Investor Sentiment and the Near-term Stock Returns

Evidence from Chinese stock market

Jiang Yumei
School of economics & management
Tongji University
Shanghai, 201804, P.R. China
jym7829@hotmail.com

Wang Mingzhao
School of economics & management
Tongji University
Shanghai, 201804, P.R. China
wangmz_tj@163.com

Abstract—**Using a vector autoregression (VAR) model, we study how investor sentiment and near-term stock returns interact each other. We find that both past market returns and sentiment are important determinants of investor sentiment. Sentiment has predictive power for near-term future stock returns. Our results suggest asset pricing models should consider the role of investor sentiment. In addition, our evidence does not support the conventional wisdom that sentiment primarily affects small stocks and extreme growth stocks, on the contrary, it appears that the stronger relationship exist between investor sentiment and large-cap value stocks in China A-share market.**

Keywords- investor sentiment; near-term stock returns; VAR model; Chinese stock market;

I. INTRODUCTION

Investor sentiment has been a subject of interest in the finance literature for a number of years. The question whether sentiment matter for stock returns is more controversial, and supporters from the behavioral side and critics from the rational camp each have arguments in favor of this view or against it. While theoretical models have early incorporated the existence of noise traders into equilibrium asset pricing, empirical evidence on the relevance of investor sentiment does not provide clear findings [1].

China's mainland stock markets have grown rapidly since their inception and have become an important emerging market for international investors. However, as the history of modern China stock market is relatively short, the immature market is even depicted as irrational. Since investor sentiment plays an obvious important role in the market, it is necessary to investigate the relationship between investor sentiment and stock returns in China A-share market.

In this paper, we propose a composite index to measure investor sentiment in the stock markets by employing the principal component analysis as means of extracting composite unobserved sentiment measures. Using the composite investor sentiment index, we examine how investor sentiment and near-term stock returns interact with a vector autoregression (VAR) model.

The rest of the paper unfolds as follows: the next section gives an overview over related research and Section 3 describes the methodology and the data set we use. Section 4 shows the construction of our sentiment index and the empirical results from VAR model estimations, Section 5 concludes.

II. RELATED RESEARCH

The notable work of De Long, Shleifer, Summers, and Waldmann (DSSW (1990) hereafter) models the influence of noise trading on equilibrium prices [2]. Noise traders acting in concert on non-fundamental signals can introduce a systematic risk that is priced; investor sentiment affects security prices in equilibrium. The "noise trader" model of DSSW has motivated empirical attempts to explore the predictive power of sentiment for returns, the results that have been found are mixed.

Neal and Wheatley (1998), Simon and Wiggins (2001) and Wang (2001) find that sentiment can predict returns. Neal and Wheatley (1998) find that two measures of individual investor sentiment predict equity returns, one compiled from the discounts on closed-end funds and the other redemptions of mutual funds [3]. Wang (2001) uses the positions held by large traders in the futures markets as a proxy for sentiment and discovers that they are useful for predicting the returns on futures in a subsequent period [4]. Simon and Wiggins (2001) also find that sentiment measures are able to predict returns on futures. However, not all papers that have studied the relationship between sentiment and returns have come to these conclusions [5].

Fisher and Statman (2000) find that the causality between equity returns and sentiment can be significant in both directions [6]. Brown and Cliff (2004) find that past market returns are an important determinant of sentiment. Although sentiment levels and changes are strongly correlated with contemporaneous market returns, sentiment has little predictive power for near-term future stock returns [7]. Brown and Cliff (2005) provide evidence that sentiment affects asset valuation. Future returns over multiyear horizons are negatively related to sentiment. That is, they find weak evidence of short-run predictability but a strong correlation between sentiment and long-horizon (2-3 years) returns [8]. Baker and Wurgler (2006) study how investor sentiment affects the cross-section of stock returns and find that a wave of investor sentiment has larger effects on securities whose valuations are highly subjective and

978-1-4244-4639-1/09/$25.00 ©2009 IEEE

difficult to arbitrage: small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks [9].

