Do Speculative Bubbles Migrate in the Chinese Stock Market?

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Abstract

In this paper, a duration dependence test for speculative bubbles in the Chinese stock market is developed. It is found that bubbles in the aggregate stock price existed before the split share reform. After the reform, we observe the phenomenon of bubble migration across industries. In particular, bubbles migrate from the telecommunications industry to the health care industry. Moreover, we find that monetary policy used to have a significant impact on the bubble size before the reform but the impact diminished after the reform.

Keywords: Survival analysis; Speculative bubbles; Non-tradable shares reform

JEL Classifications: G12

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1. Introduction

The 2008 financial crisis triggered by the burst of the subprime mortgage market bubble has had a profound impact on the global economy (Brueckner et al., 2012). The Chinese stock market experiences similar boom and bust cycles. The market rose by approximately 400% from 2001 to 2007, but experienced a bust in 2008 in which the Shanghai composite index dropped by more than 75.74%. Whether this is a normal market cycle or a burst of bubbles has not yet been fully addressed. Given China's crucial role as a global economic power, the understanding of equity bubbles and the boom and bust cycle of this market therefore becomes increasingly important for international investors and policy makers.

A number of studies in the literature have attempted to detect bubbles in equity markets (Hamilton, 1986; West, 1988; Fukuta, 2002). A strand of literature regards equity bubble as the deviation of actual price from the fundamentals, and develops a variance bounds test to detect the bubbles, e.g., Shiller (1981) and LeRoy and Porter (1981). However, the variance bounds test relies on linearity assumption that relates all the observations to the value of prior observations. Gurkaynak (2008) suggests that bubbles demonstrate nonlinear patterns in return, and one cannot attribute the violation of the variance bound in data to the existence of a bubble. Another strand of the literature examines the statistical attributes of equity bubbles. For example, Blanchard and Watson (1983) develop autocorrelation and kurtosis tests for equity bubbles. Evans (1987) detects bubbles in the foreign exchange market using a skewness test. Diba and Grossman (1988) implement both unit root and co-integration tests to detect equity bubbles. However, these statistical features can also be driven by fundamental values and made them difficult to conclusively test equity bubbles. To incorporate the nonlinearity patterns on equity return, McQueen and Thorley (1994) develop a duration dependence test for bubbles, by allowing the probability of ending a bubble to depend on the length of positive or negative abnormal returns. The duration dependence test is more closely related to bubbles than other measures such as autocorrelation and skewness (McQueen and Thorley, 1994; Lunde and Timmermann, 2004). This method has been widely used to detect rational speculative bubbles in both developed and developing countries, such as, Asian countries (Chan et al., 1998), Malaysia (Mokhtar and Hassan, 2006), Thailand (Jirasakuldech et al., 2008) and more recently US (Wan and Wong, 2015).

In this paper, we apply the duration dependence test to examine bubbles in the Chinese stock market. Zhang (2008) also applies the duration dependence test in the Chinese stock market for a sample period of 1991-2001. However, He does not consider the important link between structural changes at the industry level and dynamic changes in bubbles at the aggregate level. Moreover, the relationship between monetary policy and bubbles is yet to be studied. Our study addresses the above issues by investigating bubbles in stock prices at the industry level, and the impact of the split share reform on the dynamics of bubbles. Thus, our study has valuable policy implications on both capital market and monetary policy in an emerging market economy such as China.

One of the most important capital market reforms in China has been the alleged “split share reform” of listed enterprises. From the beginning, a so-called “split share structure” was established to maintain the State’s dominant role in corporate operation in the Chinese stock market. Most government-owned shares, together with shares issued to other investors before IPOs (legal person shares), were strictly prohibited from trading in the secondary markets. Before 2005, only approximately one-third of the shares in listed firms were freely tradable. There were a plenty of speculative transactions, as stock prices are not driven by their fundamental values (He et al., 2017). In addition, corporate managers have less incentive to improve firms' value as they do not benefit from an increase in share prices. In April 2005, the China Securities Regulatory Commission (CSRC) published Guidance Notes on the split share reform of Listed Companies. The reform was aimed to convert all non-tradable shares into legitimate tradable shares in the secondary market. It improves market liquidity and overall operational efficiency of listed firms, since all shares are priced at market values. Thus, the split share reform provides us a unique opportunity to examine the relationship between trading restrictions and speculative bubbles.

Consistent with Zhang (2008), our results show that bubbles exist in China's stock market. However, the contribution of a bubble to the overall stock price is moderate after the split share reform. This suggests that the release of trading restrictions help mitigate speculative bubbles. Looking at the speculative bubbles at the industry level, we find a migration of bubbles from the telecommunications sector to the health care sector after the reform. In addition, we find that monetary policy tools are effective in suppressing bubbles in particular for the period prior to the split share reform.

Harman and Zuehlke (2004) suggest that duration dependence tests for speculative bubbles are sensitive to model specifications. To check the robustness, we repeat our empirical studies across various specifications. Our empirical results remain robust to the method correcting for discrete observation, the use of equally-weighted and value-weighted portfolios, and the use of weekly versus monthly stock returns.

The rest of the paper proceeds as follows. Section 2 briefly introduces the duration dependence test. Section 3 reports the empirical results. The impact of monetary policy on bubbles is discussed. We also conduct a variety of specifications to examine the robustness of our results. The conclusion is presented in Section 4.

2. The Duration Dependence Test

Following McQueen and Thorley (1994), we assume that the price of an asset is equal to its intrinsic value plus a bubble, i.e.:

$$p_t = p_t^* + b_t \tag{1}$$

where b_t is the bubble, $E_t[b_{t+1}] = (1 + r_{t+1})b_t$,and $p_t^* = \sum_{i=1}^{\infty} \left\{ E_t\left[d_{t+i}\right] / \prod_{j=1}^{i} (1 + r_{t+j}) \right\}$

is the fundamental value, d_{t+i} is the dividend, r_{t+1} is the required rate of return.

