The momentum effect in the Chinese market and its relationship with the simultaneous and the lagged investor sentiment

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Abstract

Motivated by the lack of investigation on the behavioral interpretation on the momentum premium, this paper addresses this issue by focusing on the effect of investor sentiment on a sample of the comprehensive Chinese A-share index covering the period from 2006 to 2015. Expect for uncovering the momentum effect in the A-share market by calculating the momentum returns of ten zero-cost portfolios differed on the formation period, we compare the momentum returns under different sentiment states during the sample period. The difference is obvious that the momentum returns are more evident during the optimistic sentiment period where estimated investor sentiment is over zero. This paper also examines whether the investor sentiment explains the momentum returns and its predictive power on the subsequent momentum premiums. We find the contemporaneous linear relationship between investor sentiment and the momentum returns is less pronounced. Even the slopes of sentiment are positive, only three of them are significant. However, the investor sentiment exhibits strong predictability on future returns of momentum strategy in the short-run, suggesting it can be a contrarian predictor of expected returns of momentum in the short-run.

1. Introduction

Momentum effect, as a persistent anomaly in the equity market challenging the efficient market theory, attacks financial academics to explore its natures and causing factors. According to Jegadeesh and Titman (1993), who firstly explore this phenomenon in the US market, it refers to a tendency that stocks with high profits will continue to achieve the high returns in the following period while stocks with lousy performance persistently realize lower yields in the subsequent period. The momentum strategy is the way that investors utilized this anomaly to make profits. The significant abnormal profits of momentum are continuously uncovered in many equity markets by financial analysts (Drew and Veeraraghavan, 2001; Griffin, Ji, and Martin, 2003; Timmermann and Wermers, 2006; Fama and French, 2012).

However, even the existence of the momentum has been well-discussed through time (different periods) and space (different stock markets), there is still no consensus view on what drives the profitability of momentum strategy. There are mainly two directions the explanation, the traditional explanation, and the behavioral explanation. In the beginning, the researchers tied to explain the momentum based on the concept of the efficient market. Mainly, they assume the investors in the market are all rational. Under this circumstance, the excess returns are considered as the compensation of bearing the risk; namely the higher risk, the higher return. However, this phenomenon is hard to in line with the efficient-market hypothesis since the abnormal returns realized by momentum strategy cannot be described by whether the traditional Capital Asset Pricing Model or the augmented Fama-French three-factor model (Fama and French, 1993). After that, some scholars transferred their focus on employing momentum as a new parameter in the asset pricing model such as Carhart (1997)'s four-factor model, while others turned their direction on the behavioral financial area. Precisely, they attribute the presence of momentum effect to investors' cognitive biases.

One main aspect of this view is that the profitability is driven by the initial overreaction and initial under-reaction of irrational investors, evidenced by the results of Hirshleifer and Subrahmanyam (1998), and Barberis et al. (1998). The other cognitive biases such as disposition effect and anchoring behavior have also been investigated their internal relationship with the momentum returns (Grinblatt and Han, 2002; Liao, Chou, and Chiu, 2013). The behavioral models of explaining the momentum premium are variously based on the different views. There are still no consistent results about which factor can drive the premium within the different market and based on the different behavior model. It provides a gap of investigating the behavioral model on the less developed equity market such as the Chinese equity market.

Same with other equity markets, the Chinese stock market used to be under the strict supervision during the beginning stage of the Chinese market. The China Securities Regulation Committee (CSRC) banned the short sales in case of aggravating market volatility and market instability before 2010. With the rapid growth, the Chinese equity market is more efficient and stable. Even under the trouble of the global financial crisis in 2008, it quickly recovered and became active after this disaster. Also, the distinct features such as the retail-investor-dominated market attract the researchers to investigate the phenomenon of the Chinese equity market.

Investor sentiment, which is a typical behavior bias that is showing the systematic effect on the asset returns, attracts investors to investigate the relationship with the momentum phenomenon. The general literature on the investor sentiment is on the predictability on the future profits that can help investors to find the opportunity to arbitrage by exploring this bias. Its long-term constrain predictability has been proved by the empirical evidence on various equity market (Baker and Wurgler, 2006; Schmeling, 2009; Huang et al., 2015; Baker et al., 2012). Investigators also find its roles on the asset price in the Chinese stock market while the results are not consistent (Kling and Gao, 2008; Chi et al., 2012; Chen et al., 2014).

Since it is the continued concern on whether the investor sentiment affects the asset returns, this paper adds to the literature by further exploring this issue on the effect of sentiment on stock momentum returns. First, this study constructs the monthly market-specific Chinese investor sentiment index during the period of the year 2006 to 2015. Following Baker-Wurgler (2007) and Chen et al. (2014), the monthly investor sentiment index is constructed based on five proxies using the principal component analysis (PCA). Also, for the momentum mechanism used in the regression tests, the momentum portfolios are formed by means of Jegadeesh and Titman’s (1993). The momentum strategy is based on the monthly data and the monthly returns of the first month of holding horizon are acquired as the momentum mechanism. Different with the previous works, this paper not only analyses the momentum premiums in the Chinese A-share market but also shows the impact of investor sentiment by comparing the momentum returns in different sentiment periods, that is, the period of pessimism or optimism. Also, the regression tests including single- and multi-factor models are conducted to examine whether the investor sentiment can explain the premium of momentum. Moreover, the short-run predictive ability of sentiment on future momentum returns are also revealed by various predictive regression tests.

The remainder of the article is organised as follows. Section 2 introduces the current situation and the distinctive features of Chinese equity market and reviews the previous literature related to the topic. The third section describes the recourse of the data and the method to construct the investor sentiment index and momentum portfolios. Section 4 analysis the preliminary results of the momentum effect and the influence of investor sentiment in the Chinese market. Section 5 provides the regression results on the relationship between investor sentiment and the concurrent momentum returns as well as the momentum premiums in the subsequent period. The last part of paper concludes the main finding of this paper.

2. Literature review

2.1 Chinese equity market

The security market of China mainly refers to shares of companies listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). With the standardization of the securities market, the capitalization of these two exchanges has proliferated since the 1990s. At the end of 2015, the Shanghai Stock Exchange (SHSE) has become the fifth largest market in the world and second largest in Asian market while the Shenzhen Stock Exchange (SZSE) has become the eighth largest stock market in the world and 4th in Asia based on their market capitalization.

The booming development and distinctive features of the Chinese market attract academic attention across the globe. To delve into the Chinese equity market, the three unique characteristics that distinguish the Chinese market from others need to be mentioned in this paper. First, shares of companies listed on the Chinese stock exchanges are fully segmented into two classes, A-shares and B-shares. There are significant differences between A-shares and B-shares. The A-shares can only be quoted in local currency (Chinese yuan) and purchased by Chinese citizens before 2003, while the B-shares are available for both Chinese and foreign investors since 2001 and are using the external currency (US dollars in SHSE and Hong Kong dollars in SZSE) to quote. Besides, the Chinese stock market is under the heavy regulation. Although some restrictions, such as that foreign investors cannot access to the A-share market, have been lifted since 2003, local and international investors still hardly access the B-shares and A-shares due to the currency exchange and the tight supervision of the Qualified Foreign Institutional Investor (QFII) system. Since these two markets are relatively less open and independent between each other, the investigators usually examine on either A-shares or B-shares market. The Chinese security market also shows its power in terms of its incredible trading volume. The trading volume of A-shares is much higher than B-shares. The main reason for this situation is that the high proportion of the domestic individual investors leads to a significant amount of the short-term trading and extremely high liquidity in the Chinese A-shares market. Another feature in the Chinese market needs to be mentioned is the short-selling restriction. The Chinese market used to forbid the short-selling before 2010. The previous works have found that the short-selling activities play a significant role in efficient price discovery, increase of market liquidity and stabilization of the market. (Bris et al., 2007; Alexander and Peterson, 2008; Saffi and Sigurdsson, 2011; Boehmer and Wu, 2013). Since the allowing short selling and margin purchase in the Chinse market may influence the efficiency of market, the explanatory power of sentiment on the deviation of returns may be weaken by the shift in policy. Thus, this paper also conducts a robust check on the impact of releasing short-selling.

Since the A-shares market accounts for most of stocks in the market and B-shares are mainly traded among foreign institutional investors, this study focuses on exploring the anomalies of the Chinese A-shares and their potential relationship with investors' behavioral bias, especially that of retail investors.

