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The Initial Public Offering Quandary:
Is There a State and Time Dependency?

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Michael D. Herley

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Dissertation Supervisor: Dr. Lucjan T. Orlowski Signature:

Committee Member: Dr. Malvina Marchese Signature:

Committee Member: Dr. W. Keener Hughen Signature:

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Doctoral Dissertation Paper

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Abstract:
An entrepreneur or private-equity-backed firm's decision to pursue an initial public offering (IPO) is a complex process that can lead to many sleepless nights for company founders. Nevertheless, there is a pathway to going public for most companies. Understanding the critical drivers of IPOs and how they react under different conditions or states should be of paramount concern to those considering an IPO and their advisors. Using a monthly net IPO volume series for Amex-, NYSE-, and Nasdaq-listed stocks for the period 1990–2019, my results suggest the interplay of the VIX Index and Wilshire 5000 returns, along with IPO lagged values, promote both state and time dependency in the IPO market. My dissertation takes a fresh approach to the IPO quandary, leveraging a series of stochastic and nonstochastic, nonparametric models, including threshold autoregressive, self-exciting threshold autoregressive, logistic smooth threshold autoregressive, and Markov switching. A five-regime threshold autoregressive model yields the best out-of-sample forecast performance of all the models tested, with a 1-month lag of the VIX Index's monthly average as the switching variable. A two-state Markov-switching model reveals a high degree of instability in the IPO market up to October 2000. Since then, there has been a clear, well-defined one-state pattern of IPO activity.

Keywords: IPOs, regime-switching models, Markov switching, time-series forecasting
JEL classification: G17, G24, G32, C52, C32

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1. **Introduction**

Initial public offerings (IPOs) continue to play a critical role in the capital markets[1] and the overall economy. With the total number of IPOs[2] remaining considerably below historic levels, developing a more thorough understanding of their drivers and how they vary under different conditions could benefit market participants and regulators. In this dissertation, I consider the relevant academic literature and extend the paradigm that stock market growth positively influences IPO activity, and market volatility tempers IPO volume—while also accounting for the present instability in the data through a regime-switching[3] approach.

I will show that the interplay of the Chicago Board Options Exchange Volatility Index (VIX Index) and the Wilshire 5000 Total Market Index (Wilshire 5000 Index) returns, along with lagged IPO values, create both state and time dependency in the IPO market. These intertemporal results are meaningful for investment bankers, academic scholars, law firms, and professional investors participating in the IPO market.

Each of these constituencies should find the time-varying and state-dependent nature of IPOs meaningful and, subsequently, consider factoring this information when making recommendations on new equity issues to their clients. Government regulators, policy experts,

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[1] Some authors have suggested that what happens in the IPO market is a "leading indicator" of the financial markets (Beaulieu & Bouden, 2015).

[2] Consistent with other studies, I focus on net IPOs, which excludes closed-end funds, real estate investment trusts (REITs), acquisition companies, offer prices below $5, American depositary receipts (ADRs), limited partnerships, units, banks, and savings and loans (S&Ls).

[3] Merriam-Webster's dictionary has multiple definitions for the word "regime," which broadly fall into two categories: (1) "a government in power" and (2) "the characteristic behavior or orderly procedure of a natural phenomenon or process." When thinking about "regime-shifting" models to describe IPO behavior, I mean an equation that follows an orderly process of moving from one state of IPO activity to another state of activity. More specifically, a regime shift will typically mean moving from a "lower" state of IPO activity to a "higher" state, or vice versa. I would like to thank Hamaker et al. (2010) for providing a similar analogy in their paper "Regime-Switching Models to Study Psychological Processes," which helped shape my explanation here.

and political leaders interested in reenergizing the IPO market should also pay particular interest to these findings.

As Hansen (2001 p. 127) inquired in his seminal study on the importance of identifying and understanding the impact of structural breaks on time-series data, “Is this break permanent or transitory?” My research aims to shed new light on the IPO market by addressing such questions.

An entrepreneur or private-equity-backed firm’s decision to pursue an IPO is complicated. The IPO process officially begins in the public arena by filing the S-1 registration statement with the Securities and Exchange Commission (SEC). Once this happens, market anticipation begins to build, and so does a company’s anxiety. Company executives must follow strict guidelines about what they can and cannot say during the period leading up to the IPO, formally known as the quiet period.[4] Investor demand and the broader market outlook are two significant and interrelated drivers of IPO activity. Conversely, when the equity markets become unsettled, and the investor fear index, formally known as the VIX Index, spikes, the IPO window can close abruptly for companies.

IPO activity is essential to the equity markets because institutional and retail investors depend on an ample supply of newly public companies to replace firms delisted because of a bankruptcy, a merger or acquisition, or a go-private transaction.[5] Today in the United States, there are significantly fewer public companies than 20 years ago, which means more private companies do not follow the regular cycle of public disclosures required by the SEC. And

[4] Please see Latham & Watkins LLP’s US IPO Guide (2020) for a thorough discussion of communications allowed during the IPO quiet period.

[5] According to Doidge et al. (2017), publicly listed firms delist for three primary reasons: (a) they no longer meet the exchange’s listing requirements, (b) they were acquired, or (c) they decided to delist voluntarily.

although a U.S. public corporation today may not be a perfect model of transparency, it does provide a significantly higher level of financial information than most private companies.

The Wilshire 5000 Index, which measures the equity performance of all publicly traded companies in the United States, ballooned to 7,562 companies by July 31, 1998. As of December 31, 2019, the Wilshire had only 3,473 members—a decline of 54.073% from its peak. On a per-capita basis, only 11 publicly listed companies operated for every million residents in the United States through 2016, down from 23 companies in 1976 (Stulz, 2018). According to Stulz, this percentage decline puts the United States only slightly ahead of Venezuela among countries that have seen a decline in their equity listings.

The decline in IPO volume presents a challenge for those looking to save for retirement because an increasing percentage of retirement assets in the United States are held in defined contribution accounts that invest primarily in equity-based mutual funds. By definition, having fewer publicly traded companies means it is more difficult for individual investors to diversify the equity holdings in their retirement portfolios because professional money managers must choose from among a smaller investment pool.

Companies going public today are also more mature than those that have gone public in the recent past. A *Wall Street Journal* article on IPOs from 2019 cited research from IPO scholar Jay Ritter (n.d.) on how the median age of technology companies going public in 2018 was 12 years, compared with 4 or 5 years in 1999 and 2000 (Cimilluca, 2019). Thus, stock market investors today have access to fewer high-growth companies. Given the convergence of these factors, it is no surprise that both individual investors and public pension funds (which serve public school teachers, police officers, firefighters, etc.) have needed to temper their expected return assumptions in recent years.

A contributing factor to the drop-off in public companies may be that technology firms, rich with intangible assets, prefer to stay private longer, so they need not disclose confidential information to competitors in required filings (Stulz, 2019). Concurrently, technology firms benefit from private capital and the “specialized knowledge” they bring as investors during the early growth phase compared with investors in a traditional public company (Stulz, 2019).

Scholars have studied IPOs extensively over the past two decades, with many analyzing why IPO activity has declined from previous levels, particularly compared with those in the 1990s. Indeed, a Google Scholar search of the term “initial public offerings” on January 3, 2021, for the period 1999–2019, yielded 23,600 results. Numerous papers have explored whether the decline in IPO volume results from market regulations such as the Sarbanes–Oxley Act of 2002 (Sarbanes–Oxley) or deregulation such as the National Securities Markets Improvement Act (NSMIA) of 1996, which increased the supply of private equity capital. Other researchers have contended the decline is the result of weak investor demand in the market.

My dissertation takes a novel approach to reexamine IPO activity through a series of stochastic and nonstochastic, nonparametric models, including threshold autoregressive (TAR), self-exciting threshold autoregressive (SETAR), logistic smooth threshold autoregressive (LSTAR)–first order, and Markov switching (MS). I will show that IPO activity varies according to equity returns, market volatility, and previous IPO levels while responding differently under statistically determined regimes that create both state and time dependency. According to M. Marchese, personal communication from, March 29, 2021:

> [in] finance, we care not just for modeling the relationships among variables/quantities but also about forecasting the target quantities (not only conditional mean returns but also variances or correlations). If, and when, such relationships are subject to instability over

time, then such instability needs to be modeled and predicted. Regime switching models are a set of relatively recent and innovative statistical tools that are used to detect and predict instability (the discontinuities referred to above) in statistical relationships.

Because the MS and TAR model series do not nest, I compare the static out-of-sample forecasts of each to determine which produces the most accurate estimates. Such an approach is beneficial since industry participants long for more precise predictions. Model assessment results include several evaluation statistics for each of the models: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), symmetric mean absolute error (SMAPE), Theil U1, and Theil U2.

Of all the models across all of the evaluation statistics (RMSE, MAE, MAPE, SMAPE, Theil U1, and Theil U2), the best static out-of-sample forecast performance is achieved by a five-regime TAR model. The top-performing IPO forecasting model has a one-period lag of the VIX monthly average as the switching variable, IPO volume as the dependent variable, and a one-period lag of the VIX monthly average, the Wilshire 5000 return, and 12 one-month lags of IPO volume as the independent variables.

The TAR model also outperforms all of the chosen forecast averaging methods. These include simple mean, simple median, least-squares, mean square error, mean square error (MSE) ranks, smooth Akaike information criterion (AIC) weights, and Schwarz information criterion (SIC) weights.

