A Principal Component Approach to Measuring Investor Sentiment in China

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22 November 2013

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22/11/2013

Abstract: This paper develops a new investor sentiment index for the Chinese stock market. The index is constructed via the principal component approach (PCA), taking six important economic and market factors into consideration. The sentiment index serves as a threshold variable in a threshold autoregressive model to identify the stock market regimes. Our findings show that the Chinese stock market can be divided into three regimes: namely, a high-return volatile regime, a low-return stable regime and a neutral regime. The sentiment index is shown to have good out-of-sample predictability.

Keywords: Principal Component Analysis; Market Sentiment; Market Turnover; Threshold Model.

JEL Classifications: C43, G14.

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[1] We would like to thank Jing Han and Nayoung Lee for their valuable comments. We would also like to thank Vivian Wong, Min Chen, Sophia Lok, Margaret Loo and Ceara Hui for able research assistance. Haiqiang Chen acknowledges the financial support from the National Natural Science Foundation of China Grant #71201137. Any remaining errors are ours. Corresponding Author: Terence T.L. Chong, Department of Economics and Institute of Global Economics and Finance, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong. Email: chong2064@cuhk.edu.hk. Webpage: http://www.cuhk.edu.hk/eco/staff/tlchong/tlchong3.htm.

1. Introduction

Investor sentiment is a reflection of the current status of the financial market and measuring such sentiment with high accuracy has become a subject of increasing academic interest in recent years. Brown and Cliff (2004, 2005) use survey data as a measure of investor sentiment to predict market returns and Schmeling (2009) uses consumer confidence as a proxy for individual investor sentiment. Two popular survey-based sentiment measures in the market are the ING Investor Dashboard sentiment index[2] and Investors Intelligence sentiment index[3]. A number of empirical studies use market-based indicators as a measure of sentiment. For instance, Baker and Stein (2004) suggest that liquidity, such as market turnover, can serve as a sentiment indicator. Instead of using a single variable as a proxy, recent studies combine different sentiment proxies into a composite sentiment index. Baker and Wurgler (2006, 2007) construct a composite index of sentiment based on the first principal component of six variables. Chen, Chong and Duan (2010) develop a composite investor sentiment index for the Hong Kong stock market via the principal component approach. The aforementioned studies focus on developed markets, while

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[2] The ING Investor Dashboard sentiment index is published quarterly, covering 13 markets across Asia, including Australia, China, Hong Kong, India, Indonesia, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Taiwan and Thailand. It is based on interviews of mass affluent respondents across all markets. For the case of Hong Kong, mass affluent is defined as person aged 30 or above and with disposable asset of USD 100,000 or above.

[3] The Investors Intelligence sentiment index is released daily, summarizing the forecasts of a number of newsletter writers who issue independent advice from their publications and commentary. It is based on contrarian propositions, which assumes that a consensus trend is always about to reverse. Fisher and Statman (2000) find that the relationship between the Investors Intelligence Sentiment Index and future S&P 500 returns is statistically insignificant, and that there is only a weak correlation between Index and major market turning points. It will be an interesting future research topic to compare the accuracy of this sentiment index with our index.

studies on emerging markets are scant. [4]

The objective of this paper is to provide a new measure of investor sentiment for China, which is the biggest emerging stock market in the world. Due to its short history, little light has been shed upon the behavior of the relatively immature Chinese stock market, which varies vastly from the U.S. stock market. It possesses a number of unique features; for instance, individual investors dominate the Chinese stock market, short selling is forbidden, and there are price limit regulations restricting the movements of stock prices. These measures prohibit arbitrage activities and generate inefficiency (Chong, Lam and Yan, 2012).

In this paper, we construct a principal component based composite sentiment index for the Chinese stock market. The economic factors that we used include interest rate, exchange rate, the change in industrial production and the change in money supply, whereas the market-based factors include market turnover and the number of new investor accounts. Our sentiment index is shown to have good predictability for the market movements. A threshold autoregressive model of Hansen (2000) is estimated to identify the market state. Our results divide the Chinese stock market into three regimes: (1) a high-return volatile regime, (2) a low-return stable regime, and (3) a neutral regime. Our model outperforms other commonly used time series models in the out-of-sample forecast.

The remainder of this paper is organized as follows. Section 2 provides an overview of the Chinese stock market. Section 3 describes the data and methodology. A threshold autoregressive (TAR) model using the sentiment index as the threshold

[4] ING Investor Dashboard sentiment index covers Chinese capital markets. Compared to the ING Investor Dashboard sentiment index, our sentiment index is computed monthly and thus can provide investors with a more rapid update of market sentiment. On the other hand, the ING Investor Dashboard sentiment index is based on survey results from professional investors who might have more private information about the market, which would be a more leading index, while our index is based on published market and macroeconomic data, which may be a slightly lagging index.

variable is estimated in Section 4. Section 5 concludes the paper.

