1. THE IPO CYCLES IN CHINA'S A-SHARE IPO MARKET: DETECTION BASED ON A THREE REGIMES MARKOV SWITCHING MODEL[1]

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Abstract

This paper expands the IPO market conditions from two states to three states, which include hot periods, cold periods and interim periods, and improves upon measures used to detect IPO market cycles given cycle strength in China's IPO market. We use a model based on the three Markov regime switching models to conduct regressions with respective proxy variables. By analyzing regression results, filtered probability and smoothed probability, we extract ten differing IPO cycles corresponding to ten different proxy variables. Further, this paper highlights results of various IPO market cycles in China's A-share market from January 1994 to June 2012. Results confirm the relationship between IPO market cycles and IPO numbers in addition to effects from underpricing, market conditions and government regulation. The aforementioned all enrich the theory of IPO cycles.

Keywords: Markov regime switching model; hot/interim/cold periods; IPO market cycles; A-share market; government regulation

JEL Classification: G10; G30; C22

1. Introduction

Many IPO studies focus on the "three puzzles": IPO underpricing, IPO long-run underperformance, and hot issue markets. The phenomenon of hot issue markets, describing a certain period of time when many companies go public, was first noted in Ibbotson and Jaffe (1975). The cyclical fluctuations of IPO numbers can be defined as

[1] This study was presented at 2013 Global Business, Economics, and Finance Conference, Wuhan University, China, 9-11 May 2013.

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IPO market cycles. Ritter (1984) confirmed the existence of hot issue markets and cyclical fluctuations of IPO numbers by using 1,028 issuances of SEC-registered initial public offerings of common stock from 1977 to 1982. Ibbotson, Sindeler and Ritter (1988) found that there is a positive correlation between initial returns and IPO numbers, and that there appears to be a lead-lag correlation between them.

Later, scholars turned to explore the causation of IPO market cycles, and whether they are caused by fluctuating IPO numbers or by the initial high returns. Much literature focuses on the relationship between offering price, firm value or initial returns and the fluctuation of IPO numbers (Ritter, 1991; Lowry and Schwert, 2002). Scholars argue that these variables of price and value lead to the cyclical fluctuations in IPO numbers. Furthermore, from a perspective of behavioral finance, variables on price also connect with investor sentiment. For example, high investor sentiment can cause high stock prices in the secondary market, which increases optimism among pre-IPO companies and leads to more companies being listed (Rajan and Servaes, 1997; Bouis, 2009). It is also argued that the economic environment, rather than the companies or investors themselves, matters when studying IPO market cycles. For instance, in the presence of economic growth (Yung, Colak and Wang, 2008; Pastor and Veronesi, 2005) or in the development of the IPO's sector (Pagano, Panetta and Zingales, 1998; Draho, 2007) there are impacts on the fluctuations of IPO numbers. However, studies based on pricing, behavioral finance or economic environment do not take into account IPO market cycles' as a dynamic mechanism. As a result, scholars have attempted to justify the asymmetric information theory accordingly. For example, they divided pre-IPO companies into a pioneer group or a follower group; and divided investors into an insider group or an unwitting group. Then they constructed a series of models combining specific assumptions to extract explanations for IPO market cycles (Alti, 2005; Colak and Gunay, 2011).

These studies confirm the existence of IPO market cycles, and analyze various perspectives. Even so, scant literature focuses on the turning points of hot and cold cycles or the detection of IPO market cycles. When studying IPO cycles, the difficulty lies in the structural changes of IPO timing. More importantly, we need to calculate the probability of each regime switch to deduce the regime at every point of time while maximizing the probability of being correct. In order to solve the issue of IPO market cycle deductions, the Markov regime switching model can adapt to a time series with simple structural changes.

The Markov regime switching model has accomplished much for economic analysis where time series data undergoes structural changes. Hamilton (1989) first proposed this model by using the U.S. real GNP time series to depict how the U.S. business cycle periodically shifts from a positive growth rate to negative. Moreover, Hamilton (1990) introduces an EM algorithm used to obtain maximum estimates for parameters that are subject to the discrete shifts of autoregressive parameters. The simplicity of the EM algorithm invites application to the larger vector system. With Hamilton's basic work, scholars have applied this model to the analysis of macroeconomic cycles (Krolzig, 2003; Kim and Nelson, 2001), interest rates and exchange rates (Garcia and Perron, 1996; Chen and Huo, 2009), capital markets (Guo, Chen and Huang, 2011; Chkili *et al*., 2011) and major international commodities (Bhar and Malliaris, 2011; Chiu and Shieh, 2009).

Scholars looking into IPO market cycles also prefer this approach. Brailsford *et al.*, (2000) examined four monthly measures of IPO activity over the period from 1976 to 1998 to provide a multidimensional characterization and identification of the hot and cold IPO markets. More specifically, they distinguish the turning points of hot and cold periods regardless of the interim periods. Guo, Brooks and Shami (2010) introduced a set of observations to measure Chinese A-share IPO market activities, which included IPO numbers, levels of underpricing, market conditions and duration time from prospectus and listing, and thus using this model to depict the turning points of the hot and cold market periods from 1994 to 2005. It is added that the inclusion of more proxy variables applied to the IPO cycle study would make the results more meaningful.