At this juncture, it is fundamental also to demonstrate how the TAR model performs against the ordinary least squares (OLS) regression model using the same independent variables. If the TAR model outperforms the OLS regression model following the same static out-of-sample forecast approach, there is additional justification for adopting a regime-switching approach. Again, the TAR model outperforms across all the evaluation statistics.

The MS model shows undefined, frequent swings in the IPO market before October 2000. Since then, there has been a clear, well-defined one-state pattern, demonstrating time dependency in the IPO market.

A significant contribution of my dissertation is that I examine IPO volume vis-à-vis a combination of leading state and time-dependent models. Indeed, I found no scholarly research that accounts for the present instability in the IPO market following a comprehensive regime-switching approach while assessing forecast performance through an out-of-sample process.

The balance of my dissertation is organized as follows: Section 2 presents my literature review; Section 3 introduces my sample data and the descriptive statistics; Section 4 discusses the regime-switching models used in the analysis; Section 5 presents the forecast results for all the models; Section 6 examines the findings of my top state and time-dependent models; and Section 7 offers concluding remarks.

2. Literature Review

One of the most frequently cited studies and perhaps the seminal paper on IPO volume trends is Lowry (2003). Lowry segmented the market forces that drive fluctuations in the IPO market into three main categories: (a) capital demands, (b) information asymmetry, and (c) investor sentiment.

The foundation of the capital demands hypothesis is that a strong economy and bright outlook stimulate businesses' desire to seek additional capital for growth. Although various mechanisms exist to raise capital, a rational manager will pursue an IPO when this form of capital is more advantageous than other financing options (Lowry, 2003).

The information asymmetry hypothesis postulates that the IPO market's reasonable efficiency incentivizes firm managers to take their companies public when their valuations are high. Thus, investors will lower the value they assign to a firm when it goes public (Lowry, 2003). The firm seeking to raise capital will go public only when the IPO's worth exceeds both the direct-issue cost and any adverse-selection costs. In other words, when information asymmetry is high, companies usually choose different types of financing as an alternative to going public.

The investor sentiment hypothesis proposes that investor enthusiasm in the equity markets drives IPO volume (Lowry, 2003). When markets are strong, investors are willing to pay more (and sometimes overpay) for shares in an IPO, which leads to increases in IPO volume. When investor enthusiasm is low, investors may undervalue firms going public, contributing to declines in IPO volume.

Similarly, Pastor and Veronesi (2005) showed that companies seeking to go public tend to do so during periods of favorable market conditions to improve their valuations, contributing to what has become known as IPO waves. Beaulieu and Bouden (2015) developed a vector autoregressive (VAR) model to demonstrate that riskier firms are more likely to go public during an IPO wave to maximize their valuations; Ritter's (1984) and Chui's (2008) research echoed similar points about waves. At the same time, Beaulieu and Bouden (2015) inferred that most companies are generally rational in their approach and decide to go public when the market appropriately values their shares.

Loughran et al. (1994) were among the first to document the stock market performance's positive influence on IPO volume. Their foundational research influenced the construction of Lowry's (2003) time-series model.

Tran and Jeon (2011) used a vector error correction (VEC) model to show that the S&P 500 Index stimulates IPO activity. The authors extended the interpretation of their VEC model by running impulse response functions. They found that the innovation, or the shock, to IPOs occurs during the first 3 months—and that the shock is only modest.

Gao et al. (2013) developed time-series regressions to explain scaled IPO activity. They hypothesized that "economies of scope" and "speed in bringing products to market" have driven the decline in IPOs over recent years, predominantly among smaller companies. The results were statistically significant and more "pronounced" for smaller firms. The authors concluded that IPO levels will not return to their previous levels because smaller firms are "not necessarily the profit-maximizing form of organization" (p. 1691).

Blum's (2011) research showed that the VIX Index negatively correlates to the IPO market at the 0.01 level, supporting Lowry's (2003) investor sentiment hypothesis. Firms tend to shy away from going public during periods of high volatility, as measured by the VIX Index. Schill (2004) found that, during periods of high market volatility, the number of IPO transactions declines by 13%, and the amount of capital raised drops by 21%.

Beaulieu and Bouden's (2015) VAR model revealed that high VIX levels in the current month decrease IPO volume in the subsequent month. At its foundation, the authors interpreted these results to mean that more companies will initiate an IPO once the VIX declines from an elevated level. Why? So, the owners can benefit from an increased valuation.

Brau and Fawcett (2004) undertook another critical study on IPOs; however, their research was based on a survey of 336 CFOs that included information about their decision to go public or stay private. When determining when to take their company public, CFOs reported placing less importance on the IPO market's robustness and instead emphasized market and industry stock returns. CFOs of venture-capital-backed companies or those with lower insider ownership levels reported a tendency to weigh market timing issues over other topics.

Another factor when considering IPO volume is how long a company typically takes to go public following the filing of its registration statement with the SEC. Bouis's (2009) survey of IPOs from 1986 to 2007 found the average registration period is approximately 85 days, although this number varies by issuer. According to the study, when market volatility is high, many firms that have filed their IPO registration statements ultimately withdraw their filing to go public. Lowry et al. (2017, p. 12) noted in their compendium of research on IPOs that "20% of IPOs are withdrawn" before completing the process. Of these companies, few go on at a later point to become a public entity. However, it is worth noting that nothing stops a company from delaying going public once it makes its S-1 registration statement with the SEC if market sentiment turns negative.

Congressional testimony delivered by New York Stock Exchange (NYSE) President Thomas W. Farley in 2017 suggested that public companies' current regulatory environment—most notably Sarbanes–Oxley—negatively affects corporate owners' decision to take their companies public. Other key influencers have echoed this same point over recent years. Wang and Yung (2019) found no statistical breaks in their 1970–2015 IPO data series related to Sarbanes–Oxley. They concluded that weak investment conditions more likely drove the decline in IPO volume, a finding consistent with Gallardo and Phillippon's (2016) research.

Tran and Jeon (2011) found that including a dummy variable in their OLS benchmark IPO regression for Sarbanes–Oxley did not add meaningful information. Ritter (2012) attributed only a small part of the drop-off in IPO volume over recent years to Sarbanes–Oxley. Gao et al. (2013) found little support for the idea that market regulations affect small-cap companies' IPO levels. They instead postulated that there are fewer independent small companies today because of structural changes in the economy that make selling out to a larger firm more advantageous because sellers' businesses can then benefit from more significant economies of scale. Wang and Yung (2019) noted that the cost of going public is not cheap, with the SEC estimating the initial compliance cost as $2.5 million—with another $1.5 million spent each year after that. These compliance costs seem to lessen the desires of small companies to pursue an IPO.

Ewens and Farre-Mensa (2020) argued that the implementation of NSMIA has created an environment where late-stage private companies can delay going public because there is an ample supply of private capital available to support their growth needs. The authors' results suggested that NSMIA has created a "new equilibrium" where fewer new ventures ultimately pursue an IPO, and those that decide to go public do so at a later point in their growth cycle. The authors also noted that staying private is not without its downside for the economy. These venture-backed companies tend to operate with a lower degree of transparency than their publicly traded counterparts.[6]

As previously noted, there is relatively limited research on applying a regime-switching approach to model IPO activity. Brailsford et al. (2000) employed an MS model to investigate the phenomenon of hot and cold IPO markets. The authors followed the traditional definition of hot and cold markets established by Ritter (1984) and Ibbotson and Jaffe (1975): high IPO activity and large underpricing. They demonstrated that several states existed in the IPO market during the 1976–1998 period and further explored the results through a VAR model. Brooks et

[6] One clear benefit of going public is that it typically provides a firm with a lower cost of capital. However, the downside is that agency costs can affect managers' decision-making to choose appropriate positive net present value (NPV) projects (Lowry et al., 2017).

al. (2010) also leveraged an MS model to study IPO states, but they instead focused on the Chinese A-share market.

Brailsford et al. (2004) developed a generalized autoregressive conditionally heteroscedastic model to examine the theory of hot and cold IPO markets, utilizing the 13 lags of IPO volume, IPO underpricing, and market returns. They found that almost all of the coefficient signs were positive, contributing to greater IPO activity. They also cited research from Lipman (1997) on how entrepreneurs cannot move so quickly because taking a company public requires 3 to 6 months at a minimum.

3. Data

I use monthly net IPO volume for Amex-, NYSE-, and Nasdaq-listed stocks for the 1990–2019 period. IPO volume data come from the IPO website of Jay R. Ritter (n.d.), a leading scholar in the IPO field. The benefit of using Ritter's IPO data is that the data have been reviewed extensively for errors. Consistent with other studies, my dissertation focuses on net IPOs, which exclude closed-end funds, REITs, acquisition companies, offer prices below $5, ADRs, limited partnerships, units, banks, and S&Ls. I obtained data on the VIX Index monthly average values from Federal Reserve Economic Data (FRED; 2020) and Wilshire 5000 Index data from Yahoo Finance (2020).

Although these IPO data do not include S&Ls, one cannot underestimate the impact the S&L crisis had on the financial markets throughout the 1980s. With the passage of the Financial Institutions Reform, Recovery and Enforcement Act of 1989 and the bulk of the S&L issues worked through the system up to this point, the 1990–2019 period is appropriate to model the current IPO market. Moreover, FRED first reported VIX Index monthly average values starting in 1990.