2. The Chinese Stock Market

There are two stock exchanges in China. The Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) were established in November 1990 and April 1991, respectively.[5] Since its inception, the market has experienced a rapid expansion and was ranked the second largest stock market in Asia within a decade of its launch. After the establishment of the Securities Law on July 1, 1999, the Chinese stock market entered a relatively healthy and orderly phase of development, characterized by the segregation of domestic and foreign investors up until 2001. Domestic investors only had access to *A* shares in the past, as *B* shares were solely for foreign investors. These two classes of shares are legally identical in terms of voting rights and dividend streams but are traded separately. Investors were restricted to trade their own class of shares. After February 2001, *B* shares were opened to domestic individual investors. In addition to the segregation of domestic and foreign investors, the Chinese stock market is still dominated by individual investors, although the number of institutional investors has grown rapidly after the reform of non-tradable shares in 2005.

3. Chinese Investor Sentiment Measure

3.1 Data and Variables

The variables for investor sentiment used in this paper include the value of market turnover, number of newly opened investor accounts, change in industrial production, change in money supply, 30-day National Interbank Offered Rate, and exchange rate.

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[5] The SHSE and SZSE are self-regulated, and cross-listing is not allowed.

A total of 168 monthly observations are obtained from the CEIC database, covering the period from January 1997 to December 2010.

The SHSE Composite Index is plotted in Figure 1 and the stock return, defined as $y_t = 100 \times \frac{(P_t - P_{t-1})}{P_{t-1}}$, is shown in Figure 2. We introduce each variable below and discuss how they relate to the market sentiment.

<u>Figure 1 About Here</u>

<u>Figure 2 About Here</u>

Market Turnover

Baker and Stein (2004) argue that market liquidity can serve as a sentiment measure because investors generally have higher sentiment in bull market states and lower sentiment in bear market states (Pagan and Sossounov, 2003). As a measure of liquidity, market turnover is incorporated as one of the variables in our sentiment index. The market turnover should be high when the market is bullish and low when market is bearish (Karpoff, 1987).[6] To normalize the series, the turnover is divided by its moving average. The turnover ratio at time *t*, denoted as MT_t, is defined as

$$MT_t = \frac{Turnover_t}{TMA5_t},$$

where $Turnover_t$ is the monthly value of market turnover at time *t*, and $TMA5_t$ is the average market turnover for the previous five months, or 100 trading days.[7] Figure 3 plots the series of turnover ratios.

[6] Chiang, Qiao and Wong (2010) find strong bidirectional nonlinear Granger causality between return volatility and trading volume.

[7] We have tried other moving average windows for the turnover ratio. It is found that the 100-days moving average window generates the best prediction results.

Figure 3 About Here

Number of New Investor Accounts

The number of new investor accounts is reflective of investor sentiment. Specifically, given the unique features that retail investors are still the major force driving stock market movements in China,[8] an increasing number of new accounts implies a larger demand for stocks from investors. Thus, the number of new accounts is a good proxy for market sentiment. We define the new account ratio at time *t*, NA_t, as

$$NA_t = \frac{NewAcc_t}{NAMA5_t},$$

where $NewAcc_t$ is the number of new investor accounts at month *t*, and $NAMA5_t$ is the average number of new investor accounts for the previous five months, or 100 trading days. The series of account ratios is shown in Figure 4.

Figure 4 About Here

Early studies demonstrate a strong correlation between the sentiment index and macroeconomic variables (Sehgal, Sood and Rajput, 2010; Grigaliūnienė and Cibulskienė, 2010). Therefore, apart from the two market variables, we also use four economic variables to construct our sentiment index.

Change in Industrial Production

The change in industrial production at time *t*, GIP_t, is defined as

[8] The short selling mechanism is not very popular among investors due to high transaction costs and a lack of stock lenders.

$$GIP_t = 100 \times \frac{IP_t - IP_{t-12}}{IP_{t-12}},$$

where IP_t is the industrial production at time *t*, and IP_{t-12} is the industrial production at time $t-12$. A higher growth rate of industrial production suggests the economy is in good shape, which drives up stock prices. The monthly changes in industrial production are plotted in Figure 5.

<u>Figure 5 About Here</u>

Change in Money Supply

We also include the change in money supply M2 in our sentiment measure to reflect the liquidity in the stock market. Since Chinese retail investors have limited investment channels, a loose monetary policy adopted by the central bank can create excessive capital in the stock market. Therefore, a higher growth in money supply leads to a higher investor sentiment. The change in $M2$ at time *t*, $GM2_t$, can be expressed as

$$GM2_t = 100 \times \frac{M2_t - M2_{t-1}}{M2_{t-1}},$$

where $M2_t$ is the $M2$ of the current month and $M2_{t-1}$ is the $M2$ of the previous month. Figure 6 shows the series of monthly changes in $M2$.