2.2 Momentum effect

The momentum effect is a phenomenon in the equity market that the previous winners (stocks with high profits) will continue to achieve the high returns while the past losers (stocks with lousy performance) persistently realize lower yields in a subsequent period. This phenomenon was first found by Jegadeesh and Titman (1993) in the U.S. market. Jegadeesh and Titman (1993) also claim that investors have the arbitrage opportunity by holding the long position in well-performed stocks and selling the securities with low performance, which is the so-called momentum strategy. Since then, the literature continues to explore and investigate the momentum effect in different equity markets and finds persistent evidence on significant abnormal profits by applying the momentum strategy (see, e.g. Rouwenhorst, 1998; Drew and Veeraraghavan, 2001; Griffin, Ji, and Martin, 2003; Timmermann and Wermers, 2006; Fama and French, 2010; Fama and French, 2012).

The persistent evidence of momentum returns has proved its existence as an anomaly to the efficient market hypothesis. Therefore, the scholars turn to focus on the investigation of momentum as a driver for stock price such as the four-factor asset pricing model proposed by Carhart (1997). The recent focus of momentum literature is on the explanation of risk premium realized by the momentum phenomenon. The two aspects of researchers' opinions are the traditional explanation and the behavioral explanation.

2.2.1 Traditional explanation of the momentum effect

The traditional explanation of the momentum effect based on the rational sources mainly refer to the risk-based explanation. That is, the high risk realized high returns. However, as in Jegadeesh and Titman (1993), the traditional Capital Asset Pricing Model (CAPM) fails to explain the excess returns realized by the momentum portfolio (winners minus losers). After that, Fama and French (1993) propose a new three-factor model to replace the CAPM by adding two other systematic risk factors. Despite all that, in their later work, they verify that both three-factor model and CAPM cannot explain the momentum premiums, and point out that the current pricing model is insufficient because of the lack of new financial parameters (Fama and French, 1996).

The defect of the evidence on the risk-based drives of momentum effect brings the academics to explore other further economic variables that can bring about this phenomenon. For instance, Moskowitz and Grinblatt (1999) ascribe the momentum premiums to industry returns while Lee and Swaminathan (2002) examine the roles of volume in these excess returns. Besides, the effect of macroeconomic factors (Chordia and Shivakumar, 2002) and the influence of market states (Cooper et al., 2004) on momentum effect also have been considered. Still, none of them has succeeded in fully interpreting the profits from momentum strategy. The unsatisfactory of the previous efforts on the traditional explanation leads to another direction to explain this phenomenon, which refers to the inception based on the behavioral finance concept.

2.2.2 Behavioral explanation of the momentum effect

Different from the traditional finance literature, the behavioral finance theory is under the situation that not all the investors act rationally, and the information of the market might not process efficiency. In that case, their irrational decisions during information processing may provide the opportunity to arbitrage. This new concept leads researchers to focus on the role of investors' behavioral biases rather than the market factors in explaining the effect of momentum.

One of the main views of scholars is that momentum premiums are the results of initial overreaction and initial under-reaction. Investors tend to be overconfident in their decisions that their will arbitrage by their trading activities and trade more than average. In contrast, conservative investors commonly take fewer transactions and underreact to the market information. Besides, some people pay more attention to the most recent information of the stocks and take actions relying on that. However, the valuation of stocks' fundamental value should consider the relatively comprehensive evidence. The temporarily high or low performance would not last too long. The existence of overreaction and underreaction in the market has been found by Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999). Also, the prior literature has investigated the roles of the overreaction and underreaction of the market on the momentum and reversal anomalies (DeBondt and Thaler, 1985, 1987; Lakonishok, Shleifer, and Vishney, 1995; Barberis et al., 1998). Based on the cognitive psychology concept, Daniel, Hirshleifer, and Subrahmanyam (1998) suggest that overconfidence and self-attribution bias could be the drivers of the momentum phenomenon and the long-term reversal, respectively. However, Barberis et al. (1998) test another behavioral bias and find a distinct result that underreaction rather than overreaction is the cause of short-term momentum.

There are also other behavioral biases found related to the momentum. Disposition effect was firstly indicated by Shefrin and Statman (1985), and Grinblatt and Han (2002) propose a model relating it to momentum. The main logic behind this model is that there are both disposition investors and rational investors in the market. Disposition investors hurry to sell stocks with good performance in case that the stock prices will fall afterwards while they prefer to hold their under-performed stocks and wait the price raise back since they believe the bad performance is only in a short period. Their irrational behavior leads to the underreaction of the stock price. In other words, disposition investors undervalue the winner stocks and overvalue loser stocks. Once rational investors notice the potentials of the arbitrage opportunities, they will begin to buy the winner or short-sell the loser. Afterwards, these trading activities will raise the price of the winner stocks and lower the price of losing shares. Thus, the investors' disposition behavior induces the momentum effect. Grinblatt and Han (2002) also disaffirm the view that the long-term reversals are similar to momentum phenomena and argue that researchers should describe them in the distinct explanation models. However, the recent findings on the relation between disposition effect and momentum are not significant. Birru (2015) finds that the disposition effect has the impact but cannot explain the momentum in a single model. Besides, Kong, Bai and Wang (2015) test the Grinblatt and Han’s model in the Chinese market and find no relationship between the disposition effect and momentum, contradicting with the results in the U.S market (Grinblatt and Han, 2005).

The recent studies also pay attention to another cognitive bias, anchoring, and recognize it as a driver of momentum. During investment, anchoring in the equity market refers to that investors rely more on the irrelevant information, usually the initial price when they buy stocks, but not the fundamental value used to estimate the stock value. Under this circumstance, investors always hold investments for too long and look forward to that it will raise back its original price. Liao, Chou, & Chiu (2013) propose a model relating foreign institutional investors' momentum trading behavior to anchoring effect. The results indicate that anchoring effect is not associated with the momentum premium in the Taiwan stock market. However, Hao et al. (2016) also investigate the Taiwan equity market and find the opposite results with Liao et al. (2013).

The previous works on exploring models to explain the momentum effect are numerous. These studies have various views on the cause of momentum and the findings based on behavioral explanations play a dominant role in the recent literature. Besides, the lack of investigations on the less developed equity markets creates a gap in the literature of behavioral finance. Therefore, this study addresses the effort on testing the applicability of a behavioral model in the Chinese stock market. Also, the behavioral bias discussed in this research is the investor sentiment.

2.3 Investor sentiment

Investor sentiment refers to the investor's systematic bias toward future expectations, first proposed by Lee, Shleifer, and Thaler (1991). At first, it is a concept in the closed-end fund that the noise traders' prospect of the profit will influence the price of the fund. However, the recent studies prefer treating investor sentiment as a reflection of investors' investment willingness and market expectation. Moreover, how investor sentiment influences market fluctuation and expected returns remains attractive for the literature.

2.3.1 Investor sentiment & return predictability

The systematic effect of investor sentiment on market return is long-lasting interest since the behavioral finance theory is against the classical view on the market efficiency theory. Generally speaking, the bullish investor sentiment leads to the overdrive of the market price while the bearish sentiment leads to undervaluation of the stocks price. One of the views by De Long et al. (1990a) argue that this systematic deviation on returns provides the opportunity to arbitrage and their arbitrage activities could stop or even reverse the trend of mispricing, which leads to a negative impact of sentiment on the following returns. Meanwhile, the "price pressure" assumption proposed by Warther (1995) is that the deviations from fundamental values of stocks are just a result of price pressure associated with high-demand sentiment , following a price reversal in the subsequent period. Previous work provides strong supportive evidence on the negative relationship between investor sentiment and excess returns. Fisher and Statman (2000) state that the investor sentiment is negatively related to future returns. Baker and Stein (2004) employ market liquidity as the proxy of sentiment index and find liquidity can be used as a predictor of future stock returns. Brown and Cliff (2004) indicate the magnitude of sentiment has an impact on the stock price and returns and Brown and Cliff (2005) confirm that this effect of sentiment is enduring for the market. Moreover, Baker and Wurgler (2006, 2007) also test the return predictability of investor sentiment in the U.S equity market by using cross-sectional data. Also, they employ a composite multi-factor model for evaluating investor sentiment. Besides, the literature also finds the consistent evidence that the sentiment can be a long-term predictor in other developed markets (Schmeling, 2009; Huang et al., 2015; Baker et al., 2012).

2.3.2. Investor sentiment in China

There are also some studies that have investigated the role of investor sentiment in Chinese stock market. Kling and Gao (2008) focus on the institutional investor sentiment and find it cannot predict the future returns based on the daily survey data. In contrast, Chi et al. (2012) find the positive relation between investor sentiment and stock returns during the period from 2004 to 2008. The opposite results in the Chinese market may be attributed to the different proxy for investor sentiment. Fong and Toh (2014) relate sentiment to the max effect and find the impact of individual and institutional investor sentiment on the market price. Chen et al. (2014) suggest a composite market-wide sentiment index and provide empirical evidence on its predictability on the expected market.

