. If the arbitragers believe the trading price of a given asset does not reflect its fundamental characteristics, they will take an opposing position – short-selling over-priced assets and borrowing to purchase under-priced assets – to obtain riskless benefits. By doing so, the trading price of this asset will be corrected (short-selling over-priced assets will drive trading prices down and borrowing to purchase under-priced assets will push trading prices up). The benefit of arbitrage will diminish as the trading price of a mis-priced asset draws closer to its true price, and arbitragers will stop their trading once the benefit is zero. Normally, the window of opportunity for arbitrage trading will be very short, as large numbers of arbitragers are constantly monitoring the market. Therefore, the trades of arbitragers will result in asset prices reaching their fair values almost immediately.

However, in reality, arbitragers are not as aggressive as theory might suggest. Shleifer and Vishny (1997) demonstrate that almost all arbitrage requires capital to initialise, and in some cases, can be extremely risky. Effective and professional arbitrage can only be conducted by investors who have great accessibility to the capital of others and the market. Only the transactions of these investors have significant power to adjust mis-priced assets.

Wurgler and Zhuravskaya (2002), Amihud and Mendelsohn (1986), D’ Avolio (2002) and Jones and Lamont (2002) evaluated the risks and costs associated with arbitraging stocks with different characteristics. They show that indeed arbitraging is not without risk. If the influence of the over- or under-reaction of investors is large, arbitragers need a large amount of capital to take the opposite position. As a consequence, arbitragers may ignore such an investment opportunity if they have only restricted access to a large amount of capital. Interest cost, as the compensation offered to the capital suppliers of arbitragers, combined with the transaction costs can significantly reduce the earnings of arbitragers. Taking these costs into account, arbitragers may be unwilling to trade illiquid, young, small, unprofitable, growth and highly volatile stocks as trades on these stocks normally involve higher costs. These stocks may have shorter trading history, fewer comparable competitors, and greater uncertainty compared with other stocks. Therefore, their valuation may be highly subjective. It can take a long time for the market to realise their fair value, and thus, arbitragers who trade these stocks may face the risk that their positions can be left open for an extended period if risk-averse investors are reluctant to trade. In addition, it may also take some time for the price to move into a profitable range. For these reasons, empirical evidence suggests that arbitrage is extremely risky and costly for stocks which are young, illiquid, small, unprofitable, growth, distressed, and highly volatile. Consequently, given arbitrage is limited, the influence of over- or under-reaction of investors on some stocks may be significant and long-lived.

2.5. Investor Sentiment:

The second assumption always employed by behavioural finance researchers is that propensity to speculate is driven by the fluctuation of investor sentiment (Baker & Wurgler, 2006). Unforeseeable changes in propensity to speculate induce unexpected changes in demand. They may directly affect the demand and supply equilibrium and induce stock prices to deviate from their fair levels.

Baker and Wurgler (2007) state that investor sentiment is the central component of behavioural finance. It refers to the feeling, mood and expectation of investors about the performance of stocks. It also reflects the beliefs of investors regarding the future profitability and growth opportunities of stocks. It is one of the main factors that impact the investment decision making process.

According to Brown and Cliff (2004), Lee et al. (1991) and Baker and Wurgler (2006), stock market investors can be divided into two categories – rational investors and irrational investors. They define rational investors as market participants who make decisions based on quality information and appropriate evaluation methodologies. In contrast with rational investors, irrational investors, or as they are also known, noise traders, are defined as investors who have less background knowledge, trading experience, or trading skills. These investors are less equipped to judge the quality of the information they rely on, and are more emotional when it comes to investment decision making than rational investors. In other words, the expectations of irrational investors on stock returns may be highly influenced by their sentiment. Investor sentiment is the combined expectation of both rational and irrational investors. As the evaluation of rational investors should reflect the fair value of stocks, the component of investor sentiment that results in prices moving away from their fundamental level must be driven by irrational investors.

2.5.1. Why Does the Influence of Sentiment Exist?

Due to a lack of trading skills, experience, and background knowledge, the decision making process of irrational investors can be easily impacted by noisy information and hence induce the deviation of trading prices from their equilibrium (Brown & Cliff, 2004). Nevertheless, the majority of studies overlook the impact of investor sentiment. Baker and Wurgler (2006, 2007), Brown and Cliff (2004), Kumar and Lee (2006), Canbas and Kandir (2009) and Delong et al. (1990) explain that as previous studies assume the market is inherently efficient, there is no clear linkage or correlation among the trades of irrational investors. Generally, they assume that trades by irrational investors, those which may generate noise, are quoted in the market randomly. If the trading volume of these irrational investors is large and covers the majority of securities of the market, the influence of the trades may cancel each other out and leave stock prices fluctuating narrowly around their true prices. For example, some investors may over-estimate the value of a given stock and subsequently purchase it. On the other hand, some investors may under-estimate the value of a given stock and therefore decide to sell it. The overall effect of trades by these two kinds of investors on the stock price will be roughly zero as they offset each other. Lee et al. (1991) suggest that the risks are not intended to be persistent as an efficient stock market is monitored by both rational investors and arbitragers who are constantly searching for mispriced assets. For this reason, investor sentiment is more likely to be treated as an idiosyncratic risk that irrational investors impose on individual securities, and should not be included in the asset pricing model following the suggestion of classic asset pricing theory as it can be diversified away in a portfolio.

However, the reality is not that simple. First of all, as illustrated in the previous section, arbitrage is not as effective in sustaining market efficiency as argued in theory. Second, conflicting with the assumption that the trades of investors are random, Delong et al. (1990) argue that a large proportion of irrational investors in the market follow a positive feedback strategy. They purchase when the market rises and they sell when the market falls. In this case, market performance can drive irrational investors in the same direction. Hence, these trades may be positively correlated with each other through the performance of the market, and may cause systematic biases in the stock market. Baker and Wurgler (2006) and Brown and Cliff (2004) suggest that once a large proportion of irrational investors are positively correlated, the trades of irrational investors may influence the entire market at the same time. Thus, in this case, the risks imposed by the sentiment of irrational investors cannot be diversified, and hence, should be included in the asset pricing model.

Kumar and Lee (2006) and Frieder and Subrahmanyam (2005) provide further detailed studies on the correlation of trades among irrational investors. They argue that given irrational investors normally have poor stock picking skills, explanations for the correlation among trades of investors can be summarised as follows:

1) Irrational investors form their expectations or beliefs based on published information or even rumours. Normally they are less able to judge the quality of the information and lack the knowledge and skills to derive a rational evaluation from the information. For this reason, they are more likely to over- or under-estimate the future performance of the market under the impact of the information. As the information may be widely accessible, it is not surprising that the majority of irrational investors may share a common or similar belief. In this case, they may trade the same stock or similar stocks within the same industry because they form their conclusions based on the same information, and thus induce a high positive correlation.

2) Irrational investors have an incentive to mimic the transactions of institutional investors and some large individual investors. This incentive can be explained as institutional investors and some large individual investors are recognised to have the advantage of information, excellent trading skills and experience. However, although institutional investors or these large individual investors may trade at roughly the appropriate time, the irrational investors who follow their actions may act on a delay. As the range of the trading lag can fluctuate from a few minutes to a few days, the time lag may cause the irrational investors to trade at inappropriate times, and hence, generate noise in the market.

2.5.2. How Investor Sentiment Affects Stock Prices

Baker and Wurgler (2006), Brown and Cliff (2004) and Lee et al. (1991) state that if arbitrage is partly restricted or limited, the influence of sentiment on stock prices can be reflected as a uniform demand shock. They believe the shift of demand can be categorised into two parts. One is the demand driven by rational investors whose expectations are related to quality information and rational evaluations. Therefore, the shift in demand induced by this part is foreseeable and hence may have already been reflected in the stock prices. The other part of the demand relates to the influence of the sentiment which reflects the expectation of the irrational investors. As the sentiment factor may be biased by information that is not related to the fundamental characteristics of stocks, an unexpected wave of sentiment may shift demand by an unforeseeable amount, and lead to unexpected changes in the stock price. For example, as Baker and Wurgler (2006) suggest that the propensity to speculate during a bubble period is high. This may increase the sentiment of investors. They may become over-optimistic about the future performance of the market and provide extra liquidity to the market. Consequently, this may induce the stock prices in the market to be pushed up by an inappropriate percentage that does not reflect the fundamental value of the stocks. In the opposite situation, during a recession period, as the propensity to speculate is low, the investor sentiment may decline. Irrational investors in this case may be less willing to provide capital to the stock market even when some stocks are probably under-estimated as they become over-pessimistic.

2.5.3. Findings of Empirical Research:

Empirical researchers use several factors to proxy investor sentiment. Lee et al. (1991) made use of NYSE data to study the relationship between sentiment and expected returns directly, employing closed-end fund discounts as a proxy for sentiment. Their finding was that after controlling for size effects, closed-end fund discounts are negatively correlated with portfolio returns, which means that high sentiment may normally induce lower returns. One possible explanation is that if sentiment at the beginning of a period was high, irrational investors were more likely to over-estimate the value of some stocks. For this reason, they had a high motivation to purchase these stocks, which would push up their trading prices. At the end of the same period, as the ending prices of the stocks would normally be determined by their actual fundamental characteristics which might fall distinctly with the expectations of the irrational investors, the realised returns would be lower. Leonard and Shull (1996) conducted a similar study to Lee et al. (1991) by using the same dataset and proxies. They showed that investor sentiment can significantly explain the variation of stock returns over their entire sample period, which ran from July 1965 to December 1994. However, this relationship disappeared in their second sub-period which is from April 1980 to December 1994. ~~the~~

Neal and Wheatley (1998) studied the explanatory power of three sentiment proxies which included closed-end fund discounts, the ratio of odd-lot sales to purchases, and net mutual redemptions on stock returns. By using data from 1933 to 1993 supplied by Wall Street, they provided significant evidence to show that discounts and net redemptions induce a size premium between large firms and small firms and that the explanatory power of odd-lot ratios is relatively weak compared with the other two proxies. Consistent with Lee et al. (1991) and Leonard and Shull (1996), their study also supported the argument that high sentiment in the previous period would induce a lower return in the following period.

Brown et al. (2002) made use of daily mutual fund flows to construct their sentiment index. The outcome supported the hypothesis that the sentiment factor should be priced. In addition, they also revealed that sentiment proxy is negatively correlated with stock performance in the Japanese market, but positively in the U.S. market.

On the other hand, Lemmon and Portniaguina (2006) employed consumer confidence indices which were conducted through surveys of the Conference Board and the University of Michigan Survey Research Center to construct a sentiment index. The empirical results showed that a sentiment index could significantly forecast the returns of small stocks and stocks with dispersive ownership. Consistent with previous studies, they also suggested that sentiment was negatively correlated with stock returns, and that their sentiment index could successfully explain the size premium.