<u>Figure 6 About Here</u>

Interest Rate

Interest rates reflect the cost of capital. The weighted average of the 30-day National Interbank Offered Rate is used as our interest rate variable, which is denoted as IR_t. A higher interest rate implies a higher opportunity cost of investing in the stock market. Thus, a higher interest rate will lower investor sentiment. The series is shown in Figure 7.

<u>Figure 7 About Here</u>

Exchange Rate

The movement of exchange rate is closely related to international capital flows. A continuous appreciation of RMB attracts more demand for Chinese assets from international investors, leading to a higher investor sentiment index. Monthly series of the end-of-period national currency per USD, denoted as EX_t, is plotted in Figure 8.

<u>Figure 8 About Here</u>

Note that the exchange rate begins to fall from the commencement of the 2005 reform of the RMB exchange rate. The descriptive statistics of the six variables are reported in Table 1.

Table 1. Summary statistics of variables

	MT_t	NA_t	GIP_t	$GM2_t$	IR_t	EX_t
Mean	1.0781	1.1318	13.436	1.3526	3.3749	7.8821
Median	1.0010	0.9041	13.750	1.2627	2.7300	8.2767
Maximum	2.9000	7.4791	23.900	6.3259	11.190	8.2921
Minimum	0.2420	0.1779	–2.240	–0.9699	0.4400	6.6230
Std. Dev.	0.3931	0.9111	4.1818	1.0269	2.1179	0.5885

3.2 Principal Component Analysis

A composite measure of investor sentiment is developed by applying the PCA to the six variables. First, we standardize the six variables and obtain the eigenvalue and eigenvector of their covariance matrix. We then construct the sentiment index as a linear combination of the six variables by using the eigenvector associated with the largest eigenvalue as the corresponding weight.

3.3 Investor Sentiment Index

The investor sentiment index at time *t* is denoted as SMI_t, which is the first principal component estimated by the following linear combination of the standardized variables.

$$\begin{aligned} SMI_t &= 0.641\times \widetilde{MT}_t + 0.641\times \widetilde{NA}_t + 0.252\times \widetilde{GIP}_t \\ &\quad + 0.105\times \widetilde{GM}2_t - 0.294\times \widetilde{IR}_t - 0.133\times \widetilde{EX}_t \end{aligned}$$

Notably, the market turnover ratio and the ratio of the number of new investor accounts both positively affect the sentiment index and explain a large proportion of the variation of investment sentiment. As expected, both the changes in industrial production and money supply are positively related to the sentiment index. The negative impact of the National Interbank Offered Rate on the sentiment index is also observed. Since an appreciation of RMB attracts global capital into China, the exchange rate variable appears to be negatively related to the sentiment index. The estimated investor sentiment index is shown in Figure 9. Figure 10 shows that the sentiment index moves in tandem with the stock return. It is high when the stock return is high, and vice versa.

<u>**Figure 9 About Here**</u>

<u>**Figure 10 About Here**</u>

4. Threshold Autoregressive Model

4.1 The Model

In this section, we use the sentiment index to divide the states of the Chinese stock market. A threshold autoregressive (TAR) model (Tong and Lim, 1980) which captures the nonlinear movements of a financial time series is estimated.[9] We use the composite investor sentiment index as the threshold variable. The sentiment-based TAR model is defined as

$$y_t = \begin{cases} \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_{p1} y_{t-p1} + \varepsilon_{1t} & \textit{if } SMI_{t-d} \le r_1 \\ \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \ldots + \beta_{p2} y_{t-p2} + \varepsilon_{2t} & \textit{if } r_1 < SMI_{t-d} \le r_2 \\ \gamma_0 + \gamma_1 y_{t-1} + \gamma_2 y_{t-2} + \ldots + \gamma_{p3} y_{t-p3} + \varepsilon_{3t} & \textit{if } SMI_{t-d} > r_2 \end{cases},$$

where SMI_{t-d} is the threshold variable and y_t represents the return in the stock market at time t.

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[9] Tsay (1998) develops a multivariate TAR model for the arbitrage activities in the stock market and uses the first lagged stock return as the threshold variable to identify the market regimes. Chen, Chong and Bai (2012) develop a TAR model with two threshold variables and apply it to classify the stock market regimes of Hong Kong.

4.2 Results

We use the sentiment index as the threshold variable to split samples. The results of the Lagrange Multiplier test of Hansen (2000) for the presence of threshold effects are shown in Table 2.

Table 2. Test for threshold effects

	Value1	Value2
Threshold Estimate	0.658	–0.678
Bootstrap p-value	<0.0001	0.0530

Two threshold values are obtained. The first threshold value, 0.658, is statistically significant at the 1% level, whereas the second, –0.678, is marginally significant at the 5% level. This implies that the market can be divided into three regimes according to these two threshold values, as shown in Figure 11.