2.3.3. Investor sentiment & momentum

Relating investor sentiment with momentum profits is a relatively new direction in the study of behavioral finance s. However, there are only a few papers on this topic, and it still needs to be further explored. Li and Yeh (2011) investigate the impact of individual stock sentiment on stocks' momentum profits and find the high sentiment contributes to the momentum profits. Antoniou et al. (2013) provide the empirical results that the optimistic sentiment drives the momentum profits. Hao et al. (2016) directly divide investor sentiment into optimistic periods and pessimistic periods and find the momentum portfolios earn positive returns during optimistic periods and negative returns during pessimistic periods in the Real Estate Investment Trust (REIT) market. Although these papers have made some efforts to explain momentum in light of investment sentiment, there is still a gap in the literature regarding the linear relationship between the market-wide sentiment and the momentum premiums. Specifically, this paper extends the literature by testing the explanatory power of investor sentiment on the profitability of the different momentum strategies. According to the previous works, we examine whether these momentum profits can be explained by the investors' behavioral bias, that is, investor sentiment. This article further explores the role of sentiment as a predictor of the future momentum premiums in the short-run.

2.3.4 Investor sentiment proxies

A number of studies have investigated the investor sentiment and employed the different proxies and various methodologies to construct the sentiment index. In the early stage, the literature is more likely to employ a single factor as the proxy of sentiment. These proxies are mainly divided into two parts: subjective indicators and objective indicators. For instance, the survey data used by Brown and Cliff (2004) and consumer confidence used by Schmeling (2009) are typical subjective indicators of investor sentiment. These data usually are directly collected by questionnaires which ask questions of the investor's views of the market. Another kind of factors is objective indicators, mainly referring to market-based variables which are the trading information availingon the equity market. Baker and Stein (2004) employ the trading volume, and Ljungqvist et al.(2006) use the amount of initial public offerings (IPOs) and first-day returns on IPOs as the proxies of investor sentiment, respectively. These subjective and objective indicators have both advantages and disadvantages. Although subjective indicators can directly show the feelings of investors, their validity cannot be guaranteed. On the other hand, the objective indicators can measure investors' trading behavior under a more objective circumstance; however, how they are related to investor sentiment is still not sure yet (Baker and Wurgler, 2007). Given so, the literature turns to combining various variables in a multi-factor model to measure the investor sentiment. Baker and Wurgler (2006) apply six objective market-based indicators to construct an investor sentiment composite index. Chen et al. (2014) use the principal component approach to construct sentiment index for the Chinese market. However, these papers only includ market-based sentiment proxies in their index.

Based on the previous works on investor sentiment, this paper constructs the specific index for the Chinese market, considering the principal component approach used by Baker and Wurgler (2006) and Chen et al. (2014). Using a model including both subjective and objective indicators of investor sentiment can combine the advantages of these two indicators. Hence, the accuracy of the sentiment measurement can be increased. This study carefully selects six proxies to construct market-wide investor sentiment for the Chinese equity market based on the avaiable variables. The six sentiment proxies employed in the model include three objective indicators (market turnover, market-wide PE ratio, and closed-end fund discount) and two subjective indicators (number of new opened individual investor accounts in Shanghai stock exchangeand investor confidence index).

3. Data and methodology

3.1 Sample period and main variables

The sample for this study is justified on the following points: the target market, sample period, sample size, the data frequency of variables and sample source.

Since the A-shares and B-shares markets employ two different financial reporting formats and trading volume of A-shares market is far more than that of B-shares in the Chinese equity market, this paper only investigates the investors' behavioral bias and the stock behavior of the integrated Chinese A-shares market. With the rapid growth of the Chinese market, the policy and regulation of this emerging market also have changed. For instance, the A-shares market lifted the restrictions for qualified institutional and foreign investors in 2003 and allowed the short-selling activities after 2010. Since verifying the role of the shorting-selling restriction is one of the primary purposes of the study, the sample extends the examining period to be five years before and after allowing the short-selling. That is, the sample period is from January of 2006 to December of 2015. Also, to minimize errors and biases in the regression analysis, we maximize the sample size to achieve the desired statistical level. Then, this study employs a dataset that is composed of the whole A-shares index including all tradeable A-shares stocks listed in the Shanghai Stock Exchange and Shenzhen Stock Exchange during the same period. Notably, this sample excludes the financial firms, the firms marked as ST (special treatment) stock and *ST (risk admonition) stock and the companies with missing data of variable indicators. The market and financing information on the selected firms in the integrated Chinese A-shares index is employed to construct variables. Specifically, the monthly investor sentiment index is constructed for the Chinese market since the proxies of sentiment are mainly in monthly frequency. To test the liner relationship with the investor sentiment, the monthly data are employed to construct the momentum portfolio and caculate the momentum premiums. These data are collected from CSMAR Database and RESSET Database, which are the two top databases providing both financial and marketing data of Chinese capital market. They are the primary resources for obtaining the specific market-level and firm-level information of the stocks.

3.2 The investor sentiment index

This study carefully combines the method used in Baker-Wurgler (2007) and Chen et al. (2014) to construct the investor sentiment index. The first step is to justify the typical proxies of sentiment and identify the reliable proxies used in this study. In the previous work on investor sentiment, the proxies that literature uses to conduct calculation are different. Based on data availability and market characteristics of the Chinese security market, three objective indicators including Market Turnover, Market-wide PE ratio, and closed-end fund discount and two subjective indicators including Number of newly opened individual investor accounts in Shanghai stock exchange and consumer confidence index are employed to form the market-wide sentiment index. Also, four economic variables are used as the control variables to eliminate the "rational effect" by orthogonalization procedure. The calculation process of each variable and the detail procedure to construct the sentiment index are discussed below.

3.2.1 Proxies of sentiment index

Market Turnover (MT) is one of the principal objective variables that have been verified by Baker and Stein (2004) to reflect the market-wide sentiment, commonly referred to as a measurement of the market liquidity. Specifically, it is the frequency of buying and selling shores, reflecting investors' demand to speculate to some extent. To eliminate the impact of trading days on the market turnover, the formula of the value-weighted monthly Market Turnover applied in this paper is:

$$Turnovert_t = \frac{Monthly\ market\ turnover}{The\ average\ market\ capitalization\ of\ the\ recent\ two\ months} * \frac{The\ average\ number\ of\ recent\ two\ months'\ trading\ days}{The\ total\ number\ of\ the\ trading\ days\ in\ each\ month}$$

The monthly data used to calculate the Market turnover is obtained from the CSMAR Database.

Market-wide PE ratio (PE) is namely the value-weighted price-earnings ratio of the market. Han and Li (2017) use PE ratio as a proxy for sentiment, which is used to estimate the increased money flowing into the market. Han and Li (2017) employ this proxy for the Chinese market since the historical data shows a consistent relationship between the high PE ratio and the price bubbles. This paper applies the market-wide PE ratio of A-shares including both Shanghai and Shenzhen exchange. The monthly PE ratio is directly collected from the CSMAR Database.

Closed-end fund discount (DCEF) is a widely-used proxy for investor sentiment (Baker and Wurgler, 2006 & 2007). Individually, the trading price of the closed-end fund on the exchange depends on supply and demand of investors, which deviates from its net asset value. This difference with its net asset value realized a premium of a discount, which is called the closed-end fund discount. Previous studies also argue that this discount would increase when the investors are pessimistic about the future of the stock market (Lee, Shleifer, and Thaler, 1991; Neal and Wheatley, 1998). Thus, this study utilizes the traditional monthly closed-end fund discount acquired from CSMAR.

The number of newly opened investor accounts (NA) is one of the two subjective indicators for sentiment chosen for this paper. Chen et al. (2014) apply it to replacing the equity share in total new issues and shows that it is an essential indicator for investor sentiment in the Chinese market. In China, the retail investors (irrational investors) are still the dominant participants in the market. (Han and Li, 2017) The number of new investor accounts reflects the enthusiasm of the over-the-counter investors to participate in the market transactions and thus this variable represents the demand for more stocks. Therefore, this paper selects the number of newly opened individual investor accounts in the Shanghai stock exchange as an alternative indicator for investor sentiment. Also, the monthly data for this variable obtained from CSMAR is denominated in ten thousand.

The last indicator of sentiment adopted in this paper is the consumer confidence (CC). Theoretically, the investor confidence index is better than the consumer confidence index on reflecting investors' changes in emotion. However, some of the data on the investor confidence is missing while the literature has found that consumer confidence can better measure the changes in investor sentiment (Schmeling, 2009). Thus, this study employs the investor confidence as another subjective indicator of sentiment considering the availability of data. The monthly consumer confidence index can be directly collected from CSMAR database.