Brown and Cliff (2004) examined the forecasting power of several investor sentiment proxies proposed in prior research. Additionally, they constructed a sentiment measurement using survey data. In contrast with previous research, they also constructed a single sentiment index, employing Principle Component Analysis (PCA) to abstract the correlated component among several sentiment proxies. Furthermore, they employed Vector Auto Regression to investigate the causal relationship between sentiment index and expected returns. The results showed that the majority of the sentiment proxies are highly correlated with the direct sentiment proxy they derived from the survey. Although the changes of sentiment level are strongly linked to contemporaneous market performance, the predictive power in sentiment index for near-term future stock returns is relatively weak and rarely significant.

Baker and Wurgler (2006) followed a similar methodology as proposed by Brown and Cliff (2004), applying PCA to six sentiment proxies suggested in previous studies to construct a single sentiment index (which included closed-end fund discounts, the number of IPO, averaged first day return of IPO, market turnover, share of equity issues and dividend premium). In addition, they controlled for firm-specific characteristics, and introduced macroeconomic factors in their asset pricing model. Their results illustrate that when the beginning-of-period sentiment index is low, small stocks, young stocks, growth stocks, and poor performance stocks tend to have relatively high returns. These stocks are hard to value objectively, and thus, are also rarely monitored by arbitragers (Baker & Wurgler, 2007; Sheleifer & Vishny, 1997). For this reason, these stocks are more likely to be influenced by changes in sentiment. When sentiment is low at the beginning of year, the prices of these stocks may be less likely to be over-estimated and more likely to be under-estimated, thus, their returns may be relatively high. According to this logic, if sentiment at the beginning of a set period is high, the returns of these stocks should be relatively low as high sentiment may induce over-valuation on these stocks, and reduce the realised returns.

Baker, Wurgler, and Yuan (2009) applied the methodology developed by Baker and Wurgler (2006) to a study of global markets. They included both global and local factors to determine the differences in impact of sentiment across different countries, and measure the contribution of the global component of sentiment on the stock pricing mechanism of highly integrated markets. Consistent with previous work, this study also supported the theory that stocks which are difficult to value and arbitrage tend to be more influenced by the fluctuation of sentiment. The fluctuation of sentiment is inversely correlated with stock returns.

However, given most of the past studies in this area have concentrated on developed markets, such as the U.S. and U.K., the impact of investor sentiment on other markets – particularly emerging ones – is unclear.

2.6. The Difference between Developed Markets and Emerging Markets:

Wang, Shi and Fan (2006) and Kang, Liu and Ni (2002) suggest that developed markets tend to be well organised and managed. They have complete regulation frameworks to protect investors' rights and regulate the activities of listed companies. In contrast with investors in emerging markets, investors of developed markets have more trading experience. Their investment decisions are mainly based on the information available and less likely to be affected by rumours. Thus, developed markets are thought to be more efficient and those investing in these markets may bear less risk. Risso (2008b) investigates the information efficiency of emerging markets and developed markets. His study suggests that in contrast with developed markets, the lack of a complete regulation framework is one of the main factors which induce anomalies in emerging markets. Compared with developed markets, emerging markets are undergoing a rapid process of growth and industrialisation in social and business activities. As proposed in the studies of Chen, Rui, and Xu (2004) and Li, Malone and Zhang (2004), emerging capital markets have unique investment environments. Both the institutional and individual investors in these markets have less trading experience than the investors of developed markets, and may be highly influenced by social and cultural factors. These factors are expected to develop and evolve rapidly as the countries move up the development ladder. Consequently, given these differences between developed and emerging markets, developed markets are thought to be more efficient when it comes to asset pricing. For these reasons, the degree of influence of investor sentiment in emerging markets may differ from that of developed markets, and its effect may not be constant due to the influence of the development of the country and market on its domestic investors.

2.7. The Chinese Stock Exchange Market:

In recent years, a body of research has been conducted to analyse the role of investor sentiment in the asset pricing mechanism of emerging markets (Ng & Wu, 2007; Canbas & Kandir, 2009; Li, Malone & Zhang, 2005). Within these studies, the Chinese stock exchange markets, as one of the new rising stars, have attracted considerable attention.

In contrast with other stock exchanges, the Chinese stock market is dominated by individual investors. According to Ng and Wu (2007), the number of trading accounts increased from 2.2 million in 1992 to at least 70 million in 2005. Of these accounts, 95% have been opened by individual investors. Kang, Liu and Ni (2002) and Wang, Shi and Fan (2006) show that most individual Chinese investors have limited knowledge of investing and act like pure speculators. Their trading strategies mainly depend on limited public information, their own professional advisors, market rumours, the activities of institutions and historical data. Chinese investors tend to overreact to realised information and past performance. Hence, it is normal to see the price of a particular stock in the Chinese market pushed up quickly in the short-term. And because short selling in this market was forbidden until April 2010, mispriced assets were not adjusted by the market back to the fundamental price quickly. This argument suggests that the influence of investor sentiment on stock prices would have persisted.

The features of the Chinese markets are distinct from those of other developed and emerging markets. Due to the newness of this market, the regulatory framework is not yet fully developed. In contrast with other markets, the Chinese markets face a high level of information asymmetry and insider trading problems (Wang & Iorio, 2007; Kang, Liu & Ni, 2002). In addition, these markets are also highly affected by the government. Most of the blue-chips are owned by the government to ensure they are controlled locally (Wang, Shi & Fan, 2007), with the result that the amount of liquid shares available for trading in the markets is normally less than 50%. This shareholding structure of listed companies may cause agency problems for minority shareholders whereby the government dictates firm policy for the betterment of the nation as a whole, not the shareholders of the company. This may undermine pricing mechanisms. As a result, with the hope of balancing this agency cost, regulations are frequently changed.

However, this has resulted in many institutions and individual investors becoming policy speculators. Balsara, Chen and Zheng (2007) suggests that both the variance of the best 26 and worst 25 stocks in Chinese markets are related to adjustments of regulation, and plenty of investors in these stocks make their investment decisions based on the announcements of probable regulatory changes. These investors predict the possible adjustment of policies and aim to benefit from these changes, not from more traditional strategies which are based on fundamental analysis of the true value of listed companies. Hence, these activities may not help to adjust the mispricing occurring in the markets as a result of sentiment.

2.7.1. The Empirical Findings in the Chinese Markets:

Given these specific features, it is reasonable to assume that asset pricing in the Chinese markets is less efficient than in other, more developed markets. As a lack of effective forces to sustain pricing efficiency (such as an arbitrager) is present in these markets, the sentiment of Chinese investors may be a significant force driving the fluctuation of the market. Therefore, it is expected that investor sentiment should be priced in the Chinese markets (Kang & Liu & Ni, 2002).

Consistent with this hypothesis, Feng and Seasholes (2004) provided empirical evidence to support the influence of investor sentiment on Chinese markets. In their study, they discovered that the transactions of individual investors are highly correlated if they are geographically divided. Investors who lived near a listed company or an institutional investor were much more likely to attend the presentations or free workshops held by the company or the institutional investor. These investors may be more likely to follow the advice and the trading activities of the company or the institutional investors, and induce the correlation among the trades of individual investors within a certain location. Consequently, this finding implies that the noises created from the trades of irrational investors may be not diversified.

However, in contrast with the expectation introduced by Kang, Liu, and Ni (2002) and Feng and Seasholes (2004), a body of study including empirical analysis of the relationship between investor sentiment and stock returns in China provides conflicting results. Ng and Wu (2007) employed a unique data set which contained trades of both institutional investors and individual investors to study the factors which drive trading behaviour and how trades affect the stock market. In their study, they argued that the volume of trades of institutional investors and individual investors might reflect their sentiment. For this reason, they used the volume of trades of each type of investors as a sentiment proxy. The findings suggest that institutional and wealthier investors follow a momentum trading strategy. Individual investors are speculators, and their expectations are based on the information of institutional investors and their personal advisors. The sentiment index constructed based on institutional and large individual investors may affect the volatility of stock prices. Nevertheless, neither institutional investors nor individual investors seemed to demonstrate price predictability.

Kling and Gao (2008) employed daily survey data of 75 leading institutional investors conducted by Chinese Central Television Station to measure the fluctuation of investor sentiment, and used a GARCH model to derive statistical results. Their findings suggested that in the short run, past performance is the trading trigger of institutional investors. They tend to be optimistic about past winners, and pessimistic regarding past losers. Furthermore,

the outcomes also demonstrate that although a drop in the sentiment measurement will increase the market volatility, investor sentiment does not predict stock returns.
Meanwhile, Li, Malone and Zhang (2004) investigated the market efficiency hypothesis and asset pricing model of Chinese stock markets by using closed-end fund discounts to measure the influence of investor sentiment, and applied the AR-GARCH model to test the possible relationship. However, their findings provided no evidence to support the role of investor sentiment in the asset pricing model.

In an effort to explain why these studies derived conflicting empirical results, Kling and Gao (2008) and Wang, Shi and Fan (2006) suggested two possible reasons: first, poor sentiment proxies were employed to construct the sentiment index; and secondly, examinable data was limited due to a short trading history. For these two reasons, the empirical findings of some previous studies could be biased as their sentiment proxies might include low predictability with the actual investor sentiment, or they might be highly influenced by the specific events which occurred during the short sample periods they covered.

Lin (2008) avoided the possible issues discussed above by employing a relatively longer sample period compared with some of the other studies, and using multiple factors to capture the features of investor sentiment. The data of all trading stocks on both Chinese exchanges between 1998 and 2006 were included, and closed-end fund discounts, the number of IPOs, the average first day return of IPO, and the market turnover were employed to construct a sentiment index by using Principle Component Analysis (PCA). Consistent with the findings from developed markets, the results suggested that stock returns were negatively influenced by the sentiment index for the whole sample period.

Much like Lin (2008), Liu (2008) employed closed-end fund discounts, the number of IPOs, the average first day return of IPO, enterprise confidence index and business confidence index to construct a sentiment index. PCA was applied to compress these proxies into a single index. The findings supported the conclusion of Lin (2008), with a negative relationship between the sentiment index and stock returns. Furthermore, this study suggested its sentiment index could explain the difference of returns of growth stocks and value stocks, but it failed to account for the size premium in the Chinese markets.

