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Can the Greater Fool Theory Explain Bubbles? Evidence from China

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20 August, 2018

Abstract

Many have noticed the phenomenon that naïve investors are attracted to the market as stock prices soar, yet few empirical studies have tested for this bubble phenomenon. This paper presents previously unused data on the aggregate number of newly opened brokerage accounts in China and tests the role of new investors in bubble formation. I find that new investors, attracted by soaring stock prices and the intensive trading activities of others, drove the Chinese stock market bubbles in 2007 and 2015, supporting the Greater Fool theory of bubbles. The inexperienced and naïve new investors appear more likely to be the “greater fools.” Using the residual orthogonalization method, I build a data-driven structural model system, where shocks from the new accounts variable explain 40-55% of Chinese stock return variation.

JEL classification: G1, G12, G41

Keywords: bubble, individual investors, volume, Chinese stock market

1 Introduction

“Insiders [who] destabilize by driving the price up and up, selling out at the top to the outsiders who buy at the top and sell out at the bottom...[T]he professional insiders initially destabilize by exaggerating the upswings and the falls, while the outsider amateurs who buy high and sell low are...the victim of euphoria, which infects them late in the day.”

— Charles Kindleberger (1978)¹

Numerous studies have described a similar scenario in history: overheated asset markets attracted naïve and inexperienced investors, even though it was widely believed that the prices were far higher than the discounted future cash flows. These new investors bought assets hoping to sell at higher prices to “greater fools,” suggesting the Greater Fool theory of bubbles. Eventually, when either all possible new investors have entered or some exogenous shocks hit the market,² bubbles burst. Although the same story has repeated itself over centuries and has been widely discussed among investors, few studies investigate the role of new investors in bubble formation.

Asset bubbles are broadly defined as asset prices persistently higher than the fundamental values for months or even years. One popular explanation

¹First cited by De Long, Shleifer, Summers, et al. (1990b)

²The government tried to control the bubble by increasing interest rates or implementing other restrictive measures, or smart and experienced investors sensed the limit and started to dump the assets.

of bubbles in behavioral finance is investors' irrational sentiments, such as animal spirit, overconfidence, and biases, which lead to herd behavior, momentum trading, trend chasing, and positive-feedback effects.³ Because of institutional limits, such as short-sale constraints, the high cost of arbitrage, and lack of coordination, rational and sophisticated traders cannot easily arbitrage and eradicate bubbles.⁴ Asset bubbles usually feature soaring trading volume, but the rational bubble theory fails to explain either the large trading volume or reasons for the existence of bubbles.

The dynamics of asset price and trading volume is explained by two key models. Building on Harrison and Kreps (1978), Scheinkman and Xiong (2003) and Hong, Scheinkman, and Xiong (2006) attributed trading volume to investors' heterogeneous beliefs on signals about the fundamental values of risky assets. They developed a similar version of the Greater Fool theory called the Resale Option theory, which states that, with short sales constraints, risky assets are overpriced because optimists are willing to buy assets at prices higher than their optimistic belief about fundamental, because they hope to resell the assets to even more optimistic investors in the future. Barberis, Greenwood, et al. (2018) argued that the past rapid growth of risky asset prices attracts extrapolators, or positive-feedback investors, to buy overpriced assets from fundamental investors and then trade with other extrapolators to realize profits and to reenter the market. Both models at-

³See Shiller (1981), Lux (1995), De Long, Shleifer, Summers, et al. (1990b), De Long, Shleifer, Summers, et al. (1990a), Daniel, Hirshleifer, and Subrahmanyam (1998), and Odean (1998).

⁴See Shleifer and Vishny (1990), Hong and J. Stein (2003), Hong and J. Stein (2007), Abreu and Brunnermeier (2003), and Ofek and Richardson (2003).

tribute large trading volume to disagreements, but disagreements are treated as exogenous shocks in the former model and as endogenous in the extrapolation process. Therefore, the causality directions are different in the two models. According to the Resale Option theory, exogenous disagreement shocks cause higher asset prices and trading volume at the same time, and in extrapolation, good news increases asset prices, which attracts extrapolators and then drives up trading volume. In this paper, I empirically test the causality implications of these two models and measure the contribution of extrapolators (or optimists, positive-feedback investors, or individual retail investors) to bubbles.

Moreover, most theories of bubbles assume that irrational or “noise” investors constitute a fixed percentage of the asset trading participants, but this is not a sound assumption because an indisputably large number of inexperienced individual investors usually enter the market during bubble expansion periods. This phenomenon not only happens in emerging markets (Xiong and Yu, 2011), but also existed in advanced countries⁵, especially during the recent housing bubble in the United States (Bayer, Mangum, and Roberts, 2016 and DeFusco, Nathanson, and Zwick, 2017). However, empirical studies often simply measure individual company returns or trading anomalies, which might be due to a lack of data. This paper uses a unique data set of the aggregate number of newly opened brokerage accounts in China, which

⁵A blog article of Zerohedge (<https://www.zerohedge.com/news/2017-04-22/last-time-happened-market-crashed>) described how retail investors rushed to open new brokerage accounts during the dotcom bubble. According to a survey of the Student Loan Report in 2018 (<https://studentloans.net/financial-aid-funding-cryptocurrency-investments/>), more than 20% of American college students have used student loans to buy cryptocurrencies.

is not available in many advanced countries, and provides empirical evidence for the Greater Fool theory in explaining asset bubbles.

The Greater Fool theory has existed as a conventional wisdom for ages, and its implication of contagious irrational speculation and bubble-riding behavior is similar to Shoeshine-boy theory, Survivor Investing, and Keynesian Beauty Contest Principle. Xiong and Yu (2011) examined a bubble in China's warrants market that occurred from 2005 to 2008, in which out-of-money warrants were traded heavily at substantially high prices. They found that bubble size positively correlated with trading volume and return volatility and negatively correlated with asset float. Yet they were puzzled about why this bubble lasted three years because some experimental studies suggested that naïve investors would learn from experience and then the belief divergence would attenuate quickly (Dufwenberg, Lindqvist, and Moore, 2005, Haruvy, Lahav, and Noussair, 2007 and Hussam, Porter, and Smith, 2008). One possible explanation they suggested is that a steady inflow of new investors sustained the bubble, despite the learning of previous investors. This hypothesis was supported by a case study in China (Gong, Pan, and Shi, 2016), that found that the inflow of new capital to trade BaoGang call warrant was positively correlated with the price. They found that new investors initiated and sustained the bubble and played a more important role than turnover, volatility, or market return.⁶ In an experimental paper, Xie and

⁶However, they suggested that the inflow of new investors was an exogenous shock; that is, new investors were not attracted by the bubble. They provided two types of evidence: investors started to rush into Baosteel warrant trading on the first day of its issuance, and when the bubble shrank, new investors were still flowing in. However, looking at a bigger picture, during their sample period of August 2005 to August 2006, the Chinese stock market started to enter the huge stock bubble of 2006–07. The corresponding annual

Zhang (2012) also confirmed the importance of the inflow of new investors. This paper contributes to the literature on bubbles by establishing the link between new investors and bubble formation in a bigger picture.

This paper analyses the impact of the inflow of new investors in the Chinese stock market bubble using a unique data set of aggregate newly opened brokerage accounts, which is not available in many advanced countries. It provides empirical evidence for the Greater Fool theory in explaining asset bubbles. Using the Granger causality test, I find that increasing stock returns and trading volume Granger led to an increase of new accounts, not only during bubble periods but also in other periods. This confirms the Greater Fool theory that naïve investors were attracted to the frenzied speculation by the surging stock prices and intensive trading activities of other investors. The causality from past stock returns to new accounts disappeared during the run-ups, and new investors were only driven by the trading volume, implying the psychological biases of individual investors or the contagion property of bubbles. By applying the residual orthogonalization method, I can disentangle the instantaneous dynamics between stock price, trading volume, and new accounts. During the sample period, new investors contributed to the stock price by trading frequently, while during the run-ups, trading volume pushed up the price by attracting new investors. Based on these data-driven structures, I build recursive structural models of errors, which explain 40-55%

growth rate of SHCI was 43%, so, unsurprisingly, investors were eager to trade warrants even on their first issuance day. As for why new investors were not intimidated by the declining prices, it is possible that new investors were attracted by the previous high returns of the warrants or of the whole asset market and hoped to take advantage of the low prices.

of Chinese stock return variations between 2003 and 2018.

The remaining parts of this paper are organized as follows. Section two briefly introduces the background of Chinese stock market bubbles and describes the structure and composition of the new datasets. Section three explains the methodology of residual orthogonalization, and section four presents the empirical results and implications. Section five places this study in the context of literature on bubbles, and concludes.

2 Background and Data Description

2.1 Chinese Stock Market Bubbles in 2007 and 2015

On December 19, 1990, and July 3, 1991, respectively, the Shanghai Stock Exchange and Shenzhen Stock Exchange opened. Starting from the base of an index of 100, the Shanghai Stock Exchange Composite Index (SHCI) reached its highest point of 6092 on October 16, 2007, as shown in Figure 1. Although the stock index followed along bullish and bearish movements, it often displayed high levels of volatility as in many other emerging markets, partly because of frequent changes in government regulations and policies. Some of these actions may have contributed to the bubbles and subsequent busts. An overview of the Chinese stock market is in Appendix A.