Though there are ample cases where the Markov regime switching model identifies hot and cold market cycles, a deep discussion is needed. Compared with the research of Brailsford *et al.*, (2000) and Guo, Brooks and Shami (2010), this paper offers two unique contributions. First, this paper expands the IPO market conditions to three states: hot periods, cold periods and interim periods. According to the two states theory, a point in time with high IPO numbers or increasing IPO numbers should be classified as a hot period, otherwise, it is considered a cold period. However, if at a point in time there is mid-range or steady IPO numbers, that time could be misclassified as a hot or a cold period. Thus, by adding an interim period we can solve the misclassification. Second, this paper improves the measures used to detect IPO market cycles by examining cycle robustness, IPO numbers, underpricing levels, market conditions and government regulations within a comprehensive perspective.

The organization of this paper is as follows. In section 2, we introduce the Markov regime switching model adapted for researching IPO cycles. Section 3 is a study design to describe data, variables and descriptive statistics. Section 4 discusses our empirical results, which include dynamic path tests, structural change tests of variables, and the detection of IPO cycles. This paper is concluded in section 5.

2. The Markov Regime Switching Model Adapted to IPO Cycles Research

This paper combines the research of Hamilton (1989) with an auto-regressive model to expand IPO market conditions to three states in a MS (3)-AR (*P*) model. Next, we calculate the filtered probability and smoothed probability by employing the filter iterative method (Krolzig, 1997, p.254). The approach herein is similar to that of Brailsford *et al.*, (2000) or Guo, Brooks and Shami (2010). However, we offer some improvements. First, as mentioned above, we overcome the inaccurately classified points in time with characteristics of an “interim period” and position this work as a three-regime Markov switching model. Second, this paper uses the MSVARlib, a Gauss and Ox-Gauss compliant library, to make regressions and calculate smoothed probabilities (Bellone, 2005).

The form of the model is:

$$\begin{cases} y_t = v\left(S_t\right)+\sum_{i=1}^{p}\delta_i\left(S_t\right)\cdot y_{t-i}+u_t \\ u_t \sim \left(0\ ,\ \sigma^2\left(S_t\right)\right) \end{cases},t=1,...,T \tag{1}$$

Above, y_t is a measure for IPO market cycles, which includes numbers of IPOs issued, IPO proceeds; IPO initial returns; IPO initial returns weighted by IPO proceeds; IPO initial returns revised by stock market returns; IPO initial returns weighted by IPO proceeds and revised by stock market returns; trading volumes of the secondary stock market; duration days from offering to listing; an oversubscription multiple; and the IEC (Issuance Examination Committee of China Securities Regulatory Commission) examination pass rate. $S_t \in \{1,2,3\}$ is defined as an unobserved variable from the three states, following a first order Markov Chain. When S_t =1, 2, or 3, it can be concluded that the market states measured by those proxy variables are respectively in a cold period regime, an interim period regime or a hot period regime. The regime switching probability is as the follows:

$$P_{ij} = P\left[S_t = j \,\middle|\, S_{t-1} = i, S_{t-2} = k, S_{t-3} = l, \ldots\right] = P\left[S_t = j \,\middle|\, S_{t-1} = i\right],$$

$$\sum_{j=1}^{3} P_{ij} = 1; i = 1,2,3 \tag{2}$$

Here, $v(S_t)$, $\delta_i(S_t)$ and $\sigma(S_t)$ represent the intercept coefficients, autoregressive coefficients and residuals, all of which have state of transition characteristics. Additionally for clarification, $v(1) < v(2) < v(3)$.

Above, S_t is connected with the measures of IPO market cycles represented by y_t, revealing characteristics of structural changes. However, it is impossible to know S_t congenitally. Hence we first select the proxy variables and then deduce filtered probability from these proxy variables to detect IPO market cycles.

Specifically, the filtered probability of S_t is:

$$p\left(S_t = i \,\middle|\, I_t; \Theta\right) = \frac{p\left(S_t = i, y_t \,\middle|\, I_{t-1}; \Theta\right)}{f\left(y_t \,\middle|\, I_{t-1}; \Theta\right)} = \frac{p\left(S_t = i \,\middle|\, I_{t-1}; \Theta\right) \cdot f\left(y_t \,\middle|\, S_t = i, I_{t-1}; \Theta\right)}{f\left(y_t \,\middle|\, I_{t-1}\right)} \tag{3}$$

where: I_{t-1} is the information set of observations before t-1, namely $\{y_{t-1}, y_{t-2}, \ldots, y_1\}$. Θ is the set of estimated parameters in cold, interim or hot regime, $\{P_{ij}, v(S_t), \delta_i(S_t), \sigma(S_t)\}$.

By the Bayesian formula $p(S_t=i|\, I_{t-1;}\Theta)$, we can get the predicted probability of S_t. Then, the conditional distribution density function of y_t, the formula of $f(y_t|\, I_{t-1;}\Theta)$ and predicted probability of S_t are plugged into the filtered probability of S_t:

$$p\left(S_t = i \,\middle|\, I_t; \Theta\right) = \left(2\pi\sigma^2\left(S_t\right)\right)^{-\frac{1}{2}} \cdot \exp\left\{ -\frac{\left(y_t - v\left(S_t\right) + \sum_{i=1}^{p} \delta_i\left(S_t\right) \cdot y_{t-i}\right)^2}{2\sigma^2\left(S_t\right)} \right\}$$

$$\cdot \sum_{j=1}^{3} p_{ji} \cdot p\left(S_{t-1} = j \,\middle|\, I_{t-1}; \Theta\right) \cdot \left(\sum_{i=1}^{3} p\left(S_t = i \,\middle|\, I_{t-1}; \Theta\right) \cdot f\left(y_t \,\middle|\, S_t = i, I_{t-1}; \Theta\right) \right)^{-1} \tag{4}$$

It can be seen that the calculation of the filtered probability is based on the current sample information; likewise, for the whole sample information, the smoothed probability can be calculated.