3. Methodology and Data:

3.1. Investor Sentiment:

Previous studies have proposed a body of proxies for investor sentiment. There are no perfect or uncontroversial measures as most of the proxies employed are reasonable. All seem to be related to investor sentiment in some manner. Each of them may capture some components of the sentiment factor, and each of them may also include its own idiosyncratic component. Therefore, to efficiently capture the fluctuation of the sentiment factor in this study, 6 proxies are employed to form a composite sentiment index. These proxies include: the closed-end fund discount, A-share market turnover, the number of IPOs, the average first-day returns on IPOs, the number of new accounts opened, and consumer confidence index. The following paragraphs will first introduce each proxy individually, and then state how the sentiment index is constructed in this study.

3.1.1. The Closed-End Fund Discount:

Zweig (1973) and Delong et al. (1990) argue that if closed-end funds are partly held by individual investors, the average discounts of closed-end funds (measured as the average difference between the Net Asset Value (NAV) and the trading price of the fund) can effectively measure the degree of investor sentiment. In contrast with open-end funds, to liquidate a closed-end fund, investors can only sell their holdings to other investors rather than redeem the funds by NAV (open-end fund holders can redeem their funds by NAV at any time before the fund expires). When investors sell the funds, if they are optimistic about its future, they will sell the funds with a premium or smaller discount as they believe their holdings may be worth more in the future. However if the fund holders are pessimistic, they will sell the funds with a large discount as compensation for the buyers. For these reasons, large discounts observed in a given period suggest that investors are bearish, and narrow discounts indicate that the investors are bullish. Consistent with this argument, Lee et al. (1991) and Leonard and Shull (1996) suggest that closed-end fund discounts reflect the expectations of investors, and are inversely related to the sentiment factor. In this study, closed-end fund discount is defined as CEFD. The value-weighted average discount on closed-end stock funds is employed. There are 84 closed-end funds traded in the Chinese markets. 13 of them are bond-type funds and are excluded from this study as the discounts of these funds may reflect the sentiment of investors on bond markets, not stock markets. The historical data of CEFD between January 1998 and August 2010 are collected monthly from the TX Database which is one of the academic databases employed by many major Chinese security companies for research purposes.

3.1.2. A-Share Market Turnover:

A-share market turnover is computed by dividing the total trading volume over the averaged number of shares outstanding. Baker and Stein (2004) and Jones (2001) suggest that turnover may reflect the sentiment of investors if short-selling is limited in some ways. Share turnover, or market liquidity, measures the amount of funds available on the markets. Irrational investors are only willing to add more liquidity to the markets if they are optimistic about the future performance of the markets. In other words, if investor sentiment is high, irrational investors are more likely to trade, which may increase the market liquidity and induce overvaluation. Hence, high turnover may have a negative influence on market returns. Following the suggestion of Baker and Stein (2004) and Jones (2001) this study defines TURN as the natural log of the market share turnover. The monthly data of TURN from January 1998 to August 2010 is collected from the TX Database.

3.1.3. The Number of IPOs and the Average First-day Return of IPOs:

In previous research, the IPO market was always regarded as a reflection of the expectation and beliefs of investors. Stigler (1964) and Baker and Wurgler (2006, 2007) argue that firms are more likely to decide to offer new stocks to the public when investor sentiment is high. In these periods, investors are normally over-optimistic on the newly issued shares which may induce higher first day returns and create more benefit for the new listed firms. Hence, in a given period, if there are more IPOs and the average first day return of these IPOs is higher compared with other periods, this may imply that sentiment in this period is higher than that of other periods. In other words, the number of IPOs (NIPO) and the average first-day return of IPOs (RIPO) may be positively related to investor sentiment. The historical data between January 1998 and August 2010 of both of these proxies is acquired from the TX Database on a monthly basis.

3.1.4. The Number of New Accounts Opened:

The number of new accounts opened is a simple statistical reflection of the amount of new trading accounts opened by individual investors. Wang, Shi and Fan (2006) suggest more individual investors tend to open accounts and trade if market performance is good and sentiment is high. This study defines NO. A/C as the total number of new accounts opened, and the monthly historical data of NO. A/C is obtained from the China Securities Regulatory Commission. As the China Securities Regulatory Commission started to record and report the NO. A/C from December 2002, this proxy can only be included in the construction of the sentiment index after this date.

3.1.5. Consumer Confidence Index:

The consumer confidence index is the combined expectations and beliefs of investors on the fundamentals of the economy and markets. Lemmon and Portniaguina (2006), and Qiu and Welch (2007) argue that the consumer confidence index forms a direct measure of the general feeling of investors, and changes can measure the fluctuation of the stock returns, especially for small firms. In this study, the historical data of consumer confidence indices are acquired from the National Bureau of Statistics of China. The changes are defined as CCI. As the National Bureau of Statistics of China only began to disclose CCI after January 1999, this proxy can only be included in the formation of the sentiment index from this date.

3.1.6. Construction of sentiment index:

This study follows the same methodology introduced by Baker and Wurgler (2006) and Brown and Cliff (2004) to form a sentiment index. I employ PCA to extract the common components which are correlated with the sentiment index and isolate the impact of the idiosyncratic components from the sentiment proxies.

One of the major issues of constructing a sentiment index is that the proxies may have a non contemporaneous relationship with sentiment. Baker and Wurgler (2006) suggest the changes of some proxies may not reflect the simultaneous shift of sentiment, and these proxies may need longer to fully reveal the true fluctuation of sentiment.

To address this issue, this study first applies PCA to the six proxies and their 1st lags. The first principal component provides 12 loadings to these proxies and lags. After that, the original proxies and lags can be transformed into a first-stage index through the first principle component. This process can be presented as:

$$Sentiment = \beta_1 \, CEFD_t + \beta_2 \, TURN_t + \beta_3 \, RIPO_t + \beta_4 \, NIPO_t + \beta_5 \, NO.A/C_t + \beta_6 \, CCI_t + \beta_7 CEFD_{t-1} + \beta_8 \, TURN_{t-1} + \beta_9 \, RIPO_{t-1} + \beta_{10} \, NIPO_{t-1} + \beta_{11} \, NO.A/C_{t-1} + \beta_{12} \, CCI_{t-1}, \quad (1)$$

where β_i defines the loading derived from the first principle component for each proxy and lag.

After that, the correlation of each proxy and lag with this first-stage index is computed to determine whether the proxies can reveal the variation of the sentiment simultaneously. The correlation of each proxy and its lag with the first-stage index is measured and compared. The variable with higher correlation is retained in the sentiment index. This selection process reduces the total number of variables to six. Finally, the sentiment index employed in this study is derived from the first principle component of these six variables.

As mentioned previously, the National Bureau of Statistics of China and the China Securities Regulatory Commission only started to measure and report the CCI and NO. A/C regularly from January 1999 and December 2002, respectively. Therefore, these two proxies can only be added into the sentiment index from these dates. For this reason, this study constructs three sentiment indexes: the first one includes CEFD, NIPO, RIPO and Turnover; the second one adds CCI in; and CCI is replaced by NO. A/C in the last one (the reason will be discussed in the following paragraph). All of these three sentiment indexes are used to forecast the stock returns.

Table I below summarises the statistical data of all proxies, their correlations with the sentiment index, and the correlations with each other. In Panel A, the sentiment index is constructed through CEFD, TURN, NIPO and RIPO. In Panel B, CCI is added into the proxies. The first column of each panel shows the loadings derived from the first principle of the proxies after the selection procedure. These loadings do not tend to be constant across the three panels not only because new proxies are added into the sentiment index, but also a different sample period is used due to the limitation of the data. The correlation of each proxy with their corresponding sentiment index is presented under the column "correlation with sentiment". The correlations among proxies are presented under the column "correlation with others". According to Baker and Wurgler (2006) and Brown and Cliff (2002), all the sentiment proxies are expected to be significantly correlated with their corresponding sentiment index as the sentiment index is constructed through the component of these proxies. Therefore, they also suggest that each proxy should be highly correlated with others as they are all assumed to be highly correlated with the sentiment factor.

Table I

Summary Statistics of Sentiment Proxies

The summary statistics of each proxy show its first principle component loading, mean, standard deviation, minimum, and maximum observation. The column of correlation with sentiment shows the correlation of each proxy with the sentiment index. The columns under correlations with others display the correlations among proxies. In Panel A, the sentiment index is comprised of CEFD, TURN, NIPO and RIPO based on the data of the entire sample period. In Panel B, the sentiment index is comprised of CEFD, TURN, NIPO, RIPO and CCI based on the data of the period between March 1999 and August 2010. In Panel C, the sentiment index is constructed by CEFD, TURN, NIPO, RIPO, CCI, and NO. A/C based on the data of the period between January 2003 and August 2010. The superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A:CEFD, TURN, NIPO and RIPO

	Summary Statistics					*Correlation*	Correlations with Others			
Variable	Loading	Mean	SD	Min	Max	*with Sentiment*	CEFD	TURN	NIPO	RIPO
CEFD$_{t-1}$ *(%)*	0.67	14.26	20.72	-98.82	40.88	0.99^{a}	1.00			
TURN$_{t}$	0.42	18.99	1.75	14.97	22.20	0.42^{a}	0.41^{a}	1.00		
NIPO$_{t}$	-0.15	8.39	7.95	0.00	37.00	-0.23^{a}	-0.17^{a}	0.23^{a}	1.00	
RIPO$_{t-1}$ *(%)*	-0.60	104.99	98.45	0.00	744.95	-0.61^{a}	-0.59^{a}	-0.17^{b}	0.17^{b}	1.00

Panel B:CEFD, TURN, NIPO, RIPO and CCI

	Summary Statistics					*Correlation*	Correlations with Others				
Variable	Loading	Mean	SD	Min	Max	*with Sentiment*	CEFD	TURN	NIPO	RIPO	CCI
CEFD$_{t}$ *(%)*	0.67	18.40	12.33	-9.66	40.88	0.98^{a}	1.00				
TURN$_{t}$	0.37	19.14	1.71	14.97	22.20	0.31^{a}	0.32^{a}	1.00			
NIPO$_{t-1}$	-0.26	8.16	7.91	0.00	37.00	-0.42^{a}	-0.23^{a}	0.22^{a}	1.00		
RIPO$_{t}$ *(%)*	-0.58	95.57	77.87	0.00	384.26	-0.46^{a}	-0.43^{a}	-0.13	0.13^{a}	1.00	
CCI$_{t-1}$	-0.12	0.01	1.33	-10.38	3.70	-0.08	-0.03	-0.06	0.14	0.00	1.00

Panel C:CEFD, TURN, NIPO, RIPO and NO.A/C

	Summary Statistics					*Correlation*	Correlations with Others				
Variable	Loading	Mean	SD	Min	Max	*with Sentiment*	CEFD	TURN	NIPO	RIPO	NO.A/C
CEFD$_{t-1}$ *(%)*	-0.43	24.39	9.42	4.96	40.88	-0.87^{a}	1.00				
TURN$_{t-1}$	0.50	19.95	1.44	17.19	22.20	0.60^{a}	-0.41^{a}	1.00			
NIPO$_{t}$	0.40	8.48	9.24	0.00	37.00	0.83^{a}	-0.51^{a}	0.39^{a}	1.00		
RIPO$_{t}$ *(%)*	0.35	71.35	68.28	0.00	334.64	0.37^{a}	-0.29^{a}	0.31^{a}	0.22^{b}	1.00	
NO.A/C$_{t}$	0.54	12.35	1.52	10.21	15.25	0.67^{a}	-0.50^{a}	0.84^{a}	0.42^{a}	0.49^{a}	1.00

The Table I shows that, in the first two panels, the proxies are all highly correlated with the sentiment index at the 1%, expect for CCI. And the majority of proxies are highly correlated with each other, except for CCI. Based on these results, CCI seems to have little in common with the sentiment index and the other proxies. This may imply that CCI may not be a strong proxy for investor sentiment as is proposed by prior work in the Chinese markets. For this reason, in Panel C, I use NO. A/C to replace CCI. The correlation analysis in this panel shows all proxies are highly significant when correlated with each other and the sentiment index, which is consistent with the first two panels.

