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IPOs in the U.S. from 2005 to 2015: Using the Spline Regression Technique to Estimate Aggregate Issuance and Performance

Zachary Alexander SMITH - Saint Leo University, Donald R. Tapia School of Business, United States (zacharyasmith@gmail.com)

Muhammad Zubair MUMTAZ - National University of Sciences and Technology, School of Social Sciences & Humanities, Pakistan (zubair@s3h.nust.edu.pk) *corresponding author*

Abstract

The objective of this paper was to explore the relationship between IPO returns and performance on the U.S. Equity Exchanges from 2005 to 2015. To conduct this analysis, we used two independently drawn samples, a primary sample, which ran from 2005 to 2015 and, an out of sample comparison, which ran from 1996 to 2008. While conducting our analyses we incorporated a new heat variable and compared its ability to describe aggregate issuance and performance against a standard heat variable, we illustrated how events can affect IPO issuance and performance and incorporated those events into a model of performance and volume, and to incorporate these events into our models we integrated the spline regression technique into our model, which improved the fit of our model substantially over methods that could be seen as alternative modeling techniques. We believe that our use of events in the modeling process provides a more accurate representation of the underlying dynamics of the processes that are causing changes in IPO performance and issuance and that our application of the spline regression technique to model IPO performance and issuance provides researchers with an important tool that could help them to better estimate, model, and understand the true determinates of IPO performance and issuance.

1. Introduction

The idea or notion of 'hot IPO markets' and cycles have been acknowledged for a long time in the field of financial economics. Ibbotson and Jaffe (1975), Ibbotson, Sindelar, and Ritter (1994), and Lowry and Schwert (2002) documented that IPO cycles seem to exist. They indicate that the high level of abnormal returns on the first trading day seems to create more demand for IPOs, which in turn leads to a large number of new offerings (Ibbotson et al., 1975; Ibbotson et al., 1994; Lowry et al. 2002). Thus, the prevailing theory is that there is a lead-lag relationship between IPO performance and IPO issuance. When a firm decides to list its shares on a stock exchange there are a number of factors that could contribute to the level of underpricing, some of which are the number of unseasoned issues coming to the market and the prevailing economic and market conditions. These factors seem to be used by market participants to frame the prospective market conditions for unseasoned IPOs (Loughran, Ritter, & Rydqvist, 1994). When there is a surge in the number of IPOs issued, the firms observe over- or under-subscription of their new issues. This repetitive process tends to classify markets as either hot or cold IPO activity periods.

In short, a 'hot' market refers to a market in which many shares are being issued to the market, high initial returns, and conducive market conditions (Ritter, 1984; Yung, Colak, & Wang, 2008).

Throughout the literature, most of the studies that we examined on hot and cold IPO cycles tend to attempt to identify the signals of hot IPO markets. The main objective of these studies was to investigate the relationship between the high level of initial returns following a spike in the volume of IPOs (Lowry, 2003; Guo, Brooks, & Shami, 2010). At the end of the nineties, IPO markets were considered 'hot' and in the U.S., there was strong growth in the issuance of new shares and initial performance of IPOs. Helwege and Liang (2004) argued that the hot markets show unpredictable swings in initial returns. Lowry (2003) concluded that hot issues' markets have some similar characteristics, which are a high volume of offerings, severe underpricing, oversubscription, and concentration in particular industries. Conversely, cold IPO markets are associated with fewer offerings, lower underpricing, and under subscription. Lowry and Schwert (2002) also identified a significant linear relationship between IPO volume and the initial performance obtained by the IPOs analyzed in their study. They reasoned that IPO firms tend to obtain high initial returns in 'hot' periods which seems to reduce the money left on the table effect because investment bankers seem to incorporate the markets recent valuation of IPOs into the price of the new issue (Lowry & Schwert, 2002). Purnanandam and Swaminathan (2004) and Derrien (2005) reported that IPOs which are issued during 'hot' markets may be overpriced relative to 'cold' markets because the issuers are attempting to take advantage of the higher prices obtained by issuers in 'hot' IPO issuance activity period, which is referred to as the Window of Opportunity Hypothesis. More recently, Gao, Ritter, and Zhu (2013) reported a decrease in new offerings which is attributed to variations in the economy that affect the earnings of small firms. They distinguished this condition as the *Economies of Scope Hypothesis* (Gao, Ritter, & Zhu, 2013).