Based on the peaks and troughs of the SHCI index prices (see Table A.1 in Appendix A.1), the entire history of the Chinese stock market can

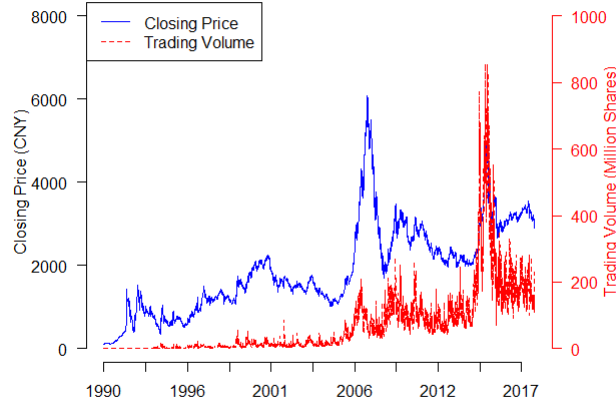


Figure 1: SHCI Price and Trading Volume during December 1990–May 2017

Source: the Shanghai Stock Exchange. This graph shows the price and trading volume of Shanghai Stock Exchange Composite Index from December 19 1990 to May 2 2017. Stock price surged and dropped dramatically in 2006–07 and 2015.

be divided into six periods, among which the bubbles and busts in 2006–2007 and 2014–2015 are most striking. In the boom of 2006–07, stock prices soared to nearly 500%, with an annualized growth rate of more than 100%. In contrast, the annualized return of the SP500 in 2006 was 15.8%. At the peak, the total market value for the Shanghai and Shenzhen stock exchanges hit CNY 21,000 billion, with a ratio of market value to GDP of more than 100%. The government took many actions to depress the bubble, but the market kept rising. Until November 2007, when the Political Bureau of the Communist Party of China Central committee made an announcement and many policies ensued, the SHCI declined from 6,000 to 2,000 and the sluggish decline lasted until 2014 (details in Appendix A.2).

In 2014, the SHCI increased 53%, ranking first in the global financial

market performance. Starting from 3,300 in January 2015, the SHCI price soared to 5,166 in five months and then collapsed to its original level in only two months. In the boom of 2014–2015, the stock return was 160%, about one-third the size of the previous bubble, but the trading volume was more than six times that of 2007, and its volatility was about four times larger. In 2015, the Chinese financial market seemed to have been on a roller coaster, and the instruments of leverage, such as margin trading and outside-the-stock-market margin financing, played a crucial part in the frenzy (details in Appendix A.3).

Can these Chinese stock market manias be considered as bubbles, or were they justified by fundamentals? According to classical definitions of bubbles, asset prices exceed the fundamental valuation of future cash flows for months or even years, accompanied by massive trading volume and speculation. Chinese stock market booms and busts meet these criteria. More discussions and graphs are provided in Appendix B.

2.2 The New Brokerage Accounts

2.2.1 Data from China Clear (Official)

The distinguishing feature of these booms was the large number of individual investors who moved their deposits from banks into the stock market, shown by the spike in newly opened brokerage accounts during the booms. In Figure 2, there is an obvious positive correlation between new accounts and stock

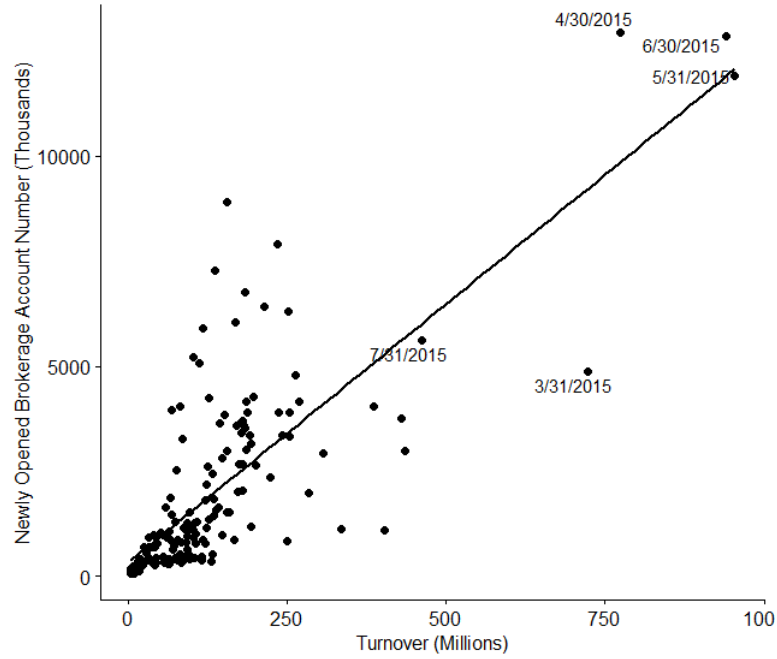


Figure 2: New Accounts and Index Price

Source: the Shanghai Stock Exchange; China Clear. This graph shows the relationship between new accounts and Shanghai Stock Exchange Composite Index price, during December 2003 - March 2017. Both new accounts and index price increased and dropped dramatically during 2006-07 and 2015.

prices.

The official data on new accounts are released in the weekly and monthly reports of the China Securities Depository and Clearing Corporation Limited (China Clear), whose shareholders are the Shanghai Stock Exchange and the Shenzhen Stock Exchange. China Clear started to release monthly reports beginning in January 2005. The total number of brokerage accounts is the sum of accounts for trading A shares, B shares, and closed mutual funds. They stopped reporting these data after June 2015 and started to release the “Newly Increased Investor Number” monthly starting in April 2015 and

weekly in May 2015. This account is called “Yimatong”, which can trade A shares, B shares, and closed mutual funds. The overlapping three months of monthly new account number data enables me to splice them together (details in Appendix C.1).

2.2.2 Data from EastMoney Database (Unofficial)

An unofficial database, EastMoney⁷ that reported weekly new brokerage accounts from January 7, 2008 to May 29, 2015, and China Clear began to release weekly new investor numbers starting on May 4, 2015. Again the overlapping four weeks enables me to put together a full set of weekly data (details in Appendix C.2, with a creditability check with monthly data). But because of the limited time period, these data only capture the latest surging number of new accounts during the 2014–2015 stock boom. This weekly data are used for a robustness check.

2.3 Composition of Accounts

The composition of brokerage accounts reveals many interesting facts about the Chinese stock market, although the data cover only a short period.

⁷<http://data.eastmoney.com/cjsj/yzgptj.html>

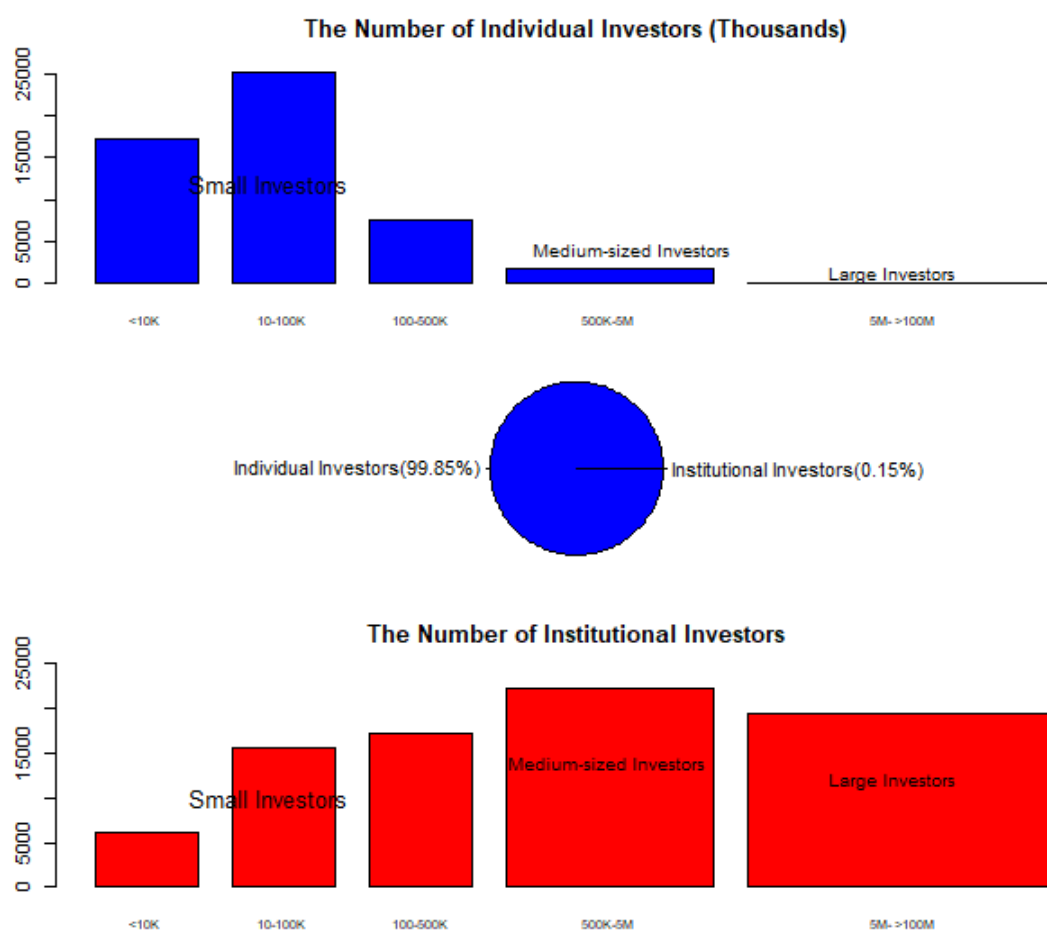


Figure 3: Share of Individual and Institutional Investors

Source: China Clear. The data are the average levels from June 2009 to February 2016.

2.3.1 Size

The data for accounts of different sizes were released quarterly in 2009 and 2010 and then monthly from 2011.⁸ Individual investors had more than 99.85% of total brokerage accounts in the Chinese stock market, as shown in Figure 3. More than 96% of accounts were held by individuals with stocks worthing less than CNY 500,000 (equivalent to about USD 73,000). About one third of total accounts belonged to people holding stocks worthing less than CNY 10,000 (equivalent to about USD 1,500). This proportion confirms that the majority of investors in the Chinese stock market are small individual investors.

We consider the brokerage accounts with balances less than CNY 500,000 small investors, accounts with balances between CNY 500,000 and CNY 5,000,000 medium-sized investors, and accounts with balances above CNY 5,000,000 large investors. The small investors constitute about 96.5% of individual accounts and the medium-sized investors less than 3%, while the large investors owned more than half of the market value at the peak of bubble in 2015 (see the calculation in Appendix C.3). As shown in Figure 4, the number of new medium-sized and large accounts closely followed the stock market movement, whereas the small accounts appeared not to follow the trend and even increased when market started to collapse. This might reflect the fact that those small account holders are usually inexperienced and new investors who do not have full access to the new information or do

⁸Again, since October 2014, they have counted Yimatong accounts, so my data are somewhat fragmented.

not have the ability to analyze information, as the medium-sized and large investors do. They are usually the “greater fools” who bought high-priced stocks from smart investors and could not find buyers.