3.2. Control Variables:

Wang and Di Iorio (2007) suggest the major systematic risk factors in the Chinese markets can be efficiently captured by the FF-3 factors. For this reason, to isolate the impact of investor sentiment from the influence of other major systematic risk factors, FF-3 factors which include the market beta (β_m), market equity value (ME) and book-to-market ratio (BE/ME), are employed to solve this issue.

This study follows the same methodology proposed by Fama and French (1993) to account for the effect of FF-3 factors on cross-sectional stock returns. The return of the Chinese A-share index (RMKT), which contains all active A shares in the Chinese markets, is employed to proxy the market factor. The size effect is accounted for by the Small-Minus-Big (SMB) portfolio, which measures the historical excess return of firms with small ME over firms with large ME. The influence of BE/ME is captured by a High-Minus-Low (HML) portfolio which is computed as the excess return of value firms (firms with high BE/ME ratio) over growth firms (firms with low BE/ME ratio).

The historical data of the A-share market index is acquired from DataStream at a monthly interval. The ME and BE/ME are measured at the beginning of each year and their historical data is collected from DataStream. This implies the portfolios constructed to measure SMB and HML monthly are rebalanced yearly.

3.3. Portfolio Returns:

As Lee et al. (1991) and Baker and Wurgler (2006) suggest, the cross-sectional impact of sentiment is significantly related to firm-specific characteristics. To test whether the effect of the sentiment factor on the cross-section of stocks is different, I form stock portfolios based on two firm specific characteristics – ME and BE/ME.

Following the suggestion of Baker and Wurgler (2006) and Brown and Cliff (2004), stocks of financial companies are excluded as they operate differently from firms in other industries. Businesses with negative equity are also excluded from the sample of this study. Generally, a negative book value is more likely to be observed in a firm which suffers persistent unsustainable losses and has a high leverage ratio. This kind of firm is recognised as extremely risky for investors and may have a high probability of defaulting, and therefore, should not be included in the study.

All active trading stocks which were alive between January 1st 1998 and August 31st 2010 are included in this study. I collected historical monthly prices of these stocks from DataStream. As the Chinese exchanges are relatively young compared with other exchanges, there are only 434 stocks involved in this study (as of January 1st 1998). Due to the development of the markets and the economy in general, by the beginning of 2010, the sample size had grown to 1506.

To form stock portfolios, taking firm-specific characteristics into account, stocks are sorted into deciles according to their MEs or BE/ME ratios. Each decile contains 10% of the total stocks. The first decile includes firms with the smallest 10% MEs or BE/ME ratios, and the tenth decile is comprised of firms with the largest 10% MEs or BE/ME ratios. To capture the variation of these two characteristics induced by the development of the firms, the economy and the country, each portfolio is rebalanced at a yearly frequency. Lee et al. (1991), Baker and Wurgler (2006), and Brown and Cliff (2004) suggest large firms tend to be less influenced by investor sentiment. Therefore, value-weighted portfolios which favour large firms may dilute the impact of sentiment factor. For this reason, all portfolios are equally weighted.

Table II below contains the summary statistics of the portfolio returns and firm characteristics for the whole sample. Panel A presents the characteristics of the monthly returns of each portfolio, sorted based on ME. It clearly displays a size effect pattern; on average, portfolio returns are inversely related to market value. Portfolio 1, with the smallest 10% of firms, has the highest average return, 1.24%, for the period 1998-2010. For the same period, portfolio 10, which contains the largest 10% of firms, has the lowest average return of 0.08%. The last row of Panel A presents the statistical data of differences between the return of portfolio 10 and that of portfolio 1. It demonstrates that on average, in the whole sample period, the smallest 10% of firms out-performed the largest 10% firms by 1.15% per month. However, the t-test shows that the t-value which tests the null hypothesis that the mean return of portfolio 1 is indifferent with that of portfolio 10 is 1.35, which means that there is no significant evidence to reject the null hypothesis.

Table II

Summary Statistics, 1998 – 2010

Table 1 presents the summary statistics of each portfolio and firm-specific characteristics. Panel A summarises the returns of portfolios sorted by ME. Panel B summarises the returns of portfolios sorted by BE/ME. Panel C displays the statistical data of ME and BE/ME of stocks.

	Mean	**SD**	**Min**	**Max**	**T-value**
Panel A: Size Sorted Portfolios					
$PR_{(1)}(\%)$	1.24	10.49	-28.21	26.55	
$PR_{(2)}(\%)$	0.91	10.77	-33.75	27.10	
$PR_{(3)}(\%)$	0.83	10.79	-33.45	25.64	
$PR_{(4)}(\%)$	0.85	10.66	-34.32	26.87	
$PR_{(5)}(\%)$	0.76	10.72	-34.54	28.33	
$PR_{(6)}(\%)$	0.64	10.39	-34.19	25.59	
$PR_{(7)}(\%)$	0.42	10.54	-34.61	26.88	
$PR_{(8)}(\%)$	0.46	10.19	-34.27	25.36	
$PR_{(9)}(\%)$	0.26	10.14	-36.14	27.23	
$PR_{(10)}(\%)$	0.08	9.55	-33.72	22.09	
$PR_{(1-10)}(\%)$	1.16	5.09	-12.60	12.48	1.35
Panel B: BE/ME Sorted Portfolios					
$PR_{(1)}(\%)$	-0.20	10.55	-31.65	27.43	
$PR_{(2)}(\%)$	0.35	10.34	-33.41	24.21	
$PR_{(3)}(\%)$	0.43	10.39	-33.16	23.33	
$PR_{(4)}(\%)$	0.62	10.49	-33.58	23.41	
$PR_{(5)}(\%)$	0.58	10.37	-32.92	25.18	
$PR_{(6)}(\%)$	0.69	10.45	-33.95	26.29	
$PR_{(7)}(\%)$	0.62	10.50	-32.55	29.28	
$PR_{(8)}(\%)$	0.95	10.63	-34.81	28.99	
$PR_{(9)}(\%)$	0.77	10.54	-34.48	28.57	
$PR_{(10)}(\%)$	0.99	10.68	-36.79	30.03	
$PR_{(10-1)}(\%)$	1.19	4.28	-8.82	13.47	0.93
Panel C:Firm Specific Characteristics					
ME_t （￥）	4805.99	4251.22	116.82	5013104	
$BE/ME_t(\%)$	38.42	15.63	0.07	5.56	

Panel B of table II reveals the summary statistics of portfolio returns, sorted according to their BE/ME. Consistent with the arguments of Stattman (1980), Rosenberg, Reid, and Lanstein (1985) and Fama and French (1992, 1993), Panel B shows that the portfolios with higher BE/ME ratios tend to have higher returns than others. Portfolio 10 contained the 10% of firms with the highest BE/ME ratios and recorded the highest average return of 0.99 % over the entire sample period. Portfolio 1, which contains the 10% of firms with the lowest BE/ME ratios, had the lowest average return for the same time period, -0.2%. The last row of Panel B illustrates that on average, portfolio 10 outperformed portfolio 1 by 1.19% per month. However, similar to Panel A, the difference between portfolio 1 and portfolio 10 still fails on the t-test (T-value = 0.93). This result may suggest that on average portfolio 10 provides similar returns with portfolio 1. There is no statistical evidence to prove the performance of portfolio 10 is different with that of portfolio 1.

Wang, Shi, and Fan (2006) and Ng and Wu (2007) argue that both the Chinese stock exchange markets and domestic investors may accumulate trading skills, experience and knowledge over time since the markets are relatively young. Hypothetically, there may be an observable learning effect in the markets which could affect the impact of investor sentiment on stock prices. Investors may become more rational and the markets may establish a more complete regulatory framework. To capture this potential learning effect and enable the test of the evolution of the influence of investor sentiment, the entire sample period is further split into 3 sub-sample periods. Each period contains 4 years' data. If a learning effect indeed exists in the Chinese markets, it is expected that the influence of the sentiment index would display a diminishing trend over time. Furthermore, as Kling and Gao (2007) suggest, the volatility of investor sentiment in bear periods is different from that of bull periods, implying that the impact of investor sentiment varies across bull periods and bear periods. To further investigate this hypothesis, the entire sample period is separated into eight sub-sample periods. The separation is based on the bull periods and bear periods as determined by the China Securities Regulatory Commission.

Table III below shows the average return of portfolios sorted by size and book-to-market ratio within each sub-period, as formed to test the learning effect. As mentioned in the last paragraph, each sub-period covers 4 years. Panel A shows the mean return of the portfolios sorted by size, and in Panel B, portfolios are constructed based on book-to-market ratio. Panel A shows that the return difference between portfolio 1 and portfolio 10 is significant in

Table III

Portfolio Mean of Each Sub-Period – Learning Effect

This table shows the mean of returns of portfolios of each sub-period which is formed to test the learning effect. In Panel A, all portfolios are sorted by size, and in Panel B, all portfolios are sorted by book-to-market ratio. The superscripts a, b, and c denote the statistical significance at 1%, 5% and 10%, respectively.