In domestic research, Wang Meijin &Sun Jianjun (2004) find that sentiment has significant impact on the return and volatility. The results also show that the two markets have similar characteristics of risk and return, the institutional investors probably are the source of noise-trading risk [10]. Wu Yanran and Han Liyan (2007) explain "Chinese Closed-end-fund puzzle" by using the sentiment of imperfectly rational investors, which is proved to be the key factor of asset pricing. They find that there exists the long-term negative and the short-term positive influence between sentiment and stock market return [11]. Q. Zhang, S. Yang, and H. Yang (2007) find that the institutional investor sentiment has significant influence on stock price, the change of institutional investors' sentiment is not a systematic risk and the individual investor's sentiment has no influence on stock price, including the small size stocks. investors' emotional fluctuation affect the cross-section stock returns [12].

III. METHODOLOGY &DATA

A. Investor Sentiment Measures

Capturing investor sentiment is a difficult task. Prior work suggests a number of proxies for sentiment variables. Each has its own weaknesses and strengths. There are no definitive or uncontroversial measures yet [9]. We follow the approach similar to Baker and Wurgler (2006) and form a composite index of sentiment that is based on the common variation in four underlying proxies for sentiment: the closed-end fund discount, China A-Share turnover, consumer confidence index, the number of new accounts for each month. We first introduce each proxy separately, and then discuss how they are formed into overall sentiment indexes in next section.

The closed-end fund discount (CEFD), is the average difference between the net asset values (NAV) of closed-end stock fund shares and their market prices. Prior work suggests that CEFD is inversely related to sentiment [9]. We compute the month-end equal-weighted average discount on closed-end stock funds with the data from Wind Financial Database.

Baker and Stein (2004) suggest that turnover, or more generally liquidity, can serve as a sentiment index: In a market with short-sales constraints, high liquidity is a symptom of the fact that the market is dominated by irrational investors, and hence is overvalued. The China A-Share turnover is based on data from Wind Financial Database.

The number of new accounts is also thought to be closely related to investor sentiment; large number of new accounts can be seen as a sign of investors being enthusiastic about the investing environment. The number of new accounts is obtained from the website of China Securities Depository and Clearing Corporation Limited.

Lemmon (2002) report evidence that consumer confidence regarding economics conditions predicts the future quarterly premium of small stocks returns over large stocks returns, after controlling for a number of other macroeconomic factors [14]. Other related research also support consumer confidence serve as an investor sentiment index. We obtain the consumer confidence data from China Monthly Economic Indicators.

All the sentiment proxies are measured monthly from January 1999 to April 2008. We exclude the number and average first-day returns on IPOs as a proxy, because the regulators plays more important role than the market-timing for IPOs in China mainland stock market, which make the monthly data of number and average first-day returns on IPOs is inconsistent.

B. VAR model

Some of the earlier research suggests that market returns and sentiment may act as a system [7]. Hence, we estimate a set of VAR models with the sentiment series and market returns to investigate the relationship between sentiment and market returns.

The VAR model can be expressed as:

$$Y_{\mathrm{t}} = C + \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t \tag{1}$$

Where Y= [SENTIMENT, RBIGPV, RSMALLPG] for the monthly VAR, p indexes lag length and t denotes time, C is a vector of constants, ε is a vector of random error terms.

The variable "SENTIMENT" is the composite investor sentiment index by employing the principal component analysis, the variable "RBIGPV" is the return on the large-cap pure value stocks portfolio, the variable "RSMALLPG" is the return on the small-cap pure growth stocks portfolio.

For the monthly sample, we use the S&P/CITIC 100 Pure Value Index as the portfolio of large-cap pure value stocks, and the S&P/CITIC Small Cap Pure Growth Index as the portfolio of small-cap pure growth stocks. Returns are based on the month-end closing prices when possible. In cases where the end of the month prices are not available due to holidays, etc., the most recent previous price is used instead. In the VAR model, the sample period includes monthly observations of variables from Feb 2004 to Apr 2008, due to the S&P/CITIC indices are available since Feb 2004. The indices data is obtained from Wind Financial Database.