2.3.2 Age

China Clear reported the age composition of brokerage accounts every six months from June 2007 to December 2010. The age composition of investors in the Chinese stock market was quite constant during the sample period. The average percentage for each group is calculated in Table 1. According to the age composition of the 2009 National Population Census of China, investors of ages ranging from 30 to 50 more actively participated in stock trading than investors of other ages.

	Under 20	20–30	30–40	40–50	50–60	above 60
Investors	0.42%	16.92%	30.38%	26.66%	15.73%	9.90%
Census	8.62%	16.84%	19.08%	21.14%	16.88%	17.44%

¹ Source: Chinese Statistical Yearbook 2009.

² I use the number of 15–19 years old to calculate “Under 20” for “Census.”

Table 1: Age Distribution of Brokerage Accounts and National Consensus

2.3.3 Active Account Number

China Clear has reported the number of accounts that held positive positions in A shares and traded A shares in the past year and month since June 2007 and January 2011, respectively. I calculate the ratio of active accounts to

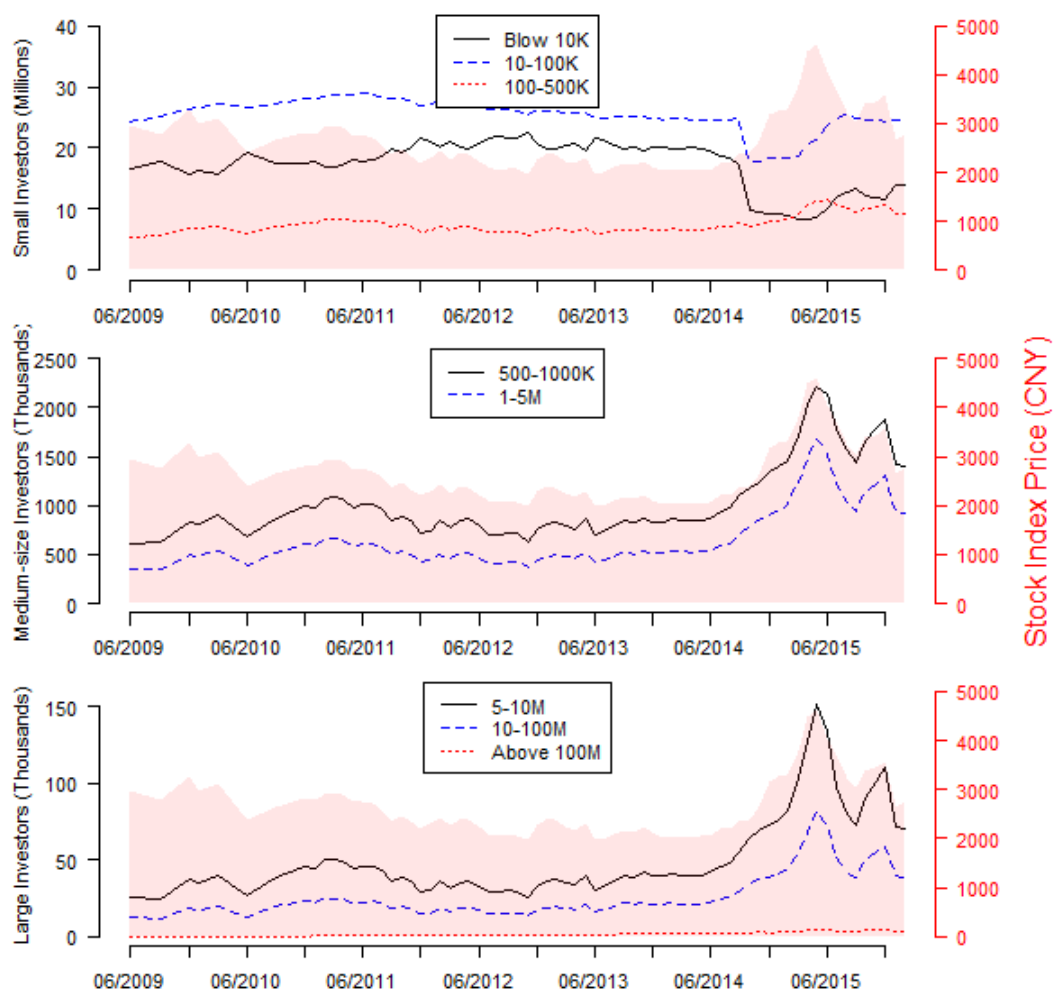


Figure 4: Number of Individual Investors of Different Account Sizes

Source: China Clear. This graph shows that individual investor accounts of different sizes behaved differently with the movement of the stock index. Note that small investor accounts are shown in millions, and medium-sized and large accounts are shown in thousands. Although small investors constitute more than 96.6% of total individual investor accounts, they did not follow the trend of stock prices as medium-sized and large investors did.

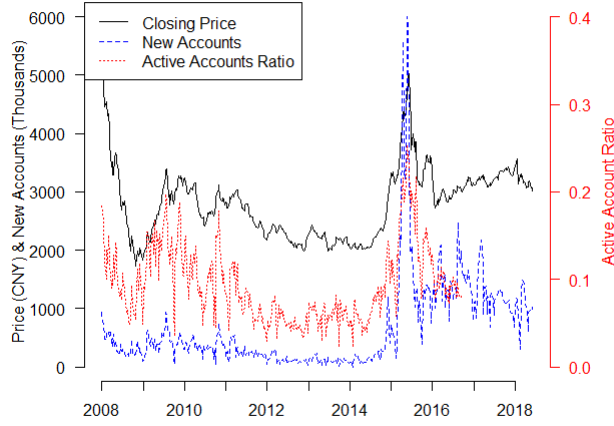


Figure 5: Active Account-to-Total Account Ratio with SHCI Price and New Accounts Number

Source: the Shanghai Stock Exchange; China Clear; EastMoney. This graph shows the ratio of the accounts that were active within the last one year to total accounts, compared with the SHCI price and new accounts. The sample period is June 2007–June 2018, and the ratio of accounts that were active within recent one month is available for January 2011–September 2016.

total accounts and plot it in Figure 5. There is an obvious upward trend of active account number during the run-up in 2014–2015. Investors tended to trade more during market booms and less during busts, which confirms the Greater Fool theory.

2.4 Description of Key Variables

I use the monthly data for the analyses in section four, and I use weekly data for the robustness check in Appendix E.

I collect the official monthly number of new accounts from the reports of

ENTIRE	Index Price	Turnover Rate	New Accounts
N=174	(CNY)	(Thousands)	(Thousands)
Min.	1,061	4	69
Max.	5,955	954	12,947
Mean	2,602	126	1,874
Std.	931	144	2,292

BUBBLES	Index Price	Turnover Rate	New Accounts
N=67	(CNY)	(Thousands)	(Thousands)
Min.	1,081	5	70
Max.	5,955	954	12,947
Mean	2,789	160	2,410
Std.	1,244	211	3,069

RUN-UPS	Index Price	Turnover Rate	New Accounts
N=47	(CNY)	(Thousands)	(Thousands)
Min.	1,081	5	70
Max.	5,955	954	12,947
Mean	2,565	162	2,441
Std.	1,300	237	3,553

* The entire period of monthly data is December 2003 to June 2018. The bubble periods cover June 2005 to November 2008 and January 2014 to January 2016. The run-up periods include June 2005 to October 2007 and January 2014 to June 2015. The unit of index price is CNY. The unit of turnover rate and new accounts is a thousand.

Table 2: Statistical Summary of Monthly Data

China Clear. The data are available from December 2003 to the present (June 2018). I collected the corresponding SHCI price and its monthly average trading volume from Shanghai Stock Exchange website. The monthly average turnover rate of the SSE is from the Qianzhan Database⁹ and is defined as trading volume divided by the number of outstanding shares. The basic statistical summary of the data is shown in Table 2.

MONTHLY	Corr(P,T)	Corr(N,P)	Corr(T,N)
ENTIRE	0.58	0.74	0.77
BUBBLES	0.49	0.73	0.77
RUN-UPS	0.57	0.82	0.77

* P represents the stock index price; T represents turnover; N represents the number of new accounts. The entire period of monthly data is December 2003 to June 2018. The bubble periods cover June 2005 to November 2008 and January 2014 to January 2016. The run-up periods include June 2005 to October 2007 and January 2014 to June 2015.

Table 3: The Correlations between Variables

To see the relationships between the stock index price, trading volume (proxied by turnover rate), and new accounts, I first examine their correlations for the entire period, bubble periods, and run-up periods. As shown in the Table 3, the stock index price and trading volume are highly correlated with the number of new accounts, our indicator of the entry of “fools,” with a correlation around 70% to 80%, which is even higher than that between price and trading volume. Although the correlations increased in the run-up, those in bubble periods slightly decreased.

⁹<http://d.qianzhan.com/>

3 Methodology

Testing the Greater Fool theory is equivalent to checking whether the boom in the asset market drew new investors into the speculative trading game and whether the entry of new investors reinforced the frenzy. Specifically, I test the causality direction among stock price, trading volume, and new investors by testing the Granger causality and instantaneous causality. I also use residual orthogonalization method to construct a data-driven structural model system to measure the extent to which the trading activities of new investors contributed to the stock bubbles in China. Weekly data are checked for robustness.

3.1 Granger Causality

A simple Granger causality test can show the correlation between two variables in successive periods. Specifically, a bivariate linear autoregressive model of X and Y , which is conducted for pairwise analysis for stock price, trading volume, and new investors, is shown below. The maximum number of lagged observations is twelve,¹⁰ because many studies used past-twelve-month observations for prediction. A , B , C , and D are coefficients of lagged observations, or the contribution of past values to the predicted value of X or Y . ϵ_t is the residual for each model. Whether Y Granger causes X can be checked by an F-test with the null hypothesis of $B = 0$.