One critical issue needing to be noticed during data processing is that the time trend might have impacts on the individual proxies of sentiment (Baker and Wurgler 2007). To address this issue, which is so-called the deterministic trend, Baker and Wurgler (2007) and Chen et al. (2014) recommend a detrended procedure that divides each variable by their average value for prior five months. This paper also follows the method to eliminate the deterministic trend. After the detrended procedure, the five processed variables are denoted as MT_t, PE_t, $CEFD_t$, NA_t, and CC_t, respectively[1].

3.2.2 Orthogonalization procedure for proxies of sentiment index

Furthermore, the overall condition of the market also has an impact on those proxies of sentiment (Verma and Soydemir, 2009). It is not just the change of investor sentiment, but also the evolution in macroeconomic that leads to the variation of variables. Therefore, Baker and Wurgler (2006) and Verma and Soydemir (2009) employ the orthogonalization procedure to mitigate the influence of the economic condition. This study follows their method to include a series of economic variables, which are the growth of industrial production, the growth of money supply, short-term interest rates, and foreign exchange rates. During the calculation, these variables are defined as GIP_t, GM_t, IR_t, and ER_t, where *t* represents the time. Specifically, this paper uses the added value growth rate of industries above a designated scale in China to represent the change of industrial production. It utilizes the weighted average one-month Shanghai Interbank Offered Rate serving as the variable of short-term interest rates. We also employ the ratio of Chinese Yuan (CNY) to the US Dollar (USD) as the exchange rate used in the study. Besides, the data of the growth rate of the money supply directly collected from the database. Additionally, the data of all of those

[1] They are Market Turnover, Market-wide PE ratio, Closed-End Fund Discount, Number of newly opened individual investor accounts, Consumer Confidence, respectively.

four variables is collected at the montly interval. The detailed process of orthogonalization is shown as follows. This procedure is mainly using four macroeconomic variables as the independent variables (x). Each proxy of sentiment as the dependent variables (y) is used to conduct the orthogonal regression. Then the five corresponding residuals of each regression for each proxy after the orthogonalization procedure will be employed as the final variables to estimate investor sentiment. After the process of orthogonalization, the five variables will be represented as MT_t^ε, PE_t^ε, $CEFD_t^\varepsilon$, NA_t^ε, and CC_t^ε, where ε represents the residual of orthogonal regression.

Table 1 Summary statistics of investor sentiment proxies: 2006-01 to 2015-12

Descriptive statistics	MT_t^ε	PE_t^ε	$CEFD_t^\varepsilon$	NA_t^ε	CC_t^ε
Mean	0.00	0.00	0.00	0.00	0.00
Median	-0.06	0.01	0.00	-0.12	0.00
St. Dev	0.34	0.15	0.19	0.77	0.03
Variance	0.12	0.02	0.03	0.60	0.00
Minimum	-0.67	-0.36	-0.55	-1.44	-0.07
Maximum	1.17	0.45	0.74	3.44	0.11
Obs.	120	120	120	120	120

Correlation coefficients	MT_t^ε	PE_t^ε	$CEFD_t^\varepsilon$	NA_t^ε	CC_t^ε
MT_t^ε	1	0.47	0.24	0.63	0.06
PE_t^ε	0.47	1	-0.02	0.55	0.13
$CEFD_t^\varepsilon$	0.24	-0.02	1	0.00	-0.04
NA_t^ε	0.63	0.55	0.00	1	0.07
CC_t^ε	0.06	0.13	-0.04	0.07	1

Table 1 illustrates the descriptive statistics and correlation coefficients of investor sentiment proxies. The arithmetic means of these variables are all equal to zero after the orthogonalization procedure. The pairwise correlation is relatively low among $CEFD_t^\varepsilon$ and CC_t^ε with other proxies suggesting these two variables may be relativly weak on explaining the sentiment.

3.2.3 Formation of Sentiment Index

After the five components (the residuals of five sentiment indicators) are obtained, we formulate the sentiment index. The principal component analysis (PCA) is used. This measurement of investor sentiment has been used by Baker and Wurgler (2007)and Chen et al. (2014) to capture the variation of the time-series investor sentiment. In specific, the first step of PAC is to standardize the five proxies of sentiment and acquire the eigenvalue and eigenvector of their covariance matrix from the PCA eigendecomposition. The next is to obtain the eigenvectors of the component with the largest eigenvalue. The last step is using these eigenvectors as the corresponding weight on each sentiment proxy to formate a sentiment model. This liner model with the uncorrelated variables can explain the largest proportion of the time-series variance of the market-based investor sentiment index of the Chinese market.

The formulated sentiment index is showed as below:

$$IS_t^{PAC} = 0.58MT_t^{\varepsilon} + 0.54PE_t^{\varepsilon} + 0.11CEFD_t^{\varepsilon} + 0.59NA_t^{\varepsilon} + 0.12CC_t^{\varepsilon} \quad (1)$$

where IS_t^{PAC} is the market-wide investor sentiment index at time *t*. Accordingly, all the coefficients of the five indicators are positive, proving that they all have positive impacts on the market sentiment. The first component, which is the market turnover, comprises the 43% of the variance of the sample. The market turnover, PE ratio and the number of new accounts show more weight on capturing the variation of sentiment by higher coefficients.

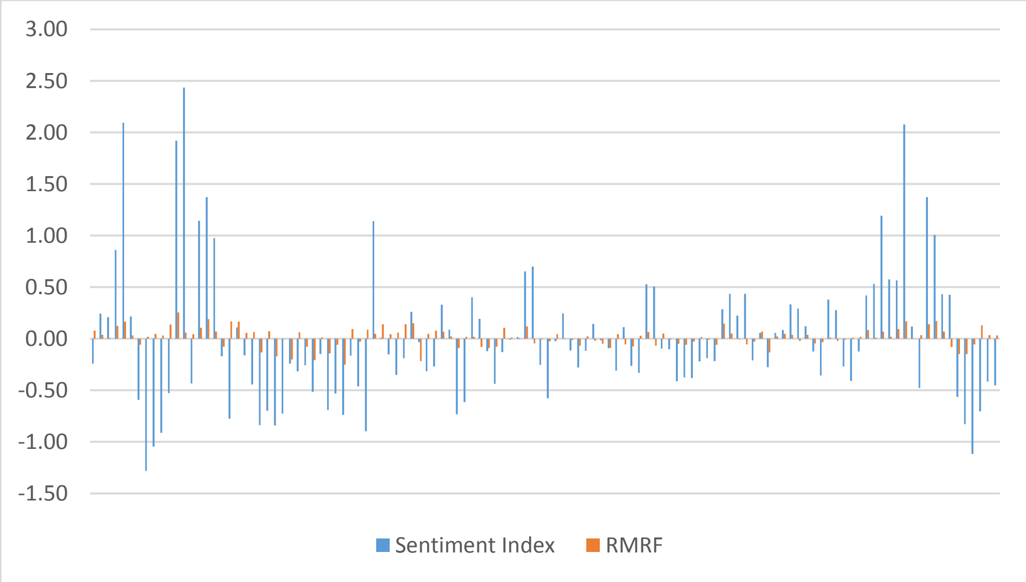
4.2.4 Investor Sentiment Index and Market Excess Returns

Table 2 presents the descriptive staistics of investor sentiment index and market excess returns while Figure 1 shows the variation of investor sentiment index and the risk premium which is the difference between market return and risk-free rate during sample period from January of 2006 to December of 2015. the three-month interest rate published by China People Bank is employed as the risk-free rate in this paper. The figure 1 illstrate the comovement of these two variables. The blue bar denotes the market-wide investor sentiment index calculated based on the principal component analysis while the orange bar describes the excess return of the market portfolio of A-shares index subtracting the risk-free rate. Both variables are monthly time series. Accordingly, the market-wide sentiment index in the Chinese market represents a pessimistic trend since observed value of the investor sentiment is mostly under 0. Meanwhile, the corresponding market risk premiums are relatively low and even under 0 when the sentiment is pessimistic and vice versa, showing a strong correlation between market premium and investor sentiment. Also, the fluctuation of sentiment index is basically in line with several major events in the Chinese stock market. When the Chinese market suffered the stock bubble in 2007, the sentiment index displayed the significant positive value. After that, the pessimistic tendency was evident during the period of the 2008 financial crisis. The value of investor sentiment was still relatively low during the subperiod of the crisis. Even there were some rises after the crisis from 2009, the increased magnitude was not large and the value of investor sentiment was back to negative very quickly. Until July of 2014, the investor sentiment consistently exhibited the positive value to the peak in December of 2014. It was consistent with the bullish market of China in 2014 which showed significant 53% and 34% of increases in the SSE Composite Index and the SZSE Component Index, respectively. And the trough from July of 2015 was concurrent with the market crash in 2015.