IV. EMPIRICAL RESULTS

A. Composite Investor Sentiment Index

Each of the aforementioned sentiment proxies doubtless includes a sentiment component and a non-sentiment component. To isolate the common sentiment component, we use principal component analysis to form an overall sentiment index [15]. The composite index "SENTIMENT" is formed that captures the common component in the four Proxies:

$SENTIMENT_t = 0.662*TURN_t + 0.691*ACCOU_t + 0.246*CFI_t - 0.155*CEFD_t$

Where “SENTIMENT” is the composite investor sentiment index, t denotes time, CEFD is the closed-end fund discount, TURN is A-share turnover, CFI is the consumer confidence index, and ACCOU is the number of new accounts.

Where each of the index components was first standardized. The first principal component explained 46% of the total sample variance of the raw sentiment proxies, indicating one factor captures much of the common variation.

B. VAR Model Estimation Results

Before proceeding with the main results, we first check the time series properties of each variable by performing unit root tests. The results of unit root tests using Augmented Dickey Fuller (ADF) test indicate the null hypothesis of nonstationarity is rejected in each time series.

According to VAR lag order selection criteria suggested by Eviews5, the appropriate number of lags is determined to be five, then we excluded third lag by performing lag exclusion test after preliminary estimation.

Table 1 reports the results from estimating the monthly sample VAR using sentiment levels. The blocks of rows indicate the contribution of each independent variable at lags 1,2,4,5.

TABLE I. MONTHLY VAR-RETURNS AND COMPOSITE INVESTOR SENTIMENT INDEX

Independent variables	**Dependent variables**		
	SENTIMENT	***RBIGPV***	***RSMALLPG***
SENTIMENT(-1)	0.451996**	0.001186	-0.014728
	[2.29835]	[0.05058]	[-0.64630]
SENTIMENT(-2)	0.047764	-0.040512**	-0.016156
	[0.32015]	[-2.27658]	[-0.93454]
SENTIMENT(-4)	0.330822*	0.043534*	0.062435***
	[1.74677]	[1.92714]	[2.84500]
SENTIMENT(-5)	-0.187077	-0.033998*	-0.057054***
	[-1.19906]	[-1.82693]	[-3.15590]
RBIGPV(-1)	0.924190	0.352927	0.479588*
	[0.39309]	[1.25851]	[1.76041]
RBIGPV(-2)	2.655923	0.583974*	0.495496*
	[1.08656]	[2.00296]	[1.74941]
RBIGPV(-4)	4.529802*	0.188276	0.148276
	[1.92779]	[0.67176]	[0.54458]
RBIGPV(-5)	0.213208	-0.460299	-0.309386
	[0.08390]	[-1.51858]	[-1.05068]
RSMALLPG(-1)	3.240359	-0.299213	-0.354994
	[1.37845]	[-1.06714]	[-1.30327]
RSMALLPG(-2)	-1.526225	-0.100737	-0.010560
	[-0.63280]	[-0.35017]	[-0.03779]
RSMALLPG(-4)	-0.823345	0.230782	0.101168
	[-0.36086]	[0.84800]	[0.38266]
RSMALLPG(-5)	-1.075084	0.874860***	0.562739*
	[-0.43738]	[2.98399]	[1.97578]
R-squared	0.882358	0.590732	0.569024
Adj. R-squared	0.843143	0.454309	0.425366
F-statistic	22.50100	4.330157	3.960951
Block Exogeneity	0.0002***	0.0001***	0.0003***

The number in [] Indicate t-statistics. * Indicate significance at the 10% level. ** Indicate significance at the 5% level. *** Indicate significance at the 1% level.