Panel A: Size Sorted Portfolio Means			
Time:	Jan 98 - Dec 01	Jan 02 - Dec 05	Jan 06 - Aug 10
$PR_{(1)}(\%)$	2.60	-2.18	2.99
$PR_{(10)}(\%)$	-0.13	-1.56	1.67
$PR_{(1-10)}(\%)$	2.72^{b}	-0.62^{c}	1.32^{c}
Panel B: BE/ME Sorted Portfolio Means			
Time:	Jan 98 - Dec 01	Jan 02 - Dec 05	Jan 06 - Aug 10
$PR_{(1)}(\%)$	0.15	-2.89	1.80
$PR_{(10)}(\%)$	1.52	-1.06	2.29
$PR_{(10-1)}(\%)$	1.37	1.83	0.48

all three sub-periods. However, the size effect can only be supported by the 1st and the 3rd sub-period, as they suggest that during these two periods small firms have significantly higher returns than large firms. Compared with the other two periods, during January 2002 – December 2005, large firms provided higher returns than small firms. In this period, the Chinese markets largely suffered from the reform of the shareholder structure of listed companies. The China Securities Regulatory Commission suggested that prior to 2001, the Chinese stock markets had experienced a period of rapid development. Since 2001, more small firms which were not required to become listed companies were registered in the Shanghai market or Shenzhen market. Normally, these small firms would raise their profile through public trading. However, these firms tended to be firms with worse shareholder structures than those large firms which had already developed a relatively fair shareholder structure, due to the fact that these large firms were more likely to be monitored by the public and the country. For this reason, during the process of reforming the shareholder structure of listed companies, many small firms suffered to a greater degree than large firms.

Panel B of this table illustrates that none of the return differences between portfolio 1 and portfolio 10 is significant. Although it shows that the portfolio with higher BE/ME ratio tends to outperform the portfolio with lower BE/ME ratio on average, there is no statistical evidence to support this result.

Table IV

Portfolio Means of Each Sub-Period – Bull and Bear Periods

Panel A contains the mean of returns of size sorted portfolios in each sub-period. Bull markets and bear markets are separately displayed. Panel B reveals the average returns of BE/ME sorted portfolios in each sub-period.

Panel A: Size Sorted Portfolios Means				
Bull Markets:	Jun 99 - Jun 01	Jan 03 - May 04	Jul 05 - Oct 07	Jan 09 - Aug 10
$PR_{(1)}(\%)$	3.89	-1.14	5.22	5.42
$PR_{(10)}(\%)$	1.73	0.29	5.05	2.67
$PR_{(1-10)}(\%)$	2.16	-1.43	0.17	2.75
Bear Markets	Jan 98 - May 99	Jul 01 - Dec 02	Jun 04 - Jun 05	Nov 07 - Dec08
$PR_{(1)}(\%)$	2.95	-2.83	-5.01	-5.63
$PR_{(10)}(\%)$	-1.58	-2.67	-3.83	-7.54
$PR_{(1-10)}(\%)$	4.53	-0.16	-1.18	1.91
Panel B: BE/ME Sorted Portfolios Means				
Bull Markets:	Jun 99 - Jun 01	Jan 03 - May 04	Jul 05 - Oct 07	Jan 09 - Aug 10
$PR_{(1)}(\%)$	2.62	-2.10	4.26	4.18
$PR_{(10)}(\%)$	3.01	0.78	5.90	3.57
$PR_{(10-1)}(\%)$	0.39	2.88	1.64	-0.61
Bear Markets	Jan 98 - May 99	Jul 01 - Dec 02	Jun 04 - Jun 05	Nov 07 - Dec08
$PR_{(1)}(\%)$	-1.91	-3.36	-5.49	-7.08
$PR_{(10)}(\%)$	-1.10	-2.44	-3.26	-7.68
$PR_{(10-1)}(\%)$	3.01	0.92	2.23	-0.60

Table IV above shows the means of the first portfolio, the tenth portfolio and their differences during each sub-period which is split based on bull and bear markets. In Panel A, stocks are sorted by size. It shows that the majority of the time, small firms outperformed large firms on average except during the 3 periods between July 01 and Jun 05. In Panel B, stocks are sorted according to their BE/ME ratios. This reveals that firms with high BE/ME ratios dominate firms with low BE/ME ratios except during the period between Nov 07 and Aug 10.

3.4. Theoretical Approach:

As discussed in previous sections, to most accurately determine the role of investor sentiment in the asset pricing model, both the impact of sentiment factor and the impact of other pricing factors should be controlled. For this reason, in theory, the predictive equation can be presented as:

$$R_{it} = \alpha + \beta_1 \, IS_{t-1} + \beta_2 \, X_{it} + \varepsilon_{it}, \quad (2)$$

where R_{it} represents the expected return of stock *i* at time *t*, α picks up the constant component of the stock expected returns, IS_t is the sentiment factor at time t, X_{it} is a vector of other factors which may influence the stock returns and ε_{it} is the error term. The coefficients β_1 and β_2 determine the influence of the investor sentiment and other factors on the stock performance, respectively.

As Baker and Wurgler (2006), Lee et al. (1991) and Brown and Cliff (2004) suggest stock returns can be influenced by the impact of the previous investor sentiment, this study uses the 1st lag of sentiment to forecast the stock returns.

Ordinary Linear Regression (OLS) is used to compute the corresponding coefficients. Li, Malone and Zhang (2005) and Brooks (2008) argue that time series financial data may have a high chance of inducing autocorrelation and the heteroskedasiticity problem. Autocorrelation is raised if the error terms of OLS are correlated in some ways, and the heteroskedasiticity problem occurs when the variance of the error term is not constant. Either of these issues may induce errors in the estimation of standard errors of coefficients by using OLS as they break the standard assumptions of regression. To control for these issues, Newey-West estimation is employed. Newey-West estimation is used to adjust the errors if the standard assumptions of regression analysis do not hold. It can improve the accuracy of the standard errors and t-ratios conducted from the OLS.

3.5. Empirical Approach:

Because this study focuses on whether investor sentiment can explain the cross-sectional difference between returns among stocks with different characteristics when the influence of the FF-3 factors is controlled for, the estimation equation should be written as:

$$PR_{(10)t} - PR_{(1)t} = \alpha + \beta_1 IS_{t-1} + \beta_2 RMKT_t + \beta_3 SMB_t + \beta_4 HML_t + \varepsilon_t, \quad (3)$$

where $PR_{(10)t} - PR_{(1)t}$ determines the excess return of portfolio 10 over portfolio 1 when sorted by size or book-to market ratio, α is the constant component of the stock expected returns, IS_t represents the sentiment factor, RMKT is the market excess return, SMB is the mimicking portfolio for the size effect, HML is the mimicking portfolio for the book-to-market ratio effect, and ε_t is the error term. The coefficients β_1 to β_4 determine the impact of investor sentiment, market, size, and book-to-market ratio on the stock performance, respectively.

In this equation, $PR_{(10)t} - PR_{(1)t}$ determines the differences between the returns of portfolio 10 and portfolio 1. Given these two portfolios have distinct characteristics, if investor sentiment can significantly predict these differences after other FF-3 factors are controlled for, it may imply that investor sentiment is one of the factors that influences differences between cross-sectional stock returns. In other words, the impact of the sentiment factor on the stock returns varies according to the characteristics of stocks.

4. Empirical Results

4.1. Impact of Sentiment on Future Returns across Deciles

Table V studies the impact of sentiment on future returns across deciles that are sorted based on the ME and BE/ME ratio. First of all, the returns of each decile are sorted into two categories, high – if the sentiment of the previous calendar year is higher than the average sentiment of the whole sample, and low – if the sentiment of the previous calendar year is lower than the average sentiment of the whole sample. After that, the weighted average monthly returns for each decile within both the high sentiment group and low sentiment group are computed. The patterns formed by the average monthly return of each decile can be used to roughly account for the cross-sectional effects of investor sentiment on securities. Consistent with Table IV, Table V also presents the outcomes derived by using all three sentiment indexes. In Panel A, the sentiment index is constructed through CEFD, TURN, NIPO and RIPO. In Panel B, CCI is added in the index formation. In Panel C, CCI is replaced by NO. A/C.

The first three rows of each panel show the impact of sentiment and conditional return differences, given that the size effect is controlled for. In Panel A, across deciles within the same sentiment group (high or low), there is a clear pattern: on average the firms with smaller sizes tend to have higher returns. The average return of small firms is 1.75%, which is 0.98% higher than the average return of large firms if the sentiment is low (displayed in the second row). This difference is reduced to 0.7%, if the sentiment is high (displayed in the first row). The last two columns show the return difference between the large firms and the median size firms, and the return difference between the median size firms and small firms. On average these two columns also show that the smaller firms tend to earn higher returns. The return patterns revealed in the first two rows of Panel A display that on average, small firms outperform large firms in each sentiment scenario. Sentiment may only affect the magnitude of the difference between the average return of small firms and that of the large firms. Higher sentiment induces a smaller difference. The difference row (the third row) shows that on average, high sentiment will induce a lower return for all deciles. This finding echoes the conclusions drawn from previous work (Baker & Wurgler, 2006; Lee et al., 1991). It implies that there is a negative relationship between investor sentiment and stock returns. However, according to the results of t-tests, all of the differences presented in Panel A are insignificant.

Table V

Future Returns by Controlling Sentiment Index and Market Capitalization/Book-to-Market Ratio

Table IV shows the patterns of average returns across deciles given the sentiment of the previous year. The sentiment index in Panel A is constructed by CEFD, TURN, NIPO, and RIPO. CCI is included into the sentiment formation in Panel B. The sentiment index of Panel C excludes CCI but includes NO. A/C. The difference of each portfolio is computed by using the return of the High group minus the return of the Low group. The t –ratio of each difference is presented in the bracket.