<u>Figure 11 About Here</u>

In each regime, a linear AR model is estimated. The autoregressive order in each regime is chosen by Akaike's information criterion (AIC). The estimation results of the TAR model are as follows:

$$y_t = \begin{cases} -3.8180 - 0.2303\mathrm{y}_{\mathrm{t\text{-}1}} + 0.2364 y_{t-2} + \varepsilon_{1t} & \text{if } SMI_t \le -0.678 \\ \\ 0.0686 - 0.1975\mathrm{y}_{\mathrm{t\text{-}1}} + 0.1530 y_{t-2} - 0.1319 y_{t-3} & \\ +0.1890 y_{t-4} + \varepsilon_{2t} & \text{if } -0.678 < SMI_t \le 0.658. \\ \\ 5.1603 + 0.3526\mathrm{y}_{\mathrm{t\text{-}1}} - 0.6823 y_{t-2} + 0.1778 y_{t-3} & \\ +0.3072 y_{t-4} - 0.2903 y_{t-5} + 0.0101 y_{t-6} + 0.5129 y_{t-7} + \varepsilon_{3t} & \text{if } SMI_t > 0.658 \end{cases}$$

Maheu and McCurdy (2000) divide the U.S. stock market into a high-return stable state and a low-return volatile state, referring to them as bull and bear markets, respectively. According to our TAR estimation results, the Chinese stock market can be divided into three regimes: Regime I with SMI_t>0.658 is considered a high-return volatile regime. Regime II is a neutral regime with -0.678<SMI_t<0.658. Regime III with SMI_t<-0.678 is a low-return stable regime. Table 3 provides a chronology of major events and the corresponding stock market regimes from 1997 to 2010.

Table 3. The chronology of major events and the corresponding stock market regimes

Date	Event	Regime
1997.7–1998	Asian financial crisis	III
1999.6	The cut of stamp tax on B shares	I
2000.3	Global technology stock boom	I
2001.2	The opening of B shares to domestic individual investors	II
2001.6	The decrease in state-owned shares	III
2001.11	The admission of China into the WTO	II
2002.12	The launch of QFII	I, II
2003.2–2003.6	The outbreak of SARS	II, III

2005.7	The reform of RMB exchange rate	II
2006.5	New IPO regulations	II, III
2006.12	The completion of non-tradable shares reform	I
2007.8–2008	U.S. subprime mortgage crisis	III
2009.12–2010.3	European debt crisis	III
2010.10	The launch of China's 12th Five-Year Plan	I
2010.12	China's shift to prudent monetary policy	II, III

4.3 Forecasting Performance

In this section, we investigate the out-of-sample forecasting performance of the TAR model. Let m denote the number of observations used for model estimation and $n = T - m$ denote the number of out-of-sample forecasts, where T is the total number of observations. We compare the TAR model with both the simple AR model and the martingale model. These two models are commonly regarded as benchmark models for comparison in related literature. The martingale model is defined as $y_t = \mu + \varepsilon_t$, where ε_t is a zero-mean martingale sequence.

For each model, at time t, we use a sample series $\{y_{t-m+1}, \ldots, y_t\}$ of size m to estimate the model parameters. The estimated model is then used to generate a one-step-ahead forecast sequence $\{\hat{y}_{t+1}\}_{t=m}^{T-1}$. The forecasting performance is evaluated by using standard forecast appraisal criteria, which are the mean absolute forecast error (MAFE) and the mean squared forecast error (MSFE). The two criteria are defined as follows:

$$MAFE = \frac{1}{n}\sum_{t=m+1}^{T} |\hat{y}_t - y_t|,$$

$$MSFE = \frac{1}{n}\sum_{t=m+1}^{T} (\hat{y}_t - y_t)^2 .$$

Table 4 reports the forecasting performance of the three models, with $m = 120$ and $n = 43$. The sentiment-based TAR model has the smallest MAFE and MSFE among the three models. Thus, our model beats both AR and martingale models in the out-of-sample forecast.

Table 4. Forecasting results

Model	*MAFE*	*MSFE*
TAR	8.095	108.36
AR	9.192	133.86
Martingale	9.117	131.79

To determine whether the sentiment-based TAR model performs better than the other two models, we apply the Diebold-Mariano (DM) statistic (Harvey, Leybourne and Newbold, 1997) to test the difference in MSFE and the difference in MAFE between the models. The p-value for the difference in the MSFE between the sentiment-based TAR model and the AR model is 0.088, while that between the sentiment-based TAR model and the martingale model is 0.029. Similarly, the corresponding p-value for the difference in the MAFE between the sentiment-based TAR model and the AR model (martingale model) is 0.108 (0.053). The results show that the sentiment based TAR model outperforms the other two models at the 10% significance level.