Table 2 Descriptive statistics of Investor sentiment and market excess returns

	Mean	Median	St. Dev	Kurtosis	Skewness	Minimum	Maximum	Obs.
$\mathbf{IS_t^{PAC}}$	0.00	-0.12	0.65	2.49	1.27	-1.28	2.44	120
RMRF	1.41%	2.08%	0.09	0.50	-0.31	-25.04%	25.55%	120

Figure 1 Comovement between Sentiment index and risk premium: 2006-01 to 2015-12



3.3 Construction of Momentum Portfolios

This paper constructs momentum portfolios following the way that Jegadeesh and Titman's (1993) use to uncover the momentum effect. The momentum strategy is namely buying the stocks with higher returns in the prior period (winners) and taking a short position on the shares with poor performance (losers). The profits realized by the zero-cost momentum portfolios constructed based on momentum strategy represents momentum premium. In particular, if there is an arbitrage opportunity by buying winners and shorting losers, then there is a momentum effect in the market. In other words, the significant positive returns realized by the zero-cost momentum portfolios can prove extensive of momentum. Also, this paper will test whether these momentum premium driven by the simultaneous investor sentiment and the predictive power of sentiment on the future returns of momentum stratetegy.

Here is the specific process of forming the zero-cost portfolios. The first step is ranking the stocks in the A-shares index based on the cumulative returns in the previous 3 to 12 months in each month *t*. The stocks are listed from high to low. The top ten percent equities are defined as the winner stocks while the bottom ten percent shares are specified as the loser stocks. The next step is to calculate the weighted average returns of the winner and loser stocks in each month *t*. Since the zero-cost momentum strategy is buying winner stocks and selling loser stocks, the excess return of the zero-cost portfolio in each month is that the average return of winner stocks subtract the average return of loser stocks, denoted as MOM_t. The ten portfolios construsted based on different formation period (3 to 12 months) are donated as $MOM3_t$, $MOM4_t$...... $MOM12_t$, respectively. In addition, the *t*-test statistic is applied to check the significance of momentum premium. The critical values for the samples of 120 observation are 1.289 at the 10 percent significance level, 1.658 at the 5 percent significance level, and 2.358 at the 1 percent significance level, respectively.

3.4 Control variables

While testing the relations between momentum returns and investor sentiment, the impacts of the macroeconomic factors may lead to the biased results. Consider the method of Han and Li (2017), this paper includes three control variables, the growth of industrial production (GIP_t), the growth of money supply (GM_t) and the market-wide PE ratio (PE_t) in the regression model. For the lack of data on the business cycle indicator, the growth of money supply is added to replace it.

4. Preliminary analysis

First, we show the preliminary analysis of the momentum effect in the Chinese A-shares index and the average returns of momentum portfolios under different investor sentiment. This test provides the overall understanding of the momentum effect in the Chinese market as well as the influence of investor sentiment.

4.1 Momentum effect

Table 3 displays the summary statistics of the monthly average excess returns of the ten zero-cost momentum portfolios formed in different formation period from 3 to 12 months over the whole sample. Among the ten momentum portfolios, most of them generate the positive returns except for the portfolios with three- and four-month formation period. Besides, the momentum premium is more outstanding in the momentum portfolios with longer formation periods. In specific, the zero-cost portfolio with ten-month formation period realizes the largest average return of 1.74% which is significant at 5% level. The average momentum gain of the portfolio formed on previous seven-month returns is 1.47% with a 1.33

t-value, significant at 10% level. Also, the average excess return generated by the portfolio with one-year formation period is 1.31% with a 1.42 t-value, significant at the 10% level. In sum, the momentum premium of portfolios with long formation period is relatively substantial.

Table 3 Monthly average returns of zero-cost momentum portfolios

	MOM3	MOM4	MOM5	MOM6	MOM7	MOM8	MOM9	MOM10	MOM11	MOM12
Mean	-0.80%	-0.05%	0.67%	0.77%	1.47%	0.62%	0.77%	1.74%	0.14%	1.31%
t-statistic	-0.70	-0.07	0.65	0.80	1.33*	0.58	0.71	1.70**	0.14	1.42*
Median	-1.44%	-0.13%	-0.23%	0.11%	-0.01%	0.14%	0.25%	0.08%	-0.11%	-0.07%
St. Dev	12.49%	8.43%	11.36%	10.61%	12.07%	11.78%	11.86%	11.19%	10.95%	10.06%
Minimum	-42.34%	-45.90%	-51.43%	-37.48%	-25.05%	-72.54%	-67.16%	-19.83%	-74.22%	-19.64%
maximum	89.12%	41.35%	84.17%	84.30%	86.77%	83.59%	90.98%	86.64%	74.83%	76.34%

Note: *, 10 per cent significant level; **, 5 per cent significant level; ***, 1 per cent significant level. The arithmetic mean, t-statistic, median, standard deviation, minimum, and maximum is reported.

4.2 Momentum effect under different sentiment period

This paper also sheds light on the influence of the investor sentiment on the momentum returns by conducting a comparison analysis about the momentum profits on different sentiment state. In specific, based on the different conditions of investor sentiment, this paper classifies each sentiment period in the sample as pessimistic or optimistic. Mainly, the pessimistic period is the time when the value of sentiment index estimated by PAC is less than zero (IS_t^{PAC} < 0) while the optimistic period is the one when the value of sentiment index calculated by PAC is greater than 0 (IS_t^{PAC}> 0). The next step is to identify whether each month t when the momentum portfolios can be pessimistic or optimistic. Then the monthly average returns of each momentum portfolio during the period under pessimistic and optimistic sentiment states are calculated, respectively. Accordingly, from January of 2006 to December of 2015, there are totally 120 months in the sample period, within which 71 months are classified as the pessimistic period and 49 months are defined as the optimistic period. This consists with the results observed in Figure 1 that investors are more likely to hold a pessimistic view of the equity market during the sample period.

Table 4 Monthly average returns of zero-cost momentum portfolios under different investor sentiment periods (Pessimistic vs. Optimistic)

Pessimistic	MOM3	MOM4	MOM5	MOM6	MOM7	MOM8	MOM9	MOM10	MOM11	MOM12
Mean	-1.43%	-0.39%	0.80%	0.75%	2.03%	-0.56%	-0.28%	1.86%	-0.25%	1.87%
t-statistic	-0.86	-0.36	0.51	0.52	1.19	-0.33	-0.17	1.14	-0.15	1.28
Median	-1.59%	-0.13%	-0.08%	0.12%	-0.05%	-0.15%	-0.15%	-0.14%	-0.21%	-0.13%
St. Dev	14.10%	9.14%	13.17%	12.19%	14.39%	14.20%	14.42%	13.72%	13.64%	12.29%
Minimum	-42.34%	-45.90%	-51.43%	-37.48%	-15.45%	-72.54%	-67.16%	-19.83%	-74.22%	-19.64%
maximum	89.12%	41.35%	84.17%	84.30%	86.77%	83.59%	90.98%	86.64%	74.83%	76.34%

Optimistic	MOM3	MOM4	MOM5	MOM6	MOM7	MOM8	MOM9	MOM10	MOM11	MOM12
Mean	0.12%	0.43%	0.49%	0.80%	0.65%	2.34%	2.30%	1.56%	0.70%	0.49%
t-statistic	0.09	0.41	0.42	0.71	0.60	2.45***	2.51***	1.83*	0.97	0.63
Median	-0.67%	-0.20%	-0.48%	0.09%	0.11%	0.88%	0.94%	0.84%	0.05%	0.16%
St. Dev	9.76%	7.36%	8.18%	7.90%	7.60%	6.69%	6.41%	5.97%	5.04%	5.41%
Minimum	-19.13%	-12.53%	-11.68%	-25.76%	-25.05%	-8.01%	-7.94%	-7.51%	-7.06%	-14.10%
maximum	24.72%	19.25%	22.73%	18.82%	19.86%	21.47%	21.42%	21.69%	13.88%	11.92%

Note: *, 10 per cent significant level; **, 5 per cent significant level; ***, 1 per cent significant level.
The arithmetic mean, t-statistic, median, standard deviation, minimum, and maximum is reported. The upper part of table shows the monthly average returns of zero-cost momentum portfolios in the period that the value of investor sentiment index is under zero while the lower part of table shows the monthly average returns of zero-cost momentum portfolios in the period that the value of investor sentiment index is greater than zero.

Table 4 illustrates the difference in momentum premiums on the pessimistic and optimistic periods, respectively. Since the momentum strategies employed in this paper are restricted to the one-month holding period, the focus is on the impact of the simultaneous investor sentiment on the profits. Basically, the average returns among trading strategies with the longer construction period are relatively higher in both pessimistic and optimistic states. It is consistent with the momentum phenomenon observed in the integrated A-shares market.