Most of the research on hot and cold IPO markets was conducted in the nineties, which was a period of heightened IPO issuance, but a few studies examined the pricing performance of new unseasoned issues after 2000. Over the last fifteen years (i.e. from 2000 to 2015) there have been years that IPO issuance was relatively high and years that were relatively low, but IPO issuance has not reached the levels seen in the nineties during this period. Over the past six years (i.e. from 2010 to 2015), the IPO market seems to be improving in terms of the number of IPOs issued and the initial performance of these IPOs. The objective of the study is to analyze the initial performance results for IPOs issued in the hot and cold market on U.S. equity exchanges during the period lasting from January 2005 to December 2015. Our study uses the performance of volume of 1,332 IPOs issued on the U.S. exchanges during this period and found that IPOs are underpriced by 12.03% on average.

2. Literature Review

During the time frame of this study, it is apparent that the underpricing of IPOs has changed. It is well documented that the underpricing of unseasoned equity issues has been a well-researched and a pervasive phenomenon for decades. The changes in the level of underpricing that occurred due to 'hot' and 'cold' IPO markets varies from country to country and across different time periods. Earlier studies reported that a ‘hot’ IPO market is generally classified on the basis of the number of offerings. For example, the 1980s was categorized as hot IPO market relative to 1970s (Loughran & Ritter, 1995). In an early study, Ibbotson and Jaffe (1975) defined the hot issues markets as a market in which the first month’s performance of IPOs was abnormally high. Their study covered 128 events during the 1960 to 1970 period in which they divided their sample into two components based on the IPOs first and second month’s performance residuals (Ibbotson et al., 1975). The IPOs that were above the ‘median’ average residuals were put in the ‘hot market’ cohort and the IPOs that were in the below the ‘median’ average residuals were put in the ‘cold market’ cohort. Ibbotson et al. (1975) found the evidence of statistically significant autocorrelation in both the number of IPOs issued in a month and the average residuals of the current month with previous months.

Ritter (1984) examined the hot issue market in the U.S. from January 1980 to March 1981. He documented that the average initial return of unseasoned IPOs was 48.4%, which was relatively higher than cold or non-hot markets (i.e. 16.3%) during the period lasting from 1977 to 1982. Further, Ritter (1984) argued that underpricing in ‘hot’ markets is attributed to abnormal returns obtained by IPOs that are associated with the natural resources sector. By excluding this sector from the sample, there was insufficient evidence to conclude that unseasoned IPOs obtained abnormal performance results (Ritter, 1984). Ibbotson (1988) endorsed this periodic pattern of initial returns when they increased the sample period. Besides the cyclical waves in initial returns, studies (Ritter, 1984; Ibbotson et al., 1988, 1994) have also argued that there is a lead-lag relationship between the number of offerings and initial returns, which seems to illustrate that firms cautiously time their IPOs. While measuring the relationship between a number of offerings and the initial abnormal returns over hot and cold markets, Lowry and Schwert (2002) found a positive relationship between volume and performance, which indicates that periods of high abnormal returns are associated with high IPO issuance.

Benninga, Helmantelc, and Sarig (2005) illustrated that ‘hot markets’ are often associated with waves of IPOs that are concentrated in particular industries, and that during these periods these industries may have better investment opportunities when compared to other periods. However, authors such as Pagano, Panetta, and Zinales (1998) and Loughran, Ritter, and Rydquist (1994) found that issuance during hot IPO markets does not seem to lead to increases in subsequent fundraising. These hot markets seem to pop-up during times that investors are placing relatively high valuations on all firms, both public and private. Therefore, in summary, their model predicts that there will be waves of IPOs during the good times where firms are generating high cash flows and waves of re-privatizations when firms are not generating high cash flows (Loughran et al., 1994; Pagano et al. 1998). They state that the value to ‘reprivatize’ is greater for the newly issued firm when compared to a seasoned firm and cite Eckbo and Norli (2001), who illustrated that IPO firms are less risky than non-IPO firms (Loughran et al., 1994).

Helwege and Liang (2004) examined the hot and cold IPO markets in the U.S. from 1975 to 2000. They used the three-month moving average to gauge abnormal returns and found that in ‘hot’ IPO markets investors obtain higher returns relative to the ‘cold’ IPO markets (Helwege et al., 2004). Gao, Ritter, and Zhu (2013) examined the U.S. IPO activity from 1980 to 2012 and reported that on average 310 IPOs were issued per year from 1980 to 2000, but the average fell to 99 IPOs per year from 2001 to 2012. They evaluated the performance of small and large IPOs using two theories: (a) *economies of scope hypothesis* and (b) *regulatory overreach hypothesis* (Gao et al, 2013). Over the period, the number of small firms that issue their shares has declined due to the changes in the economy that have adversely affected the earnings (Gao et al, 2013). Contrary to this, they found that on average large firms earn more profits achieving economies of scope and by investing in latest technology to foster innovation (Gao et al, 2013).