Comparing the smoothed probability of the cold period regime, interim period regime and hot period regime, if one smoothed probability of regime-*i* in time point-*t* is greater than the smoothed probability of regime-*i*, then we can determine that the corresponding-*y* is in regime-*i* in time point-*t*. In the end we can more adeptly identify and detect IPO market cycles.

3. Study Design

3.1 Data and Sample

The data sample is comprised of ordinary China A-share IPOs obtained from the CSMAR solution of GTA and the iFinD financial data terminal of THS, which includes data such as IPO dates, IPO proceeds, the initial performance of new issues, the Shanghai and Shenzhen Stock Exchange indexes, trading volumes of the secondary stock market, oversubscription multiples, and the IEC examination pass rate.

We prefer long term data when analyzing IPOs because a larger sample bolsters a model's effectiveness and better reflects true characteristics of an IPO market. Moreover, we took account of the non-standardization of China's stock markets in its inception, thus our data sample intentionally includes those 2,171 ordinary A-share IPOs issued[4] from January 1st 1994 to June 30th 2012.

3.2 Variables and Descriptive Statistics

Guo, Brooks and Shami (2010) introduced four measures of IPO activity to include numbers of IPO issued, levels of underpricing, market risk and market condition. Shao *et al*., (2010) sought to avoid neglecting the scale of volume among different IPOs by substituting IPO proceeds for the numbers of IPOs issued. Brailsford *et al*., (2000) normalized underpricing measures weighted by IPO proceeds and substituted the normalized measures into the regime switching model to identify hot and cold cycles.

This paper utilizes existing methods of variable selection. However, for China's IPO market, we introduce a new set of observations to measure IPO activities via the application of the oversubscription multiple and the IEC examination pass rate. Proxy variables[5] are shown in Table 1.

1. The number of IPOs issued is the most direct and immediate variable to reflect the cycle of IPO offering. We define the month of the offing date as the "IPO month", where the number of IPOs issued in a specific month is the sum of IPO companies in the "IPO month". This measure is denoted as N_t, where *t* represents month.

2. IPO proceeds consider the volume of each IPO as it compares with numbers of IPOs issued. Of course, IPO proceeds are influenced by inflation rates and in turn, the

[4] *There are additional 1,836 IPOs without GEM from the corresponding period.*

[5] *Months without IPOs are not included for proxy variable 3 to 6 and 8 to 10 and the data of proxy variable 9 and 10 are available only after June 2006. Hence, the time range of proxy variable 1,2 and 7 is 222 months, the time range of proxy variable 9 and 10 is 65 months, and the time range of others is 187 months.*

IPO proceeds are revised by CPI considering the time span of our data sample. V_t represents IPO proceeds in the month *t*:

$$V_t = \sum V_{t,i} \tag{5}$$

where: $V_{t\,i}$ is the proceeds of the *i*-th IPO in the month *t*.

Table 1

Definitions and Serial Numbers of Proxy Variables

No.	Definition of proxy variable	Notation of proxy variable	Category
1	Numbers of IPOs issued	N_t	IPO numbers
2	IPO proceeds	V_t	
3	IPO initial return	AR_t	Levels of underpricing
4	IPO initial return weighted by IPO proceeds	WAR_t	
5	IPO initial returns revised by stock market return	MAR_t	
6	IPO initial return weighted by IPO proceeds and revised by stock market return	$MWAR_t$	
7	Trading volume of the secondary stock market	$TrdV_t$	Market conditions
8	Duration days from offering to listing	WD_t	
9	Oversubscription multiple	AOM_t	
10	IEC examination pass rate	$RPAN_t$	Government regulations

3. This paper prefers IPO initial return on the 21st trading day after offering as the measure of IPO underpricing. Thus, AR_t is the average IPO initial return in the month *t*:

$$R_{t,i} = \frac{P_{t,i}^{tr} - P_{t,i}^{is}}{P_{t,i}^{is}}, \quad AR_t = \frac{\sum_i R_{t,i}}{N_t} \tag{6}$$

where: $P_{t,i}^{tr}$ is the closing price of stock *i* issued on the 21st trading day in the month *t* and $P_{t,i}^{is}$ is the offering price of stock *i* issued in the month *t*. $R_{t,i}$ is the IPO initial return of stock *i* in the month *t*.