Bubbles can grow and burst; more specifically, we define

$$b_{t+1} = \begin{cases} (1 + r_{t+1})b_t / \pi - (1 - \pi)a_0 / \pi, & \text{with probability } \pi \\ a_0, & \text{with probability } 1 - \pi \end{cases} \tag{2}$$

Bubbles grow with probability π, which compensates the loss of the investors when bubbles burst (with probability $1 - \pi$). When bubbles burst, the price reverts to the initial price with a small initial bubble value, a_0. McQueen and Thorley (1994) show that, for a bubble to exist, the probability of a negative abnormal return conditional on a sequence of prior positive abnormal returns decreases with the duration of the prior period with positive abnormal returns. The duration dependence test is based on the logistic transformation of the log of the length of the prior run of positive abnormal returns:

$$h_i = \frac{1}{1+e^{-(\alpha+\beta \ln i)}} \tag{3}$$

where h_i is the conditional probability of a negative abnormal return, and *i* is the length of the prior run of positive abnormal returns (hazard function). The log likelihood of the hazard function is $L(\theta \mid S_T) = \sum_{i=1}^{N} N_i ln h_i + M_i ln(1-h_i)$, where N is the total number of runs, $\theta = (\alpha, \beta)'$, S_T is the data set. N_i is the count of complete runs of length i, while M_i are the count of runs with a length greater than i. A likelihood ratio test is conducted to test for the null hypothesis of no bubble by testing $\beta = 0$. The test statistic $L = \frac{\sup_\theta L(\theta \mid S_T)}{\sup_\theta L(\theta \mid S_T, \beta = 0)}$ follows $\chi^2(1)$ under the null hypothesis.

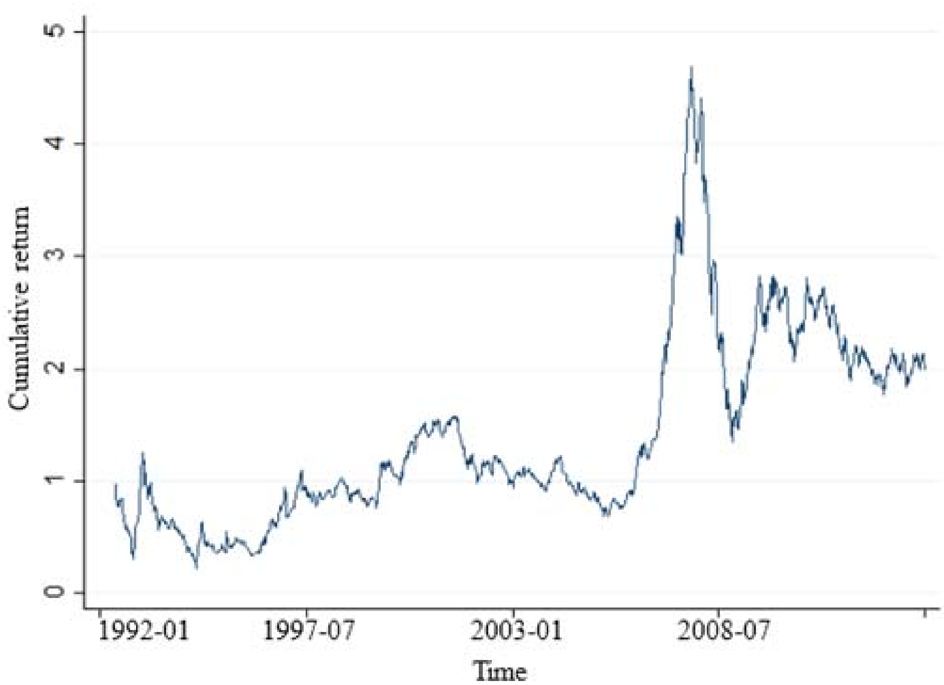
3. Empirical Results

3.1. Main results

For the aggregate analysis, the weekly value-weighted A-share returns of the Shanghai and Shenzhen stock exchanges from June 1, 1992 to December 31, 2013 is used. For the industry level analysis, weekly industry returns from January 4, 2002 to December 31, 2013 are drawn from the 10 China Securities Index Company Limited (CSI) sector indices. CSI uses an industry classification system that classifies firms into 10 categories according to their primary business activity, including energy, material, industry, consumer, daily consumer, health care, finance, IT, telecom services and utilities.[3] As China implemented the split share reform in April, 2005, we split the sample into the prior and post-reform period, with the first week of April 2005 as the cut-off point. All data are retrieved from the CSMAR database.

Figure 1 shows the weekly continuously compounded nominal returns for the Chinese comprehensive A-share stock market from June 1992 to December 2013. It shows that the Chinese stock market is quite volatile over the past two decades. The compounded stock returns vary with a range from 0.5 to 1.5 over the period 1992-2005. The stock returns increased almost fivefold from 2005 to 2007. During the global financial crisis around 2008, stock market fell by more than 60%. Even though China implemented a number of stimulus policies, e.g. a lower interest rate and bank reserve ratio[4], the stock market did not recover by the end of 2013.

Figure 1. Weekly continuously compounded nominal returns (Equally-weighted)



[3] The China Securities Index (CSI) Company Limited is a joint venture between the Shanghai Stock Exchanges and the Shenzhen Stock Exchange. It provides the creation and management of indices and index-related services. To measure the stock performance of different industries, the company launched 10 industry indices on January 4, 2002.

[4] To offset adverse global economic conditions, the Chinese government launched a CNY 4-trillion stimulus plan on Nov. 9, 2008, to boost domestic demand by providing extra liquidity.

To conduct the duration dependence test, we first calculate the abnormal returns and divide them into two states (positive versus negative). McQueen and Thorley (1994) estimate a multi-factor model and use the residuals as abnormal returns. The factors in their model include the term spread between AAA bonds and government bonds, yield and dividend. As the dividend distribution system in China is under-developed, it is inappropriate to use the dividend to measure the fundamentals of the Chinese stock market (He and Rui, 2016). Lunde and Timmermann (2004) discuss the impact of inflation on the drift of nominal stock prices. Thus, we also include a proxy of inflation in our regression model. Note that the volatility of weekly stock returns is serially correlated, which will affect the duration distribution. To account for the effect of volatility clustering, we employ Engle and Lee (1999)'s generalized autoregressive conditional heteroscedasticity model with an ARCH-in-mean effect (C-GARCH) [5]. Following Mcqueen and Thorley (1994), we allow the C-GARCH model with lagged returns of up to three orders[6]. More specifically, we use the following model to calculate the abnormal returns in the Chinese stock market:

$$R_t = \alpha + \beta_1 IFLA_{t-1} + \gamma_1 R_{t-1} + \gamma_2 R_{t-2} + \gamma_3 R_{t-3} + \rho\sigma_t + \varepsilon_t, \quad \varepsilon_t \sim N(0,\sigma_t^2),$$

$$\sigma_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(\sigma_{t-1}^2 - q_{t-1}),$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{4}$$

where R_t is the compounded weekly returns on the equally-weighted portfolios.[7] IFLA is the consumer price index (CPI) inflation rate. The weekly inflation rate is

[5] In unreported results, we conduct an ARCH test and find conditional heteroscedasticity in weekly stock return series.