The categorization of whether IPOs are issued in hot or cold markets remains an important and controversial subject. Yung, Colak, and Wang (2008) documented that the number of issues that go public during quarter using a moving average – hot periods in which the issuance was in the top third of the sample, the cold issuance periods in which the issuance was in the bottom third of the sample, and the remainder are 'normal'. Lowry (2003) used the quarterly percentage changes in real private non-residential fixed investment as a proxy for private firms' demand for capital. Pastor and Veronesi (2005) state that the fluctuation in IPO volume is well known, that many describe the time variation in IPO volume using the concept of market inefficiency and by stating that increases in volume are linked to periods in which shares are overvalued. Furthermore, Pastor et al. (2005) contend that there are informational asymmetries which allow the owners of these firms to detect these relatively hot markets, but investors seem to be unable to identify them. The model that Pastor et al. (2005) presented does a good job at providing a general description of IPO volume by analyzing market factors that might cause the general economy to contract or expand. In this analysis, we integrated integrate events and policy initiatives that had the potential to affect the issuance and performance of IPOs to obtain a better understanding of the relationship between IPO performance and volume and their lags as well as the heat variables that have previously been used to model IPO performance and volume.

The IPO literature provides a number of reasons why researchers and investors would want to distinguish between hot and cold markets. The theoretical reason for this exploration is that the performance of IPOs or whether they are currently in hot or cold markets provide investors with a signal about their future performance; therefore, the current market condition is a signaling mechanism. Signaling models classify the hot market as periods where a large number of firms decide to go public (Grinblatt & Hwang, 1989; Allen & Faulhaber, 1989; Welch, 1989). In addition, the IPO literature supports the conjecture that a hot market is the result of crazy bullish behavior which is caused by irrational investor behavior (Lerner, 1994; Loughran & Ritter, 1995). This idea may relate to the 'window of opportunity' hypothesis, in which firms take advantage of temporary market dislocations and issue their shares when the benefits of issuance are greater. Beveniste, Busaba, and Wilhelm (2002) documented that the firms that choose to go public in hot markets are generally affiliated with technological advancements. Stoughton, Wong, and Zechner (2001) argued that hot markets are depicted by a bunch of small risky IPOs issuing their shares from certain industries.

With regard to firm characteristics, Lowry and Schwert (2002); Helwege and Liang (2004); Howe and Zhang (2005) documented that the age of firm, industry, issue size, and the sales effect leads to changes in the composition of IPOs over different time periods in, particularly hot and cold markets. According to Helwege and Liang

(2004), firm characteristics are more or less similar in hot and cold activity periods. But some researchers, such as Lowry and Schwert (2002) and Howe and Zhang (2005) have suggested that some firm characteristics including age of firm and the underwriter's prestige can determine the cyclical waves of IPOs. Yung, Colak, and Wang (2008), however, reported that these studies do not point out the reasons as to why observed variations occur related to firm characteristics. In short, prior studies identified the firm characteristics that seem to cause cyclical patterns in IPO performance but do not identify the reasons behind the changes in firm characteristics over time that effect this performance and, in this study, we focus on highlighting events that affected IPO issuance and performance from 2005 to 2015.

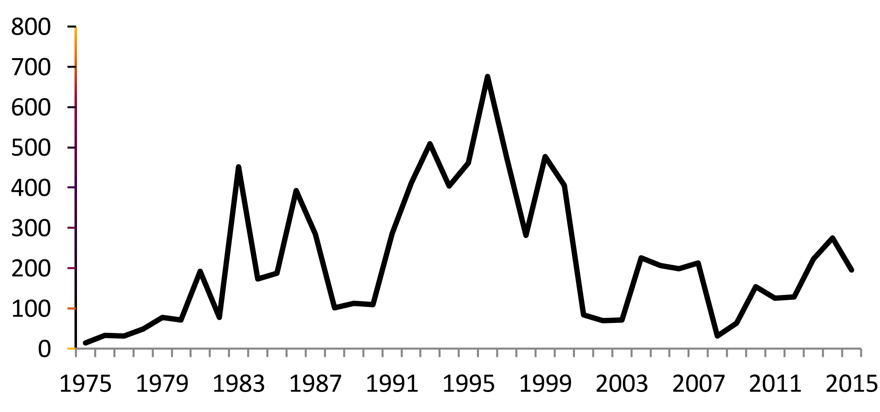
Hu and Wang (2013) examined IPO performance in China's A-share market using a three-regime Markov switching model. The Hu et al. (2013) paper was interesting because their research expanded the types of 'regimes' that the IPO markets experience from two regimes (i.e. hot and cold) to three regimes (i.e. hot, normal, and cold). Hu et al. (2013) built upon the foundation that Brailsford, Heaney, Powell, and Shi (2000) and Guo, Brooks, and Shami (2010) laid when they conducted their analysis using a two-period regime switching model. This idea leads us to question whether events (Benninga, Helmantelc, & Sarig, 2005; Beveniste, Busaba, & Wilhelm, 2002; Ritter, 1984; Stoughton, Wong, & Zechner, 2001) or multiple regime changes (Dai, Singleton, & Yang, 2007) could help us to describe IPO issuance and performance.