4. The purpose of using IPO initial return weighted by IPO proceeds is to avoid any problems resulting from traditional arithmetic average measures where underpricing is subject to influence from small “penny” stocks (Loughran and Ritter, 1995).

$$WAR_t = \frac{\sum_i \left(R_{t,i} \times V_{t,i}\right)}{V_t} \tag{7}$$

5. We introduce the Shanghai A-share index as a market revising factor for IPO initial returns. MAR_t is the average IPO initial returns revised by stock market return in the month *t*:

$$MR_{t,i}=\frac{P_{t,i}^{tr}-P_{t,i}^{is}}{P_{t,i}^{is}}-\frac{IND_{t,i}^{tr}-IND_{t,i}^{is}}{IND_{t,i}^{is}},\quad MAR_t=\frac{\sum_i MR_{t,i}}{N_t} \tag{8}$$

Above, $IND_{t,i}^{tr}$ is the closing index of the Shanghai A-share corresponding to $P_{t,i}^{tr}$, while $IND_{t,i}^{is}$ is the closing index of Shanghai A-share corresponding to $P_{t,i}^{is}$. MR_t is the IPO initial return revised by the market return of stock *i* in the month *t*.

6. We derive the IPO initial return weighted by IPO proceeds and then revised by stock market return with this formula:

$$MWAR_t=\frac{\sum_i\left(MR_{t,i}\times V_{t,i}\right)}{V_t} \tag{9}$$

7. The trading volume of the secondary stock market depicts both the performance of the stock market and market sentiment. Further, the trading volume in the secondary stock market is revised by the CPI (considering the long time span of the data sample) so that inflation rates do not affect the data. This is denoted as $TrdV_t$, where *t* represents month.

8. The duration of days from offering to listing are denoted by the time interval from prospectus day to listing day. In China's IPO market, an optimistic market sentiment can accelerate the IPO process. Therefore, this variable also measures market condition.

$$WD_t=\frac{\sum WD_{t,i}}{N_t} \tag{10}$$

9. A higher oversubscription multiple implies that larger investor demands exist with a lower winning rate. If investors fail to acquire stocks in the primary market, they will turn to the secondary market. In this way, initial returns increase, while an apparent underpricing occurs in the secondary market. Hence, the oversubscription multiple can explain IPO cycles to some extent. AOM_i is the average oversubscription multiple in the month *t*:

$$AOM_t=\frac{\sum_i OM_{t,i}}{N_t} \tag{11}$$

where: OM_{ti} is the oversubscription multiple of the *i*-th IPO in the month *t.*

10. To a certain extent government regulation influences IPO market in China's stock issuing system. This work employs the monthly IEC examination pass rate to reflect the impact of policy making on IPO cycles. $RPAN_t$ is the monthly IEC examination pass rate:

$$RPAN_t=\frac{PAN_t}{AN_t} \tag{12}$$

where: AN_t is the number of examined companies by IEC, and RAN_t is the number of examined and passed companies by IEC.

Table 2

Descriptive Statistics of Proxy Variables

No.	Notation	Time range	Mean	Median	Std. deviation	Minimum	Maximum
1	N_t	222	8.31	7.00	0.79	0.00	41.00
2	V_t	222	103.94	31.82	10.82	0.00	859.61
3	AR_t	187	1.01	0.91	0.05	0.0045	4.00
4	WAR_t	187	0.81	0.71	0.05	0.0034	4.32
5	MAR_t	187	1.01	0.90	0.05	0.0018	3.99
6	$MWAR_t$	187	0.81	0.70	0.05	0.0018	4.31
7	$TrdV_t$	222	96.80	30.01	8.42	0.53	559.00
8	WD_t	187	26.38	17.86	1.69	8.89	159.00
9	AOM_t	65	309.20	131.23	54.64	17.81	1,884.32
10	$RPAN_t$	65	0.80	0.80	0.02	0.45	1.00

Note: The proxy variable 2 is degraded by 10,000,000, and the proxy variable 7 is degraded by 10,000,000,000. Neither of them is adjusted by CPI.

Table 2 depicts descriptive statistics for IPO market activities vis-à-vis ten different proxy variables. The number of IPOs issued averaged 8.31 IPOs per month; where the minimum is zero during an IPO suspension period and the monthly maximum is 41. Here, IPO proceeds display analogous statistical characteristics. The four IPO initial return proxy variables do not show much variation in their measures; i.e. most of them are not greater than 1. Trading volumes of the secondary stock market underwent dramatic change with the maximum being nearly 1,000 times greater than the minimum. Without considering IPO suspension periods, the average duration of days from offering to listing is 26.38 days. Our oversubscription multiple ranges from 17.81 to 1,884.32. The last proxy variable, the IEC examination pass rate, averages 0.8.

4. Empirical Results

4.1 Dynamic Path Tests and Structural Changes Tests

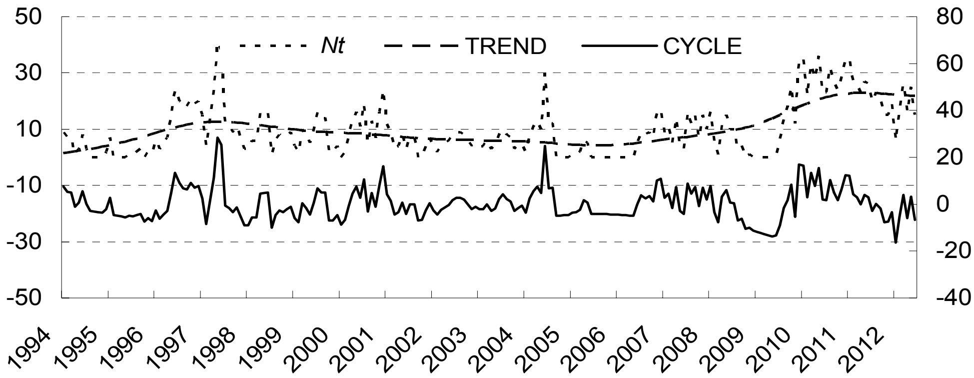
The descriptive statistics above do not reveal the tendencies of our sample. Therefore, we proceed to apply the Hodrick-Prescott Filter to demonstrate dynamic paths for the variables. The Hodrick-Prescott Filter separates trends and fluctuations of data to better illuminate the periodicity of time series. The dynamic path test of variable 1 is shown in Figure.1[6].