[6] We obtain similar results by using a GARCH-in-mean model with lag returns up to three orders.

[7] Engle and Lee (1999) show that under mild assumptions, the variance equation of model (4) can be rewritten as an equation with five coefficients, which identifies the five underlying parameters.

calculated in the same way as Lunde and Timmermann (2004)[8]. σ_t is the conditional standard deviation, q_t is the temporary component of σ_t and ω is the permanent component of σ_t.

Table 1 summarizes the duration statistics of aggregate and industrial abnormal returns and the duration dependence tests of equation (3) for full sample[9]. The result from Panel A of Table 1 suggests that there is a bubble in the aggregate stock price. The results of the industrial-level analysis in Panel B suggest that the bubble originates from the health care sector. This result is consistent with market expectations. By 2013, the price-earnings ratio of the health care sector has exceeded 36, nearly 4 times the price-earnings ratio of the market. It reflects that the risk of innovations, such as new medicine and new medical apparatus, in this sector is underestimated.

Table 1 Summary Statistics of duration
Panel A Summary Statistics of durations for aggregate market

Run Length	Positive			Negative		
	Death Total 238	Survival	Hazard Rate	Death Total 239	Survival	Hazard Rate
1	133	105	0.5588	108	131	0.4519
2	41	64	0.3905	61	70	0.4656
3	23	41	0.3594	19	51	0.2714
4	17	24	0.4146	20	31	0.3922
5	10	14	0.4167	12	19	0.3871
6	1	13	0.0714	5	14	0.2632
7	6	7	0.4615	8	6	0.5714
8	3	4	0.4286	3	3	0.5000
9	2	2	0.5000	2	1	0.6667
10	1	1	0.5000	0	1	0.0000
11	1	0	1.0000	1	0	1.0000
Log-Logistic Test						
α	-0.1400	(0.3402)		0.2045	(0.4625)	

[8] The monthly CPI is converted into weekly inflation rates by solving the weekly inflation rate such that the weekly price index grows smoothly and at the same rate between subsequent values of the monthly CPI.

[9] It should be noted that h_i in equation (3) refers to population probability, whereas the h(i) refers to the sample probability used in the likelihood tests.

β	0.4651	(0.0901)		0.1667	(0.4962)
$\chi^2(1)$	2.7250	(0.0901)		0.4631	(0.4962)

Panel B Summary Statistics of durations for industrial returns

Run	Energy	Material	Industry	Consumer	Daily-C	Health	Finance	Info.	Telecom	Utility
1	0.508	0.465	0.503	0.516	0.536	0.519	0.522	0.485	0.475	0.514
2	0.424	0.400	0.473	0.495	0.592	0.568	0.535	0.460	0.495	0.528
3	0.434	0.350	0.449	0.435	0.655	0.632	0.550	0.444	0.521	0.524
4	0.467	0.333	0.407	0.500	0.600	0.500	0.556	0.633	0.522	0.450
5	0.563	0.423	0.563	0.615	0.750	0.571	0.625	0.727	0.636	0.545
6	0.286	0.533	0.571	0.600	1.000	1.000	0.333	0.667	0.750	1.000
7	0.400	0.429	0.333	1.000			0.500	1.000	1.000	
8	0.333	0.500	0.500				1.000			
9	0.500	0.500	1.000							
10	1.000	1.000								
Log-Logistic Test										
β	0.206	0.163	0.099	0.038	-0.373	**0.680**	-0.071	-0.229	-0.259	-0.120
	(0.80)	(0.52)	(0.88)	(0.95)	(0.90)	**(0.01)**	(0.98)	(0.36)	(0.67)	(0.86)
Obs.	187	187	187	188	153	183	180	194	181	183

The run length i represents that the number of weeks for which a series of abnormal returns lasts. The abnormal returns are errors estimated by the C-GARCH model in equation (4). The sample hazard rate is calculated by $h(i) = \frac{N_i}{M_i + N_i}$, where N_i represents the number of death, and M_i represents the number of survival. The parameter of α, β is estimated by $L(\theta|S_T) = \sum_{i=0}^{\infty} N_i \, ln h_i + M_i ln(1 - h_i)$, where S_T is the data set, $h_i = 1/1 + e^{-(\alpha+\beta \ln i)}$. P-values are in the parentheses.

The split share reform started in April 2005. To account for the potential market structural change caused by this reform, we estimate the model and conduct duration test of equation (3) for subsample periods. The results are summarized in Table 2.

Table2. Summary Statistics of durations for subperiods

Run Length	Positive			Negative		
	Death Total 152	Survival	Hazard Rate	Death Total 152	Survival	Hazard Rate
Panel A: Pre-reform period						
1	89	63	0.5855	67	85	0.4408
2	28	35	0.4444	38	47	0.4471
3	13	22	0.3714	10	37	0.2128
4	11	11	0.5	16	21	0.4324
5	5	6	0.4545	7	14	0.3333
6	0	6	0	5	9	0.3571
7	4	2	0.6667	7	2	0.7778

9	1	1	0.5	1	1	0.5
11	1	0	1	1	0	1
Log-Logistic Test						
α	-0.2812	(0.4007)		0.2810	(0.3777)	
β	0.4692	(0.0828)		0.1172	(0.6559)	
$\chi^2(1)$	3.0094	(0.0828)		0.1986	(0.6559)	
Panel B: Post-reform period						
1	44	42	0.5116	41	46	0.4713
2	13	29	0.3095	23	23	0.5000
3	10	19	0.3448	9	14	0.3913
4	6	13	0.3158	4	10	0.2857
5	5	8	0.3846	5	5	0.5000
6	1	7	0.1250	0	5	0
7	2	5	0.2857	1	4	0.2000
8	3	2	0.6000	3	1	0.7500
9	1	1	0.5000	1	0	1
10	1	0	1			
Log-Logistic Test						
α	0.0903	(0.7411)			0.0604	(0.8994)
β	0.4374	(0.1153)			0.2747	(0.4374)
$\chi^2(1)$	2.4805	(0.1153)			0.6030	(0.4374)

The run length i represents that the number of weeks for which a series of abnormal returns lasts. The abnormal returns are errors estimated by the C-GARCH model in equation (4). The sample hazard rate is calculated by $h(i)=\frac{N_i}{M_i+N_i}$, where N_i represents the number of death, and M_i represents the number of survival. The parameters α, β are estimated by maximizing the log-likelihood $L(\theta|S_T)=\sum_{i=0}^{\infty} N_i\, lnh_i + M_i ln(1-h_i)$. P-values are in the parentheses.