Figure A1 graphs monthly IPO volume versus the VIX Index monthly average from 1990 to 2019. As the graph shows, once the VIX Index begins to spike above approximately 25, IPO levels drop off precipitously. The correlation coefficient between IPO volume and the VIX Index monthly average is modestly negative at -0.257989. A VIX Index lower than 15.2 equates to a low volatility state; intermediate volatility exists when the VIX Index is between 15.2 and 25.0, and high market risk exists when the VIX Index exceeds 25.0 [L. Orlowski, personal communication, February 24, 2021, updating the original Bai–Perron Threshold test conducted in Orlowski (2017)].

… insert Figure A1…

Figure A2 graphs the Wilshire 5000 Index returns for the 1990–2019 period. These are the differences in the Wilshire 5000 Index's logarithmic values for the period indicated.

… insert Figure A2…

Table 1 presents the descriptive statistics for IPO volume, VIX Index, and Wilshire 5000 Index Returns. I use EViews 12 to conduct the statistical tests and econometric modeling throughout my dissertation.

The median number of IPOs each month over the sample period is 12, the median for the VIX Index monthly average is 17.38689, and the median for the Wilshire 5000 Index return is 0.012316. I reject the Jarque–Bera normality test for all three variables at the 1% level of significance. The levels of skewness and kurtosis both support the rejection of normality.

The augmented Dickey–Fuller unit root test for monthly IPO volume is rejected at the 0.05 level of significance. Past research has indicated that IPO volume is somewhat nonstationary, so this finding is not surprising. For this version of the Dickey–Fuller unit root test, I included the trend and intercept in the test equation. Both the VIX Index and Wilshire 5000 Index Returns were stationary at the 0.01 level of significance.

Table 1

Descriptive Statistics for IPO Volume, VIX Index, and Wilshire 5000 Returns

	IPOs	*VIX*	*Wilshire 5000 Return*
Number of Obs.	360	360	360
Mean	18.23611	19.16071	0.006287
Median	12.00000	17.38689	0.012316
Standard dev.	16.86510	7.441267	0.042389
Minimum	0.000000	10.12545	-0.195293
Maximum	90.00000	62.63947	0.107879
Skewness	1.333163	2.029740	-0.890911
Kurtosis	4.330301	9.819401	4.934359
Jarque–Bera	133.1849	944.7542	103.7495
Probability	0.000000	0.000000	0.000000
ADF	-3.713302	-4.371656	-17.85496
Probability	0.0226	0.0004	0.0000

Tables A2, A3, and A4 present the OLS regression Bai–Perron breakpoint tests for IPO volume versus IPO volume (-1) and IPO volume (-2); IPO volume versus VIX Index; and IPO volume versus Wilshire 5000 Index returns. I include a 1- and 2-month lag of IPO volume for the VIX Index monthly average and Wilshire 5000 Index return OLS regression models to address the first-order autocorrelation, bringing the models' Durbin–Watson statistics close to 2.

… insert Table A2…

… insert Table A3…

… insert Table A4…

In all three instances, I reject the null hypotheses that there are no structural breaks in the IPO volumes series for 0 versus 1 and 1 versus 2 at the 0.05 level of significance because the scaled F-statistics are greater than the critical values. These baseline outcomes justify undertaking a more in-depth examination of these relationships' robustness to determine whether state and time dependency exist in the IPO market.

4. Model Framework

To expand upon the preliminary Bai–Perron breakpoint test results and show whether state and time dependency exist in the IPO market, I employ a sequence of regime-switching modeling techniques: TAR, SETAR, LSTAR, and MS.

I have chosen this approach because there is significant instability in the IPO data from 1990 to 2019. It is vital to account for structural breaks when building economic and financial models. As Hansen (2001) noted, "Structural change is pervasive in economic time series relationships, and it can be quite perilous to ignore. Inferences about economic relationships can go astray, forecasts can be inaccurate, and policy recommendations can be misleading or worse" (p. 127).

Consequently, to develop an IPO model that is both stable and one that produces the most accurate forecasting results, it is essential to leverage an approach that seamlessly adjusts for state and time dependency. The models I apply meet these criteria.

TAR

Tong (1980) developed the TAR model, providing several deep reflections on its contributions to time-series modeling 30 years later in another influential paper. Although there are numerous ways to explain a TAR model, Tong described it as follows:

$$X_t = a_0^{(J_t)} + \sum_{i=1}^{p} a_i^{(J_t)} X_{t-i} + b^{(J_t)} \varepsilon_t, \qquad (1.1)$$

where ε_t s are independent and identically distributed (iid) $(0, \sigma^2)$, and $\{J_t\}$ is an (indicator) time series taking values in $\{1, 2, . . . , J\}$. Here the indicator, J_t, operates as the switching mechanism.[7]

SETAR

Tong[8] (1990) developed the SETAR model, which is represented by the equation below. Here Tong stated that the indicator J = 2. Next, he let $J_t = 1$ if $X_{t-d} \leq r$ and $J_t = 2$ if $X_{t-d} > r$ for some real threshold "r" and some positive integer "d," which he defined as the delay parameter. In essence, the self-exciting component, the "SE" of the "SETAR," is the lagged values of the dependent variable driven by r.

$$X_t = \begin{Bmatrix} \alpha + \beta X_{t-1} + \varepsilon_t \text{ if } X_{t-d} \leq \text{r;} \\ \gamma + \delta X_{t-1} + \phi\varepsilon \text{ if } X_{t-1} > \text{r,} \end{Bmatrix} \qquad (1.2)$$

where $\alpha, \beta, \gamma, \delta,$ *and* ϕ are real constants.

Smooth Threshold Autoregressive (STAR)

The regime switch that occurs in a TAR or SETAR model is discrete, whereas the switch in a STAR model is continuous and occurs smoothly,[9] as its name implies. Chang and Tong (1986) were the first to introduce and develop these models under the STAR name.

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[7] According to Tong (2010), "The basic idea of a threshold model is piecewise linearization through the introduction of the indicator time series, $\{J_t\}$" (p. 9).

[8] Tong (2010) went out of his way to note that the SETAR model has at times been misconstrued, "perhaps because of its popularity," as representing the "entire family of TAR models, which it does not" (p. 9).

[9] Teräsvirta (1994) noted that the main economic benefit of using a STAR model is that there are typically many players at work in macroeconomic time-series data, even if these agents still behave discretely. As a result, a regime-switch model that accounts for these transitions through a smooth process may present a more accurate depiction of economic reality because these processes are typically observed in aggregate.

There are two primary forms of the STAR model today: one follows a logistic function, and the other follows an exponential function. My dissertation focuses on the logistic function, precisely the first order. Teräsvirta (1994) formulated the LSTAR model, which has been used widely in economic time-series models:

$$Y_t = c_0 + \phi_{01} Y_{t-1} + \phi_{02} Y_{t-2} + \cdots + \phi_{0p} Y_{t-p} + (c_1 + \phi_{11} Y_{t-1} + \phi_{12} Y_{t-2} + \cdots + \phi_{1p} Y_{t-p}) G(s_t, \gamma, c) + \varepsilon_t, \tag{1.3}$$

where $\varepsilon_t \longrightarrow N(0, \sigma^2)$, and $G(s_t, \gamma, c)$ is the continuous transition function bounded by s_t.

The logistic function within the LSTAR model is described as follows:

$$G(s_t, \gamma, c) = \frac{1}{1 + \exp\{-\gamma(s_t - c)\}} \qquad \gamma > 0 \tag{1.4}$$

MS

A significant difference between MS and the TAR series of models is the mechanism of the switch. Within the TAR family, the switch can be pinned to an observable exogenous or endogenous variable. A latent or unobservable variable will instead drive the different states in an MS model—this is a critical distinction between the two classifications of models. Hamilton's (1989) seminal paper introduced econometricians to MS models.

I outline the two-state MS process below:

State 1 is prescribed by the following:

$$Y_t |_{s_t=1} \rightarrow N(\mu_1, \sigma^2) \tag{1.5}$$

$$Y_t |_{s_t=2} \rightarrow N(\mu_2, \sigma^2) \tag{1.6}$$

The transition probabilities between the states in an MS model are defined as $P(s_t = j | s_{t-1} = i) p_{ij}$ Henceforth, if we were in state i yesterday, our probability of moving to state j is p_{ij}.

The transition probability matrix for a two-state MS model is as follows:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} \tag{1.7}$$

5. Out-of-Sample Forecast Results

As shown in Table 5, my TAR model has the best static[10] out-of-sample forecast performance across all my evaluation statistics: RMSE, MAE, MAPE, SMAPE, Theil U1, and Theil U2. The evaluation period is the last 6 months of the sample period[11] of 2019. I selected this evaluation period for a few reasons: (a) companies can start and complete the IPO process within 3 to 6 months if the stars align properly (Lipman, 1997); (b) once a company files its S-1 registration statement with the SEC, and it is declared effective, a company has a degree of latitude as to when it ultimately decides to go public; and (c) financial advisors such as investment bankers understand that forecast accuracy matters, and the longer the forecast, the less likely it is going to be accurate.

The TAR model also outperforms several of the more commonly used forecast averaging[12] methods, including simple mean, simple median, least-squares, MSE, MSE ranks, smooth AIC weights, and SIC weights.

It is also essential to demonstrate whether the TAR model performs better than the OLS regression model using the same independent variables and following the same static out-of-sample forecast approach. Once again, the TAR model outdoes the OLS model, as shown in

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[10] When lagged values of the dependent variable are also explanatory variables in the model, the static forecast produces more robust and reliable results than a dynamic forecast. The dynamic out-of-sample forecast result for the last 6 months of the sample period may, however, be found in Table A13 in the Appendices.