[6] *Due to the length limitation of this paper only the dynamic path test of proxy variable 1 is given. If readers need the dynamic path tests of proxy variables 2-10, please contact the author.*

Proxy variables 1, 3-6, and 10 fluctuate through the entirety of the sample, while the others experience fluctuations for more than half the data sample. Although Figure 1 depicts the degree of fluctuation directly, it fails to verify whether there are structural changes or not.

Figure 1

Dynamic Path Test of Variable 1



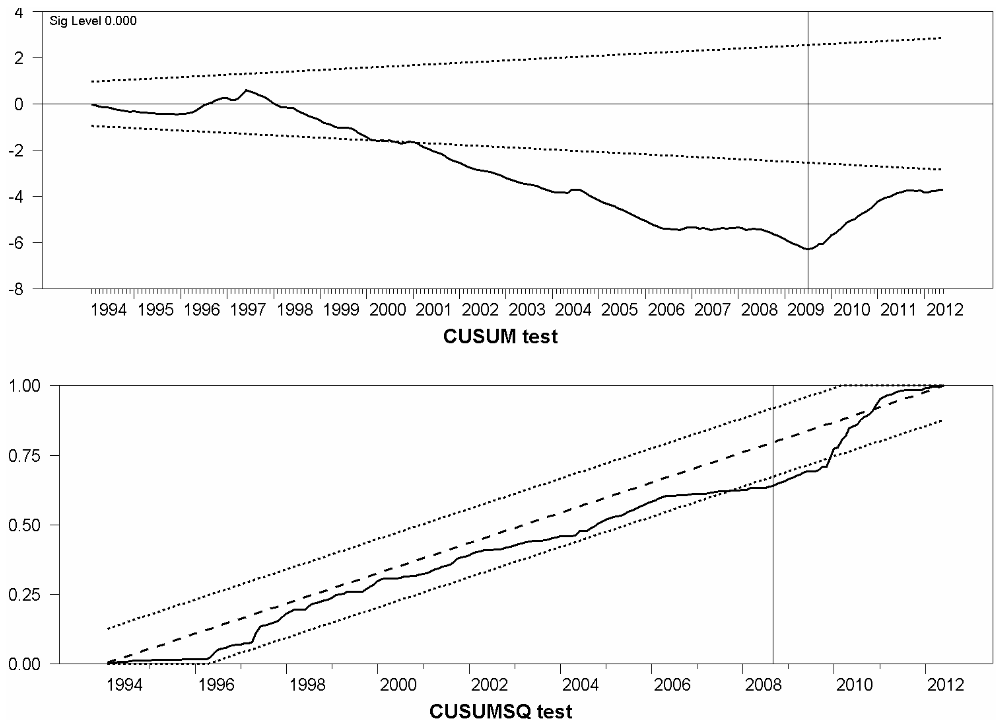
Blondell *et al*., (2002) offered a new CUSUM (Cumulative Sum) approach for the detection of turning points in a financial time series which is subject to cyclical mean levels and volatility regime shifts. They applied the new CUSUM approach to detect turning points in "hot issue" markets for IPOs and thus provided a multi-dimensional characterization of states of the IPO cycle. In other words, the CUSUM, CUSUMSQ test and Chow test can be applied to testing structural changes in financial time series. The Chow test requires identifying a-priori turning points; therefore, this paper uses CUSUM and CUSUMSQ test to analyze the structural changes of the ten proxy variables.

From the test results[7], varying structural changes exist within a 5% significance level. However, these traditional CUSUM and CUSUMSQ tests cannot provide results accurate enough to identify turning points. To resolve this deficiency, we employ the Markov regime switching model to identify these IPO market cycles.

[7] *Due to the length limitation of this paper only the structural changes test of proxy variable 1 is given. If readers need the structural changes tests of proxy variables 2-10, please contact the author.*

Figure 2

Structural Changes Test of Variable 1



4.2 Detection of IPO Cycles

Previous studies have partitioned IPO market conditions into two states: hot and cold periods; while the Markov regime switching model has been defined as MS (2)-AR (*P*). This paper expands IPO market conditions into three states: hot periods, cold periods and interim periods. This work then goes on to apply a three-regime Markov switching model to conduct regressions on proxy variables. We compare the smoothed probabilities of ten proxy variables, determine hot and cold periods, and finally classify the remaining as interim periods. In this way, we deduced China's A-share IPO market cycles.

We fixed the lagged differences of proxy variables 1 to 10 respectively as: 2, 2, 3, 3, 3, 3, 2, 3, 2, and 1 according to the Akaike Information Criterion (AIC), Schwarz Criterion (SC), Log Likelihood and Jarque-Bera Statistic.