Before the reform, there were 152 duration spells for both positive and negative abnormal returns. After the reform, there are 86 observations of duration spells for positive abnormal returns and 87 observations of duration spells for negative abnormal returns. Statistics for the hazard rate are also reported. Note that the hazard rate of durations drops initially and rises thereafter. It is evident that beyond a certain duration, the existence of bubbles is highly dependent on the length of the duration. After nine spells, a bubble bursts. The results of the LR tests are reported in the last three rows of Table 2. Before the split share reform, the null of $\beta=0$ conditional on positive abnormal returns is rejected at the 10% level, which shows the presence of bubbles and their dependence on durations; after the reform, the p-value for the null of $\beta = 0$ conditional on positive abnormal returns is 0.1153. The “no bubble” hypothesis cannot be rejected at the conventional confidence level. Thus, the aggregate analysis suggests that the reform was effective in eliminating the bubble.

Figure 1 shows that Chinese stock market index increased fourfold and dropped at the same extent from 2006 to 2008. Someone may suspect that there is a bubble in the post-split share reform period. A possible explanation is that split share reform is effective in mitigating the conflicts between tradable and non-tradable shareholders, and improves the corporate operation efficiency. A large number of studies have shown that the reform has a strong positive influence on the corporate performance. (Firth et al., 2010; Liao et al., 2014, He et al., 2017). Corporate managers are more willing to serve for the benefits of shareholders so as to increase firm’s operating and market performance. The rise of stock market index is more likely to be driven by better economic fundamentals rather than speculative bubbles. The financial crisis around 2008 led to a global economic recession. Stock market fell by more than 60%, as investors expected a slowing down of Chinese economy due to this adverse external shock.