[11] For those with an interest, Table A14 in the Appendices includes the out-of-sample forecast results for the last 18 months of the sample period. Again, the TAR model performs best.

[12] Aiolfi et al. (2010) noted that forecast-averaging approaches have gained much popularity among central banks, private sector forecasters and in the academic communities as a way to "improve and robustify the forecasting performance over that offered by individual models." (p. 2)

Table 5. These results provide additional justification for deviating from the traditional OLS model and adopting a regime-switching approach.

Table 5

Static Out-of-Sample Forecast Results: 6 Months

Sample: 2019M07 2019M12

Included observations: 6

Evaluation sample: 2019M07 2019M12

Training sample: 1991M01 2018M07

Number of forecasts: 13

	Evaluation Statistics					
Forecast	**RMSE**	**MAE**	**MAPE**	**SMAPE**	**Theil U1**	**Theil U2**
OLS Basic**	9.775285	8.945902	166.2339	76.40927	0.366289	1.684608
Markov Switch #1	12.70535	12.01901	219.9646	89.44313	0.428915	2.170828
Markov Switch #2	12.63677	11.95339	218.8366	89.21564	0.427565	2.155906
Markov Switch #3	11.33661	10.60261	197.1937	83.97953	0.401987	1.896729
TAR	**3.876475**	**3.698322**	**58.69378**	**47.30564**	**0.209524**	**0.517348**
SETAR	6.658230	4.948723	108.5760	53.60089	0.293929	1.252227
LSTAR	10.10101	9.378666	174.1840	78.78778	0.373570	1.701290
Simple mean	9.114182	8.255411	158.8266	73.54116	0.352431	1.587618
Simple median	10.69626	9.990636	185.6889	81.53747	0.387462	1.798114
Least-squares	4.977734	4.074578	84.37482	49.92903	0.242842	0.816705
Mean square error	9.018328	8.152878	157.1960	73.04419	0.350127	1.570927
MSE ranks	8.119535	7.176121	141.4235	68.04912	0.327654	1.423151
Smooth AIC weights	9.139164	8.280320	159.2404	73.65655	0.353049	1.592084
SIC weights	8.621043	7.723170	150.1902	70.88969	0.340353	1.510312

* Trimmed mean could not be calculated due to insufficient data.
** OLS basic forecast results excluded from the averaging forecast results.

6. State- and Time-Dependent Models

TAR Model Results

Table A6 illustrates my top-performing model results—the five-state TAR model with a one-period lag of the VIX monthly average as the switching variable[13]. IPO volume is the dependent variable, and a one-period lag of the VIX monthly average, the Wilshire 5000 return, and 12 one-month lags of IPO volume are the independent variables. It is essential to underscore that the VIX monthly average value's 1-month lag drives the TAR model's threshold values, creating state dependency. The TAR model includes five distinct states that pin to specific VIX monthly average values.

The IPO volume TAR model has an R-squared of approximately 83.49%, indicating that the independent variables (in their five states) explain a high degree of variation in the dependent variable. The Durbin–Watson statistic of 1.99 shows there is no first-order autocorrelation present. The Breusch-Godfrey-LM test indicates no higher-order serial correlation up to and including the 12th lag. The Breusch-Pagan Godfrey test indicates heteroskedasticity is present; hence, the white coefficient covariance matrix is selected.

… insert Table A6…

In State I, the VIX monthly average (-1) includes 113 observations, with a threshold value of less than 14.489999. For State II, the VIX monthly average (-1) consists of 55 observations, with a threshold value $\geq$14.489999 and < 16.91863. In State III, the VIX monthly average (-1) includes 52 observations, with a threshold value $\geq$16.91863 and < 19.66227. For State IV, the VIX monthly average (-1) includes 67 observations, with a threshold value $\geq$

[13] The sequential L+1 threshold vs. L is chosen as the threshold specification, with a maximum of 5 breaks. Up to 12 lags of IPO volume were considered for the switching variable.

19.66227 and < 24.7459. In State V, the VIX monthly average (-1) includes 61 observations, with a threshold value $\geq$ to 24.7459.

At each level of the prior month's VIX average level, the preceding month's IPO coefficient is positive and statistically significant. It is noteworthy that the 1-month lag of IPO volume is also the switching variable in my SETAR model (see Table A8 in the Appendices).[14]

When evaluating the coefficients, it can help to think about the five states operating within three broad market volatility levels: low, intermediate, and high as defined by L. Orlowski, personal communication, February 24, 2021, updating the original Bai–Perron Threshold test conducted in Orlowski (2017).

In State I, the prior month's IPO volume has a coefficient of 0.282746 and is significant at the 0.05 level. For State II, it has a coefficient of 0.475824 and is significant at the 0.01 level. In State III (intermediate market volatility level), it has a coefficient of 0.610776 and is significant at the 0.01 level. For State IV (intermediate market volatility level), it has a coefficient of 0.591531 and is significant at the 0.01 level. In State V (high market volatility level), it has a coefficient of 0.559336 and is significant at the 0.01 level.

In the TAR model's fourth state (intermediate volatility), where the VIX monthly average threshold is $\geq$ to 19.66227 and < 24.7459, exciting results emerge. The 12th lag of IPO volume becomes significant at the 0.01 level with a coefficient of 0.253340. In the fifth state (high volatility), where the VIX monthly average threshold is greater than or equal to 24.7459, the 12th lag of IPO volume is also significant at the 0.01 level with a coefficient of 0.326298.

One plausible interpretation of why the IPO (-12) affects current IPO volume is that companies that go public at higher volatility levels tend, on average, to receive a lower premium

[14] The Appendices includes details on all of the models referenced in the out-of-sample forecast results.

and raise less capital. Why? Because fewer companies are going public, and the investor demand is lower. Hence, investors need an enticement to participate in the offering during a higher volatility period (the opposite effect occurs during an IPO wave). If these companies are willing to accept lower proceeds by going public during a volatile market period, they probably made a firm commitment to go public internally by a certain date, regardless of VIX levels. By all accounts, this date would be earlier than when they filed their S-1 registration statement with the SEC and may align closely with the 12-month lag of IPO volume.

Buoyant stock market returns have long been a driver of IPO volume. What is unique in these TAR model results is the isolation of the Wilshire 5000 return's impact in State IV before entering the period of high market volatility. The Wilshire 5000 return produces a robust coefficient in this state of 88.26117 and is statistically significant at the 0.01 level. It is difficult to pinpoint why the Wilshire 5000 return becomes significant at this elevated VIX level and then becomes insignificant once the VIX moves into a high market-volatility state. It may result from a wave in the IPO market building from the previous lower states of volatility that accelerates as investor demand increases and the equity markets spike, creating a self-feeding mechanism. Moreover, once the VIX transfers to a higher state of volatility, IPO activity begins to temper and markets become unsettled, so it is not surprising to observe Wilshire 5000 returns become statistically insignificant as a driver of new equity issues. In the heightened state of market volatility, the VIX Monthly Average (-1) independent variable becomes significant at the 0.01 level with a coefficient of -0.168695.

MS Results

As shown in Table 5, the MS models did not perform as well as the TAR series of equations when examining the out-of-sample forecasts for IPO volume. However, this is not the end of the story because a few unique MS model properties warrant a discussion of the model's results, given my dissertation's hypotheses. MS models are nonparametric models that are particularly well suited for determining whether a dependent variable is time-varying.[15] Given the robust and statistically significant results of my MS model, I believe its outcomes and their interpretation, particularly its regime probabilities and constant expected durations, provide a meaningful contribution to this dissertation and the body of academic literature on IPOs.

The Wilshire 5000 Index return is the switching regressor in my top-performing MS model for IPOs. A one-period lag of the VIX monthly average is the nonswitching regressor, and the fifth lag of IPO volume is the probability regressor, which drives the transition matrix[16]. A first-order autoregressive term addresses the first-order serial correlation in the model, bringing the Durbin Watson statistic in-line to 2.026180.

As shown in Table A7, the model's coefficients are all robust and statistically significant. The switch from $\hat{\gamma}_1$ to $\hat{\gamma}_2$ is particularly pronounced, moving from -18.36420 to 112.8233. The nonswitching regressor, the one-period lag of the VIX monthly average, has a coefficient of -0.384689, consistent with the investor fear index's tempering activity on IPO levels.

… insert Table A7…

Figure 3 highlights the MS smoothed regime probabilities. These results clearly show the time dependency in the IPO market. Although there was a significant amount of instability in the IPO market during the 1990–October 2000 period, since then, there has been a well-defined one-state pattern. I consider the post-October 2000 period the "new normal" for IPO activity. It is no

[15] Langrock et al. (2015) noted, "In regression scenarios where the data have a time series structure, there is often parameter instability with respect to time (Kim et al., 2008). A popular strategy to account for such dynamic patterns is to employ regime switching where parameters vary in time, taking on finitely many values, controlled by an unobservable Markov chain."

[16] In a traditional MS model, the Kalman filter extracts the residuals to drive the transition matrix. With the addition of IPO (-5) as a probability regressor, the linear function of the fifth lag of IPOs is now driving the regime switch. Accordingly, one could consider the construct of this model to represent a hybrid version of an MS and SETAR model.