According to the empirical results, the difference in the performance of momentum strategy is evident in different investor sentiment states. In specific, the momentum effect is more significant under a state of positive sentiment. During the pessimistic sentiment period, half of the momentum portfolios generate the negative returns. Only does the momentum portfolio formed based on prior one-year performance realize significant positive returns at the 10% level which is 1.87%. However, the average returns of ten portfolios are all positive and more significant during the optimistic period. Almost every momentum strategy has increased in terms of the average gains compared with the state of the negative sentiment. For instance, the profit of the portfolio denoted as MOM8 is -0.56% during the pessimistic period and increases to 2.34% which is the highest among all portfolios and significant at the 1%level during the optimistic period. Besides, the spreads of the portfolio denoted as MOM9 is also significant during the optimistic period with 2.30% average return, which is much higher than 0.28% average return of the pessimistic state. These results are consistent with Antoniou et al. (2013) that investor's optimistic sentiment is the primary factor that drives the momentum effect. When investors have the optimistic view toward the market, they might be active in trading and the stock price is thus raised, especially for the well-performance stocks. Meanwhile, the price of the loser stocks will continue to go down since the investors receive and react slowly with the negative information when they are in an optimistic mood. Thus, there are a spread between buying winner and shorting loser with the investors in the bullish sentiment. Meanwhile, in the periods of pessimism, investors are less active and the magnitude of the increase of winner and the decrease of loser is less impact on the investor’s pessimistic mood. Overall, the empirical results show that the momentum gain is sensitive to the investor sentiment measured in this paper.

5. Regression test

In this section, this paper analyses the linear relationship between sentiment and momentum returns as well as the predictability of investor sentiment on the subsequent momentum premiums.

5.1 Summary statistic of explanatory factor and control variables

Table 5 provides the descriptive statistics and correlation of the explanatory factor investor sentiment ($\mathrm{IS}_t^{\mathrm{PAC}}$) and three control variables, the growth of industrial production (GIP_t), the growth of money supply (GM_t) and the market-wide PE ratio (PE_t) that are employed in the regression model. These three variables serve as the macro environmental variables to capture the variation of the macro-economy. The panel A states the descriptive statistics while the cross-correlation coefficients among explanatory variables are reported in panel B. The monthly data of the variables contains 120 observations during the sample period from 2006-01 to 2015-12.

The investor sentiment index is standardized with mean zero during the calculation in the previous part. The value of other three economic variables is all presented in percentage. The standard deviation of the investor sentiment is 0.65 while the volatility of three macro variables is much higher, which are 4.17, 1.11 and 8.90, respectively. The correlation coefficients between the sentiment index and the control variables are all relatively low. Neither the growth in production nor the growth in money supply is correlated with the investor sentiment. The market-wide PE ratio has a correlation coefficient of 0.16 with the sentiment index since it is one of the proxies of investor sentiment. Among the three macro variables, the maximum of the correlation is 0.35 which is between growth in production and the market-wide PE ratio. However, the correlation coefficient between the increase in production and the growth in money supply is zero. This situation might be due to the different focuses of two growth rates. In total, the relatively low correlation coefficients among the variables ensure the independence of each variable.

Table 5 Summary statistics of independent variables in the regression model

Panel A	$\mathbf{IS_t^{PAC}}$	$\mathbf{GIP_t}$ (%)	$\mathbf{GM_t}$ (%)	$\mathbf{PE_t}$ (%)
Mean	0.00	11.90	1.30	29.75
Median	-0.12	11.65	1.18	27.41
St. Dev	0.65	4.17	1.11	8.90
Variance	0.43	17.42	1.22	79.18
Minimum	-1.28	4.00	-1.27	17.77
Maximum	2.44	20.10	4.72	56.46
Obs.	120	120	120	120

Panel B	$\mathbf{IS_t^{PAC}}$	$\mathbf{GIP_t}$ (%)	$\mathbf{GM_t}$ (%)	$\mathbf{PE_t}$ (%)
$\mathbf{IS_t^{PAC}}$	1	0.00	0.00	0.16
$\mathbf{GIP_t}$ (%)	0.00	1	0.00	0.35
$\mathbf{GM_t}$ (%)	0.00	0.00	1	0.10
$\mathbf{PE_t}$ (%)	0.16	0.35	0.10	1

Note: The arithmetic mean, median, standard deviation, minimum, maximum and sample size are reported in panel A while the correlation metric between explanatory variables is posted in panel B.

5.2 The linear relationship between sentiment and momentum returns

The Ordinary Least Squares regression (OLS) is utilized in this paper to examine whether the investor sentiment is the driver of momentum effect.

5.2.1 Single factor model

The single factor model is the primary regression model used to test the relationship between the investor sentiment and momentum premiums. For the robustness of the results, the relationship between sentiment and market returns is also examined in this section for comparison. The single factor models applied are showed below:

$$RM_t = \alpha + \beta IS_t^{PAC} + \mu_t \tag{2}$$

$$MOM_t = \alpha + \beta IS_t^{PAC} + \mu_t \tag{3}$$

where RM_t is the monthly market excess returns (monthly returns of market portfolio subtracting the risk-free rate) at the time *t*, IS_t^{PAC} is the simultaneous sentiment index, MOM_t is the monthly average returns of the ten momentum strategies at time *t*. The equation (3) replaces the dependent variable of RM_t with MOM_t. The slope coefficient (Beta) of the investor sentiment examines whether investor sentiment is the driver of the market return and momentum returns by testing the null hypothesis (H_0:β = 0) that investor sentiment has no relationship with the variation of these returns.

5.2.2 Multiple-factor model by Adding control variables

It is notable that the market state or the variation of the economy can drive the fundamental value of the equity. To weaken the influence of these factors, this paper also introduces several macroeconomic variables as the control variable in the regression model. These are the growth of industrial production ($\mathrm{GIP_t}$), the growth of money supply ($\mathrm{GM_t}$) and the market-wide PE ratio ($\mathrm{PE_t}$). After that, whether the slop of sentiment is still consistent after adding the macro variables is examined next. The multiple-factor models applied are showed below:

$$RM_t = \alpha + \beta IS_t^{PAC} + \varphi C_t + \sigma_t \quad (4)$$

$$MOM_t = \alpha + \beta IS_t^{PAC} + \varphi C_t + \sigma_t \quad (5)$$

where C_t is the vector of the all three control variables. The slope coefficient (Beta) of the investor sentiment in the multiple-factor models is still the focus.

Table 6 Regression results of single factor and multifactor models using different momentum strategies

Panel A

Single	RMRF	MOM3	MOM4	MOM5	MOM6	MOM7	MOM8	MOM9	MOM10	MOM11	MOM12
Beta(IS_t^{PAC})	0.0635	0.0228	0.0164	0.0104	0.0118	(0.0006)	0.0270	0.0260	0.0063	0.0113	0.0003
t-stat	5.59***	1.30*	1.39*	0.65	0.79	(0.03)	1.64*	1.57*	0.40	0.73	0.02
p-value	0.0000	0.1945	0.1661	0.5180	0.4317	0.9729	0.1033	0.1189	0.6904	0.4641	0.9820
R^2	20.96%	1.42%	1.62%	0.36%	0.52%	0.00%	2.23%	2.05%	0.14%	0.46%	0.00%

Panel B

Multiple	RMRF	MOM3	MOM4	MOM5	MOM6	MOM7	MOM8	MOM9	MOM10	MOM11	MOM12
Beta(IS_t^{PAC})	0.0569	0.0227	0.0169	0.0090	0.0088	(0.0019)	0.0243	0.0228	0.0068	0.0100	0.0010
t-stat	5.13***	1.27	1.40*	0.55	0.58	(0.11)	1.45*	1.35*	0.42	0.63	0.07
p-value	0.0000	0.2071	0.1648	0.5830	0.5658	0.9332	0.1508	0.1803	0.6745	0.5280	0.9445
R^2	28.66%	2.80%	2.10%	1.30%	2.17%	0.35%	3.48%	3.48%	0.74%	1.29%	0.74%

Note: *, 10 per cent significant level; **, 5 per cent significant level; ***, 1 per cent significant level; (), negative value. Panel A states the results of single factor model using equation (2), (3). Panel B states the results of multi-factor model using equation (4), (5).

Table 6 lists the empirical results of the single factor and multi-factor models that employ the monthly excess returns of market portfolio and ten momentum portfolios as dependent variables, and investor sentiment index as explanatory variables. Since there are total 11 dependent variables that will be examined, each model realizes 11 regression results. In specific, the slope coefficients (Beta) of sentiment index for each regression test, the *t*-statistic and the *p*-value of the Beta, and the R-squared of the regression are showed in the tables.