Figure2.a Survival Function and confidence intervals for aggregate market

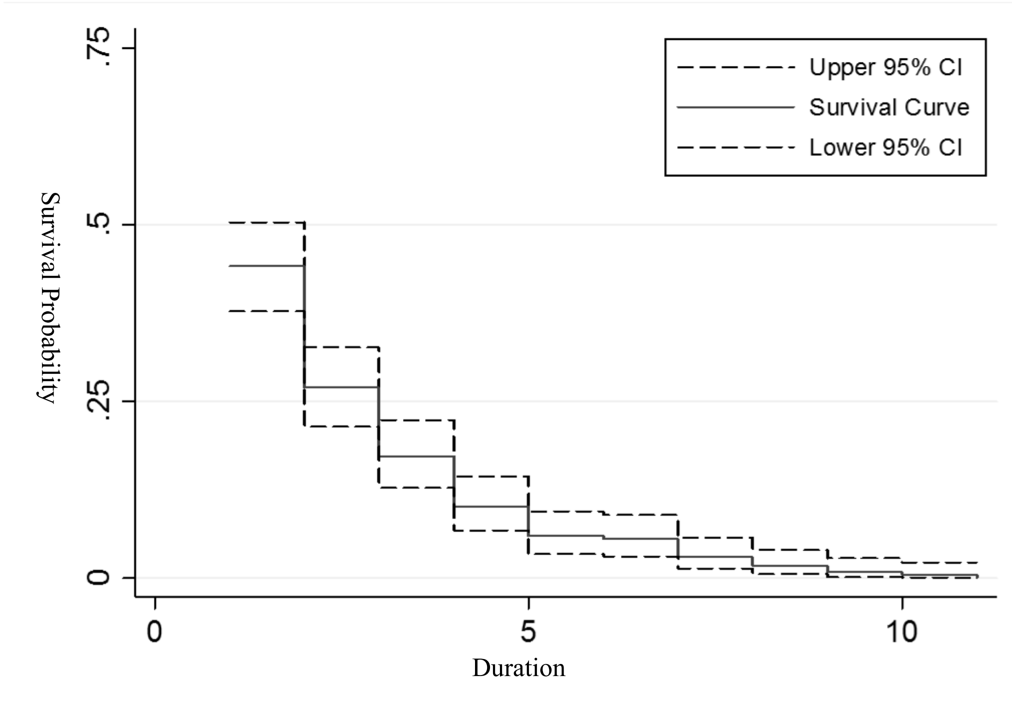


Figure 2.b Survival Function and confidence intervals before the reform

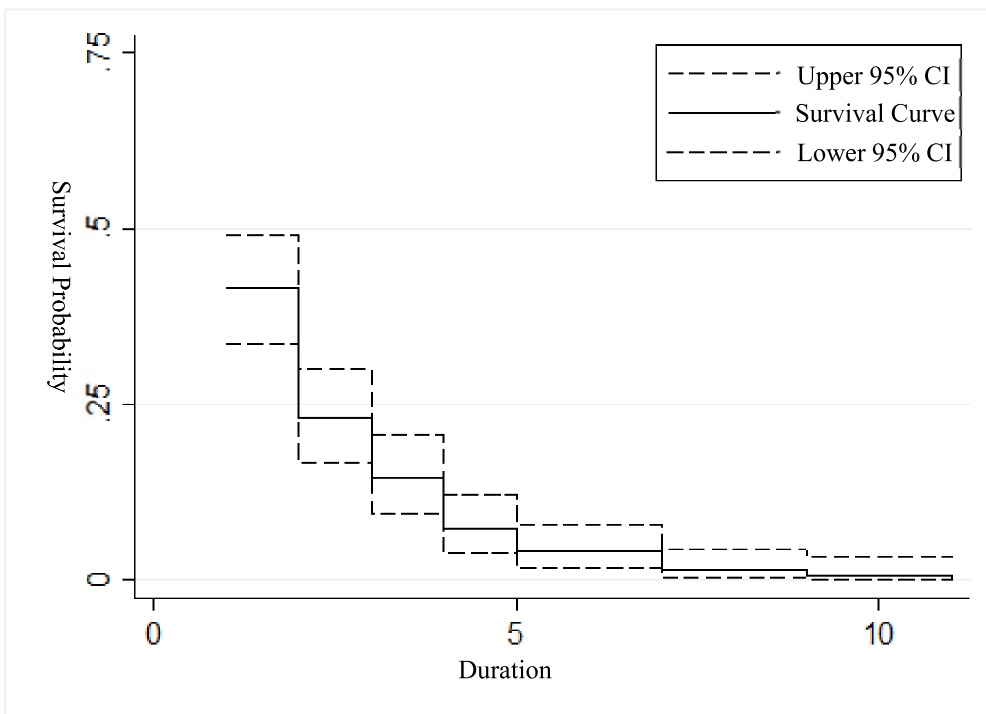


Figure 2.c Survival Function and confidence intervals after the reform

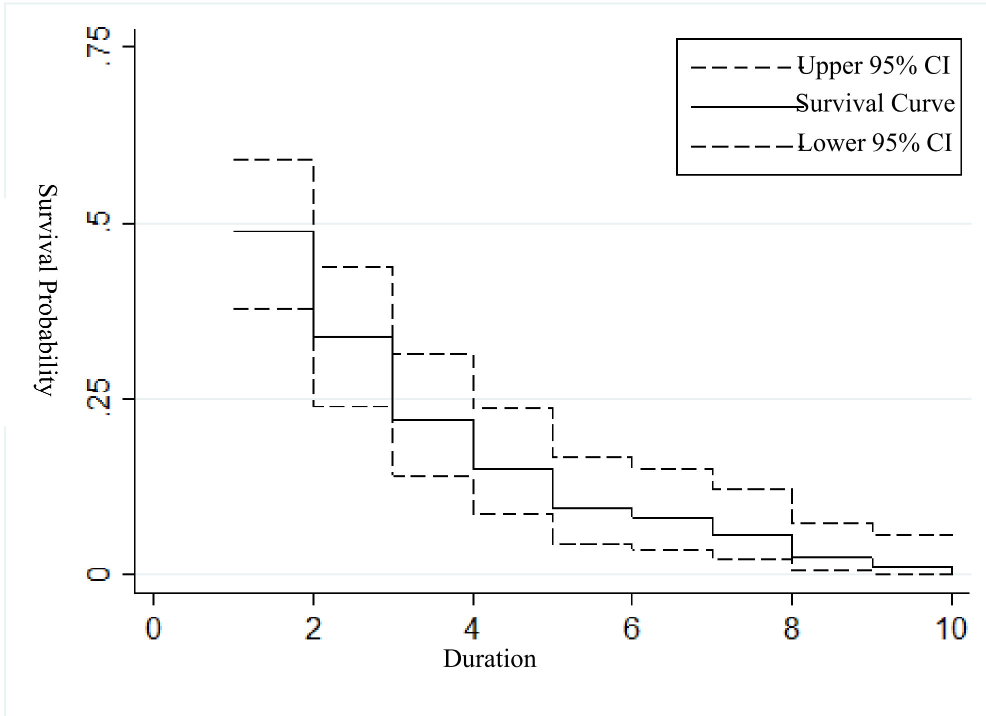


Figure3.a Cumulative Hazard Rate and confidence intervals for aggregate market

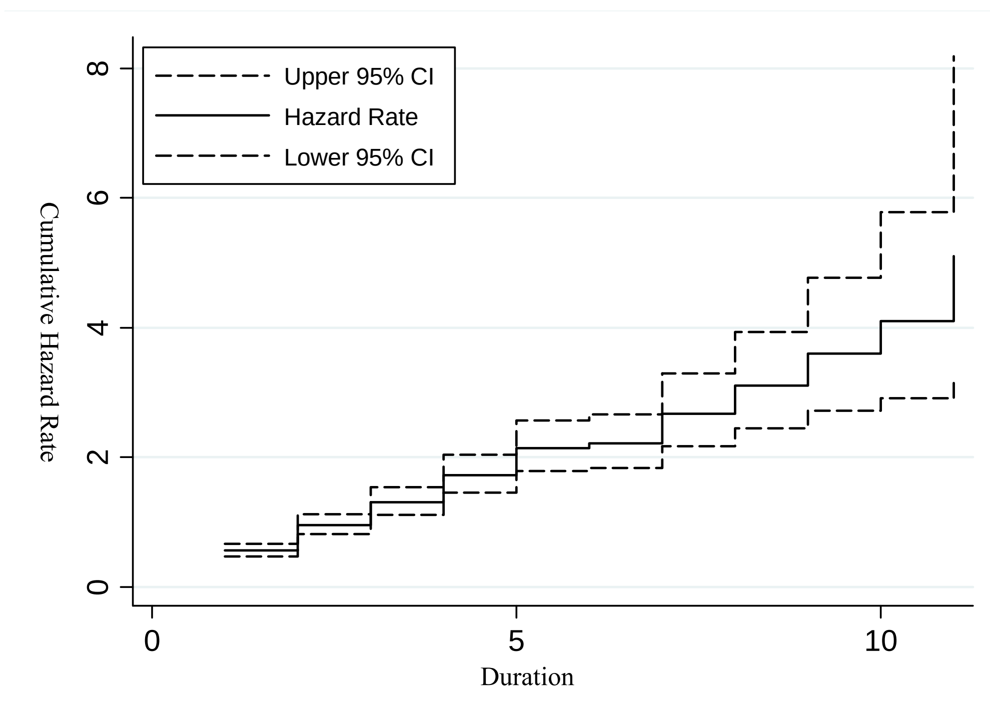


Figure 3.b Cumulative Hazard Rate and confidence intervals before the reform

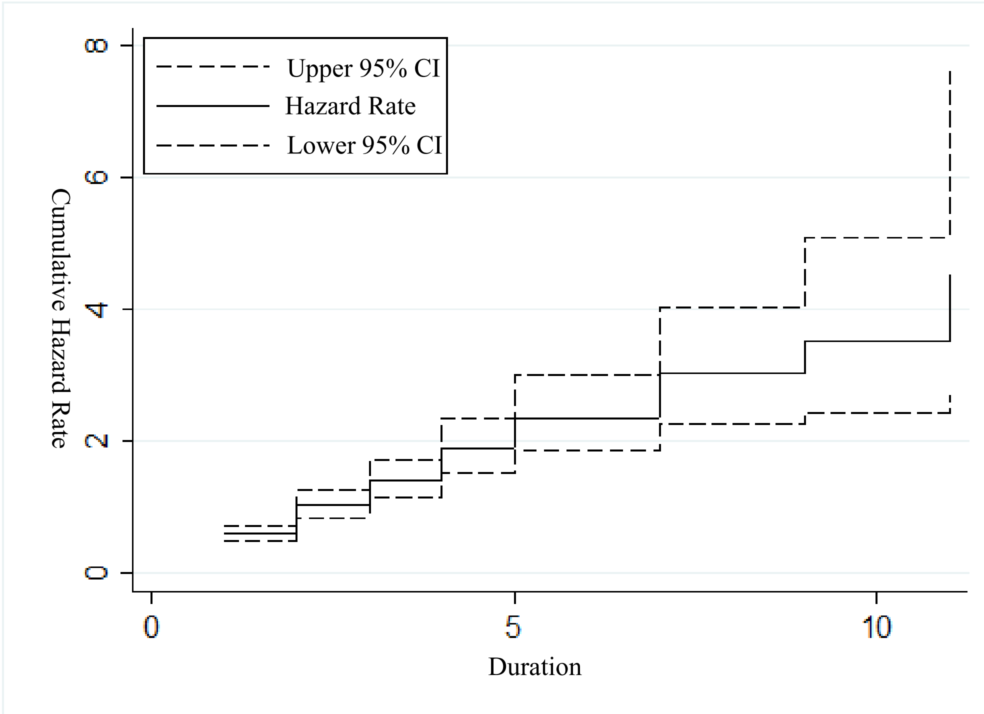
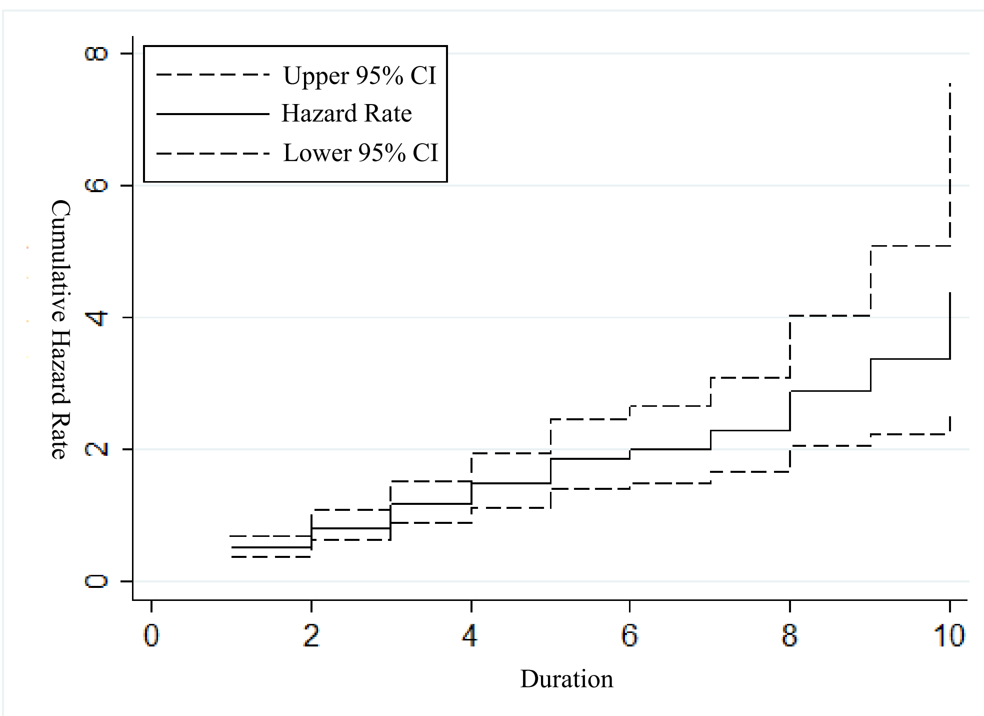


Figure 3.c Cumulative Hazard Rate and confidence intervals after the reform



Figures 2a, 2b and 2c depict the survival function and its 95% confidence intervals. Figures 3a, 3b and 3c depict the cumulative hazard rate function and its 95%

confidence intervals. All confidence intervals are calculated using a likelihood ratio test.

Table 3.Summary Statistics of durations for industrial returns in sub-periods

Run	Energy	Material	Industry	Consumer	Daily-C	Health	Finance	Info.	Telecom	Utility
Panel A: Pre-reform period										
1	0.522	0.443	0.514	0.554	0.694	0.594	0.576	0.529	0.624	0.524
2	0.438	0.359	0.500	0.552	0.727	0.577	0.571	0.545	0.467	0.467