5. Conclusion

Investor sentiment is an apt portrayal of their perceptions about the market. Measuring investment sentiment and market state with high accuracy is an ongoing challenge to empirical researchers. Previous studies in the literature focus on investment sentiment in developed markets and only employ a single measure. This paper develops a principal component based sentiment index to measure investor sentiment in China. Our sentiment index is positively associated with market turnover, number of new investor accounts, change in industrial production, and money supply while negatively related to interest rate and exchange rate. A TAR model using the sentiment index as the threshold variable is estimated. Our results show that the Chinese stock market can be divided into three regimes: a high-return volatile regime, a low-return stable regime, and a neutral regime. The estimated TAR model is shown to have a higher predictive power compared to benchmark prediction models. For future research along this line, one may extend our single-threshold-variable model to incorporate multiple threshold variables (Chen, Chong and Bai, 2012). One can also develop a duration dependent Markov switching model (Maheu and McCurdy, 2000) with the transition probabilities conditioned on the sentiment index to classify market states.[10]

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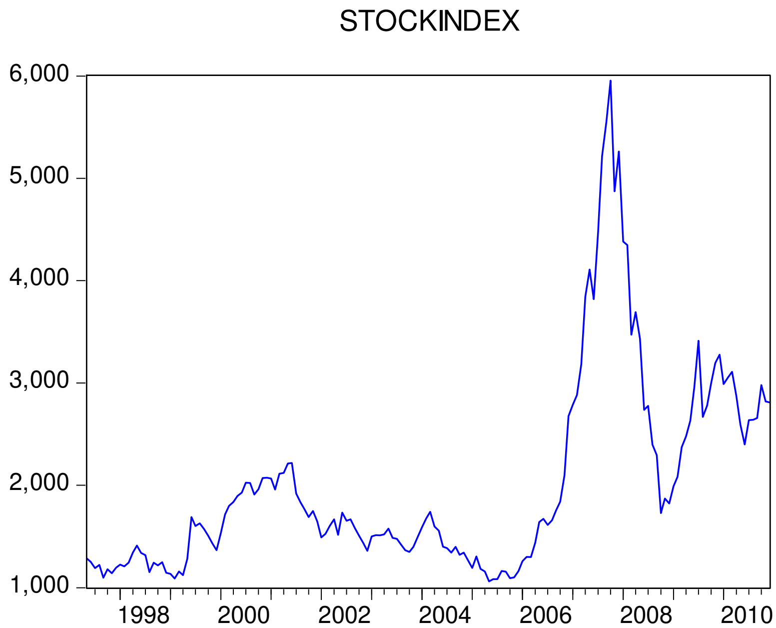