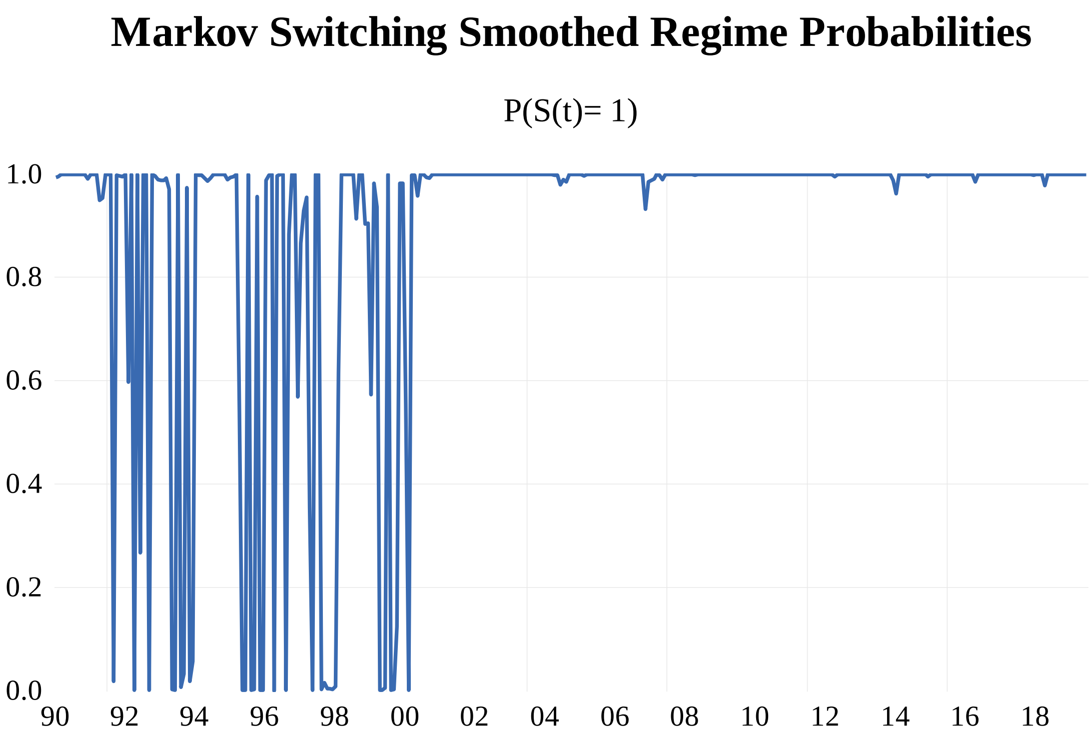
secret that, in the fall of 2000, the Nasdaq bubble began to deflate rapidly, which appears to have contributed to the shift. Indeed, according to Kleinbard (2000), the 200 stocks that comprised the Bloomberg U.S. Internet Index lost $1.755 trillion from their 52-week highs, with the bulk of those losses ending in September 2000.

The model results in Table A7 indicate left skewness in State I and right skewness in State II. As per the skewness level, the model's tail risk level is pronounced and stable over time, as per kurtosis. State I is the dominant regime, with a constant expected duration of 70.76571 months. In contrast, State II has a constant expected duration of 2.115550.

The most notable marking in the smoothed regime probabilities is May 2007 (the regime probability declines to 0.93 compared to the median of 0.985869 for the entire period). It returned to a stable state in December 2007. The subprime crisis began in April 2007 with the bankruptcy of New Century Financial. Freddie Mac, which had announced a couple of months prior that it was exiting the subprime market, undoubtedly was a contributor to New Century Financial's difficulties. These events appear to be contributors to this period's most significant marker, even though the Great Recession did not theoretically begin until the end of 2007. The probability of being in State I is 0.985869 and the likelihood of switching to State II is only 0.014131. The likelihood of being in State II is 0.527310, and the possibility of changing to State I while in State II is 0.472690.

Figure 3

MS Smoothed Regime Probabilities



7. Conclusions

My dissertation results show the essential nature of accounting for state and time dependency in the IPO market and why investment bankers, academic scholars, law firms, and professional investors should consider these findings when advising their clients on new equity issues. A five-state TAR model produces the best out-of-sample forecasts with a 1-month lag of the VIX Index's monthly average as the switching variable. Looking at time dependency, a two-state Markov-switching model shows a clear and stable one-state pattern of IPO activity since

October 2000. From 1990 up to the tranquil period, there was a considerable amount of instability in the Markov-switching smooth regime probabilities.

The U.S. capitalist system has created vast economic wealth for most people compared to any other method. History shows that the U.S. capital markets work best when there is a high degree of transparency. Public corporations are significant players in the capital markets. Despite the shortcomings of the public-entity structure, companies listed on the NYSE and NASDAQ follow the cadence of regulatory and financial disclosures with the SEC. Most public companies also hold quarterly calls with investors that are open to the public. Today, unfortunately, there are far fewer public companies, and many public companies today are more mature than the typical public company 20 years ago. Over the past two decades, the influx of private equity capital has put further pressure on the public company model, particularly for many technology-driven startups, which can now stay private longer.

It is vital for government regulators, policy experts, and political leaders to understand the critical role public corporations play in society. To do this, they need to appreciate the drivers of IPO activity to help advance transparency in the workplace and capital markets (since public corporations, by definition, are more transparent than private companies). They need to create a long-term environment for IPOs to thrive, which can stimulate economic growth. They need to improve the opportunities for average citizens to grow their retirement savings by ensuring they too can invest in a sufficient number of high-growth companies in the public arena.

Future research should look to leverage Dealogic's IPO data, which begins in 1999. So far, scholars have not had access to this data, which Jay Ritter has praised for its quality. The added benefit of Dealogic data is its geographic reach. With IPOs now a global phenomenon, it would be wise to examine new equity issues with such high-quality data, mainly to see what the state and time dependency may look like in different markets.

It would also be fascinating to extend this state and time-dependency analysis to the traditional question of hot and cold IPO markets. Many of the past studies incorporate additional independent variables. Advances in machine learning techniques, such as through a Least Absolute Shrinkage and Selection Operator (LASSO) regression, would allow one to identify the optimal variables to include in a TAR or another type of regime-switching model. By combining the power of the LASSO with traditional econometric methods, the forecast evaluations should in theory, improve.

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Appendices

Figure A1

Monthly IPO Volume (1990 to 2019) versus VIX Index

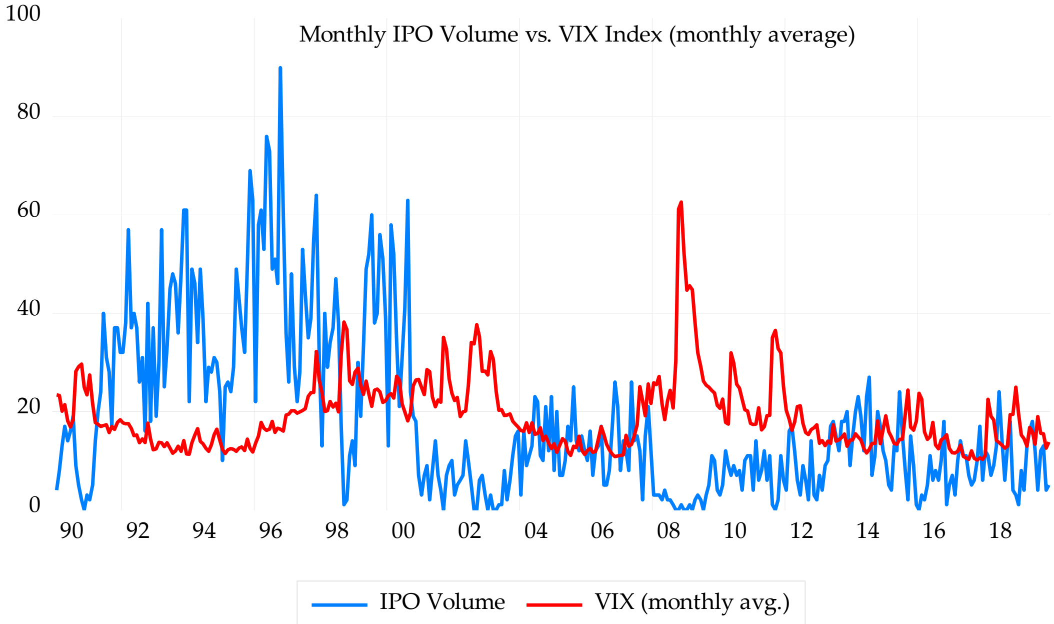

Figure A2

Wilshire 5000 Index Returns (1990 to 2019)

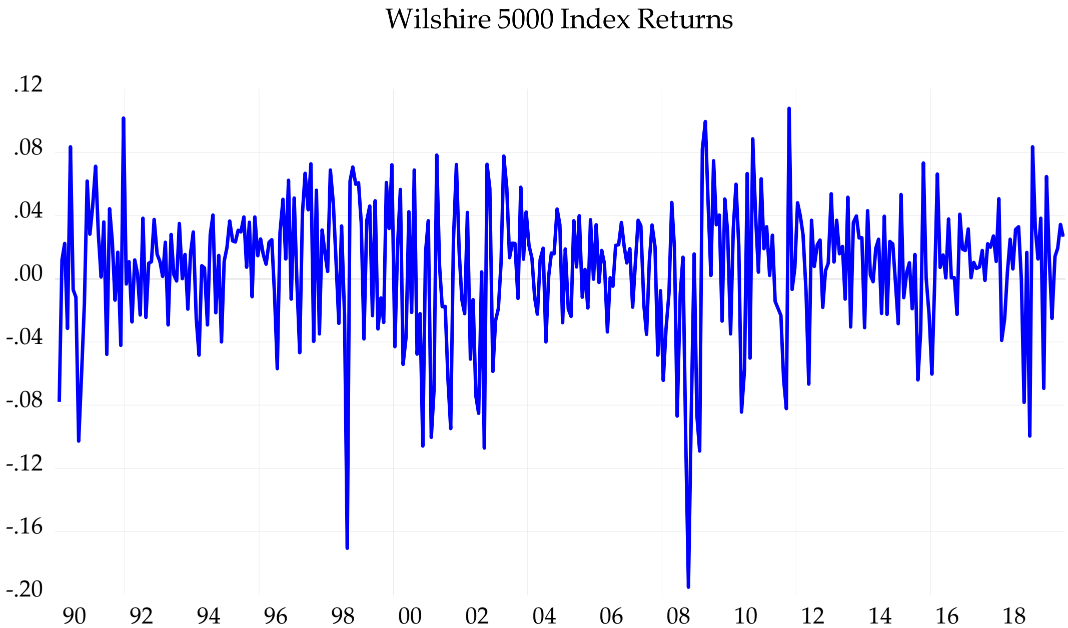

Table A2

Bai–Perron Breakpoint Tests of IPO Volume vs. IPO Volume (-1) and IPO Volume (-2)