		Decile										Comparison		
	Panel A: CEFD, TURN, NIPO,and RIPO													
	Sentiment	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P10-P1**	**P10-P5**	**P5-P1**
ME (%)	*High*	0.14	0.03	0.14	0.13	-0.02	-0.13	-0.31	0.07	-0.35	-0.56	-0.70 (-0.29)	-0.54 (-0.21)	-0.16 (-0.06)
	Low	1.75	1.43	1.11	1.14	1.27	1.13	0.89	0.82	0.87	0.77	-0.98 (-0.71)	-0.51 (-0.37)	-0.47 (-0.34)
	Difference	1.60	1.40	0.97	1.01	1.29	1.26	1.20	0.75	1.22	1.32	-0.28 (-0.30)	0.03 (0.11)	-0.31 (-0.70)
	T-ratio of diff	(0.88)	(0.75)	(0.51)	(0.53)	(0.68)	(0.66)	(0.63)	(0.38)	(0.65)	(0.72)			
BE/ME (%)	*High*	-0.91	-0.33	-0.08	0.00	-0.05	0.18	0.12	0.25	0.11	-0.01	0.90 (0.31)	0.03 (0.01)	0.87 (0.31)
	Low	0.60	0.94	1.03	1.12	1.20	0.99	1.11	1.29	1.42	1.73	1.13 (0.52)	0.53 (0.25)	0.59 (0.25)
	Difference	-1.51	-1.27	-1.10	-1.12	-1.25	-0.80	-0.99	-1.04	-1.31	-1.74	-0.23 (0.30)	-0.50 (0.78)	0.27 (0.76)
	T-ratio of diff	(-0.59)	(-0.50)	(-0.44)	(-0.44)	(-0.49)	(-0.32)	(-0.40)	(-0.40)	(-0.53)	(-0.68)			
	Panel B: CEFD, TURN, NIPO, RIPO,and CCI													
ME (%)	*High*	0.14	0.03	0.14	0.13	-0.02	-0.13	-0.31	0.07	-0.35	-0.56	-0.70 (-0.29)	-0.54 (-0.17)	-0.16 (-0.12)
	Low	1.61	1.39	1.16	1.11	1.21	1.06	0.91	0.86	0.95	0.82	-0.79 (-0.25)	-0.39 (-0.19)	-0.41 (-0.08)
	Difference	1.47	1.36	1.02	0.98	1.23	1.19	1.22	0.79	1.30	1.38	-0.09 (-0.32)	0.15 (0.21)	-0.25 (-0.39)
	T-ratio of diff	(0.16)	(0.21)	(0.13)	(0.13)	(0.23)	(0.21)	(0.25)	(0.13)	(0.31)	(0.28)			
BE/ME (%)	*High*	-0.91	-0.33	-0.08	0.00	-0.05	0.18	0.12	0.25	0.11	-0.01	0.90 (0.16)	0.03 (0.01)	0.87 (0.18)
	Low	0.64	0.85	0.99	0.99	1.22	0.92	1.01	1.29	1.39	1.51	0.87 (0.50)	0.29 (0.13)	0.58 (0.35)
	Difference	-1.55	-1.18	-1.07	-0.99	-1.27	-0.74	-0.89	-1.04	-1.28	-1.52	0.03 (0.78)	-0.26 (0.49)	0.29 (0.74)
	T-ratio of diff	(-0.14)	(-0.15)	(-0.19)	(-0.11)	(-0.23)	(-0.12)	(-0.14)	(-0.16)	(-0.27)	(-0.33)			

Panel C: CEFD, TURN, NIPO, RIPO and NO.A/C														
ME (%)	*High*	1.11	0.43	0.46	0.42	0.37	0.02	-0.28	-0.34	-0.85	-1.19	-2.30 (-0.08)	-1.55 (-0.13)	-0.74 (-0.05)
	Low	1.62	1.63	1.78	1.70	1.62	1.68	1.56	2.04	1.70	1.58	-0.04 (-0.40	-0.05 (-0.28)	0.01 (-0.13)
	Difference	0.51	1.20	1.32	1.28	1.25	1.66	1.84	2.38	2.55	2.77	2.26 (1.63)	1.50 (1.14)	0.75 (1.55)
	T-ratio of diff	(0.10)	(0.26)	(0.29)	(0.29)	(0.27)	(0.35)	(0.39)	(0.53)	(0.55)	(0.61)			
BE/ME (%)	*High*	-0.12	0.24	0.23	-0.05	0.20	0.02	0.09	0.04	-0.17	-0.58	-0.46 (-0.08)	-0.78 (-0.13)	-0.48 (0.05)
	Low	-0.02	0.54	0.88	1.07	0.99	1.38	1.30	1.51	1.58	1.88	1.90 (0.51)	1.02 (0.18)	0.84 (0.33)
	Difference	-0.10	-0.30	-0.65	-1.12	-0.79	-1.36	-1.21	-1.47	-1.75	-2.46	-2.36 (-1.63)	-1.80 (-1.14)	-1.32 (-1.55)
	T-ratio of diff	(-0.14)	(-0.20)	(-0.29)	(-0.40)	(-0.31)	(-0.45)	(-0.40)	(-0.45)	(-0.50)	(-0.59)			

These outcomes suggest that the sentiment factor may not have remarkable effect on the stock returns. In other words, by sorting stocks based on ME and BE/ME, Table V shows that the stock portfolios tend to have discrepant returns under different sentiment levels. Nevertheless, the t-tests cannot strongly support the differences among the portfolio returns are incurred by the sentiment factor.

Based on these findings, this study provides some evidence to support the argument of Baker and Wurgler (2006) and Lee et al. (1991) that on average, small firms earn relatively higher returns than large firms if sentiment is low at the beginning of the period, and vice versa. When sentiment is low, the market is relatively "clean". Less noise is introduced from the trades of irrational investors because they may be pessimistic about the future, and thus refuse to provide a large amount of liquidity to the market. In this case, small firms are less likely to be over-estimated and may even be under-estimated. For this reason, the returns of small firms realised from this period may be relatively higher than during other times. Conversely, if sentiment is high at the beginning of a period, the market may be noisier than during other times. Irrational investors have high mania to actively invest, and in this case, are more likely to over-estimate the fundamental values of small firms. Consequently, the returns of small firms realised from this period may be relatively lower than during other times. The same logic can be applied to explain why large firms earn lower returns in periods of high sentiment and higher returns in low sentiment periods. Furthermore, as the conditional difference of small firms is 0.28% higher than that of large firms, it may suggest that compared with large firms, the impact of sentiment on small firms is stronger. In other words, small firms are more sensitive to changes in sentiment.

In Panel B, like Panel A sorted in deciles according to ME, a similar pattern can be observed, but the differences among the portfolio returns are still insignificant. In contrast with the other two panels, the results of Panel C reach a slightly different conclusion from the other two panels. Although all of the t-tests of Panel C also provide insignificant results, it shows that on average, small firms tend to dominate large firms in all cases, and investor sentiment has a negative impact on stock performance. But the differences for large firms in Panel C are much larger than those for small firms, which means in this case, large firms tend to be more sensitive to changes in sentiment than small firms.

This outcome may be biased as Panel C covers a relatively shorter period (December 2002 – August 2010). Liu (2008) suggests that during this time, the Chinese exchanges had just completed a rapid growth period and entered into a relatively "smooth" development period. Although the China Securities Regulatory Commission frequently set new regulations to consummate the regulatory framework in this period, which increased market uncertainty, more and more investors were aware of stock markets as an alternative investment opportunity. As many of these investors are under-educated, they have relatively poor stock picking skills. As a result, during 2003 – 2007, the majority of them tended to invest in blue chips as these firms are frequently mentioned and reported in news (Wang, Shi & Fan, 2006; Lin, 2008). Consequently, as there are a large number of irrational investors trading on large firms, their impact on large firms might be stronger than on small firms. This may also explain why portfolio 10 has the lowest return when sentiment is high and the highest return when sentiment is low, in comparison with the other two panels.

The last three rows in each panel illustrate patterns in the returns of deciles when securities are sorted based on the BE/ME ratio. All of the differences of portfolio returns are still unable to reach the significant level. In Panel A, within each sentiment group, the effect of BE/ME is immediately obvious. Deciles with a higher BE/ME ratio tend to record higher returns than deciles with a lower BE/ME ratio. For example, the fourth row of Panel A shows that the growth portfolio's (portfolio 1) average return is 0.6% when sentiment at the beginning of the period is low, but the average return for the value portfolio (portfolio 10) under the same sentiment level is 1.73% . Furthermore, firms with higher BE/ME ratios seem to dominate the firms with lower BE/ME ratios in both sentiment groups. The last row of each panel shows the conditional difference of the returns of each BE/ME sorted portfolio. As all the three panels display negative conditional differences, these results imply that high sentiment may lead to lower returns. In other words, these results support that sentiment is negatively related with stock returns. In line with the argument of Baker and Wurgler (2006), this study (except for the evidence displayed in Panel C) provides support for the argument that after controlling for the effect of the BE/ME ratio, differences which are induced by the impact of investor sentiment display a U-shape pattern. This means that the differences between returns tend to decrease first and then increase across deciles. For example, the difference for the first decile in Panel A is 1.51%. For the sixth decile, the difference falls to 0.80% and for the tenth decile, it grows to 1.74%.

Similar patterns are also evident in Panel B and C. The only exception is that in the high sentiment group of Panel C, the growth portfolio outperforms the value portfolio. This result may be due to the fact that Panel C contains the special period which has been mentioned above, 2003 – 2007. According to Lin (2008) and Wang, Shi and Fan (2006), a large amount of new individual investors entered the market during this time. Because they had less background knowledge, stock picking skills and analysis skills, and invested with a gambling mindset, they may have been over-optimistic about the future performance of stocks that they traded. As I discussed above, these investors were more likely to trade the stocks of the companies which are large, mature and successful (and which tend to be value stocks), because these firms are more frequently reported in news, their future prospects may be over-estimated. Consequently, when the sentiment is high, it may result in growth stocks earning relatively higher returns than value stocks.

In summary, Table V provides some evidence that investor sentiment is negatively correlated with stock returns, although this relationship cannot be significantly supported. In addition, it provides weakly support on the findings of Baker and Wurgler (2006). However, Table V also presents some critical findings which are all derived from Panel C. In contrast with the other two panels, the conflicting results from Panel C may be due to the fact that Panel C covers a relatively specific trading period.

4.2. Regression Analysis for Long-Short Trading Strategy

This section tests the predictive power of the sentiment index on equal-weighted portfolios, which are comprised by longing stocks with small ME (high BE/ME) and shorting stocks with large ME (low BE/ME), respectively. As seen in Table IV, it is clear investors who hold value stocks (large stocks) may earn higher returns (lower returns) than investors who invest in growth stocks (small stocks). If investor sentiment can forecast time series differences between these portfolios, it implies that sentiment is one of the factors which induce differences in cross-sectional returns of stocks.

In this section, I employ a regression approach to carry out an analysis for testing the existence of the impact of investor sentiment on stock returns. To isolate the influence of investor sentiment from other well-known systematic factors, FF-3 factors are included in the regression equation. Furthermore, as Wang, Shi and Fan (2006) and Kang, Liu and Ni (2002) suggest, past returns seem to have some explanatory power over future performance in

Chinese markets, so the 1st lag of the past returns is also controlled for.

The regression equation employed in this section has been briefly introduced in the last section of Methodology and Data, which can be presented as:

$$PR_{(10)t} - PR_{(1)t} = \alpha + \beta_1 \, IS_{t-1} + \beta_2 \, RMKT_t + \beta_3 \, SMB_t + \beta_4 \, HML_t + (PR_{(10)t-1} - PR_{(1)t-1}) + \varepsilon_t, \quad (4)$$

Table VI summarises the regression outcomes. The results shown in Panel A, where the sentiment index is constructed using CEFD, TURN, NIPO and RIPO provide strong evidence to support the role of investor sentiment in an asset pricing model. When portfolios are sorted by size, the sentiment index has significant predictive power when it is used alone. The coefficient of the sentiment index is -0.051, which suggests that when sentiment is high, the returns of long on small stocks and short on large stocks will be reduced by 0.051% per month.