3	0.500	0.320	0.471	0.462	1.000	0.455	0.583	0.467	0.515	0.375
4	0.444	0.176	0.444	0.571		0.333	0.600	0.500	0.700	0.300
5	0.600	0.257	0.800	0.333		0.500	1.000	0.500	1.000	0.571
6	0.500	0.444	1.000	0.500		1.000		0.500		1.000
7	1.000	0.500		1.000				1.000		
8		0.333								
9		0.500								
10		1.000								
Log-Logistic Test										
β	0.028	0.213	-0.113	0.101	-0.820	0.240	-0.186	0.018	**-0.420**	0.125
	(0.17)	(0.28)	(0.88)	(0.96)	(0.53)	(0.87)	(0.89)	(0.99)	**(0.09)**	(0.82)
Obs.	67	70	70	65	36	64	66	70	63	63
Panel B: Post-reform period										
1	0.500	0.479	0.496	0.496	0.487	0.579	0.491	0.460	0.449	0.508
2	0.417	0.426	0.458	0.468	0.567	0.565	0.517	0.418	0.462	0.559
3	0.400	0.371	0.438	0.424	0.615	0.400	0.536	0.436	0.486	0.615
4	0.476	0.455	0.389	0.474	0.600	0.625	0.538	0.682	0.500	0.600
5	0.545	0.500	0.455	0.700	0.750	0.667	0.500	0.857	0.556	0.500
6	0.200	0.667	0.500	0.667	1.000	1.000	0.333	1.000	0.750	1.000
7	0.250	0.500	0.333	1.000			0.500		1.000	
8	0.333	1.000	0.500				1.000			
9	0.500		1.000							
10	1.000									
Log-Logistic Test										
β	0.198	0.013	0.134	-0.078	-0.499	**-0.657**	-0.108	-0.374	-0.256	-0.354
	(0.34)	(0.97)	(0.87)	(0.85)	(0.83)	**(0.05)**	(0.95)	(0.14)	(0.71)	(0.84)
Obs.	120	117	117	123	117	119	114	124	118	120