Break Test	F-Stat	Scaled F-Stat	Critical Value**
0 vs. 1 *	16.26229	48.78687	13.98
1 vs. 2 *	6.738022	20.21407	15.72
2 vs. 3	0.802252	2.406755	16.83
Break Dates			
	Sequential	Repartition	
1	2000M09	1995M06	
2	1995M06	2000M09	

Bai–Perron tests of L+1 vs. L sequentially det. breaks.
* Significant at the 0.05 level.
** Bai–Perron (Econometric Journal, 2003) critical values.

Table A3

Bai–Perron Breakpoint Tests of IPO Volume vs. VIX Index, with a 1- and a 2-Month Lag of IPO Volume

Break Test	F-Stat	Scaled F-Stat	Critical Value**
0 vs. 1 *	16.80998	67.2399	16.19
1 vs. 2 *	15.53661	62.14643	18.11
2 vs. 3	1.003159	4.012638	18.93
Break Dates			
	Sequential	Repartition	
1	2000M09	1995M10	
2	1995M10	2000M09	

Bai–Perron tests of L+1 vs. L sequentially det. breaks.
* Significant at the 0.05 level.
** Bai–Perron (Econometric Journal, 2003) critical values.

Table A4

Bai–Perron Breakpoint Tests of IPOs vs. Wilshire 5000 Returns, with a 1- and 2-Month Lag of IPO Volume

Break Test	F-Stat	Scaled F-Stat	Critical Value**
0 vs. 1 *	11.33562	45.34248	16.19
1 vs. 2 *	5.737324	22.94930	18.11
2 vs. 3	0.720273	2.881092	18.93
Break Dates:			
	Sequential	Repartition	
1	2000M09	1995M06	
2	1995M06	2000M09	

Bai–Perron tests of L+1 vs. L sequentially det. breaks.
* Significant at the 0.05 level.
** Bai–Perron (Econometric Journal, 2003) critical values.

Table A6

TAR Model Results

Dependent variable: IPO volume
Method: Discrete threshold regression
Sample (adjusted): 1991M01 2019M12
Included observations: 348 after adjustments
Variable chosen: VIX monthly average (-1)
Selection: Trimming 0.15, max. thresholds 5, sig. level 0.05
Threshold variables considered: VIX monthly average (-1) . . . VIX monthly average (-12)
White heteroskedasticity-consistent standard errors & covariances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STATE I: VIX Monthly Average (-1) < 14.489999, 113 observations				
C	-1.334095	9.184180	-0.145260	0.8846
VIX Monthly Average (-1)	0.336070	0.701128	0.479327	0.6321
Wilshire 5000 Return	4.640878	32.94250	0.140878	0.8881
IPO Volume (-1)	0.282746	0.117846	2.399282	0.0171
IPO Volume (-2)	0.112758	0.109879	1.026203	0.3057
IPO Volume (-3)	0.127461	0.129530	0.984032	0.3260
IPO Volume (-4)	0.267741	0.114635	2.335587	0.0202
IPO Volume (-5)	0.209085	0.136891	1.527388	0.1278
IPO Volume (-6)	0.006542	0.148221	0.044135	0.9648
IPO Volume (-7)	-0.120263	0.130327	-0.922778	0.3569
IPO Volume (-8)	0.048917	0.146508	0.333887	0.7387
IPO Volume (-9)	-0.084378	0.106002	-0.796003	0.4267
IPO Volume (-10)	-0.399583	0.112003	-3.567611	0.0004
IPO Volume (-11)	-0.030178	0.112311	-0.268702	0.7884
IPO Volume (-12)	0.524054	0.133808	3.916457	0.0001
STATE II: 14.489999 ≤ VIX Monthly Average (-1) < 16.91863, 55 observations				
C	4.129391	24.18799	0.170721	0.8646
VIX Monthly Average (-1)	-0.281624	1.546591	-0.182094	0.8556
Wilshire 5000 Return	53.13394	46.01242	1.154774	0.2492
IPO Volume (-1)	0.475824	0.133563	3.562540	0.0004
IPO Volume (-2)	-0.188566	0.110179	-1.711443	0.0881
IPO Volume (-3)	0.389613	0.160289	2.430686	0.0157
IPO Volume (-4)	-0.205685	0.130933	-1.570914	0.1174
IPO Volume (-5)	0.213298	0.132634	1.608172	0.1090
IPO Volume (-6)	-0.099440	0.149112	-0.666882	0.5054
IPO Volume (-7)	0.188269	0.165984	1.134255	0.2577
IPO Volume (-8)	0.345988	0.188471	1.835766	0.0675
IPO Volume (-9)	-0.522766	0.158747	-3.293082	0.0011
IPO Volume (-10)	0.404949	0.132245	3.062108	0.0024
IPO Volume (-11)	0.317814	0.109615	2.899367	0.0040
IPO Volume (-12)	-0.258789	0.116774	-2.216153	0.0275

STATE III: 16.91863 $\leq$ VIX Monthly Average (-1) < 19.66227, 52 observations

C	26.61603	27.80208	0.957340	0.3392
VIX Monthly Average (-1)	-1.267356	1.518848	-0.834420	0.4048
Wilshire 5000 Return	-22.77264	30.42994	-0.748363	0.4549
IPO Volume (-1)	0.610776	0.161721	3.776728	0.0002
IPO Volume (-2)	0.234422	0.203231	1.153476	0.2497
IPO Volume (-3)	-0.013666	0.138439	-0.098715	0.9214
IPO Volume (-4)	0.588700	0.087629	6.718134	0.0000
IPO Volume (-5)	-0.243573	0.198582	-1.226565	0.2210
IPO Volume (-6)	-0.200293	0.209644	-0.955391	0.3402
IPO Volume (-7)	-0.188384	0.158262	-1.190327	0.2350
IPO Volume (-8)	0.033935	0.158298	0.214377	0.8304
IPO Volume (-9)	0.315753	0.230072	1.372413	0.1711
IPO Volume (-10)	-0.467498	0.283313	-1.650112	0.1001
IPO Volume (-11)	0.307159	0.307815	0.997870	0.3192
IPO Volume (-12)	-0.318205	0.194827	-1.633267	0.1036

STATE IV: 19.66227 $\leq$ VIX Monthly Average (-1) < 24.7459, 67 observations

C	-20.75434	18.13024	-1.144736	0.2533
VIX Monthly Average (-1)	0.941966	0.819640	1.149244	0.2515
Wilshire 5000 Return	88.26117	25.02282	3.527227	0.0005
IPO Volume (-1)	0.591531	0.201663	2.933258	0.0036
IPO Volume (-2)	-0.003148	0.168588	-0.018671	0.9851
IPO Volume (-3)	0.227222	0.138395	1.641835	0.1018
IPO Volume (-4)	0.142543	0.164486	0.866599	0.3869
IPO Volume (-5)	-0.000564	0.161467	-0.003495	0.9972
IPO Volume (-6)	-0.093956	0.158690	-0.592074	0.5543
IPO Volume (-7)	-0.065971	0.150521	-0.438284	0.6615
IPO Volume (-8)	0.049810	0.124413	0.400356	0.6892
IPO Volume (-9)	-0.110129	0.159834	-0.689020	0.4914
IPO Volume (-10)	0.156312	0.118892	1.314740	0.1897
IPO Volume (-11)	-0.140639	0.124228	-1.132101	0.2586
IPO Volume (-12)	0.253340	0.099874	2.536590	0.0118

STATE V: 24.7459 $\leq$ VIX Monthly Average (-1), 61 observations

C	6.660379	2.486415	2.678708	0.0078
VIX Monthly Average (-1)	-0.168695	0.061130	-2.759623	0.0062
Wilshire 5000 Return	5.421373	9.817103	0.552238	0.5812
IPO Volume (-1)	0.559336	0.157042	3.561693	0.0004
IPO Volume (-2)	0.130775	0.210544	0.621130	0.5350
IPO Volume (-3)	-0.241127	0.131666	-1.831346	0.0681
IPO Volume (-4)	0.027916	0.104682	0.266669	0.7899
IPO Volume (-5)	-0.167395	0.131567	-1.272311	0.2043
IPO Volume (-6)	-0.094611	0.133302	-0.709748	0.4785
IPO Volume (-7)	-0.005745	0.144567	-0.039741	0.9683
IPO Volume (-8)	-0.026387	0.173111	-0.152426	0.8790
IPO Volume (-9)	0.065130	0.078838	0.826124	0.4095
IPO Volume (-10)	-0.137861	0.090334	-1.526125	0.1281
IPO Volume (-11)	0.122969	0.105016	1.170956	0.2426
IPO Volume (-12)	0.326298	0.113059	2.886082	0.0042