Looking down the first column of dependent variables, the sentiment variable is a powerful predictor of itself，both the 1- and 4-month lags are positive and significant; The impact of the large-cap pure value stock returns on sentiment is evident, but the impact of the small-cap pure growth stock returns is not evident at all. These results confirm that speculators are swayed by recent market performance partly. Lagged levels of sentiment and market returns explain substantial variation in sentiment as indicated by the high Adj. R-squared of 0.84.

The second column of dependent variables shows that the large-cap pure value stock returns is strongly positively related to its past returns and the small-cap pure growth stock’ past returns, which is consistent with momentum in returns. Looking down the third column of dependent variables, both the impact of the large-cap pure value stock returns and the small-cap pure growth stock on RSMALLPG is positive evident. Sentiment has evident effect on either large or small stock returns. The Adj. R-squared of 0.45, 0.43 of equations reveals that lagged sentiment and market returns explain much of the variability in the returns; sentiment is also a powerful predictor of market returns.

We employ impulse response functions obtained from the VAR model to interpret the results for the VAR coefficient estimation. (see Figure 1).

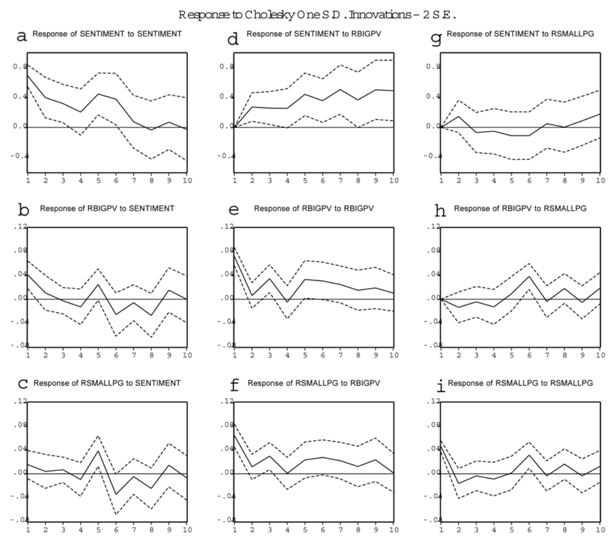

Figure 1. Impulse Response Results

The dashed lines on each graph represent the upper and lower 95% confidence bands. When the upper and lower bounds carry the same sign the response becomes statistically significant. On each graph, “percentage returns” are on the vertical and “horizon” is on the horizontal axis.

The a, b and c in Fig. 1 plot the responses SENTIMENT, RBIGPV and RSMALLPG to one time standard deviation increase in the SENTIMENT. We find that the response of SENTIMENT, RBIGPV is positive and significant at first several months and becomes insignificant thereafter. On the other hand, the response of the RSMALLPG is insignificant at first and is of relatively smaller magnitude than those of RBIGPV throughout. These results suggest that the large-cap pure value stock is more sensitive to sentiment than the small-cap pure growth stock. This evidence supports a role for investor sentiment during the asset pricing formation process. However, it is inconsistent with the argument of Baker and Wurgler (2006) that small stocks, extreme growth stocks, are more subjective to sentiment. This evidence is also contrary to the argument of Brown and Cliff (2004) that the sentiment is insignificant as predictor of monthly return.

The d, e and f in Fig. 1 plot the responses SENTIMENT, RBIGPV and RSMALLPG to one time standard deviation increase in the RBIGPV. We find significant positive effects of RBIGPV on SENTIMENT, RSMALLPG and itself throughout; the response of the RSMALLPG is of relatively smaller magnitude than those of RBIGPV throughout. Sentiment has evident effect on either large or small stock returns. These results are consistent with the positive feedback and the momentum returns.

The g, h and i in Fig. 1 plot the responses SENTIMENT, RBIGPV and RSMALLPG to one time standard deviation increase in the RSMALLPG. The responses become a little significant at sixth month slowly and then are insignificant thereafter. Compared with d, e and f, the responses induced by RSMALLPG is of relatively smaller magnitude than those induced by RBIGPV, which suggest that the effect power of RBIGPV is bigger.