Figure 1. Shanghai Stock Exchange Composite Index

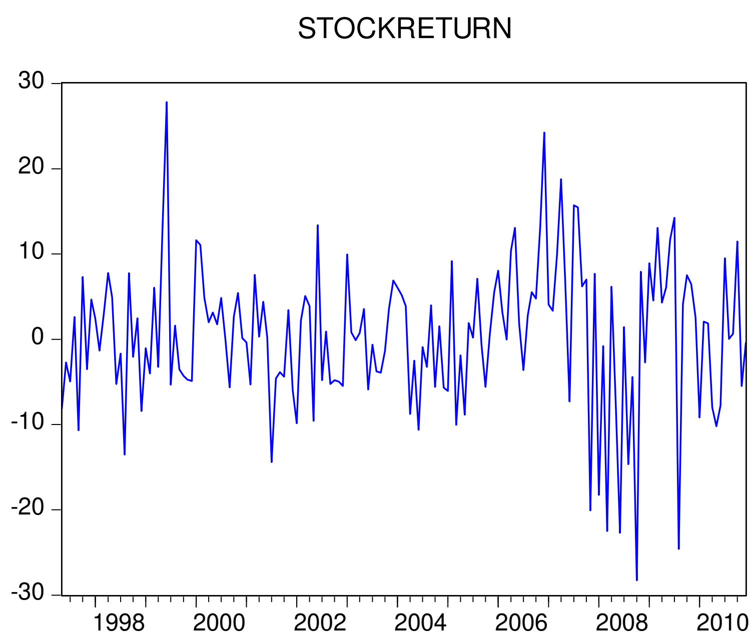

Figure 2. Return of Shanghai Stock Exchange Composite Index

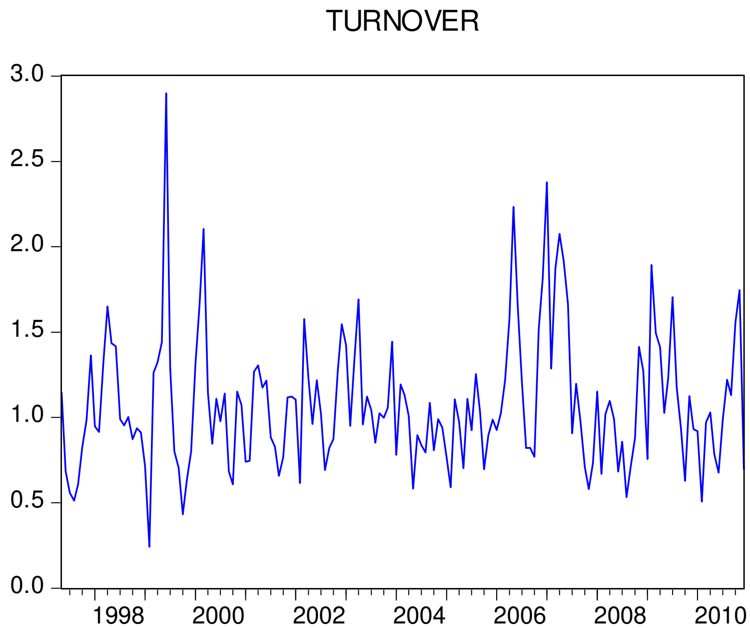

Figure 3. Market Turnover Ratio

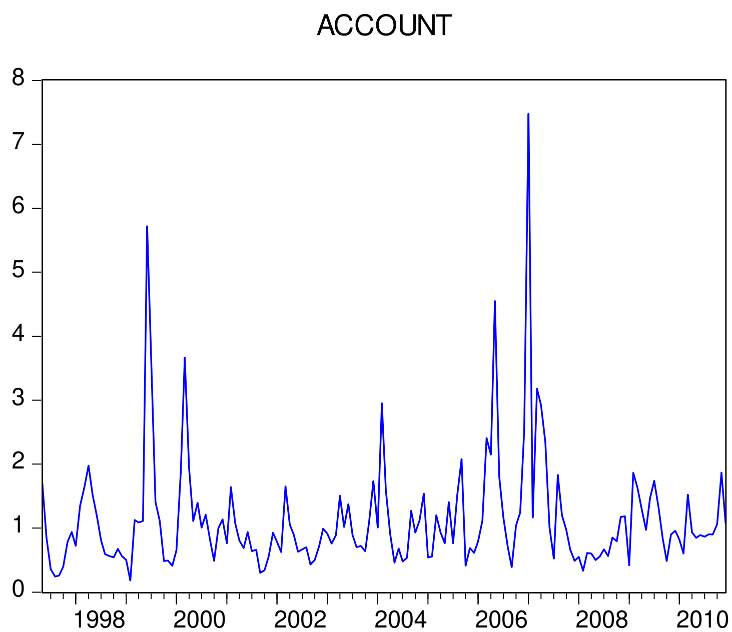

Figure 4. Ratio of Number of New Investor Accounts