2.1 IPOs in the US Market

Historically, there seems to be a relationship between the number of IPOs that are issued over time and the performance of the IPOs traded on the U.S. equity exchanges. As Ibbotson and Jaffe (1975) indicated, the choice and timing of an IPO offering is a very important event in the life-cycle of the company. The owners of the firm obviously want to extract as high of a payout as possible for their company and in Ibbotson et al. (1975) the authors indicated that investment bankers typically advised the owners at the time of the issuance to issue their shares during hot IPO markets, even though researchers have found that the companies may be better off by issuing their shares in cold markets (p. 1038). In the implications section of Ibbotson et al. (1975) the researchers outlined a few cases in terms of how the new issue premia (i.e. the proportion of the value of the company or the premium that the issuer gives up as they issue their shares to the public) should be viewed in hot and cold periods of issuance. In the first illustration, Ibbotson et al. (1975) indicate that if the premium paid by issuing shares in a 'hot market' is greater than the premium paid to issue shares in a 'cold market' the issuer should issue their shares in a cold market. Ibbotson et al. (1975) also present a scenario in which, over the short-term, the initial premium increases as the company seasons over the first month and then the premium decreases over some period of time in the 'hot market', but the premium remains fixed in the 'cold market.' In summary, Ibbotson et al. (1975) seemed to be the first paper to explore the timing of the issuance of unseasoned equity shares, they hypothesize that issuers time their issuance, that this timing may cause these hot and cold markets, and they established an interesting debate: Is it more profitable for the owner to issue their shares in a hot or cold market? The conclusion reached in Ibbotson et al. (1975) seems to be inconclusive and the issue that seems to provoke this uncertainty is a clean or clear understanding of the premia paid by the new issuer once the newly issued shares are efficiently priced.

The magnitude of underpricing or the initial premia paid by the issuer is one point that researchers have focused on when attempting to explain the cyclical patterns in the issuance of unseasoned equity shares, but this explanation focuses explicitly on the firm issuing the shares. Another vein of research has been focused on explaining increases in IPO issuance by looking at market forces that influence business conditions. Benninga, Helmantel, and Sarig (2005) provided an example of this form of inquiry by stating that ‘hot markets’ (or periods of increased issuance) seem to ‘pop-up’ during times in which investors are placing relatively high valuations on all firms, both public and private. In addition, Benninga et al. (2005) stated that ‘waves’ of IPOs seem to be concentrated in particular industries and that in a given period these industries may have better opportunities than other periods (p. 4). Their findings seem to reflect the sentiment provided in Alti (2005), which indicated that the volume of IPOs issued on public markets is often influenced by ‘pioneers’ of a particular industry. Alti (2005) illustrates that there are informational asymmetries between market participants and the prospective issuer and the issuance of an industry ‘pioneer’ will cause a cascading effect. This cascading effect is caused by a reduction in the informational asymmetries between the issuer and the investing public and cause firms with similar business models to go public regardless of whether the pioneer’s issuance was successful (Alti, 2005). Another market force that could explain the volume of new issues coming to the market, according to Yung, Colak, and Wang (2008) and Lowry (2003) is the quarterly percentage change in *real private nonresidential fixed investment*, which is an estimate of the private firms’ demand for capital. In summary, there seem to be three ‘market’ explanations for changes in the volume of unseasoned equity issuance; these are according to Lowry (2003): (a) *Capital Demands Hypothesis*, (b) *Informational Asymmetry Hypothesis*, and (c) *Investor Sentiment Hypothesis*.

Figure 1 Trend Showing Number of IPOs Issued in U.S. Equity Exchanges



Notes: The figure shows the number of issues listed in US equity exchanges during the period from 1975 to 2015.