¹⁰I also checked other numbers of lags and the results are similar.

$$X_t = \sum_{i=1}^{12} A_i X_{t-i} + \sum_{i=1}^{12} B_i Y_{t-i} + \epsilon_{1,t} \quad (1)$$

$$Y_t = \sum_{i=1}^{12} C_i X_{t-i} + \sum_{i=1}^{12} D_i Y_{t-i} + \epsilon_{2,t} \quad (2)$$

3.2 Residual Orthogonalization

To disentangle the instantaneous causality relationships between the variables of interest, I adopt the residual orthogonalization method from Swanson and Granger (1997) to build data-driven structural models of the errors in vector auto-regressions (VAR).

The first step is to construct a VAR model for variables (at the log level) and obtain residuals.¹¹ Assume a three-dimensional multiple time series x_t is generated by a stationary VAR(p) process:

$$x_t = \sum_{j=1}^p A_j x_{t-j} + u_t \quad (3)$$

where $x_t = (x_{1t}, x_{2t}, x_{3t})'$, $u_t = (u_{1t}, u_{2t}, u_{3t})'$, and u_t is a continuous random vector satisfying zero mean, nonsingular covariance, and orthogonal.

The second step is to calculate partial correlations of two variable resid-

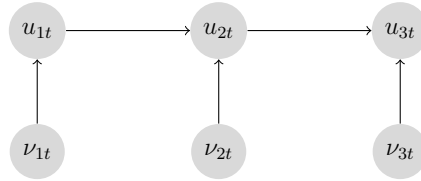
¹¹The model selection criterion I use is AIC, but using other criteria yields similar results.

uals conditioned on each other and test with the null hypothesis:

$$H_0 : \rho(u_{it}, u_{jt} | u_{kt}) = 0 \quad (4)$$

where i, j, and k are any permutations of 1, 2, and 3. If the null hypothesis cannot be rejected, then the zero partial correlation implies that the conditioned residual of the variable cuts the causal link between the other two.

The third step is to specify the causality direction by considering economic senses. After checking all partial correlations and referring to economic theories, a linear causal link can be drawn as follows.



The last step is to build recursive structural models and estimate them. A set of structural models can be built from the above linear causal link:

$$u_{1t} = \nu_{1t}, \quad u_{2t} = \beta_{21}\nu_{1t} + \nu_{2t},$$

$$\text{and } u_{3t} = \beta_{31}\nu_{1t} + \beta_{32}\nu_{2t} + \nu_{3t}$$

where ν_t are orthogonal underlying shocks to each variable. The results can be estimated by ordinary least squares.

4 Results

The Granger causality analysis shows that new investors were attracted to the Chinese stock market by both past returns and past trading volumes, which supports the Greater Fool theory and the positive-feedback effect (De Long, Shleifer, Summers, et al., 1990b). However, stock price is irrelevant to past trading volume, or vice versa, contrary to the assumptions of many behavior finance studies (e.g., Barberis, Greenwood, et al., 2018). According to the data-driven structural models, new investors pushed up stock prices by trading intensively, contributing 40% to 55% of the bubbles.

4.1 Why Did New Investors Enter the Market?

The Granger causality results on monthly and weekly data are summarized in Table D.1 and Table D.2 in Appendix D, and the implied causality directions are shown in Table 4. Across the entire sample period, increasing stock returns and trading volume in the previous periods were associated with an increase in new accounts, not the other way around. This confirms that the good performance of the stock market as well as the intensive trading activities of other investors attracted new investors to participate the speculation. Interestingly, new investors were no longer sensitive to past returns during the run-ups, contrary to the positive-feedback effect. In the context of the Chinese stock market, where more than 96% of investors are small individual investors, it is understandable that inexperienced and naive investors can be

easily affected by others' trading enthusiasm but might not be knowledgeable enough to analyze the price movement. Trading volume is a common proxy for investor sentiment, and my result confirms this assumption by connecting it to new investors.

Most importantly, the fact that the causality direction runs from stock price or trading volume to the entry of new investors, not the other way around, supports the Greater Fool theory. The number of new investors is not closely related to future returns, implying that these investors are the “greater fools.”

Entire Periods	$P \Rightarrow N \Leftarrow V$
Bubbles	$P \Rightarrow N \Leftarrow V$
Run-ups	$N \Leftarrow V$

* The entire period of monthly data is December 2003 to June 2018. The bubble periods cover June 2005 to November 2008, and January 2014 to January 2016. The run-up periods include June 2005 to October 2007 and January 2014 to June 2015.

Table 4: The Granger Causality Relationships

4.2 How Did New Investors Drive Bubbles?

In the Granger causality results, all variables have a highly significant instantaneous causality relationship with each other, which deserves deeper investigation.

Following Swanson and Granger (1997), I fit VAR models of variables and then obtain residuals. I calculate all the possible partial correlations for corresponding residuals, and list the values, test statistics, and corresponding p-values are listed in Table 5. N, P, and V are corresponding errors of new account number, stock index price, and trading volume (proxied by turnover rate). Three partial correlations are below 0.2, and one has a value of 0.21. Inspection of the P-values also shows that five partial correlations are statistically no different than 0. As implied by a simple three-variable causal model, exactly one partial correlation should be zero, and each case has one causal link.

Entire Periods				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t V_t)$	0.19	0.01	2.60	DNR
$\rho(N_t, V_t P_t)$	0.44	0.00	6.33	Reject
$\rho(P_t, V_t N_t)$	0.56	0.00	8.90	Reject
Bubbles				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t V_t)$	0.16	0.19	1.32	DNR
$\rho(N_t, V_t P_t)$	0.24	0.05	1.97	DNR
$\rho(P_t, V_t N_t)$	0.58	0.00	5.63	Reject
Run-ups				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t V_t)$	0.70	0.00	6.52	Reject
$\rho(N_t, V_t P_t)$	0.11	0.47	0.73	DNR
$\rho(P_t, V_t N_t)$	0.21	0.16	1.42	DNR

* DNR refers to "do not reject" the null hypothesis of zero partial correlation.

Table 5: Partial Correlations on Monthly Data

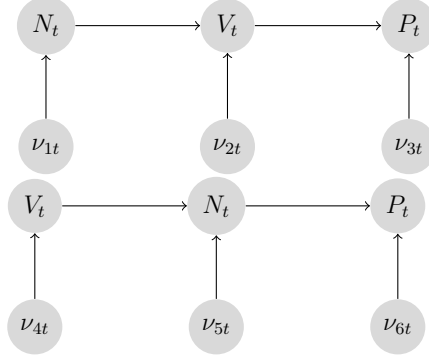


Figure 6: Instantaneous Causality Directions and Structure

* This graph summarizes the causality relations implied by the partial correlation results in Table 5. The first one presents the causality for the entire period and bubble period. The second one represents the case of the run-ups.

From the zero-valued $\rho(N_t, P_t|V_t)$, I determine that the causality is $N \Rightarrow T \Rightarrow P$, based on the common assumption in price-trading volume dynamics. For the case of the run-ups, $\rho(N_t, V_t|P_t)$ and $\rho(V_t, P_t|N_t)$ are both no different than zero, but for estimation purposes, I choose the causality direction of $V \Rightarrow N \Rightarrow P$. The causal directions are shown in Figure 6.

Intuitively, after new investors were attracted by soaring stock returns and others' trading enthusiasm as implied by the Granger test results, new investors started to trade intensively (a common characteristic of retail investors) and pushed up stock prices further. The reverse direction is also theoretically possible, but it is not plausible for an economic rationale. Many studies have provided evidence that stock prices can be pushed up by increased market liquidity, such as turnover rate, trading volume, and so on. Therefore, it is sensible to assert that the impact of new investors on stock prices is via trading volume, not the other way around.

During bubble formation periods, the causality pattern changed and trading volume contributed to the bubble by attracting more new investors.

4.3 How Much Did New Investors Contribute to Bubbles?

ENTIRE	Model 1	ν_{1t}	ν_{2t}	ν_{3t}	R-squares
$N_t = \nu_{1t}$		-	-	-	-
$V_t = \alpha_1 + \beta_1 \nu_{1t} + \nu_{2t}$		0.292***	-	-	12.18%
$P_t = \alpha_2 + \beta_2 \nu_{1t} + \beta_3 \nu_{2t} + \nu_{3t}$		0.067***	0.126***	-	40.01%
Reduced Form: $P_t = c_1 + 0.03N_t + 0.126V_t + \nu_{3t}$					
BUBBLES	Model 2	ν_{4t}	ν_{5t}	ν_{6t}	R-squares
$N_t = \nu_{4t}$		-	-	-	-
$V_t = \alpha_3 + \beta_4 \nu_{4t} + \nu_{5t}$		0.315***	-	-	15.71%
$P_t = \alpha_4 + \beta_5 \nu_{4t} + \beta_6 \nu_{5t} + \nu_{6t}$		0.071***	0.143***	-	40.88%
Reduced Form: $P_t = c_2 + 0.026N_t + 0.143V_t + \nu_{6t}$					
RUN-UPS	Model 3	ν_{7t}	ν_{8t}	ν_{9t}	R-squares
$V_t = \nu_{7t}$		-	-	-	-
$N_t = \alpha_5 + \beta_7 \nu_{7t} + \nu_{8t}$		0.762*	-	-	11.56%
$P_t = \alpha_6 + \beta_8 \nu_{7t} + \beta_9 \nu_{8t} + \nu_{9t}$		0.220***	0.181***	-	55.44%
Reduced Form: $P_t = c_3 + 0.181N_t + 0.082V_t + \nu_{9t}$					

* This table shows the results of estimation on structural models. Sample period is January 2004 to May 2018. N_t , V_t , and P_t represent the VAR errors of new account number, turnover rate, and monthly Shanghai Stock Exchange Composite Index price. ν_t proxies the exogenous shock to each variable.