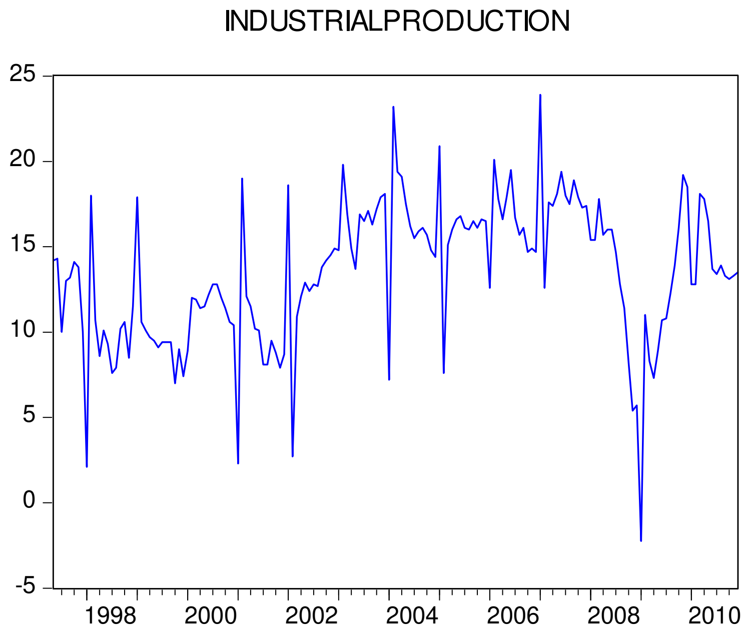

Figure 5. Change in Industrial Production

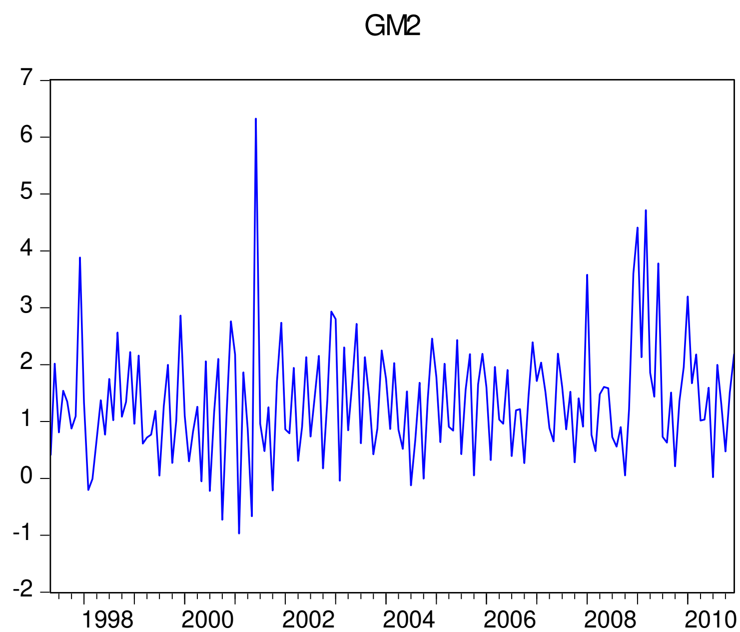

Figure 6. Change in Money Supply

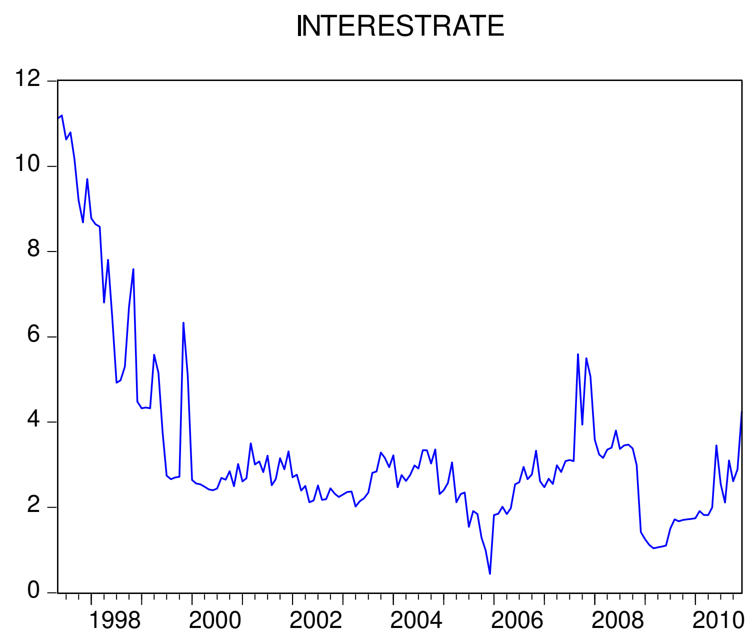

Figure 7. Interest Rate: 30-day National Interbank Offered Rate

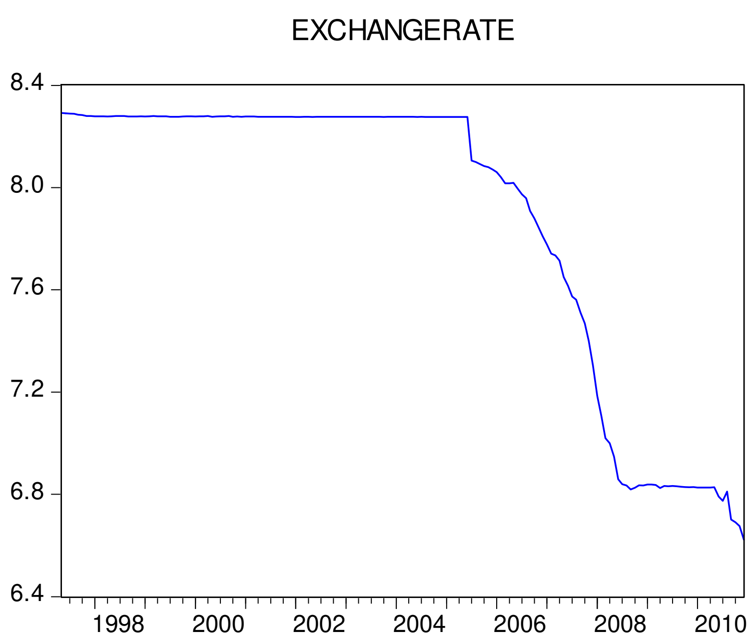