Panel A posts the regression results based on single factor model while Panel B reports the results of the multifactor model. By comparing the R-squared of each regression, the apparent increase is found from the single-factor model regression to the multi-factor regression for each dependent variable, suggesting adding the control variables in the model alleviates the noisy effects of the economic factors.

By checking the slope coefficient of each regression, the primary finding is the consistent relationship between the investor sentiment and the market returns according to the regression results. The beta of investor sentiment in panels A and B are both positive and significant at the 1 percent level, which is 6.35% and 5.69%, respectively. These results are the convincing rejection of the null hypothesis that investor sentiment cannot explain the market premium. The positive relationship between investor sentiment and market movement follows the logic of price pressure (Warther, 1995) that the increasing in sentiment or the high demand will drive the asset price going up and therefore increase the simultaneous stock returns.

For ten the momentum portfolios, investor sentiment shows a positive relationship with most of momentum returns based on the positive beta coefficients, except for the momentum portfolio formed on prior 7-month performance. However, only four of them show the significant results on slope coefficients. For the momentum portfolio MOM8, the beta of investor sentiment is 2.7% in the single-factor model and 2.43% in the multi-factor model. For the momentum portfolio MOM9, the beta of sentiment is 2.6% in panel A and 2.28% in panel B. Even there is a slight drop on the value of coefficients from single-factor regression to multi-factor regression, these slope coefficients are all significant at 10 percent level. Besides, for the zero-cost momentum portfolios formed on 3- and 4-month period, the regression results shows close relationship between their premium and the investor sentiment. Their coefficients are both positive and significant at 10% level. It is mainly the results of employing the investor sentiment accompanied with the arbitrage period of the momentum strategy instead of the investor sentiment during the formation period as the explanatory factor. Even the investor sentiment at the time to arbitrage is optimistic, the sentiment during the formation period could be different. Since investors' sentiment is not a long-lasting factor, the more lengthened formation period, the more pronounced of the variation in sentiment. Therefore, there is lesser noise effect from the previous changing investor sentiment on the returns of these two momentum strategies with shorter formation period.

Following the same rationale, it might be the main reason that the returns of momentum strategy with more extended formation period experience the more noise effect from the prior sentiment. The finding results of the regression on the profits of momentum strategy with one-year formation period, which has the most extended formation period among the sample, confirm this inference. This regression has the smallest absolute value of coefficient (nearly zero) and the lowest t-statistic. Hence, even this portfolio realizes the substantial premiums; the simultaneous investor sentiment cannot explain this premium. The investor sentiment during formation period may drive more on its performance.

Accordingly, the positive impact of the investor sentiment associated with the arbitrage period on the corresponding simultaneous momentum returns is not evident. Meanwhile, the undesirable results are mainly driven by the rapid change of investor sentiment during the formation period, which is not considered in the explanatory regression due to the difference in the formation period among portfolios. Overall, the simultaneous investor sentiment cannot serve as an explanatory factor to capture the variation of the corresponding momentum premium while the overall sentiment covering both formation period and arbitrage period could be the better option to capture the variation of the momentum return. The specific weight of the sentiment during each period is the principal concern in the future study.

5.3 The predictability of investor sentiment on the subsequent momentum returns

Except for the contemporaneous explanatory ability of investor sentiment, this paper also tests the predictability of investor sentiment on the short-run momentum returns in the Chinese market.

5.3.1 Single-factor predictive regression

Similar to the contemporaneous regression, the predictive regression begins with the single factor regression and the equations are showed below:

$$RM_{t+1} = \alpha + \beta IS_t^{PAC} + \mu_{t+1} \quad (6)$$

$$MOM_{t+1} = \alpha + \beta IS_t^{PAC} + \mu_{t+1} \quad (7)$$

where RM_t is the monthly market excess returns at the time *t*+1, MOM_t is the monthly excess returns of the momentum strategy at time *t*+1, IS_t^{PAC} is the lagged sentiment index.

Meanwhile, the previous literature has outlined the potential econometric issues of running the typical OLS predictive regression such as small-sample bias (Stambaugh, 1999). Han et al. (2017) also claim this problem when testing the predictive ability on the market return that the beta coefficient will be led toward to zero. Considering the way of Han et al. (2017) to mitigate this issue, this article employs Amihud et al. (2009)'s multiple augmented regression methods (mARM afterward) to reduce the bias on the estimation of the predictability of the sentiment on momentum returns.

The first step of the mARM method of Amihud et al. (2009) is to conduct an auxiliary AR (1) regression on the predictive variable, which is IS_t^{PAC} in this paper. The regression equation is listed below:

$$\mathrm{IS}_{\mathrm{t+1}}^{\mathrm{PAC}} = \theta^c + \rho^c \mathrm{IS}_{\mathrm{t}}^{\mathrm{PAC}} + v_{t+1}^c \tag{8}$$

where v_{t+1}^c is the error term applied to correct the potential error in the predictive regression. This term obtained from the auxiliary AR (1) regression in Equation (8) will be added in the equations (6) and (7) to enhance the accuracy of estimating the slope coefficient in the predictive regression. The augmented regression equations after mARM procedure are displayed below:

$$RM_{t+1} = \alpha + \beta IS_t^{PAC} + v_{t+1}^c + \mu_{t+1} \tag{9}$$

$$MOM_{t+1} = \alpha + \beta IS_t^{PAC} + v_{t+1}^c + \mu_{t+1} \tag{10}$$

The statistical significance of the slope coefficient β is based on the *t*-test statistic.

Table 7 Single-factor predictive regression result using OLS and mARM

Panel A											
OLS	**RMRF**	**MOM3**	**MOM4**	**MOM5**	**MOM6**	**MOM7**	**MOM8**	**MOM9**	**MOM10**	**MOM11**	**MOM12**
Beta(IS_t^{PAC})	0.0102	(0.0061)	(0.0078)	(0.0198)	(0.0227)	(0.0261)	(0.0095)	(0.0071)	(0.0222)	(0.0146)	(0.0282)
t-stat	0.79	(0.35)	(0.66)	(1.25)	(1.54) *	(1.55) *	(0.57)	(0.42)	(1.42) *	(0.96)	(2.03) **
p-value	0.4311	0.7281	0.5093	0.2130	0.1270	0.1229	0.5665	0.6721	0.1577	0.3414	0.0442
R	0.53%	0.10%	0.37%	1.31%	1.96%	2.00%	0.28%	0.15%	1.68%	0.77%	3.39%
Panel B											
mARM	**RMRF**	**MOM3**	**MOM4**	**MOM5**	**MOM6**	**MOM7**	**MOM8**	**MOM9**	**MOM10**	**MOM11**	**MOM12**
Beta(IS_t^{PAC})	(0.0226)	(0.0203)	(0.0189)	(0.0306)	(0.0348)	(0.0322)	(0.0268)	(0.0232)	(0.0311)	(0.0245)	(0.0354)
t-stat	(1.77) **	(1.04)	(1.44) *	(1.73) **	(2.13) **	(1.72) **	(1.47) *	(1.26)	(1.79) **	(1.44) *	(2.28) **
p-value	0.0795	0.2985	0.1514	0.5245	0.0353	0.0889	0.1433	0.2088	0.0764	0.1534	0.0242
R	21.20%	0.68%	1.69%	1.20%	2.60%	0.79%	2.38%	1.72%	1.12%	0.51%	2.63%

Note: *, 10 per cent significant level; **, 5 per cent significant level; ***, 1 per cent significant level; (), negative value. Panel A states the results of single factor predictive model using traditional ordinary least squares (OLS) method based on equation (6), (7). Panel B states the results of single factor predictive model using multiple augmented regression methods (mARM) based on the equation (9), (10).

Table 7 presents the single factor predictive regression results using conventional OLS procedure and mARM method. The slope coefficient of the regression represents the predictability of investor sentiment on the future returns and the subsequent momentum premiums. The significance level of the beta of investor sentiment implies whether investor sentiment can predict the future returns. The regression results based on the traditional OLS procedure are showed in Panel A, and the estimated results using augmented regression method are reported in Panel B.

For the market returns, the slope coefficient estimated by the OLS regression is positive but not significant. After adjusting bias, the slope coefficient is – 2.26%, negatively significant at the 10% level. The R-squared is dramatically increased from 0.53% to 21.20%, suggesting the bias-corrected mARM approach has successfully increased the accuracy of the estimation and therefore strengthened the analytical ability of the variation in stock returns. These results consist with the previous findings of Baker and Wurgler (2007) that investor sentiment can be a contrarian indicator of the future market returns.

By evaluating the slope coefficient of regression based on equation (10) in Panel A, the sentiment index negatively relates to the future excess momentum returns.