* *** stands for $p < 0.01$; ** stands for $p < 0.05$; * stands for $p < 0.1$.

Table 6: The Estimation of the Structural Model System

The estimation results are listed in Table 6. All the coefficients in the structural system of errors are positive and highly statistically significant,

and the R-squares are decently large. During the entire sample period and in bubble periods, the shock to new accounts explains 12–15% of trading volume variation, and new accounts together with trading volume account for 40% of the variation in stock index returns. During the run-ups, they explain more than 55% of stock return variation.

After iterating and plugging in the estimators, I write the structural system of errors in reduced form, as summarized in Table 6. The impact of the same number of new investors on stock prices during the run-ups is five times that of other periods, while the impact of trading volume on price during the run-ups drops by more than one-third. This might suggest that the number of new accounts could be a better proxy for investor sentiment than trading volume, especially during bubble formation.

5 Conclusion

In the recent Chinese stock market bubbles of 2007 and 2015, the SHCI increased by more than 3,000 points within one year, with annualized returns of 114% and 96%, respectively. Accompanying the surging stock prices was a tremendous inflow of new investors, rushing to open brokerage accounts and to actively speculate. New investors were attracted by the bubble, and bought assets at high prices in the hope of selling at even higher prices to “greater fools.” This phenomenon, usually referred to as the greater fool theory, has been widely discussed among investors but seldom tested by

researchers in empirical studies.

Using unique data on the aggregate number of new brokerage accounts, this paper provides powerful evidence for the Greater Fool theory that (a) inexperienced and new investors are attracted by soaring stock prices and the frenzied trading activities of other investors, and that (b) they are likely to be the “greater fools” who suffered in the subsequent crash. One interesting find is that during the run-ups, new investors were not sensitive to past stock returns but still were attracted by the trading activities of others. This suggests contagions of investors discussed in behavior studies, especially the housing bubbles (e.g., Bayer, Mangum, and Roberts, [2016](#) and DeFusco, Nathanson, and Zwick, [2017](#)). This ignorance of past returns’ changes during the bubble formation period helps explain the unusual phenomenon shown in Figure 4, in which small investors kept entering the market even after the market started to crash. Further evidence of “greater fools” is that past returns or trading volumes were associated with the number of new accounts, but the number of accounts could not be used to predict future returns, suggesting cases in which new investors entered the market when the bubble was approaching the peak, and thus they bought high and had to sell low.

This paper also contributes to the literature on price-trading volume dynamics by introducing the role of new investors. Empirical studies identify high trading volume or turnover as a phenomenon associated with asset bubbles or speculation, and they use it as a proxy for investor sentiment (Baker and J. C. Stein, [2004](#); Barberis, Shleifer, and Vishny, [1998](#); Baker and Wur-

gler, 2007; De Long and Shleifer, 1991; Tetlock, 2007). This paper further provides evidence that the force behind high trading volume and turnover might be naïve and new investors were attracted by asset bubbles. They drive the bubble by trading frequently, which confirms the trading behavior of individual retail investors described by many studies (e.g., Kumar and Lee, 2006). Their participation can also be understood as showing “disagreement,” which drives up both trading volume and price, confirming the hypothesis of the disagreement model (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003). Last, my data-driven structural model system can explain 40% of Chinese stock return variation, and during the run-ups, its explanatory power increases to 55%.

The universality of the greater fool theory is undoubted, although I provide evidence from a market dominated by individual retail investors. The development of information technology enables individuals to participate in trading assets globally without barriers. The cryptocurrency boom and bust of 2017–2018 can be perfectly explained by the greater fool theory. The continuous and enormous inflow of new investors could be a good indicator to identify asset bubbles.

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Appendix A. Chinese Stock Market Overview

A.1 The Business Cycle of Chinese Stock Market

Table A.1 shows the broad measures of the market by identifying the peaks and troughs of the SHCI index prices since 1990. Based on the information in Table A.1, I divide the whole history into six periods as follows.

Status	Date	SHCI	Returns	Months	Std.P.	Std.V.
Beginning	12/19/1990	99.98	-	-	-	-
Peak	5/25/1992	1,422	1322%	18	151	0.01
Trough	11/17/1992	394	-72%	6	261	0.04
Peak	2/15/1993	1,537	290%	3	299	0.04
Trough	7/9/1994	334	-78%	17	248	0.8
Peak	9/13/1994	1,033	209%	2	153	4.4
Trough	1/22/1996	516	-50%	16	82	2.0
Peak	5/12/1997	1,500	191%	16	233	3.8
Trough	5/18/1999	1,060	-29%	24	81	2.38
Peak	6/13/2001	2,242	112%	25	265	8.16
Trough	6/7/2005	1,031	-54%	48	211	7.67
Peak	10/16/2007	6,092	491%	28	1,320	44.0
Trough	11/4/2008	1,707	-72%	13	1,212	18.85
Peak	8/31/2009	2,668	56%	10	472	40.07
Trough	1/20/2014	1,911	-25%	53	365	35.31
Peak	6/12/2015	5,166	159%	17	868	193.81
Trough	1/28/2016	2,656	-49%	7	436	149.69

* Source: the Shanghai Stock Exchange. I use SHCI closing price to calculate index return and standard deviation. The standard deviation of trading volume is calculated using the daily trading volume in Shanghai Stock Exchange.

Table A.1: Bull Market, Bear Market, Bubbles and Crashes

- Beginning Years: 1991–1995

In the 1990s, especially during the first half, the stock market demonstrated a high level of volatility and low trading volume, with modest variation as indicated by the standard deviation. In booms, the stock market grew 200–300%, and its standard deviation was as high as almost 300, however, the index remained below 2000.

- Bull Market: 1996–June 2001

The index price increased from 500 to more than 2000 in five years, with an annualized growth rate of 31.2%.

- Bear Market: June 2001–June 2005

This bear market lasted four years and the SHCI declined 18%.

- Bubble and Bust: June 2005–2008

In the boom of 2006–2007, the SHCI hit 6,000 and its growth rate was nearly 500% and its annualized growth rate was more than 100%. Although this might not be comparable with the previous booms, the volatility as measured by the standard deviations of both index price and trading volume was six to ten times larger than before.

- Bear Market: 2009–January 2014

This bear market lasted about five years and the SHCI dropped 6%. But the volatility of index price and trading volume were about two times and five times higher than those of the bear market in early 2000s, respectively.

- Bubble and Bust: January 2014–present

In the 2014–2015 boom, the relative price change was not as dramatic as in 2007, and the volatility of prices was about two-thirds of the previous period, but the trading volume variation was more than four times of that in 2007.

Policies and regulations changes Although the stock market followed long bullish and bearish movements, it often displayed high levels of volatility because of frequent changes of government regulations and policies. Leading events and the corresponding index price changes are listed in the table [A.2](#).

Date	Key Regulatory Events	SHCI change/period
Dec. 19, 1990	Opening	-
May 21, 1992	SSE canceled upward circuit breaker	+105%/one day
Aug. 10, 1992	“810 Incident”	-52%/three months
Jul. 30, 1994	“Three Policies”	+33%/one day
May 18, 1995	The suspension of bond futures trading	+31%/one day
Dec. 16, 1996	“12 Gold Plaques”	-31%/ten days
May 19, 1999	“519 Event”	+4.64%/one day
Oct. 22, 2001	“Reducing State Share” policy suspended	+9.86%/one day

Table A.2: Key Events of Chinese Stock Market

On January 19, 1992, former President Deng Xiaoping started his famous southern tour of China, which was viewed by the public as a reassertion of his “Open Up” reform policy after his retirement from office. His encouragement of stock markets in the speeches precipitated the first bull market in China in 1992. The Shanghai Stock Exchange abandoned Upward Limit Circuit

Breaker since May 21, 1992,¹² and SHCI surged to 1266 from 617 on the same day. Some stocks such as the light industry machinery soared 470% in a day. It had become very popular to participate in the stock market.

In August 1992, 1.5 million investors rushed to Shenzhen, which had a resident population of only 0.6 million, to apply for IPO subscription lottery forms. At that time, to subscribe to IPO shares, you needed to buy an application form using your ID card to attend a lottery, where 10% of the subscribers won the rights to buy shares. The cost of one form was CNY 100 and one ID could buy a maximum of 10 forms. If you won the lottery, you could resell your right to buy in the secondary market and make CNY 10,000–20,000. By comparison, the monthly salary of a professor at a university in Shanghai was about CNY 400. Due to the limited number of the forms and the corruption, the stock market fever finally turned into a riot in August, the so called “810 Incident,”¹³ which directly led to the foundation of China Securities Regulatory Commission (CSRC) in October. These events led to the first bear market on both Shanghai and Shenzhen Stock Exchanges, with SHCI decreasing more than 50% within three months.

Hit by inflation, high interest rates, and the manipulation by large financial institutions, the stock market’s performance was not very satisfactory between 1993 and 1995. On July 30, 1994, People’s Daily, the most important official newspaper of Chinese Communist Party, announced the

¹²In the beginning year of the stock market, the trading volume was extremely low because of the scarcity and the unavailability of stocks, so this regulation change was intended to encourage trading. See <http://stock.hexun.com/2008-06-15/111113612.html>

¹³See <http://www.ftchinese.com/story/001042077?full=y>

implementation of the CSRC's "three policies" to stabilize the stock market. These policies were: (1) a suspension of new IPOs; (2) control on the watering of stock; and (3) encouragement of outside investors to enter the financial market. The market responded with a one-day 33% increase.

On May 18, 1995, the SHCI increased 31%, when trading in bond futures was suspended, which was not reopened until September 2013. The suspension was to remedy the loss of faith in the bond futures market caused by a crash in February. The huge amount of short-sell orders from Shanghai Wanguo Securities, the largest brokerage at that time, led to the market failure and later Shanghai Wanguo Securities' bankruptcy with a loss of more than CNY 5.6 billion.