This coefficient also shows that investor sentiment has a negative influence on stock returns, and small stocks tend to earn relatively higher returns when sentiment is low. This relationship is significant at the 1% level, and is in line with the findings of Baker and Wurgler (2006) and the results displayed in Table V. After controlling for FF-3 factors, the explanatory power of sentiment on a long-short portfolio which is sorted by size is still highly significant. The magnitude of the coefficient is almost not changed, and its significance level is increased to 1%. Furthermore, in the last two columns of Panel A, I introduce the 1st lag of the dependent variable instead of FF-3 factors to see whether the explanatory power of the sentiment index is due to it being related with past performance. Consequently, the outcome further supports the role of the sentiment index in asset pricing. After controlling for past returns, the coefficient is increased by 0.005, and it is still negative and significant at 5%.

In contrast with the size sorted portfolios, when portfolios are sorted by BE/ME, the coefficient of the sentiment index has no power to explain the return differences when it is employed as the only explanatory variable. However, if the FF-3 factors are included in the regression equation, the explanatory power of investor sentiment is slightly increased and becomes significant at the 10% level. Both of these coefficients (before and after FF-3 factors are controlled for) have a negative sign which implies high sentiment may increase the return of growth stocks relative to value stocks.

Table VI

Time Series Regressions

Table VI presents the results of time series regressions of long-short portfolio returns on a lagged sentiment index which is constructed through sentiment proxies. The regression equation used is equation (2). Consistent with previous sections, the sentiment index used in Panel A is constructed by CEFD, TURN, NIPO and RIPO. The sentiment index of Panel B is formed by further adding CCI as additional sentiment proxy. And in Panel C, No. A/C is used to replace CCI. The sample period of Panel A covers the entire sample period. Panel B contains monthly data since March 1999 and Panel C covers only the period from January 2003 to August 2010. The superscript a, b, and c denote the statistical significance at 1%, 5% and 10%, respectively.

	Sentiment$_{t-1}$		**With RMKT, SMB and HML**		**With Lag of Dependent Vari.**	
	ME（%）	**BE/ME (%)**	**ME（%）**	**BE/ME (%)**	**ME（%）**	**BE/ME (%)**
	Panel A: CEFD, TURN, NIPO and RIPO					
Coeff.	-0.051[a]	-0.006	-0.051[a]	-0.028[c]	-0.056[b]	-0.010
P-value	(0.006)	(0.818)	(0.006)	(0.071)	(0.05)	(0.834)
Adj-R^2	0.023	0.000	0.031	0.172	0.060	0.000
	Panel B: CEFD, TURN, NIPO, RIPO, and CCI					
Coeff.	-0.032	0.03	-0.028	-0.008	-0.035	0.030
P-value	(0.387)	(0.436)	(0.458)	(0.815)	(0.451)	(0.449)
Adj-R^2	0.004	0.005	0.009	0.156	0.021	0.005
	Panel C: CEFD, TURN, NIPO, RIPO, and NO. A/C					
Coeff.	-0.088	-0.06	-0.087	-0.011	-0.076	-0.061
P-value	(0.185)	(0.283)	(0.159)	(0.821)	(0.231)	(0.283)
Adj-R^2	0.014	0.012	0.118	0.211	0.020	0.012

This finding may be explained by the same logic used in the explanation of Panel C on Table V. It can be briefly stated as due to a lack of background knowledge, analysis skills, and stock picking skills, a large proportion of individual investors in the Chinese markets may be over-optimistic or over-pessimistic about the future performance of stocks. As value stocks are more likely to be reported, these irrational investors may pay more attention and trade more on the value stocks, thus introduce more noise on the value stocks. Compared with value stocks, growth stocks are impacted to a smaller degree in this case as they are less likely to be traded by irrational investors relative to the value stocks. Following this logic, when sentiment is high in the Chinese markets, growth stocks may tend to earn relatively higher returns than value stocks as they are less likely to be over-estimated. Conversely, when sentiment is low, growth stocks may earn relatively lower returns as value stocks are more likely to be under-estimated.

In contrast with Panel A, Panel B and Panel C, which further add CCI and NO. A/C into the index formation, show no evidence for the role of investor sentiment on stock pricing. This implies that, in the Chinese markets, CCI and NO. A/C may not strongly relate to the fluctuation of investor sentiment. Therefore, including these two proxies in the formation of a sentiment index may in fact induce noise and interfere with the significance of the sentiment factor. However, comparing the adjusted R^2 of each panel, the table shows that when NO. A/C is introduced into the sentiment formation, although the sentiment index does not have a significant coefficient, the model provides higher adjusted R^2 if the portfolios are BE/ME sorted. In other words, this table may suggest NO. A/C may have some power to improve the predictability of the model. However, as NO. A/C may not be strongly related with the actual fluctuation of the sentiment factor, it may not improve the coefficient of the sentiment index to become significant.

4.3. Time Series Regressions – Learning Effect:

In this section, as I discussed in the section of data and methodology, the entire sample period is further divided into 3 sub-periods to test the evolution of the impact of investor sentiment. The regression results are present in Table VII.

In Panel A of Table VII, the entire sample period is split into three sub-periods. Each of them covers 4 years' data. In Panel B, as CCI is introduced in the formation of the sentiment index and was disclosed from January 1999, the first sub-period of Panel B actually starts from that

Table VII

Sub-Period Regressions – Learning Effect

Table VI present the regression results of the sub-periods which are formed to test for a learning effect. In Panel A, the sentiment index is constructed by CEFD, TURN, RIPO and NIPO. In Panel B, CCI is introduced in the sentiment index. In Panel C, No. A/C is used to replace CCI.

Panel A: CEFD, TURN, RIPO and NIPO							
		Sentiment_{t-1}			Sentiment_{t-1} controlling for RM, SMB and HML		
Time Period	Dependent Variable	Coefficient	P-value	Adj-R^2	Coefficient	P-value	Adj-R^2
Jan 98 - Dec 01	*ME*	-0.08[a]	0.00	0.09	-0.08[a]	0.00	0.14
	BE/ME	-0.07[b]	0.02	0.05	-0.11[b]	0.02	0.20
Jan 02 - Dec 05	*ME*	0.06	0.46	0.01	0.08	0.14	0.38
	BE/ME	-0.02	0.75	0.00	0.01	0.63	0.76
Jan 06 - Aug 10	*ME*	-0.60	0.38	0.01	-0.07	0.31	0.02
	BE/ME	-0.09[c]	0.08	0.04	-0.07	0.18	0.08
Panel B: CEFD, TURN, RIPO, NIPO and CCI							
		Sentiment_{t-1}			Sentiment_{t-1} controlling for RM, SMB and HML		
Time Period	Dependent Variable	Coefficient	P-value	Adj-R^2	Coefficient	P-value	Adj-R^2
Jan 99 - Dec 01	*ME*	0.00	0.98	0.00	0.00	0.96	0.25
	BE/ME	-0.05	0.65	0.01	-0.05	0.65	0.36
Jan 02 - Dec 05	*ME*	-0.06	0.45	0.01	-0.08	0.15	0.38
	BE/ME	0.02	0.74	0.00	0.01	0.65	0.76
Jan 06 - Aug 10	*ME*	-0.06	0.51	0.01	-0.06	0.46	0.01
	BE/ME	-0.08[c]	0.08	0.04	-0.07	0.18	0.08
Panel C: CEFD, TURN, RIPO, NIPO and NO. A/C							
		Sentiment_{t-1}			Sentiment_{t-1} controlling for RM, SMB and HML		
Time Period	Dependent Variable	Coefficient	P-value	Adj-R^2	Coefficient	P-value	Adj-R^2
Jan 03 - Dec 05	*ME*	-0.24[b]	0.04	0.09	0.00	0.96	0.58
	BE/ME	0.24[b]	0.01	0.12	0.09	0.11	0.80
Jan 06 - Aug 10	*ME*	0.08	0.34	0.01	0.10	0.28	0.02
	BE/ME	-0.10[c]	0.07	0.04	-0.08	0.18	0.08

date. In Panel C, as NO. A/C is used to replace CCI in the construction of the sentiment index and CCI has been reported since January 2003, the sample period of Panel C is only split into two sub-periods. The first covers data from January 2003 to December 2005, and the second contains the remaining data.

From Table VII, there is evidence to indicate the existence of a learning effect. Panel A shows that during the first period the explanatory power of the sentiment index is highly significant even after controlling for FF-3 factors. All of the coefficients derived have negative signs which are consistent with the findings in previous sections. In contrast, the remaining two sub-periods of Panel A show that the impact of the sentiment index on the stock returns disappeared entirely. Even when the sentiment index is used alone as the independent variable, it is only weakly significant in the BE/ME sorted portfolio during the last sub-period. These outcomes may suggest that since 2002, the experience, trading skills, and background knowledge accumulated by investors had become strong enough to rule out at least part of the influence of sentiment.

In contrast with Panel A, Panel B provides no significant coefficient except the one in the BE/ME sorted portfolio during the last sub-period. The significance of this coefficient is only at the 10% level, and it is largely reduced once FF-3 factors are controlled for.

The results of Panel C conflict somewhat with Panel A in regard to when the learning effect becomes significant. In the first sub-period of Panel C, the sentiment coefficients of both size sorted or BE/ME sorted portfolios are all significant at the 5% level. However, both become insignificant after FF-3 factors are controlled for. In the last sub-period, the sentiment coefficient of the BE/ME sorted portfolio is significant at the 10% level, and again, its explanatory power is removed once FF-3 is introduced in the estimation equation. These results may indicate that in contrast with the outcomes of Panel A, the learning effect may start to become significant from January 2006.

4.4. Sub-Period Time Series Regressions – Bull and Bear Periods

In this section, I investigate the impact of the sentiment index across bull and bear periods. The same regression techniques as in the previous section are employed here again. Table VIII contains the summary report of the sub-period regressions by employing all three sentiment indexes. To facilitate the comparison among sub-periods, they are sorted into two groups – Bull and Bear.

Table VIII provides some evidence to support the role of investor sentiment in the asset pricing model. In Panel A, compared with the coefficients in bear markets, the impact of investor sentiment is rarely significant in bull periods. When the sentiment index is used alone to forecast returns, the coefficients are only significant when portfolios are sorted by ME for the periods January 2003 - May 2004. The explanatory power of the coefficient is still robust after controlling for FF-3 Factors, and the sign of the coefficients remains negative.