The run length i represents that the number of weeks for which a series of abnormal returns lasts. The abnormal returns are errors estimated by the C-GARCH model in equation (4). The sample hazard rate is calculated by $h(i)=\frac{N_i}{M_i+N_i}$, where N_i represents the number of death, and M_i represents the number of survival. The parameter of the log-logistic test is estimated by $L(\theta|S_T) = \sum_{i=0}^{\infty} N_i\, lnh_i + M_i ln(1-h_i)$. P-values are in the parentheses.

Note from Table 3 that there is duration dependence in the telecommunications industry (p-value = 0.09) prior to the reform; Thereafter, the health care industry shows significant duration dependence (p-value = 0.05). Therefore, our findings suggest that the bubble does not completely disappear after the reform. Instead, it migrates from the telecommunications industry to the health care industry.

3.2. Tests for Differences in Duration

McQueen and Thorley (1994) suggest that duration dependence should only exist in runs of positive abnormal returns when there are bubbles. In this section, two basic models suggested by Lunde and Timmermann (2004) are introduced for testing the differences in samples of duration spells. As there is no closed-form solution for any of the duration models, we apply non-parametric two-sample tests to compare the duration dependence between the subsamples (Hollander and Wolfe, 1999). Three assumptions are made:

1) the number of duration spells is $N = M_i + N_i$, N_i represents the number of deaths, and M_i represents the number of survival;

2) the two sample spaces are $\{X_1, X_2, ..., X_P\}$ and $\{Y_1, Y_2, ..., Y_P\}$;

3) X and Y are mutually independent and respectively subject to the continuous distribution functions F and G.

We first apply the Wilcoxon, Mann and Whitney test for the following null hypothesis:

$$H_0: E(X) - E(Y) = 0$$

Let s_i be the rank of Y_i in ascending order. The rank sum of Y can be written as $W = \sum_{j=1}^{n} s_j$. Under the null hypothesis, the standardized rank sum is:

$$W^* = \frac{W - E_0(W)}{\sqrt{Var_0(W)}} \sim N(0, 1) \quad (5)$$

where

$$E_0(W) = n(N+1)/2 \quad (6)$$

and

$$Var_0(W) = \frac{nm}{2}\left[N + 1 - \frac{\sum_{j=1}^{S}(t_j - 1)t_j(t_j + 1)}{N(N-1)}\right] \quad (7)$$

To test the differences between two population samples, we implement the Kolmogorov-Smirnov Test. The null hypothesis is $H_0: F(t) = G(t)$ for t∈ R. The statistic is defined as follows:

$$J = \frac{mn}{d} max_{-\infty \le t \le \infty}\{|F_m(t) - G_n(t)|\} \quad (8)$$

where $F_m(t)$ and $G_n(t)$ are empirical distribution functions of X and Y; d is the greatest common divisor of *m* and *n*. (Critical values of the sample distribution are provided by Hollander and Wolfe, 1999)). Table 4 summarizes the results for the two-sample tests and the numbers are p-values.

Table 4.Two-Sample Test

	Wilcoxon	Kolmogorov-Smirnov
	Positive-Negative	Positive-Negative

Before	**0.0102**	**0.065**
After	0.8708	0.964
	Before-After	Before-After
Positive	0.1189	0.494
Negative	0.4593	0.806

This table reports the two-sample test results (p-values) by comparing the sample of duration spells of positive abnormal returns with the sample of duration spells of negative abnormal returns (Equation 8). The tests are carried out for both periods before and after the reform. P-values<0.1 are highlighted in boldface.

Based on the two-sample test of positive and negative abnormal returns in the prior reform period, noticeable differences can be observed between the positive abnormal return rate and the negative abnormal return rate; after the reform, we find insignificant difference between these two samples. This result is consistent with our previous finding that the contribution of bubbles to the aggregate stock index has significantly been reduced after the reform. It is evident that the split share reform has suppressed the speculative bubbles.

3.3. The Impact of the Interest Rate on Bubbles

While the increase of interest rate generally has a negative impact on stock returns, there is little analysis of its influence on bubbles in the Chinese stock market. To examine this, the influences of interest rate (I) and its change (ΔI) on bubbles are analyzed under four distributional assumptions, namely, the exponential distribution, the Weibull distribution, the Gompertz distribution and the Cox proportional model. The weekly risk-free interest rate is collected from CSMAR, which is the one-year deposit rate announced by the central bank[10]. Table 5 reports the regression results for

[10] We also use the repo rate as alternative measure of risk-free interest rate. It turns out that our results remain qualitatively unchanged.

the hazard rate under the four distributional assumptions.

Table 5. Regression for Interest Rate

	(1)	(2)	(3)	(4)
COEFFICIENT	Exponential	Weibull	Gompertz	Cox
Whole				
I	0.0112*	0.0163	0.0124	0.0086
	(0.006)	(0.010)	(0.008)	(0.054)
ΔI	0.368***	0.547***	0.438***	0.318**
	(0.140)	(0.177)	(0.167)	(0.142)
Cons.	-0.892***	-1.400***	-1.071***	
	(0.090)	(0.158)	(0.136)	
Obs.	236	236	236	236
Before				
I	0.0134	0.0218	0.0169	0.0123
	(0.01)	(0.02)	(0.01)	(0.01)
ΔI	0.265***	0.373***	0.304***	0.247***
	(0.08)	(0.11)	(0.10)	(0.08)
Cons.	-0.853***	-1.408***	-1.080***	
	(0.12)	(0.19)	(0.15)	
Obs.	141	141	141	141
After				
I	0.0285	0.049	0.0421	0.0323
	(0.077)	(0.12)	(0.098)	(0.07)
ΔI	-1.415	-2.448	-1.744	-1.106
	(1.06)	(1.6)	(1.28)	(0.91)
Cons.	-0.937**	-1.532**	-1.238**	
	(0.44)	(0.66)	(0.55)	
Obs.	95	95	95	95