Overall the results of the impulse response functions are consistent with the findings of t-statistics for differences in estimated coefficients.

At last, we explore the relationship among investor sentiment, return on the large-cap value stocks portfolio and the return on the small-cap growth stocks portfolio by using the S&P/CITIC 100 Value Index as the portfolio of large-cap value stocks and the S&P/CITIC Small Cap Growth Index as the portfolio of small-cap growth stocks with the same methodology, the empirical result is similar to above results.

V. CONCLUSIONS

In summary, a composite index is proposed to measure investor sentiment in the stock markets by employing the principal component analysis. Using the composite investor sentiment index, how investor sentiment and near-term stock returns interact is examined with a vector autoregression (VAR) model.

We find that past market returns and sentiment itself are important determinant of investor sentiment. Sentiment has predictive power for near-term future stock returns. The results support the important yet controversial behavioral theories that the irrational sentiments of investors do affect asset valuation, suggesting asset pricing models should consider the role of investor sentiment.

Our research does not support the conventional wisdom that sentiment primarily affects small stocks and extreme growth stocks, on the contrary, it appears that the stronger co-movements exist between investor sentiment and large-cap value stocks; the large-cap value stocks have more significant predictive power on market return and investor sentiment than the small-cap growth stocks in China A-share market.

ACKNOWLEDGMENT

Jiang Yumei thanks Yuan Yujie and Xiong Wen for helpful advices.

REFERENCES

[1] M. Schmeling, "Institutional and individual sentiment: Smart money and noise trader risk?," International Journal of Forecasting, vol. 23, pp. 127-145, 2007.

[2] J. B. De Long, S. Andrei, H. S. Lawrence, and J. W. Robert, "Noise Trader Risk in Financial Markets," Journal of Political Economy, vol. 98, pp. 703-38, 1990.

[3] N. Barberis, A. Shleifer, and R. Vishny, "A model of investor sentiment," Journal of Financial Economics, vol. 49, pp. 307-343, 1998.

[4] C. Wang, "Investor sentiment and return predictability in agricultural futures markets," The Journal of Futures Markets, vol. 21, p. 929, 2001.

[5] Y.-H. Wang, A. Keswani, and S. J. Taylor, "The relationships between sentiment, returns and volatility," International Journal of Forecasting, vol. 22, pp. 109-123, 2006.

[6] K. L. Fisher and M. Statman, "Investor sentiment and stock returns," Financial Analysts Journal, vol. 56, p. 16, 2000.

[7] G. W. Brown and M. T. Cliff, "Investor sentiment and the near-term stock market," Journal of Empirical Finance, vol. 11, pp. 1-27, 2004.

[8] G. W. Brown and M. T. Cliff, "Investor Sentiment and Asset Valuation," Journal of Business, vol. 78, p.405, 2005.

[9] M. Baker and J. Wurgler, "Investor Sentiment and the Cross-Section of Stock Returns." vol. 61, 2006, pp. 1645-1680.

[10] M. Wang and J. Sun, "Stock Market Returns , Volatility and the Role of Investor Sentiment in China," Economic Research Journal, pp. 75-83, 2004.

[11] Y. Wu and L. Han, "Imperfect Rationality ,Sentiment and Closed-end-fund Puzzle," Economic Research Journal, pp. 117-129, 2007.

[12] Q. Zhang, S. Yang, and H. Yang, "An Empir ical Study on Investors'Sentiment and Stock Returns in Chinese StockMarket," System s Engineering, vol. 25, pp. 13-17, 2007.

[13] M. Baker and J. C. Stein, "Market liquidity as a sentiment indicator," Journal of Financial Markets, vol. 7, pp. 271-299, 2004.

[14] M. L. Lemmon and E. V. Golubeva, Consumer Confidence and Asset Prices: Some Empirical Evidence: SSRN, 2002.

[15] Baker MP, Wang J, Wurgler JA. How Does Investor Sentiment Affect the Cross-Section of Stock Returns?: SSRN, 2008.