R-squared	0.834868	Mean dependent var	18.54885
Adjusted R-squared	0.790107	S.D. dependent var	17.02923
S.E. of regression	7.801792	Akaike info criterion	7.134888
Sum squared resid	16616.95	Schwarz criterion	7.965104
Log likelihood	-1166.470	Hannan-Quinn criterion	7.465413
F-statistic	18.65163	Durbin-Watson stat	1.993811
Prob (F-statistic)	0.000000		

Table A7

Estimation of Two-State MS for Changes of IPO Volume to Wilshire 5000 Index Returns, with the VIX Index as a Common Term

Changes in IPO Volume as a Function of Wilshire 5000 Index Returns, with the VIX Index as a Common Term and IPO Volume (Fifth Lag) as a Probability Regressor	
State I	$\hat{c}_1$ = 23.21037*** (7.122334) $\hat{\gamma}_1$ = -18.36420** (-2.093516)
State II	$\hat{c}_2$ = 46.11307*** (12.55267) $\hat{\gamma}_2$ = 112.8233*** (2.583785)
Common Terms	VIX Monthly Average = -0.384689*** (-3.201134) AR(1) = 0.830709*** (26.56951) log σ = 1.962094*** (47.84981)
Transition Matrix Parameters	P11-$\hat{c}_1$ = 5.612886*** (6.824865) P11-IPO Volume (-5) = -0.105211*** (-5.273819) P21-$\hat{c}_2$ = -0.164111 (-0.138194) P21-IPO Volume (-5) = 0.004213 (0.170486)
Diagnostic Tests	Log likelihood = -1254.517 Schwartz Info. Criterion = 7.169222 Durbin Watson = 2.026180
Smoothed Regime Probabilities State I Median Skewness Kurtosis State II Median Skewness Kurtosis	 0.999889 -2.679059 8.379015 0.000111 2.679059 8.379015
Constant Transition Probabilities, Probability of Staying (Switching) State I Median Skewness State II Median Skewness	 0.985869 (0.014131) -2.849011 (2.849011) 0.527310 (0.472690) -1.313142 (1.313142)
Constant Expected Durations State I Median State II Median	 70.76571 months 2.115550 months

Note: Adjusted sample period July 1990–December 2019 (354 included observations), *** denotes significance at 1%, ** at 5%, z-statistics in parentheses.

Table A8

SETAR Model Results

Dependent Variable: IPO Volume
Method: Discrete threshold regression (SETAR)
Sample (adjusted): 1991M01 2019M12
Included observations: 348 after adjustments
Variable chosen: IPO Volume (-1)
Selection: Trimming 0.15, max. thresholds 5, sig. level 0.05
Threshold variables considered: IPO Volume (-1) … IPO Volume (-12)
White heteroskedasticity-consistent standard errors & covariances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IPO Volume (-1) < 9, 119 observations				
C	9.669728	2.296706	4.210258	0.0000
IPO Volume (-1)	0.333401	0.226881	1.469496	0.1427
IPO Volume (-2)	0.052997	0.095336	0.555899	0.5787
IPO Volume (-3)	-0.007402	0.092660	-0.079883	0.9364
IPO Volume (-4)	0.008383	0.103747	0.080805	0.9356
IPO Volume (-5)	0.015570	0.082307	0.189170	0.8501
IPO Volume (-6)	-0.051696	0.077251	-0.669187	0.5039
IPO Volume (-7)	0.075969	0.073931	1.027565	0.3050
IPO Volume (-8)	-0.043996	0.091281	-0.481985	0.6302
IPO Volume (-9)	-0.021120	0.075448	-0.279930	0.7797
IPO Volume (-10)	-0.050796	0.090739	-0.559798	0.5760
IPO Volume (-11)	0.038592	0.075808	0.509080	0.6111
IPO Volume (-12)	0.074949	0.062358	1.201914	0.2303
9 ≤ IPO Volume (-1) < 29, 147 observations				
C	7.275453	2.374595	3.063872	0.0024
IPO Volume (-1)	0.173250	0.170183	1.018023	0.3095
IPO Volume (-2)	0.261789	0.118077	2.217107	0.0273
IPO Volume (-3)	-0.020723	0.097818	-0.211851	0.8324
IPO Volume (-4)	0.243889	0.100322	2.431052	0.0156
IPO Volume (-5)	-0.058655	0.100860	-0.581550	0.5613
IPO Volume (-6)	-0.008991	0.113643	-0.079114	0.9370
IPO Volume (-7)	0.082045	0.110913	0.739717	0.4600
IPO Volume (-8)	0.140970	0.117790	1.196788	0.2323
IPO Volume (-9)	0.018386	0.123616	0.148738	0.8819
IPO Volume (-10)	-0.189261	0.129617	-1.460160	0.1453
IPO Volume (-11)	-0.079123	0.101720	-0.777844	0.4373
IPO Volume (-12)	0.200788	0.103775	1.934826	0.0539

29 $\leq$ IPO Volume (-1), 82 observations				
C	20.30994	6.942328	2.925523	0.0037
IPO Volume (-1)	0.361465	0.154115	2.345424	0.0196
IPO Volume (-2)	-0.096016	0.103981	-0.923398	0.3565
IPO Volume (-3)	0.160593	0.103752	1.547860	0.1227
IPO Volume (-4)	0.178318	0.147006	1.212994	0.2261
IPO Volume (-5)	0.304433	0.156877	1.940581	0.0532
IPO Volume (-6)	-0.088409	0.111175	-0.795222	0.4271
IPO Volume (-7)	-0.195129	0.118627	-1.644891	0.1010
IPO Volume (-8)	-0.066424	0.117234	-0.566595	0.5714
IPO Volume (-9)	-0.227483	0.153968	-1.477464	0.1406
IPO Volume (-10)	-0.103213	0.133805	-0.771371	0.4411
IPO Volume (-11)	0.099457	0.110502	0.900047	0.3688
IPO Volume (-12)	0.253488	0.084529	2.998829	0.0029
Non-Threshold Variables				
VIX Monthly Average (-1)	-0.242091	0.066172	-3.658499	0.0003
Wilshire 500 Return	23.11426	10.23405	2.258564	0.0246

R-squared	0.770710	Mean dependent var	18.54885
Adjusted R-squared	0.740835	S.D. dependent var	17.02923
S.E. of regression	8.669280	Akaike info criterion	7.267726
Sum squared resid	23073.02	Schwarz criterion	7.721577
Log likelihood	-1223.584	Hannan-Quinn criterion	7.448413
F-statistic	25.79792	Durbin-Watson stat	1.922911
Prob(F-statistic)	0.000000		

Table A9

LSTAR 1st Order Model Results

Dependent Variable: IPO Volume
Method: Smooth threshold regression (LSTAR 1st Order)
Transition function: Normal
Sample (adjusted): 1991M01 2019M12
Included observations: 348 after adjustments
Threshold variable chosen: IPO Volume (-3)
Threshold variables considered: IPO Volume (-1) … IPO Volume (-12) VIX Monthly Average (-1) … VIX Monthly Average (-12)
Starting values: Grid search with concentrated regression coefficients
HAC standard errors & covariance using outer product of gradients (Bartlett kernel, Newey-West fixed bandwidth = 6.0000)
Convergence achieved after 29 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Threshold Variables (linear part)				
C	5.467029	1.615220	3.384696	0.0008
IPO_VOLUME(-1)	0.575450	0.090036	6.391328	0.0000
IPO_VOLUME(-2)	0.076843	0.088437	0.868908	0.3856
IPO_VOLUME(-3)	0.108362	0.083439	1.298706	0.1950
IPO_VOLUME(-4)	0.058479	0.071205	0.821276	0.4121

IPO_VOLUME(-5)	0.070702	0.084936	0.832413	0.4058
IPO_VOLUME(-6)	-0.094246	0.088500	-1.064920	0.2877
IPO_VOLUME(-7)	-0.007691	0.132629	-0.057991	0.9538
IPO_VOLUME(-8)	0.025855	0.107099	0.241408	0.8094
IPO_VOLUME(-9)	-0.006397	0.065783	-0.097247	0.9226
IPO_VOLUME(-10)	-0.088972	0.067353	-1.320971	0.1875
IPO_VOLUME(-11)	-0.009687	0.060503	-0.160105	0.8729
IPO_VOLUME(-12)	0.197742	0.070660	2.798490	0.0054
Threshold Variables (nonlinear part)				
C	-0.842532	18.49908	-0.045545	0.9637
IPO_VOLUME(-1)	-0.446468	0.212904	-2.097042	0.0368
IPO_VOLUME(-2)	-0.145861	0.137012	-1.064588	0.2879
IPO_VOLUME(-3)	-0.020863	0.298976	-0.069780	0.9444
IPO_VOLUME(-4)	0.422534	0.113730	3.715226	0.0002
IPO_VOLUME(-5)	0.394702	0.159854	2.469136	0.0141
IPO_VOLUME(-6)	0.343194	0.221100	1.552210	0.1216
IPO_VOLUME(-7)	-0.153115	0.158517	-0.965923	0.3348
IPO_VOLUME(-8)	0.053538	0.173761	0.308115	0.7582
IPO_VOLUME(-9)	-0.503789	0.182131	-2.766079	0.0060
IPO_VOLUME(-10)	-0.047663	0.238979	-0.199443	0.8420
IPO_VOLUME(-11)	0.089889	0.168494	0.533485	0.5941
IPO_VOLUME(-12)	0.007367	0.133068	0.055360	0.9559
Non-Threshold Variables				
VIX Monthly Average	-0.204378	0.066847	-3.057382	0.0024
Slopes				
SLOPE	14.39808	2.20E+12	6.55E-12	1.0000
Thresholds				
THRESHOLD	41.48333	7.40E+10	5.61E-10	1.0000