Meanwhile, during the same period, when portfolios are sorted by BE/ME ratio, FF-3 factors are controlled for, and the Newey-West estimator is employed to adjust the autocorrelation issues, the coefficient of the sentiment index is negatively significant at the 5% level. In contrast with bull periods, the impact of the sentiment index in bear periods is more apparent. All the signs of coefficients derived are consistent with the findings of previous sections in this study. The predictive ability of the sentiment index is more notable in the portfolios which are sorted by BE/ME as most of the predictive power of the sentiment index on the return differences of portfolios which are sorted by ME is removed once the FF-3 factors are introduced.

In the bull periods of Panel B, when the sentiment index is tested alone, a significant coefficient can be observed from ME sorted portfolios over the period of January 2003 – May 2004 (significant at 5% level) and BE/ME sorted portfolios for the period of January 2009 – August 2010 (significant at 10% level). However, the significance of these coefficients is largely reduced if FF-3 factors are controlled for. The coefficient derived from the period between January 2003 and May 2004 becomes significant at the 5% level, and the coefficient derived from the period between January 2009 and Aug 2010 becomes insignificant. During the bear periods, when the sentiment index is tested alone, both the coefficients derived from the ME sorted portfolios and the BE/ME sorted portfolios are highly significant at the 1% level in the period of June 2004 –December 2005.

However, when FF-3 factors are controlled for, the sentiment index displays no explanatory power over the size premium. Furthermore, the sentiment index derived in Panel B cannot predict stock returns during the period between November 2007 and December 2008, possibly due to the interference of CCI.

Table VIII

Sub-Period Time Series Regressions

The sentiment index of Panel A is constructed by CEFD, TURN, NIPO and RIPO. Compared with Panel A, the sentiment index of Panel B further includes CCI. In Panel C, No. A/C is used to replace CCI. Superscripts a, b, and c denote the statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: CEFD, TURN, NIPO, and RIPO

Bull:		**$Sentiment_{t-1}$**			**Controlling for RM, SMB and HML**		
Time		**Coefficient**	**P-value**	**Adj-R^2**	**Coefficient**	**P-value**	**Adj-R^2**
Jun 99-Jun 01	*ME*	-0.11	0.31	0.05	-0.10	0.35	0.19
	BE/ME	0.04	0.74	0.00	-0.05	0.67	0.52
Jan 03-May 04	*ME*	-0.43[a]	0.00	0.08	-0.50[a]	0.00	0.74
	BE/ME	0.03	0.89	0.00	-0.13[b]	0.05	0.87
Jul 05-Oct07	*ME*	0.02	0.89	0.00	0.06	0.76	0.04
	BE/ME	0.05	0.67	0.01	0.01	0.91	0.28
Jan 09-Aug 10	*ME*	-0.04	0.52	0.02	-0.08	0.26	0.25
	BE/ME	-0.05	0.40	0.03	-0.05	0.40	0.11
Bear:							
Jan 98-May 99	*ME*	0.06	0.00	0.18	0.05	0.45	0.16
	BE/ME	-0.09[a]	0.68	0.00	-0.05[c]	0.08	0.39
Jul 01-Dec 02	*ME*	-0.63[a]	0.01	0.15	0.14	0.57	0.70
	BE/ME	-0.22	0.55	0.02	-0.05	0.78	0.78
Jun 04-Jun 05	*ME*	-0.24[c]	0.07	0.14	-0.10	0.53	0.45
	BE/ME	-0.23[a]	0.01	0.21	-0.10[b]	0.05	0.89
Nov 07-Dec 08	*ME*	-0.27	0.26	0.04	-0.59	0.12	0.19
	BE/ME	-0.15	0.22	0.03	-0.45[b]	0.02	0.58

Panel B: CEFD, TURN, NIPO, RIPO and CCI

Bull:		**$Sentiment_{t-1}$**			**Controlling for RM, SMB and HML**		
Time		**Coefficient**	**P-value**	**Adj-R^2**	**Coefficient**	**P-value**	**Adj-R^2**
Jun 99-Jun 01	*ME*	-0.09	0.31	0.05	-0.09	0.36	0.18
	BE/ME	0.03	0.84	0.00	-0.05	0.65	0.52
Jan 03-May 04	*ME*	-0.49[a]	0.00	0.03	-0.31[b]	0.03	0.70
	BE/ME	0.08	0.65	0.12	0.30	0.10	0.79

Jan 06-Oct 07	*ME*	0.06	0.54	0.00	0.01	0.12	0.87
	BE/ME	0.07	0.14	0.00	0.03	0.60	0.22
Jan 09-Aug 10	*ME*	-0.10	0.15	0.03	-0.08	0.14	0.94
	BE/ME	0.06[c]	0.07	0.17	0.30	0.45	0.79
Bear:							
Jul 01-Dec 02	*ME*	0.01	0.82	0.00	-0.26	0.35	0.72
	BE/ME	-0.22	0.60	0.02	-0.12	0.45	0.79
Jun 04-Dec 05	*ME*	-0.36[a]	0.00	0.18	-0.07	0.53	0.66
	BE/ME	-0.26[a]	0.00	0.22	-0.10[a]	0.00	0.91
Nov 07-Dec 08	*ME*	0.00	1.00	0.03	-0.11	0.52	0.09
	BE/ME	-0.22	0.33	0.05	-0.11	0.28	0.54

Panel C: CEFD, TURN, NIPO, RIPO,and NO. A/C

Bull:		**Sentimentt-1**			**Controlling for RM, SMB and HML**		
Time		**Coefficient**	**P-value**	**Adj-R2**	**Coefficient**	**P-value**	**Adj-R2**
Jan 03-May 04	*ME*	-0.01	0.94	0.00	-0.04	0.81	0.64
	BE/ME	0.09	0.24	0.01	0.10	0.30	0.77
Jan 06-Oct 07	*ME*	0.03	0.86	0.00	0.08	0.73	0.04
	BE/ME	0.04	0.76	0.00	0.01	0.96	0.28
Jan 09-Aug 10	*ME*	-0.03	0.61	0.01	-0.10	0.29	0.25
	BE/ME	-0.04	0.57	0.02	-0.04	0.59	0.09
Bear:							
Jun 04-Dec 05	*ME*	-0.35[a]	0.01	0.20	-0.07	0.59	0.67
	BE/ME	-0.29[a]	0.00	0.26	-0.11[a]	0.01	0.91
Nov 07-Dec 08	*ME*	0.00	1.00	0.00	-0.12	0.83	0.06
	BE/ME	-0.14	0.53	0.02	-0.27	0.37	0.44

In Panel C, the influence of the sentiment index is not significant in all bull periods. For bear periods, it is only significant from June 2004 – December 2005. And controlling for FF-3 factors may induce the explanatory power of the sentiment index on ME sorted portfolios to become insignificant.

In summary, based on these three panels, we can deduce that the sentiment index plays a minor role in the stock pricing mechanism of the Chinese markets during bull periods. According to the development history introduced by Liu (2008), each bull period in the Chinese markets follows major economy growth, policy changes, and development of the markets. Based on this, we can deduce that there are other variables rather than the sentiment index, such as growth of GDP, growth of industry and policy changes, which play a more dominant role on the growth of market performance. So in this case, the sentiment index may have little impact on asset returns.

In each panel, significant coefficients can be observed from June 2004 – December 2005 (bear period) in all three panels. The reason for this comes down to policy changes inducing market panic. On April 29th, 2005, the China Securities Regulatory Commission issued new regulations for reforming shareholder structures of listed companies, which induced large panic in the markets. It was recognised that this new regulation could significantly change the operating strategies and growth opportunities for a large proportion of listed companies. Following the announcement, there were increased attempts to delist in the markets. Later, on June 21st, the government announced that it would partly release currency control to allow the Chinese Yuan to fluctuate in an adequate range. This implied that currency risk would rise in the future, and further worsen the confidence and expectation of investors. Hence, as a response to these policy changes, investors were more likely to under-estimate the future of the markets, and in this case, sentiment factors may strongly influence asset returns.

5. Conclusion:

According to classical finance theory, investor sentiment plays no role in the cross-sectional asset pricing mechanism. Since the 1980s, the predictive power of sentiment factors has been proved provided the ability to arbitrage is relatively weaker than what is proposed in theory. This study intends to provide further contribution on studying the explanatory power of investor sentiment on the stock returns by employing data from the two emerging markets in China, as the majority of prior work is highly concentrated in developed markets.

The empirical findings of this study further contribute toward proving the significance of sentiment factors in the cross-sectional asset pricing process. The sentiment index is priced for the whole sample period for both ME sorted and BE/ME sorted portfolios and is negatively related to stock returns. Consistent with Baker and Wurgler (2006), this study shows that stocks with small ME are more sensitive to fluctuations in sentiment. If sentiment at the beginning of a period is low, the returns of large stocks tend to be relatively lower than that of small stocks. And if sentiment at the beginning of a period is high, the returns of large stocks tend to be relatively higher than that of small stocks. In regard to portfolios sorted by BE/ME ratio, this study provides conflicting outcomes from those of Baker and Wurgler (2006). In the Chinese markets, due to the specific features of individual investors, value stocks are relatively more likely to be influenced by the sentiment factor. Consequently, when sentiment at the beginning of a period is low, growth stocks tend to have relatively lower returns than value stocks. And when sentiment at the beginning of a period is high, growth stocks tend to have higher returns than value stocks.

Furthermore, this study suggests investor sentiment influences cross-sectional stock returns differently in bull and bear markets. The effect of sentiment is more influential in bear markets. As the impact of the sentiment factor is rarely significant since 2006, there is some evidence to show that investors accumulate knowledge, trading skills and experience across time and become more rational, reducing the influence of sentiment factors.

Compared with studies conducted in developed markets, this study covers a relatively short sample period. Due to the youth of the markets, quality statistical data on sentiment proxies, firm characteristics and stock returns is limited. It largely restricts the length of the entire sample and each sub-period, and may not ensure that the influence of the sentiment factor on these markets is fully reflected in stock prices.

Another major shortcoming of this study is the measurement of the sentiment factors. To capture the fluctuation of investor sentiment, this study employed six proxies as proposed by previous research to construct a single sentiment index. However, the results show that some of them may not be significantly related to the sentiment factor. How investor sentiment may be reflected in the Chinese stock markets, and which factors may efficiently capture this impact, still requires further investigation. Only adequate proxies may lead to accurate and reliable outcomes.

In summary, this study provides some evidence to prove the role of investor sentiment in the asset pricing model of the Chinese markets during the entire sample period. Investors may become more irrational in bear periods. Due to the learning effect, the impact of investor sentiment in the Chinese markets is largely reduced. This implies the efficiency of the Chinese markets has improved due to the evolution of the investors.

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