Thus, our model is in form MS (3)-AR (*P*), where *P*=1, 2, or 3. There are two reasons for not choosing MS (3)-VAR (*P*) form: first, the proxy variables have different time ranges; second, there is no evidence that proves the irrelevance between any two proxy variables. Specifically, the model is:

$$\begin{cases} y_t = v\left(S_t\right) + \sum_{i=1}^{p} \delta^i\left(S_t\right) \cdot y_{t-i} + u_t \\ v\left(S_t\right) = \beta_1 \cdot \xi_t^1 + \beta_2 \cdot \xi_t^2 + \beta_3 \cdot \xi_t^3 \\ \delta_i\left(S_t\right) = \delta_1^i \cdot \xi_t^1 + \delta_2^i \cdot \xi_t^2 + \delta_3^i \cdot \xi_t^3 \\ u_t \Big|_{S_t} \sim N\left(0, \sigma_{S_t}^2\right), \sigma_{S_t}^2 = \sigma_1 \cdot \xi_t^1 + \sigma_2 \cdot \xi_t^2 + \sigma_3 \cdot \xi_t^3 \end{cases} \tag{13}$$

where: ξ_t^1, ξ_t^2, ξ_t^3 represent the 1st, 2nd, 3rd column of a third order identity matrix ***I***.

Table 3

Regression Results

Parameter	Regime 1				Regime 2				Regime 3				Log Likelihood
	β_1	δ_1^1	δ_1^2	δ_1^3	β_2	δ_2^1	δ_2^2	δ_2^3	β_3	δ_3^1	δ_3^2	δ_3^3	
							N_t						
Estimate	-0.16	0.21	-0.31		-0.01	0.46	-0.42		0.50	0.74	-0.88		-240.57
T-value	-1.56	2.1	-3.69		-0.2	6.4	-5.56		1.84	4.05	-3.88		
σ	0.71				0.05				1.35				
T-value	4.96				1.81				3.25				
							V_t						
Estimate	-0.06	0.26	-0.34		0.01	0.23	-0.27		0.21	0.06	-0.38		-132.08
T-value	-1.3	3.29	-4.27		-0.31	5.25	-6.63		0.71	0.43	-2.46		
σ	0.23				0.01				3.51				
T-value	6.45				4.62				4.33				
							AR_t						
Estimate	-0.05	0.7	-0.68	0.01	-0.76	-0.57	-0.78	0.07	0.12	-0.07	-0.31	0.13	-197.72
T-value	-0.47	5.85	-5.18	0.04	-16.2	-17.1	-33.2	2.07	1.06	-0.45	-3.11	1.26	
σ	0.59				0.02				0.37				
T-value	6.04				2.35				4.69				
							WAR_t						
Estimate	0.02	0.07	-0.32	0.13	-0.04	0.4	-0.45	-0.1	-0.1	-0.43	-0.94	-0.82	-218.13
T-value	0.44	0.6	-3.05	1.23	-0.54	3.04	-3.55	-0.85	-0.34	-1.79	-6.72	-2.69	
σ	0.78				0.34				0.71				
T-value	5.41				4.01				2.00				
							MAR_t						
Estimate	-0.04	0.71	-0.69	0.01	-0.77	-0.58	-0.78	0.07	0.12	-0.06	-0.31	0.13	-197.62
T-value	-0.49	6.33	-5.67	0.13	-16.7	-17	-33.1	2.07	1.03	-0.38	-3.14	1.26	
σ	0.6				0.02				0.37				
T-value	5.96				2.53				4.76				
							$MWAR_t$						
Estimate	0.61	-0.22	-1.17	-0.07	-0.06	0.69	-0.51	-0.05	-0.02	0.14	-0.36	0.04	-240.57
T-value	5.34	-2.2	-17.5	-0.53	-0.57	6.58	-6.03	-0.47	-0.31	1.72	-4.92	0.49	
σ	0.12				0.09				0.67				
T-value	2.17				1.95				8.15				
							$TrdV_t$						
Estimate	-0.53	0.47	0.19		-0.12	0.38	-0.5		0.63	0.32	-0.67		-246.63

Parameter	Regime 1				Regime 2				Regime 3				Log Likelihood
	β_1	δ_1^1	δ_1^2	δ_1^3	β_2	δ_2^1	δ_2^2	δ_2^3	β_3	δ_3^1	δ_3^2	δ_3^3	
T-value	-3.95	5.28	2.11		-1.68	4.49	-5.59		2.5	2.17	-4.7		
σ	0.18				0.29				1.30				
T-value	2.05				4.62				3.58				
						WD_t							
Estimate	0.05	0.82	-0.88	0.4	0.01	0.05	-0.37	0.01	-0.01	-0.03	-0.53	0.14	-161.21
T-value	0.35	5.81	-6.98	2.19	0.39	0.59	-7.6	-0.05	-0.02	-0.08	-1.53	0.36	
σ	0.52				0.09				3.64				
T-value	2.39				4.05				2.32				
						AOM_t							
Estimate	-1.6	-2.43	-2.48		-0.1	0.09	-0.42		0.48	-0.27	-0.48		-74.07
T-value	-3.51	-2.88	-2.94		-0.92	0.73	-3.51		1.7	-1.38	-2.65		
σ	0.64				0.37				0.74				
T-value	1.27				4.20				2.61				
						$RPAN_t$							
Estimate	-0.04	0.71	-0.69	0.01	-0.77	-0.58	-0.78	0.07	0.12	-0.06	-0.31	0.13	-197.62
T-value	-0.49	6.33	-5.67	0.13	-16.7	-17	-33.1	2.07	1.03	-0.38	-3.14	1.26	
σ	0.60				0.02				0.37				
T-value	5.96				2.53				4.76				