The exponential regression is $h(i) = \exp(\beta_0 + \beta_1 I + \beta_2 \Delta I)$, the Weibull regression is $h(i) = \alpha i^{\alpha} * \exp(\beta_0 + \beta_1 I + \beta_2 \Delta I)$, the Gompertz regression is $h(i) = \alpha * \exp[-\exp(\beta_0 - \beta_1 I - \beta_2 \Delta I)]$, the cox regression is $h(i) = h(0) * \exp(\beta_1 I + \beta_2 \Delta I)$, where h is the hazard rate. Robust Standard Deviations are in the parentheses and *** denotes p value <0.01, ** denotes p value <0.05 * denotes p value <0.1

For the whole period, an increase in the interest rate leads to a significant increase in the hazard rate and a decrease in bubble duration. This indicates that the interest rate policy played a role in suppressing bubbles. This result is robust under four different specifications.

Looking at the periods prior to and after the split share reform, we find a significant difference. Before the reform, an increase in the interest rate leads to a significant increase in the hazard rate and a decrease in bubble duration. These indicate that the interest rate policy was effective in suppressing bubbles. In contrast, this effect no longer exists in the post-reform period. A possible explanation is that in the post-reform period, there were expectations of RMB appreciation. These expectations, together with an inflexible exchange rate regime, led to a huge stock of foreign reserve. The accumulation of foreign reserve led to excess liquidity supply, which added pressure to asset price appreciation. Much of the monetary tightening in this period was to offset the impact of the excess liquidity supply. Therefore, its impact could be weaker than the prior-reform periods in which the foreign reserve-led excess liquidity problem was not a major concern.

3.4. Robustness tests

Thus far, our primary results are based on weekly returns on the equally-weighted portfolios from June 1992 to December 2013, with the abnormal return estimated from equation (4). To check if our duration test is sensitive to the estimation method and the use of the weekly or monthly returns (Harman and Zuehlke, 2004), we repeat the test on a variety of specifications. For each specification, we report the results for both equally- and value- weighted portfolios.

In case I-IV, alternative methods are used to estimate positive and negative abnormal returns. In Case I-III, we use continuous interval and discrete Weibull models, respectively, to examine the sensitivity of our results to the method of correcting for discrete observation of continuous duration. The runs of positive abnormal returns still show a significant duration dependence, and the no-bubble hypothesis is rejected at the traditional level of significance. The runs of negative abnormal returns still fail to reject the no-bubble hypothesis. These results are robust to the use of equally-weighted or value-weighted portfolio series.

When a GARCH model with an ARCH-in-mean effect is used (Case IV), and the equally-weighted rejection of the hypothesis has a p-value of 0.0859. Similarly, the non-bubble hypothesis using value-weighted portfolio is rejected at the 0.0885 level. In the last case (Case V), monthly stock returns are used to estimate positive and negative abnormal returns. The equally-weighted (value-weighted) rejection of the no-bubble hypothesis has a p-value of 0.0749 (0.0664). We still find an insignificant duration dependence on the runs of negative excess returns.

Overall, the evidence of Table 6 suggests that for both equal-weighted and value-weighted portfolios, the rejection of the no-bubble hypothesis for the runs of positive excess return is robust to all specifications.[11] Consistent with the bubble model, there is no significant duration dependence on the runs of negative excess returns.

Table 6 Sensitivity Analysis for Duration dependence test

		Equally-Weighted			Value-Weighted	
		Positive	Negative		Positive	Negative
I. Continuous Weibull	α	-0.159	0.317	α	-0.279	0.238
	β	0.403	0.135	β	0.323	0.462
	p	**(0.0867)**	(0.474)	P	**(0.0893)**	(0.619)
II. Interval Weibull	α	-0.391	0.227	α	-0.594	0.365
	β	0.437	0.367	β	0.573	0.201
	p	**(0.0811)**	(0.315)	P	**(0.0994)**	(0.524)
III. Discrete Weibull	α	-0.282	0.498	α	-0.259	0.133
	β	0.776	0.127	β	0.727	0.505
	p	**(0.0831)**	(0.259)	P	**(0.0853)**	(0.578)
IV. GARCH	α	-0.487	0.269	α	-0.443	0.254
	β	0.200	0.199	β	0.130	0.219

[11] We also repeat various specifications of duration dependence tests on industry level and subsample period (pre-reform verses post-reform). Our results remain qualitatively unchanged. For brevity, these results are not reported, but available upon request.

	p	**(0.0859)**	(0.248)	P	**(0.0885)**	(0.571)
V. Monthly return	α	-0.198	-0.180	α	-0.484	-0.221
	β	0.628	0.780	β	0.494	0.758
	p	**(0.0749)**	(0.442)	P	**(0.0664)**	(0.783)

Notes: In Case I-III, The parameter of α, β is estimated by continuous, interval and discrete Weibull models as specified in Harman and Zuehlke, 2004. In Case IV, GARCH model with an ARCH-in-mean effect instead of CGARCH is used to estimate the abnormal return. In Case V, monthly return instead of weekly return is used. All cases include both equal-weighted and value-weighted portfolios. P-values are in the parentheses.

4. Conclusion

The rising role of China as a major economic power has sparked the interest of investors and researchers worldwide in understanding the behavior of its stock market. In this paper, we implement a duration model to examine empirically the existence of speculative bubbles in China's stock market. Evidence of the presence of bubbles is found. Before the split share reform, the probability of bursting a bubble is shown to have increased with the bubble duration. After the reform, the contribution of the bubble component to the aggregate stock price reduces. Our result suggests that this was caused by a structural change of the market at the industry level. Specifically, bubbles existed in the telecommunications industry before the reform, but migrated to the health care industry afterwards. Prior to the reform, there was segmentation of tradable shares and non-tradable shares in the primary market. In the secondary market, the non-payment of dividends also turns the market into a site for pursuing highly speculative returns rather than value investments. As a result, it was difficult to eliminate bubbles before the reform. Finally, our finding suggests that monetary policy tools were effective in suppressing bubbles prior to the split shares reform, but the effectiveness has dropped off significantly after the reform.

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