In 1996, inflation declined, interest rates fell, and the stock market revived. But the CSRC was worried about speculation and manipulation, and announced eleven regulations to suppress the boom. However, the momentum was unstoppable, and by December, the SHCI reached 1,240, more than doubled its level in March. Finally on December 16, the twelve-th regulation, a 10% upper circuit breaker was imposed again and People's Daily published an article entitled: "Correctly Recognize the Current Stock Market." The market crashed, hitting the lower circuit breaker for successive four days. The SHCI fell 31% from its peak in ten days. These twelve policies were known among Chinese investors as "12 Gold Plaques", referring to a literary quotation about an ancient Chinese national hero Yue Fei.

In the first quarter of 1997, the SHCI again increased more than 50%.

Several new regulations were imposed, including an increase of the stamp tax on securities trading. When the Asian financial crisis hit, the central bank lowered its policy interest rate four times in 1997 and 1998, but the SHCI remained around 1200.

Sluggish conditions prevailed until May 19, 1999, when the Shanghai stock market suddenly jumped by 4.64% and many Internet and high-tech companies' stock price hit the upper circuit breaker. This dramatic and unexpected rise is called "519 Event." Some analysts argued that, this occurred because of the bullish international financial market and policies for industrial reform, for state-owned companies, and for promoting stock market development. Therefore, these optimistic expectations precipitated the "519 Event". The central bank lowered the interest rate on June 10 and officials from CSRC made optimistic comments, causing 64% increase of the SHCI over the next 40 days. Yet, on July 1st when the law of securities was officially enforced, the SHCI declined 7.61% and gradually dropped to 1345 by the end of 1999.

During 2000, the SHCI reached 2000 for the first time. The turning point was on June 12, 2001, when the state council announced the interim measures for the management of "Reducing Held State Shares and Raising Social Security Funds," the stock market started to tumble. The SHCI dropped 31.6%, and then on October 22nd when the State Council suspended the policy,¹⁴ the stock index jumped 9.86% on the next day. However, this did not halt the bear market and the SHCI continued to decline, dropping to nearly 1,000

¹⁴Details see <http://finance.sina.com.cn/focus/20ygyg/>

by June 2005.

A.2 Bubble in 2006-07

In late 2005 and early 2006, a bubble started. The SHCI reached 2000 again on November 20, 2006, rising 130% with trading volume up 333.24% in 2006. The distinguishing feature of this boom was the large number of individual investors who moved their deposits from banks into the stock market, with the growth rate of domestic saving deposits declining for the first time since June 2001.¹⁵

On January 4, 2007, the trading volume in Shanghai Stock Exchange surged to more than CNY 120 million for the first time, and the ratio of total securities market value to GDP rose more than 50%. In May, the SHCI reached 4,000, and CSRC tried to emphasize that there was no state guarantee, by issuing a statement that “investors should be responsible for their own investment.” Later in May, the central bank increased the interest rate and reserve requirement for banks, but the stock market kept rising. In the evening of May 29, Treasury Department suddenly announced an increase from 0.1% to 0.3% of stamp tax on securities trading. The SHCI then dropped 6.5% on May 30 and fell below 4,000 with a 15.33% loss in four days. But the market recovered soon and the total market value for Shanghai and Shenzhen stock exchanges hit CNY 21,000 billion, with a ratio of market value to GDP of more than 100%. The SHCI rose to 5,000 on August 23 and

¹⁵http://jjckb.xinhuanet.com/caijing/2007-07/19/content_58590.htm

then 6,000 on October 15, the day of the 17th Communist Party of China National Congress, hitting a historical highest point of 6124.04 the next day.

At the same time, CPI increased rapidly, and in October the inflation was 6.5%, the highest since 1996. On November 27, 2007, the Political Bureau of the Communist Party of China Central Committee announced an effort to limit inflation and to cool the overheating economy. A bear market followed. During the subsequent winter, an unprecedented snow storm struck the south China on January 16, and the bank reserve requirement ratio was raised to 0.5%, leading to a monthly decline of 17% of the SHCI. In the first quarter of 2008, rumors about several financial institutions trying to refinance caused the index dropping more than 40%, when on April 22 Treasury Department again suddenly announced a decrease in the stamp tax on securities trading from 0.3% to 0.1%. In the next two trading days, SHCI increased 4.15% and 9.29% and the trading volume rose 191.19%. However, central bank suddenly and strangely announced an increase in the bank reserve requirement ratio by 1% to 17.5% on June 7th Saturday. On the next trading day, SHCI declined 7.73% and thousands of stocks hit the lower limit circuit breaker. The SHCI collapsed to 2,000 in September, suffering a loss of 43.06%. On September 16, the central bank benchmark lending rate decreased 0.27%, but the market continued to be pessimistic. On September 19, the stamp tax orders were changed to charge only sell-side and China Central Huijin, a government-owned investment company, started to purchase the stocks of the three biggest state-owned banks. Because of these policies, SHCI increased more than 8% daily on the following trading days, and almost all the stock

prices hit the upper circuit breaker. Yet, in October the market crashed 25.63%, but the government failed to prevent.

The bearish market became an important factor for the social instability, so the government announced many rescue policies, for example, the famous “4000 billion investment plan,” which temporarily stimulated the stock market but also accumulated a considerable amount of debt as well as the “excess production capacity.”¹⁶ The policies pushed the market up during October 2008 – August 2009, but the market began a sluggish decline until 2014.

Date	Stock Exchange	Tax Rate	Which side
Jul. 1990	SZSE	0.6%	Sell-side
Nov. 1990	SZSE	0.6%	Both sides
Oct. 1991	SHSE	0.3%	Both sides
Oct. 1991	SZSE	0.3%	Both sides
May 1997	Both	0.5%	Both sides
Jun. 1998	Both	0.4%	Both sides
Jun. 1999	Both(B share only)	0.3%	Both sides
Nov. 2001	Both	0.2%	Both sides
Jan. 2005	Both	0.1%	Both sides
May 2007	Both	0.3%	Both sides
Apr. 2008	Both	0.1%	Both sides
Sep. 2008	Both	0.1%	Sell-side

Table A.3: Summary of the Stamp Tax Rates

¹⁶<http://finance.sina.com.cn/zl/china/2016-02-01/zl-ifxznzanm3927650.shtml>

A.3 Bubble in 2015

Starting from 3,300 points in January 2015, the SHCI price soared to 5,166 points in five months and then collapsed to its original level in only two months. In 2015, Chinese financial market seemed to have been on a roller coaster. The availability of leveraging instruments, such as margin trading and outside-the-stock-market margin financing, played a crucial part in the frenzy.

In 2014, SHCI increased 53%, ranking first in the global financial market performance. Fueling this growth was margin financing, which became very popular among investors. In margin finance, investors borrow from financing companies based on the market value of their securities and pay interest. But if the market value drops to certain level, the financing company has the right to close the position of the borrowers, and the borrowers should take the loss. If they borrow from a brokerage or security company, it is called margin trading. If they borrow from outside, mainly from trust companies or “Internet financial companies.” It is relatively riskier because a brokerage or security company requires customers possessing equities worthing more than CNY 500,000 and the leveraging ratio less than 100%. The major risk comes from so called “internet financial companies”.

From late 2014 to May 2015, SHCI more than doubled its level and reached 5,166 points on June 12. Although during this period, the CSRC raised the required equities for margin trading and prohibited the security companies to sell umbrella trusts that provides a form of margin financing.

Yet, new money continued to rush to the market and pushed up the prices even higher. On June 12, the CSRC finally started to take action to close some illegal margin financing accounts, cutting off more money and new entrants to the market. The high level of stock prices were not sustainable, and the collapse led to wide-spread mandatory liquidation, resulting in a further drop of margin accounts. One-third of the stock market value was lost within one month, and major aftershocks occurred around July 27th and August 24th, so called “Black Monday.”

The government tried to rescue the market, but the efforts were not effective. On July 6, 2015, China Securities Finance Corporation Limited (CSF), a state-owned financial institution aiming to facilitate the margin transactions of securities companies in China¹⁷ and a member of so called the “National Team”, started to intervene the market with funding supported by the state-owned commercial banks. Goldman Sachs estimated that the funding used by the CSF and Huijin for market intervention from June to November was CNY 1,800 billion and owned 6% of the whole stock market in China.¹⁸ At beginning, the “National Team” focused on buying the stocks of commercial banks, securities companies, energy companies, and other large companies, attempting to maintain the price stability. However, this strategy soon became ineffective because it was easily predicted by the public. Take Petro China for an example, it was commonly viewed as a target company to be rescued by the “National Team”, but when investors noticed that its

¹⁷ [http : //www.csf.com.cn/publish/english/1071/1076/index.html](http://www.csf.com.cn/publish/english/1071/1076/index.html)

¹⁸ [http : //www.ft.com/intl/cms/s/0/7515f06c - 939d - 11e5 - 9e3e - eb48769cecab.html](http://www.ft.com/intl/cms/s/0/7515f06c-939d-11e5-9e3e-eb48769cecab.html)

stock price dropped substantially, they believed that the Chinese government had given up the rescue plan and was selling the stock. This change of belief directly led to a 9.6% decline of the price of Petro China and a 8.5% drop of SHCI.¹⁹ The rescue plan conducted by the Chinese government is very controversial, and many Chinese economists were against it. They argued that there were no evidence of systematic risk and the direct market intervention would cause market distortion, corruption, and other problems.²⁰ Soon, several senior government officials in CSRC were under investigation due to corruption and violation of disciplines.

Along with the actions of “National Team”, CSRC also investigated and closed illegal financing companies and strengthened regulations of the margin finance accounts and instruments. This effectively controlled the level of leveraging in the Chinese stock market, but some investors argued that margin trading is necessary in capital market and asked for supports.