Table 4

Regime Switching Probability Matrix

Proxy Variables	Regime switching probability matrix	Proxy Variables	Regime switching probability matrix
N_t	$\begin{pmatrix} 0.915 & 0.001 & 0.237 \\ 0.085 & 0.832 & 0.045 \\ 0.000 & 0.167 & 0.718 \end{pmatrix}$	V_t	$\begin{pmatrix} 0.945 & 0.043 & 0.078 \\ 0.043 & 0.928 & 0.001 \\ 0.012 & 0.030 & 0.921 \end{pmatrix}$
AR_t	$\begin{pmatrix} 0.905 & 0.104 & 0.089 \\ 0.095 & 0.592 & 0.001 \\ 0.000 & 0.304 & 0.910 \end{pmatrix}$	WAR_t	$\begin{pmatrix} 0.938 & 0.050 & 0.161 \\ 0.062 & 0.932 & 0.001 \\ 0.000 & 0.018 & 0.838 \end{pmatrix}$
MAR_t	$\begin{pmatrix} 0.906 & 0.100 & 0.085 \\ 0.094 & 0.603 & 0.001 \\ 0.000 & 0.297 & 0.914 \end{pmatrix}$	$MWAR_t$	$\begin{pmatrix} 0.608 & 0.235 & 0.001 \\ 0.121 & 0.765 & 0.025 \\ 0.271 & 0.000 & 0.974 \end{pmatrix}$
$TrdV_t$	$\begin{pmatrix} 0.434 & 0.015 & 0.254 \\ 0.001 & 0.960 & 0.111 \\ 0.565 & 0.025 & 0.635 \end{pmatrix}$	WD_t	$\begin{pmatrix} 0.736 & 0.136 & 0.153 \\ 0.206 & 0.864 & 0.099 \\ 0.058 & 0.000 & 0.748 \end{pmatrix}$
AOM_t	$\begin{pmatrix} 0.470 & 0.001 & 0.103 \\ 0.254 & 0.979 & 0.001 \\ 0.276 & 0.020 & 0.896 \end{pmatrix}$	$RPAN_t$	$\begin{pmatrix} 0.684 & 0.037 & 0.002 \\ 0.316 & 0.963 & 0.928 \\ 0.000 & 0.000 & 0.070 \end{pmatrix}$

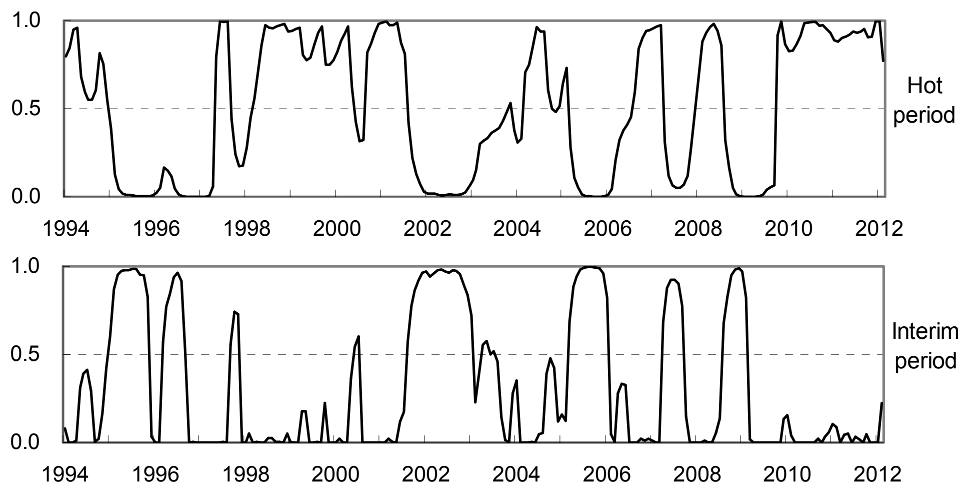
Table 3 and Table 4 display regression results and regime switching probability matrix for proxy variables 1 to 10. We discovered that more than half of the T-values for each proxy variable are significant at a 10% level. The regression results of N_t, V_t, $TrdV_t$ and AOM_i are have intercept coefficients $\beta_1<\beta_2<\beta_3$ to correspond with cold periods, interim periods and hot periods. The regime switching probability matrix depicts the switching probability from one regime to another. It can be concluded that most regimes exhibit a high stability, and that the probabilities when maintaining former regimes are steady around 0.9.

GAUSS MSVARlib also integrates the filter iterative method (Krolzig, 1997, p. 254) into a Markov regime switching model to calculate both filtered and smoothed probabilities. The smoothed probabilities are displayed in Figure 3[8].