This result is consistent with ten regressions using the returns of different momentum strategies as the explained variable. According to Goyal and Welch (2008), the R-squared of the regression when predicting the future return on the short horizon (monthly frequency) is regularly ranged from 0.3% to 5%. The R-squared of these regressions in Panel A which employing OLS method are mostly (eight of the ten) under this range. Meanwhile, not all the slope coefficients are statistically significant. These results are predictable since there is a downward deviation in the value of the beta estimated by OLS maintained in the previous part.

Accordingly, the results in panel B is more ideal. After correcting the error by mARM method, every slope has increased in the magnitude. The negative relationship between the lagged investor sentiment and momentum premiums is persistent using different estimation methods. Among the ten regressions testing the predictive power on subsequent momentum gains, the number of the significant coefficients increased form four using OLS predictor to eight when including the bias-adjusted term. Slopes of regressions on MOM5, MOM6, MOM7, MOM10, and MOM12 are all significant at 5% level while the coefficients of regressions on MOM4, MOM8, and MOM10 are significant at 10% level. The R-squared of each regression also has improved in varying degree. Overall, the negative relationship between the investor sentiment and the short-run future momentum returns is persistent among most of momentum strategies.

5.3.2 Multiple-factor predictive regression

The predictive regression needs to control for the impact of the macro-economy. Therefore, the multiple-factor predictive regression follows the way used in the contemporaneous explanatory regression. Besides, the lagged value of three control variables, the growth of industrial production (GIP_{t+1}), the growth of money supply (GM_{t+1}) and the market-wide PE ratio (PE_{t+1}), are employed as independent variables in the model. Also, since the efficiency of the bias-corrected mARM estimation is confirmed from the previous section, there is no need to follow the traditional OLS method in the multiple-factor model. The multi-factor predictive regression will be conducted directly based on the mARM estimation. Thus, the multiple-factor models applied are showed below:

$$RM_{t+1} = \alpha + \beta IS_t^{PAC} + \varphi C_t + v_{t+1}^c + \sigma_{t+1} \quad (11)$$

$$MOM_{t+1} = \alpha + \beta IS_t^{PAC} + \varphi C_t + v_{t+1}^c + \sigma_{t+1} \quad (12)$$

where RM_t is the monthly market excess returns at the time t+1; MOM_t is the monthly excess returns of the momentum strategy at time t+1; IS_t^{PAC} is the lagged sentiment index; C_t stands for the vector of three control variables and v_{t+1}^c is the bias-adjusted bias-correct term. The β, slope coefficient of investor sentiment, is still the major concern of the estimated regression results.

Table 8 Multi-factor predictive regression results with augmented regression method (mARM)

mARM	RMRF	MOM3	MOM4	MOM5	MOM6	MOM7	MOM8	MOM9	MOM10	MOM11	MOM12
Beta(SI)	(0.0263)	(0.0211)	(0.0176)	(0.0304)	(0.0368)	(0.0328)	(0.0296)	(0.0260)	(0.0291)	(0.0254)	(0.0350)
t-stat	(2.06) **	(1.07)	(1.32) *	(1.70) **	(2.23) **	(1.70) **	(1.62) *	(1.41) *	(1.64) *	(1.48) *	(2.20) **
p-value	0.0419	0.2851	0.1902	0.0910	0.0280	0.0923	0.1073	0.1615	0.1047	0.1406	0.0300
R	24.64%	6.07%	5.16%	6.54%	8.04%	3.05%	9.46%	8.74%	4.31%	7.19%	5.42%

Note: *, 10 per cent significant level; **, 5 per cent significant level; ***, 1 per cent significant level; (), negative value. This table states the results of multi-factor predictive models using multiple augmented regression methods (mARM) based on the equation (11), (12).

Table 8 displays the results of the multi-factor predictive regressions adjusted by mARM method. The monthly excess returns of market portfolio and ten momentum portfolios are included as the dependent variables while the lagged investor sentiment index and the three lagged economic factors serves the explanatory variables. The increase in the R-squared is much more substantial compared with the results in table 7 suggesting the increase in the explanatory power of the predictive regression by adding control variables.

The market excess return shows the consistent connection with the lagged investor sentiment. The coefficient beta on sentiment is -2.63% and significant at the 5 percent level. The results are robust by checking the P-value of the predictive variable investor sentiment which is 0.04. The result is even more outstanding compared with that in Table 7. Also, the R-squared has improved to 24.64%.

For the subsequent returns of momentum strategy, the sentiment index exhibits considerable explanatory power demonstrated by statistical significance of beta of sentiment index in all momentum regressions excepted for regression on the excessed returns of three-month formed momentum portfolio. There are four regressions showing the most significant results on both T-statistic and P-value, which are regressions on returns of strategies with mid-term and long-term formation period (MOM5, MOM6, MOM7, MOM12). In specific, the slope of sentiment for regression On MOM5 is -3.04% while slopes of sentiment are -3.68% for momentum strategy formed on half-year period. Besides, the slope coefficients of investor sentiment for regression on MOM7 and MOM12 are -3.28% and -3.50%, respectively. All the four slopes are statistically significant at 5 % level and with the lower P-value. The significant predictive ability on returns of the mid-term and long-term momentum strategies is consistent with the significant momentum premiums among the mid-term and long-term momentum strategies observed in table 3. Overall, the empirical results of the predictive ability of investor sentiment index on future returns and momentum premium are robust with controlling the macroeconomic factors.

The investor sentiment has a negative effect on the subsequent market returns during the sample period, supporting the explanation that the arbitrage activity will drive the asset price back to its fundamental value even in the short-run.

According to the previous results, the momentum profit is driven by the optimism of investor sentiment. During the optimistic period, the price of winner stocks will be overpriced while the loser stocks will be underpriced. When the institutional or experienced investors notice the arbitrage opportunities behind these and conduct the momentum trading quickly, the demand of the winner stocks will drive up the prices of shares while the supply of the losing shares will pull down their prices. Their arbitrage activities will induce a negative effect on the subsequence returns which is also confirmed in the previous regression test on market returns. When the retail investors notice the arbitrage opportunities behind the high investor sentiment, the subsequence stock price is going to the opposite direction, leading to the subsequent negative momentum returns. This explanation of the negative relationship between the lagged investor sentiment and momentum returns is in line with De Long et al. (1990).

6. Conclusions

The profits of momentum, which cannot be captured by the traditional risk-based pricing model such as the famous Fama-French three-factor model, causes the huge interests of economists to investigate its origin. The recent works more rely on the behavioral theory that the investors' cognitive biases drive the price momentum. As the empirical evidence of the investor sentiment's systemic effect on the asset price is continually explored in different markets, the potential relationship between the investor sentiment and the abnormal returns realized by momentum strategy is worth to investigate further. This paper extends the literature in the behavior finance area by exploring the relationship between investor sentiment and the momentum premiums. Using a comprehensive sample of the Chinese A-share index ranged from 2006-01 to 2015-12, we formed a market-wide investor sentiment index in the monthly frequency as well as the zero-cost momentum portfolios based on the various formation period.

According to the preliminary analysis, the most of momentum portfolios in the A-share index realize the positive average returns. The comparison analysis is also conducted between the profitability of momentum strategy in different sentiment period. The optimistic and pessimistic sentiment states are divided based on whether the value of measured investor sentiment index is higher or lower than zero. The momentum premium during the optimistic sentiment period is more pronounced than the profit during the pessimistic period, suggesting the investor sentiment may have a possible impact on the concurrent momentum returns.

Hence, the further regression tests are run on exploring the linear relationship between the momentum returns and the investor sentiment in the corresponding month. However, the results are less desirable. Even the investor sentiment is positively related to the market returns and the returns of most of the momentum strategies; their slope coefficients are less significant. These undesirable results might be due to the rapid change of investor sentiment during the formation period, suggesting that not the investor sentiment in the holding period applied in the regression affects the momentum returns, the sentiment state during the formation period may also influence the profitability of momentum strategy.

On the other hand, the regression tests on whether lagged investor sentiment can predict the future momentum returns provide the opposite finding results. After using mARM method to correct the small sample bias and controlling the effect of macroeconomic factors, the slope coefficients of the lagged investor sentiment are all negative, and nearly all of them achieve the statistically significant level based on the t-value. Besides, the investor sentiment is significantly negatively related to the market premium in the subsequent month, consistent with the previous view that the sentiment is a contrarian predictor. Overall, the predictive ability of investor sentiment is confirmed. It has a negative effect on the expected market returns as well as the subsequent momentum premiums in the short-run.

There is some limitation in the current work. This paper focuses on the impact of investor sentiment during the holding period. The influence of the sentiment in the formation period has not been considered. The future analysis on the investor sentiment may find a more comprehensive index including both formation and holding periods. Meanwhile, the specific weight of the sentiment during each period is the principal concern in the future study. Besides, the further works can also focus on the predictive models that can predict the long-term momentum returns.

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