¹⁹<http://cn.wsj.com/big5/20160114/mkt111855.asp>

²⁰<http://cn.nytimes.com/business/20150915/c15sino-stock/dual/>

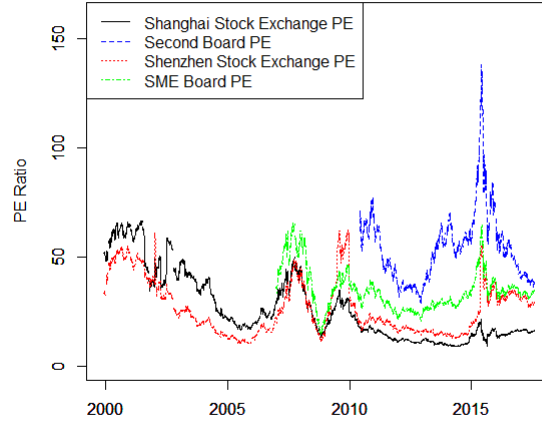


Figure B.1: PE Ratio in Different Exchanges and Boards

* Source: Shanghai and Shenzhen Stock Exchange. This graph presents the P/E ratios in Shanghai Stock Exchange, Shenzhen Stock Exchange, Second Board, and Small-medium Enterprise Composite Index during December 1999 – December 2017.

Appendix B. Bubbles v.s. Fundamental

To justify the existence of bubbles, I compare the stock prices with the P/E ratio in different exchanges, the ratio of market capitalization over GDP, and the leverage ratio.

In Figure B.1, I take the Shanghai Stock Exchange Composite Index as benchmark, and its PE ratio reached a peak of 42 during 2007 but did not increase much during 2015. However, for the Shenzhen Stock Exchange and its second board as well as the SME board, prices and PE ratios were more volatile. Particularly, the PE ratio of the Second Board soared to 140 in 2015, implying the existence of stock market bubble in 2015. Admittedly,

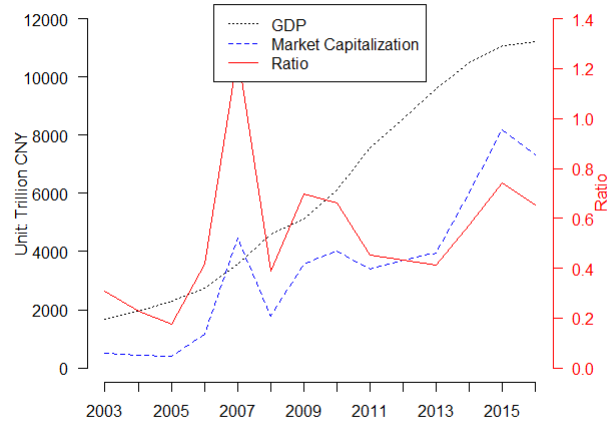


Figure B.2: Ratio of Market Capitalization/GDP

* Source: World Bank. This graph presents the ratio of market capitalization to the GDP, along with the GDP and the market capitalization values during 2003 – 2016.

PE ratio may fluctuate with cyclical profit margins.

The ratio of market capitalization over GDP is a more reasonable measure for market valuation than the P/E ratio, because it eliminates the variation of profit margins. Usually the ratio of total market capitalization to GDP should not exceed 1, but it was violated in 2007, suggesting a bubble in 2007 (See Figure B.2).

In Figure B.3, the stock market boom and bust in 2015 were closely associated with leverage, measured by the outstanding balance of margin trade in Chinese stock market. This implies that the participation of speculation fueled the stock market fever.

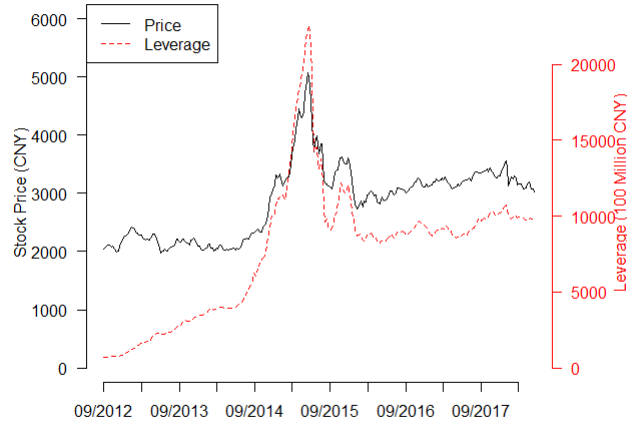


Figure B.3: Stock Price v.s. Leverage

* Source: Shanghai Stock Exchange; Bloomberg. This graph shows the prices of Shanghai Stock Exchange Composite Index and its outstanding balance of margin transaction during September 2012 – June 2018.

Appendix C. New Brokerage Account Data

C.1 Monthly data adjustment

China Clear started to release monthly reports beginning in January 2005. They ended reporting this data after June 2015, because of the security brokerage account reform in October 2014, which promotes Yimatong accounts and combines investors' accounts for trading A shares, B shares, mutual funds, and derivatives.²¹ They started to release the monthly “Newly Increased Investor Number” since April 2015 and weekly since May 2015, which is the increased number of Yimatong accounts.

²¹<http://finance.sina.com.cn/stock/stocklearnclass/20141008/165520483402.shtml>

The overlapping three months of monthly new account number data enables me to splice them together. As shown in ??, I calculate the ratio of account number to investors number, which is around 2.7. This means that each investor has 2.7 trading accounts on average, so if this ratio is held constant, then I can estimate new accounts per month from July 2015 till the present. One thing tricky about the released data is that in June 2015 the Chinese stock market reached the highest point and started to crash, and in July China Clear stopped releasing new accounts. This break makes it difficult to compare the account numbers. By using the new investor number, there is still a dramatic drop in new accounts.

	March	April	May	June	July
New Account	486.89	1294.73	1190.69	1285.54	-
New Investor	-	497.53	415.87	464.22	204.87
Account/Investor	-	2.60	2.86	2.75	-

Table C.1: Overlapping Period of New Accounts and New Investors

C.2 Weekly Data Adjustment

As shown in Table C.2, the ratio of new accounts to new investors is relatively stable with an average of 2.9. So if I hold the ratio constant, I can create a weekly new account series from 2008 to the present. The dramatic drop on May 8 2015 maybe because of the data splicing shown in table C.2. Nevertheless, the co-movement still exists in the following weeks.

To check the creditability of the unofficial weekly data, I sum up the

	5/1	5/8	5/15	5/22	5/29	6/5
New Account	295.42	245.38	238.71	263.07	443.53	-
New Investor	-	82.07	79.7	89.66	164.44	149.91
Account/Investor	-	2.99	2.99	2.93	2.70	-

Table C.2: Overlapping Period of New Accounts and New Investors

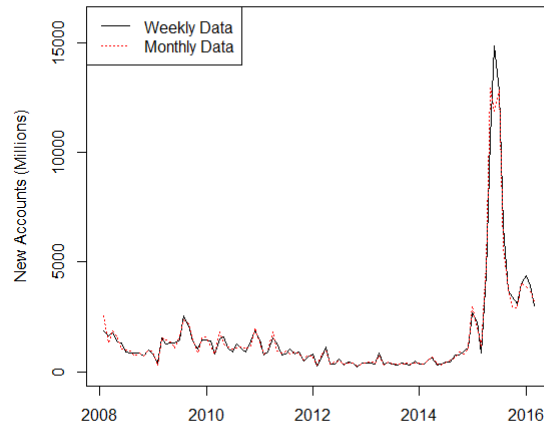


Figure C.1: Comparison of Weekly and Monthly Data

* Source: China Clear; EastMoney. This graph presents the comparison of weekly and monthly new accounts number during January 2008 – February 2016. There is not much difference between the data from two sources.

weekly account number in every month to create a monthly data set and compare it with the official monthly data. It is clear in Figure C.1 that the two sets of data match well, except for the peak time in May 2015. The simple correlation between them is 98.25%.

C.3 Investor Types and Estimated Investment Size

Unfortunately, I do not know the inflows of investments by each of the size groups. As a rough approximation, the total balance of their accounts at the market peak are estimated as follows, using the mid-points of the range. For below CNY 10,000 and above CNY 100 million, I use CNY 5,000 and CNY 200 million for simplicity. May 2015 was the peak of last stock market boom, and the monthly average CNY/USD exchange rate was 6.2. To give an idea of account size, CNY 10,000 was about USD 1,613, and CNY 100 million was equivalent to USD 16 million.

As shown in Table C.3, although small investors' accounts were more than 90% of total accounts in 2015, at the market peak the number of median-sized and large investors increased disproportionately. At the peak, large investors owned almost half of total value, medium-sized investors with 32% and small investors with 22%. The newly entered money in the bubble peak month were disproportionately from large investors. If considering the possible downward bias that I use CNY 200 million as the average size of "above 100M" accounts, the contribution percentage of large investors would be even larger. When looking at accounts of different sizes, I find that accounts with balance more than CNY 1 million contributed to the bubble peak more aggressively than small investors.

	Small Investors			Medium-sized Investors		Large Investors		
	Below 10K	10-100K	100-500K	500-1000K	1-5M	5-10M	10-100M	Above 100M
Total Acc.	8718	21374	11277	2224	1694	155	93	15
Pct.	19.1%	46.9%	24.8%	4.9%	3.7%	0.3%	0.2%	0.03%
Pct.Sum		90.8%			8.6%			0.6%
New Acc.	382	769	522	185	204	25	15	1.7
Pct.	18.2%	36.6%	24.8%	8.8%	9.7%	1.2%	0.7%	0.08%
Pct.Sum		79.5%			18.5%			2.0%
Total Value	44	1,176	3,383	1,668	5,081	1,165	5,135	2,996
Pct.	0.21%	5.7%	16.4%	8.1%	24.6%	5.6%	24.9%	14.5%
Pct.Sum		22.3%			32.7%			45.0%
New Value	2	42	156	139	612	184	847	342
Pct.	0.08%	1.8%	6.7%	6.0%	26.3%	7.9%	36.5%	14.7%
Pct.Sum		8.6%			32.3%			59.1%

¹ Total Acc. refers to the number of total accounts of different sizes, and the unit is thousand. Pct. and Pct.Sum refer to the percentage share of each account size and each category of investors.

² New Acc. refers to the account number increased in 2015 May.

³ Total Value refers to the total value of account balance, calculated by multiplying total account number to mid-point value of each account size. I use 5,000 and 200 million as the mid-point value of "below 10K" and "Above 100M". The unit is trillion CNY.