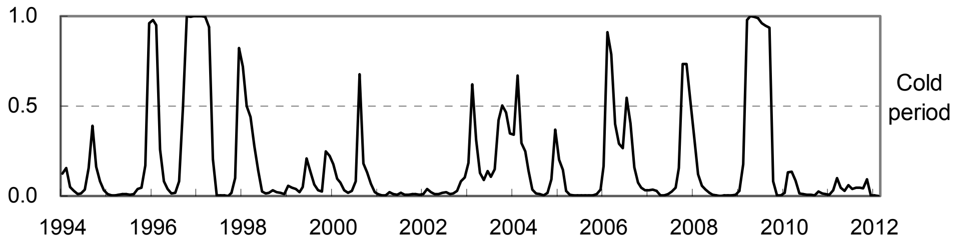
Proxy variables 1, 2 and 7 cover all 222 months. The smoothed probability of N_t fluctuates dramatically and reveals that different periods of time are situated in different regimes. However, V_t, which represents IPO proceeds, does act accordingly: for V_t the time periods in a hot market regime are significantly less than in the other two regimes, and they tend to cluster in the later stages (recent years) where IPO proceeds increased more rapidly. Data of $TrdV_t$ are analogous to the nature of the data of V_t, but there also exists differences between results. Proxy variables 3-6 and 8[9] do not contain those time periods without IPOs; and variables 3-6 represent the levels of underpricing. It was observed that the result of variables weighted by IPO proceeds differed greatly from those with non-weighted results. On the contrary, when comparing the results of variables revised by stock market returns with the non-weighted variables' results, a similar situation was not observed. Furthermore, there appears to be a lead-lag relationship between the results of IPO numbers and levels of underpricing. This paper first uses proxy variable 9 and 10 to detect IPO cycles. The goal of these two variables was primarily to test cycle robustness in their relatively short time range.

Figure 3

Smoothed Probabilities of Variable 1



[8] *Due to the length limitation of this paper only the smoothed probabilities of proxy variable 1 are given. If readers need the smoothed probabilities of proxy variables 2-10, please contact the author.*



It is obvious that different proxy variables lead to different abilities to detect IPO cycles. This is resultant of the many factors influencing IPO cycles. Though it is impossible to analyze all influential factors to the IPO cycle, the factors selected represented a variety of characteristics offering various ways in which results may differ greatly.

Based upon economic factors and investor sentiments in the stock market, Brailsford, Heaney and Shi (2004) argue that six months is an optimal duration for hot or cold periods. This paper follows their suggestion and uses six months as a minimum phase for a hot or cold period. Taking all the ten results into consideration, proxy variables 1, 2 and 7 are taken as benchmarks, whereas proxy variable 3-6 and 8-10 are used to ensure cycle robustness. After these considerations, we pinpoint the results of IPO market cycles in China's A-share market from January 1994 to June 2012. Table 5 shows the results of IPO market cycles.

Table 5

Results of IPO Market Cycles

Hot period	Nov.1995-May.1997; Apr.1999-Nov.1999; Sep.2003-Mar.2004; Apr.2006-Dec.2007; Feb.2009-Sep.2009; Mar.2011-Jan.2012
Cold period	Jan.1994-Jul.1994; Mar.1998-Mar.1999; Dec.1999-Mar.2001; Sep.2004-Mar.2005; Jan.2008-Jan.2009; Apr.2010-Sep.2010
Interim period	Feb.1995-Oct.10; Jun.1997-Feb.1998; Apr.2001-Aug.2003; Apr.2004-Aug.2004; Apr.2005-Mar.2006; Oct.2009-Mar.2010; Oct.2010-Feb.2011; Feb.2012-Jun.2012

When fixing underpricing measures, this paper compares the IPO initial return on the 21st trading day after offering to the initial return on the 1st day. For robustness, we use the IPO initial return on the 1st trading day after offering to make regressions, and the regression results show that there is no significant difference between these two measures.

There are controversies on whether GEM (Growth Enterprise Market) influences either the main market or the A-share market. Our first research carried out regression analysis on data that included GEM IPOs. To ensure robustness, we also used data without GEM IPOs to further do these regressions. However, we found no difference between either data regressions.

5. Conclusions

This paper employs a three-regime Markov switching model to carry out regressions on a series of improved proxy variables to detect IPO market cycles. These improved proxy variables reflect the effects of varying IPO numbers, levels of underpricing, market conditions and government regulation. This work then points to the results of IPO market cycles in China's A-share market from January 1994 to June 2012 by analyzing regression results, filtered probabilities and smoothed probabilities. Herein we identified six hot periods, six cold periods and eight interim periods.

First, the results reveal that correlations exist between IPO market cycles with either levels of underpricing or with IPO numbers. Second, our results confirm the myriad influences that market events and government regulations bear upon IPO market cycles, e.g. the hot market period experienced from November 1995 to May 1997. In this particular instance the government began promoting state-owned enterprises by developing a securities market during the same period.

Thirdly, the government may reference results when writing policies. Fourthly, the government can also assist IPO issuers and investors to make effective decisions to some extent.

Moreover, the research of this paper enriches studies on periodism issues and expands the range of application for the Markov regime switching model.

Much space remains for future exploration of the IPO market cycle theory. This field is constantly evolving and improving. For instance, when detecting IPO cycles, proxy variables 1, 2 and 7 were taken as benchmarks, while proxy variables 3-6 and 8-10 were mainly used to ensure the robustness of the cycles. Hence, with follow-up studies one could ascertain the quantitative correlation between each proxy variable to acquire and even more accurate result. To do so would require more advanced econometrics and statistical methods. Alternately, follow-up studies may consider utilizing the reform of non-tradable shares as a dummy variable in our model, or introduce the time interval from IPO application day to the examination pass day as a proxy variable – to replace the duration days from offering to listing. Furthermore, follow-up studies could deal with those IPOs possessing cross-listings.

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