Figure 8. Exchange Rate: National Currency per USD

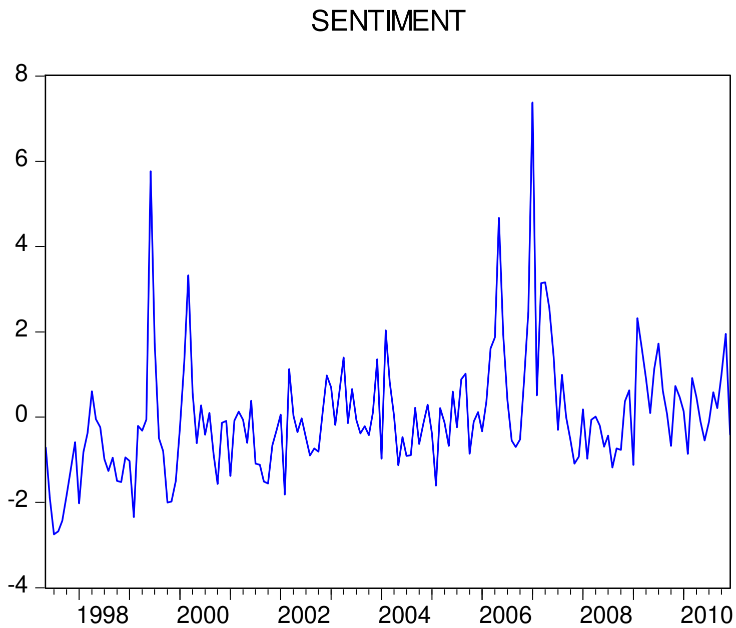

Figure 9. Investor Sentiment Index

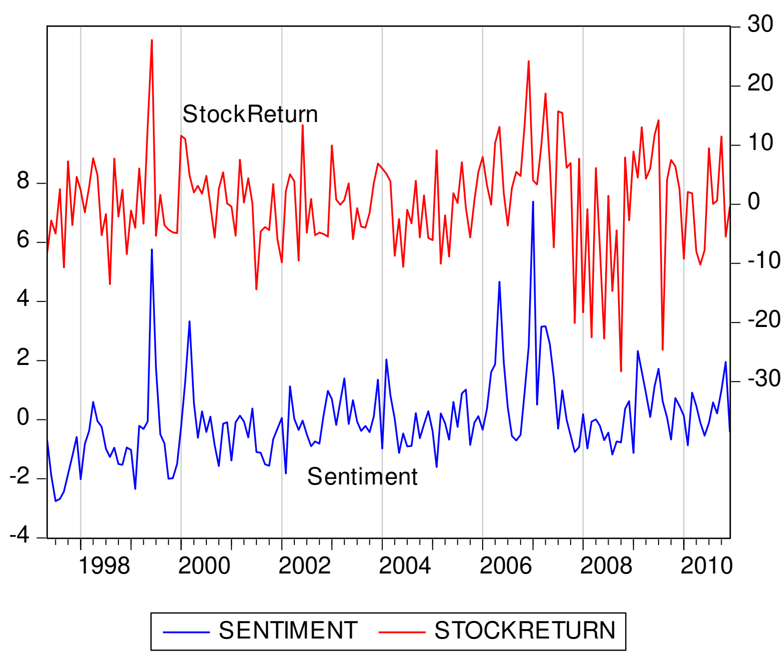

Figure 10. Comparison of Stock Return and Sentiment Index

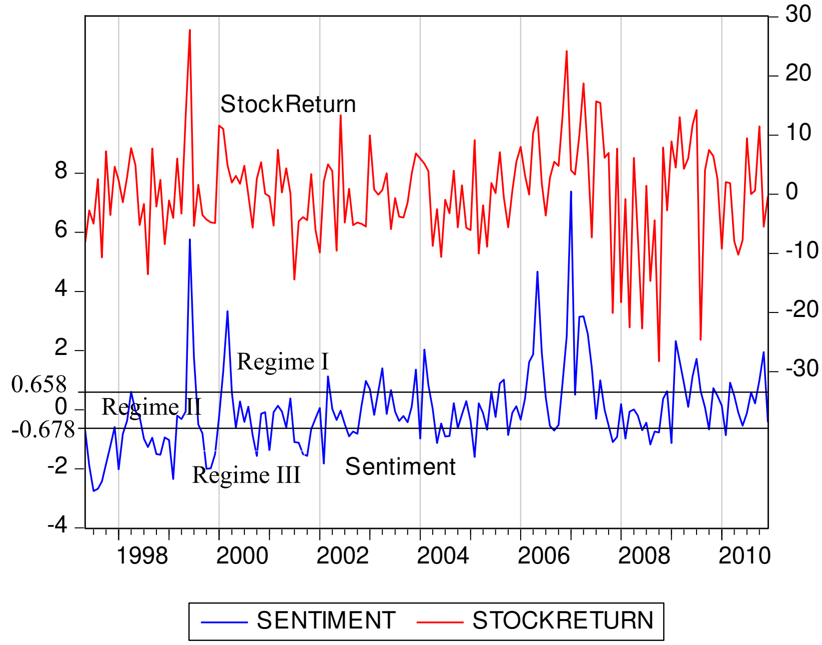

Figure 11. The Stock Market Regimes of China