⁴ New Value calculates the total balance of the accounts newly opened in 2015 May. The unit is trillion CNY.

Table C.3: Account Number and Value of Different Size Investors in 2015 May

Appendix D. Granger Causality Tests

The Granger causality tests results are listed in Table D.1 and Table D.2.

ALL	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.38	DNR
	Index Return doesn't Granger cause New Account	0.00	Reject
	Index Return doesn't Granger cause Turnover Rate	0.06	DNR
	Turnover Rate doesn't Granger cause Index Return	0.80	DNR
	New Account doesn't Granger cause Turnover Rate	0.71	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	Reject
BUBBLES	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.14	DNR
	Index Return doesn't Granger cause New Account	0.00	Reject
	Index Return doesn't Granger cause Turnover Rate	0.79	DNR
	Turnover Rate doesn't Granger cause Index Return	0.84	DNR
	New Account doesn't Granger cause Turnover Rate	0.25	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	Reject
RUN-UPS	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.44	DNR
	Index Return doesn't Granger cause New Account	0.64	DNR
	Index Return doesn't Granger cause Turnover Rate	0.28	DNR
	Turnover Rate doesn't Granger cause Index Return	0.21	DNR
	New Account doesn't Granger cause Turnover Rate	0.97	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	Reject

* DNR refers to "do not reject."

Table D.1: Granger Causality Tests on Monthly Data

ALL	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.58	DNR
	Index Return doesn't Granger cause New Account	0.00	Reject
	Index Return doesn't Granger cause Turnover Rate	0.81	DNR
	Turnover Rate doesn't Granger cause Index Return	0.00	Reject
	New Account doesn't Granger cause Turnover Rate	0.31	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	Reject
BUBBLES	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.90	DNR
	Index Return doesn't Granger cause New Account	0.14	DNR
	Index Return doesn't Granger cause Turnover Rate	0.95	DNR
	Turnover Rate doesn't Granger cause Index Return	0.00	Reject
	New Account doesn't Granger cause Turnover Rate	0.23	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	Reject
RUN-UPS	Null Hypotheses	P-value	Conclusion
	New Account doesn't Granger cause Index Return	0.51	DNR
	Index Return doesn't Granger cause New Account	0.10	DNR
	Index Return doesn't Granger cause Turnover Rate	0.22	DNR
	Turnover Rate doesn't Granger cause Index Return	0.00	Reject
	New Account doesn't Granger cause Turnover Rate	0.19	DNR
	Turnover Rate doesn't Granger cause New Account	0.00	Reject

* DNR refers to "do not reject."

Table D.2: Granger Causality Tests on Weekly Data

Appendix E. Robustness Check on Weekly Data

For weekly data analysis, I use the weekly number of new accounts and the ratio of active accounts to total accounts, collected from the database EastMoney and China Clear. The data are available from January 11, 2008 to the present (June 2018). The corresponding SHCI price and its turnover rate are from the same source. The basic statistical summary of data is shown in Table E.1.

For weekly data, all the correlations dramatically increased during bubble period, especially during the run-up.

There are 530 observations for each variable. All variables are at the log level. I fit VAR model for each variable and get corresponding residuals. N , P , and V are corresponding errors of new account number, stock index price, and trading volume (proxied by turnover rate). There are three partial correlations below 0.2 in Table E.4. Inspection of the P-values also shows that four partial correlations are statistically no different than 0. As implied by a simple three-variable causal model, exactly one partial correlations should be zero, and each case has one causal link.

The causal directions are shown in Figure E.1. The causality relationships in sample period and bubble period are the same as in the weekly data. During the run-up, the causality pattern changed and trading volume pushed up prices, which attracted more new investors. There is no implication on stock price, probably because the data interval is too short.

ENTIRE	Index Price	Turnover	New Accounts	Active Accounts
N=530	(CNY)	(Thousands)	(Thousands)	(Percentage)
Min.	1730	23	16	2
Max.	5420	1233	4435	25
Mean	2804	167	501	9
Std.	613	156	569	4
BUBBLE	Index Price	Turnover	New Accounts	Active Accounts
N=105	(CNY)	(Thousands)	(Thousands)	(Percentage)
Min.	2013	52	16	2
Max.	5074	1233	4435	25
Mean	2991	337	791	11
Std.	835	265	974	6
RUN-UP	Index Price	Turnover	New Accounts	Active Accounts
N=73	(CNY)	(Thousands)	(Thousands)	(Percentage)
Min.	2013	52	16	2
Max.	5074	1233	4435	25
Mean	2741	299	693	10
Std.	845	287	1120	6

* The weekly data are from January 2008 to June 2018. The bubble period covers January 2014–January 2016. The run-up period includes January 2014–June 2015. The unit of index price is CNY. The unit of turnover rate and new accounts is a thousand. The active account ratio is shown in percentage.

Table E.1: Statistical Summary of Weekly Data

WEEKLY	Corr(P,T)	Corr(N,P)	Corr(T,N)
ENTIRE	0.65	0.69	0.81
BUBBLE	0.90	0.85	0.88
RUN-UP	0.95	0.90	0.92

* P represents stock index price; T represents turnover; N represents the number of new accounts. The period of weekly data is January 11, 2008–June 15, 2018. The bubble period covers January 2014–January 2016. The run-up period includes January 2014–June 2015.

Table E.2: The Correlations between Variables

Entire Periods	$P \Rightarrow N \Leftarrow V \Rightarrow P$
Bubbles	$P \Leftarrow V \Rightarrow N$
Run-ups	$P \Leftarrow V \Rightarrow N$

* The period of weekly data is January 11, 2008–June 15, 2018. The bubble period covers January 2014–January 2016. The run-up period covers January 2014–June 2015.

Table E.3: The Granger Causality Relationships

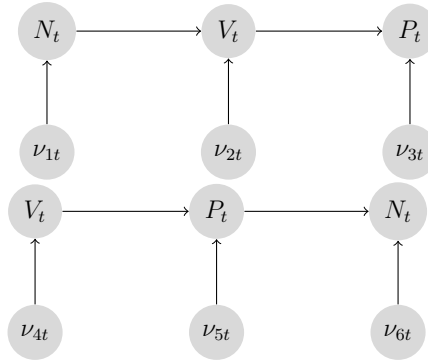


Figure E.1: Instantaneous Causality Directions and Structure

* This graph summarizes the causality relations implied by the partial correlation results in Table 5. The first one presents the causality for entire period and bubble period. The second one represents the case of the run-ups.

ENTIRE				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t V_t)$	0.07	0.12	1.55	DNR
$\rho(N_t, V_t P_t)$	0.18	0.00	4.24	Reject
$\rho(P_t, V_t N_t)$	0.39	0.00	9.73	Reject
BUBBLES				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t V_t)$	0.15	0.14	1.50	DNR
$\rho(N_t, V_t P_t)$	0.18	0.06	1.87	DNR
$\rho(P_t, V_t N_t)$	0.35	0.00	3.78	Reject
RUN-UPS				
Partial correlations	Values	P-value	Test statistics	Decision
$\rho(N_t, P_t V_t)$	0.27	0.02	2.37	Reject
$\rho(N_t, V_t P_t)$	-0.08	0.49	-0.70	DNR
$\rho(P_t, V_t N_t)$	0.38	0.00	3.48	Reject

* DNR refers to "do not reject" the null hypothesis of zero partial correlation.

Table E.4: Partial Correlations on Weekly Data

The estimation results are listed in Table [E.5](#). All the coefficients in the structural system of errors are positive and highly statistically significant, but the R-squares are not as large as in the monthly data case. During the entire sample period and bubble period, the shock to new accounts explained 5% of trading volume variation, and new accounts together with trading volume accounted for about 16% of variation in stock index return. During the run-ups, trading volume alone explained 13% of stock price variation, and price and trading volume together explained 13% of new accounts. By iterating and plugging in the estimators, I write the structural system of errors in reduced form, as summarized in Table [E.5](#).

ENTIRE	Model 1	ν_{1t}	ν_{2t}	ν_{3t}	R-squares
$N_t = \nu_{1t}$		-	-	-	-
$V_t = \alpha_1 + \beta_1\nu_{1t} + \nu_{2t}$		0.179***	-	-	4.94%
$P_t = \alpha_2 + \beta_2\nu_{1t} + \beta_3\nu_{2t} + \nu_{3t}$		0.013***	0.041***	-	16.9%
Reduced Form: $P_t = c_1 + 0.006N_t + 0.041V_t + \nu_{3t}$					
BUBBLES	Model 2	ν_{4t}	ν_{5t}	ν_{6t}	R-squares
$N_t = \nu_{4t}$		-	-	-	-
$V_t = \alpha_3 + \beta_4\nu_{4t} + \nu_{5t}$		0.175**	-	-	5.45%
$P_t = \alpha_4 + \beta_5\nu_{4t} + \beta_6\nu_{5t} + \nu_{6t}$		0.02*	0.043***	-	15.27%
Reduced Form: $P_t = c_2 + 0.012N_t + 0.043V_t + \nu_{6t}$					
RUN-UPS	Model 3	ν_{7t}	ν_{8t}	ν_{9t}	R-squares
$V_t = \nu_{7t}$		-	-	-	-
$P_t = \alpha_5 + \beta_7\nu_{7t} + \nu_{8t}$		0.03***	-	-	13.02%
$N_t = \alpha_6 + \beta_8\nu_{7t} + \beta_9\nu_{8t} + \nu_{9t}$		0.037*	5.577**	-	13.67%
Reduced Form: $N_t = c_3 + 5.577P_t - 0.13V_t + \nu_{9t}$					

* This table shows the results of estimation of structural models. Sample period is January 2008 – May 2018. N_t , V_t , and P_t represent the VAR errors of new account number, turnover rate, and monthly Shanghai Stock Exchange Composite Index price. ν_t proxies exogenous shock to each variable.

* *** stands for $p < 0.01$; ** stands for $p < 0.05$; * stands for $p < 0.1$.

Table E.5: The Estimation of Structural Model System