R-squared	0.758241	Mean dependent var	18.54885
Adjusted R-squared	0.737021	S.D. dependent var	17.02923
S.E. of regression	8.732844	Akaike info criterion	7.251714
Sum squared resid	24327.76	Schwarz criterion	7.572731
Log likelihood	-1232.798	Hannan-Quinn criterion	7.379517
F-statistic	35.73201	Durbin-Watson stat	1.876580
Prob(F-statistic)	0.000000		

Table A10

OLS Basic Model Results

Dependent Variable: IPO Volume
Method: Least Squares
Sample: 1991M01 2019M12
Included observations: 348

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	4.737414	1.631440	2.903823	0.0039
VIX Monthly Average (-1)	-0.173286	0.068692	-2.522668	0.0121
WILSHIRE 5000 Return	24.25539	11.95189	2.029419	0.0432
C	0.478802	0.053790	8.901323	0.0000
IPO Volume (-1)	0.055432	0.059788	0.927139	0.3545
IPO Volume (-2)	0.130869	0.059499	2.199518	0.0285
IPO Volume (-3)	0.176589	0.059697	2.958073	0.0033
IPO Volume (-4)	0.108016	0.060802	1.776518	0.0766
IPO Volume (-5)	-0.075745	0.060446	-1.253111	0.2110
IPO Volume (-6)	-0.071060	0.060479	-1.174970	0.2408
IPO Volume (-7)	0.076200	0.060302	1.263634	0.2072
IPO Volume (-8)	-0.088001	0.059713	-1.473734	0.1415
IPO Volume (-9)	-0.093460	0.059516	-1.570317	0.1173
IPO Volume (-10)	0.025724	0.059667	0.431131	0.6667
IPO Volume (-11)	0.191586	0.053442	3.584916	0.0004

R-squared	0.722574	Mean dependent var	18.54885
Adjusted R-squared	0.710910	S.D. dependent var	17.02923
S.E. of regression	9.156117	Akaike info criterion	7.308868
Sum squared resid	27916.88	Schwarz criterion	7.474912
Log likelihood	-1256.743	Hannan-Quinn criterion	7.374973
F-statistic	61.95140	Durbin-Watson stat	1.933404
Prob(F-statistic)	0.000000		

Table A11

Markov-Switching Results #1

Dependent Variable: IPO Volume
Method: Markov Switching Regression (BFGS / Marquardt steps)
Sample (adjusted): 1990M02 2019M12
Included observations: 359 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=1192883331)
Convergence achieved after 15 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	23.02463	2.854495	8.066096	0.0000
VIX_MONTHLY_AVG	-0.426734	0.117225	-3.640306	0.0003
WILSHIRE5000RETURN	-18.37855	8.853538	-2.075843	0.0379
		Regime 2		
C	53.67707	6.025433	8.908417	0.0000
VIX_MONTHLY_AVG	-0.646049	0.286665	-2.253670	0.0242
WILSHIRE5000RETURN	66.97432	25.91289	2.584595	0.0097
		Common		
AR(1)	0.777611	0.044924	17.30952	0.0000

LOG(SIGMA)	1.963250	0.041744	47.03086	0.0000
		Transition Matrix Parameters		
P11-C	3.069026	0.309161	9.926938	0.0000
P21-C	-0.842188	0.463884	-1.815514	0.0694

Mean dependent var	18.27577	S.D. dependent var	16.87182
S.E. of regression	10.22627	Sum squared resid	36706.39
Durbin-Watson stat	2.125183	Log likelihood	-1290.340
Akaike info criterion	7.244234	Schwarz criterion	7.352404
Hannan-Quinn criter.	7.287249		
Inverted AR Roots	.78		

Table A12

Markov-Switching Results #2

Dependent Variable: IPO Volume
Method: Markov Switching Regression (BFGS / Marquardt steps)
Date: 12/14/20 Time: 14:10
Sample (adjusted): 1990M02 2019M12
Included observations: 359 after adjustments
Number of states: 2
Initial probabilities obtained from ergodic solution
Standard errors & covariance computed using observed Hessian
Random search: 25 starting values with 10 iterations using 1 standard deviation (rng=kn, seed=127413390)
Convergence achieved after 10 iterations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Regime 1		
C	49.73231	3.439627	14.45864	0.0000
WILSHIRE5000RETURN	69.04903	27.77674	2.485858	0.0129
		Regime 2		
C	23.17072	2.850029	8.129993	0.0000
WILSHIRE5000RETURN	-19.09818	8.845625	-2.159054	0.0308
		Common		
VIX_MONTHLY_AVG	-0.436819	0.117206	-3.726920	0.0002
AR(1)	0.775921	0.047206	16.43682	0.0000
LOG(SIGMA)	1.965501	0.041725	47.10632	0.0000
		Transition Matrix Parameters		
P11-C	0.856160	0.482101	1.775891	0.0758
P21-C	-3.072430	0.312188	-9.841598	0.0000

Mean dependent var	18.27577	S.D. dependent var	16.87182
S.E. of regression	10.21490	Sum squared resid	36729.13
Durbin-Watson stat	2.123273	Log likelihood	-1290.656

Akaike info criterion	7.240426	Schwarz criterion	7.337780
Hannan-Quinn criter.	7.279140		

Inverted AR Roots	.78

Table A13

Dynamic Out-of-Sample Forecast Results: 6 Months

Dynamic Forecast Evaluation
Sample: 2019M07 2019M12
Included observations: 6
Evaluation sample: 2019M07 2019M12
Training sample: 1991M01 2018M07
Number of forecasts: 13

Evaluation Statistics						
Forecast	**RMSE**	**MAE**	**MAPE**	**SMAPE**	**Theil U1**	**Theil U2**
OLS Basic **	9.775285	8.945902	166.2339	76.40927	0.366289	1.684608
Markov Switch #1	12.70535	12.01901	219.9646	89.44313	0.428915	2.170828
Markov Switch #2	12.63677	11.95339	218.8366	89.21564	0.427565	2.155906
Markov Switch #3	11.33661	10.60261	197.1937	83.97953	0.401987	1.896729
TAR	**3.876475**	**3.698322**	**58.69378**	**47.30564**	**0.209524**	**0.517348**
SETAR	6.060751	4.498569	99.05027	51.14781	0.276567	1.131742
LSTAR	10.21063	9.611016	175.4734	80.06713	0.374282	1.719080
Simple mean	9.012021	8.173267	157.0719	73.19554	0.349591	1.564840
Simple median	10.72999	10.07593	186.0960	82.01920	0.387490	1.805916
Least-squares	5.103524	4.224135	86.42744	51.18097	0.247434	0.803329
Mean square error	8.923473	8.076428	155.5726	72.71952	0.347478	1.549479
MSE ranks	8.236481	7.297386	143.5402	68.69508	0.330796	1.438944
Smooth AIC weights	9.033339	8.195016	157.4232	73.29799	0.350115	1.568492
SIC weights	8.507315	7.630076	148.2497	70.47205	0.337103	1.485137

*Trimmed mean could not be calculated due to insufficient data
** OLS basic forecast results excluded from the averaging forecast results.

Table A14

Static Out-of-Sample Forecast Results: 18 Months

Forecast Evaluation
Date: 12/14/20 Time: 18:51
Sample: 2018M07 2019M12
Included observations: 18
Evaluation sample: 2018M07 2019M12
Training sample: 1991M01 2017M07
Number of forecasts: 13

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Equation	F-stat	F-prob
Markov Switch #1	1.045242	0.4356
Markov Switch #2	1.009360	0.4534
Markov Switch #3	0.702900	0.6321
TAR	1.032287	0.4420
SETAR	2.031089	0.1460
LSTAR	2.122908	0.1325

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
Markov Switch #1	12.36073	11.26280	280.7789	85.13356	0.393109	1.971174
Markov Switch #2	12.28155	11.17639	279.3990	84.81008	0.391696	1.955924
Markov Switch #3	11.13946	9.927327	255.0383	79.95934	0.371100	1.735792
TAR	5.611925	4.863679	115.1760	57.14372	0.240366	0.543152
SETAR	8.777298	7.202692	205.0013	67.56182	0.326205	1.358594
LSTAR	10.34077	8.722190	238.1575	74.34672	0.358521	1.539214
Simple mean	9.808474	8.423467	226.0268	73.69313	0.343323	1.495479
Simple median	10.68694	9.322313	246.5623	77.33204	0.362430	1.636146
Least-squares	6.867616	6.228894	124.3274	66.49098	0.285022	0.573022
Mean square error	9.699231	8.317778	223.5043	73.24581	0.340924	1.473759
MSE ranks	9.104689	7.733529	210.0811	70.69803	0.327891	1.357412
Smooth AIC weights	12.31502	11.21288	279.9809	84.94700	0.392295	1.962371
SIC weights	12.31502	11.21288	279.9809	84.94700	0.392295	1.962371

*Trimmed mean could not be calculated due to insufficient data