Figure 1 exhibits the number of IPOs issued on U.S. equity exchanges from 1975 to 2015. Over the 41-year period, there have been relatively hot and cold periods of issuance. On average, the number of IPOs issued in the U.S. declined from an average of 260 IPOs per year during the 1975 to 2000 period to an average of 144 IPOs per year during the 2001 to 2015 period. The decrease in the volume of IPOs remains an important concern for the analysts, policymakers, and researchers. Weild and Kim (2009) documented that the paucity of a vivid IPO market reduces business activities as well as employment opportunities. Gao, Ritter, and Zhu (2013) reported two main reasons for shrinkage in IPO activity: (i) the Sarbanes-Oxley Act of 2002 that applies some additional expenses related to the firm's public offering and (ii) lack of analyst coverage (Jegadeesh & Kim, 2010). Further, Gao et al. (2013) identified the substantial reduction in small firms that issue their shares through IPOs. At the end of the nineties the number of new offerings was at its peak but from 2000 onwards the fact remains that there has been a significant reduction in the number of new offerings. However, on average, new offerings increased thereby registering more than 200 issues per year in 2004-2007 and 2013-2014 respectively while rest of years show a small number of offering issued.

2.2 Significant Events

There are two major events policy events and one major structural change in that researchers should consider prior to attempting to model either the volume of shares issued to the market or IPO returns from 2005 to 2015. The two events are the financial collapse that lasted from 2007 to 2008 and the second was the introduction of the JOBs Act in April of 2012. The structural change in the relationship between IPO issuance and the average returns that IPO's typically obtain occurred in April 2014 when the relationship between the number of shares issued in a given month and the performance of those shares diverged and changed from a positive relationship to a negative relationship.

2.2.1 JOBS Act

According to the Job's Act, companies that have revenues of less than $1 Billion in the most recent fiscal year (a) "need not present more than 2 years of audited financial statements in order for the registration statement of such emerging growth company with respect to an initial public offering of its common equity securities to be effective" and (b) "may not be required to comply with any new or revised financial accounting standard until such a date that a company that is not an issuer [i.e. no longer defined as an Emerging Growth Company]" (Jumpstart Our Business Startups Act). These exceptions seem to be significant exceptions to the 'rule' and it seems as though auditors are questioning whether these exceptions make sense based on the findings presented by Dambra, Field, and Gustafson (2015) in the following paragraph.

According to Dambra, Field, and Gustafson (2015), although IPO issuance is below its pre-2001 levels since the initiation of the JOBs Act in the U.S. from April 2013 to March 2014, IPOs issued by small issuers was the largest since 2000 (p. 137). Dambra et al. (2015) contend "that the JOBS Act has increased IPO volume by 21 IPOs a year since its passage, which represents a 25% increase over the 2001-2011 levels" (p. 137). While the JOBs Act seems to have succeeded in generating IPOs from emerging high growth companies, Dambra et al. (2015) stated that auditors have been issuing statements about these companies questioning their ability to 'continue as a going concern' and many of these companies are not yet profitable (p. 138). Mello and Parsons (1999) provided an examination of why firms decide to go public and one interesting and noteworthy suggestion that they provide is that 'going public' might not be the owners intended exit from the firm, but "a step in a more complete process of selling the firm is the result of considering the inherent asymmetry of investors together with the strategic behavior on the part of the seller" (p. 103). Thus, issuing new shares may not be the intended exit for the founder of the firm or its founders, it may be a repositioning of the firm's assets to negotiate a better exit point.

To quantify whether this act has had a significant impact on the type of companies that are issuing their shares to the public we ran a Wilcoxon Signed Rank Test on the distribution of IPOs issued prior to the JOBs Act and since the JOBs Act was put in place. To run the test, we categorized as the IPOs as Large (coded as 1) if the company's issue size was greater than \$195MM, as Medium (coded as 2) if the company's issue size was greater than \$85MM but less than \$195MM, and as Small (coded as 3) if the company's issue size was less than \$85MM. The following Table illustrates how the distribution of new issues has changed since the implementation of the JOBs Act and it indicates that there has been a statistically and economically significant impact on the type of issues that are finding their way to the market.

Table 1 Illustrates the Change that the JOBs Act Had on IPO Volume

Issue Size	*IPO activity period*		*Wilcoxon Signed Rank Test*	
	Pre-JOBS Act	*Post-JOBS Act*	*Post JOBs - Pre JOBs*	
Small (<\$85 MM)	27.55%	39.43%	*Description*	*Statistic*
	165	289	Negative Ranks	167
			Positive Ranks	227
Medium (\$85-\$195 MM)	36.06%	30.01%	Ties	205
	216	220	Total	599
Large (>\$195 MM)	36.39%	30.56%	*z* value	-3.57
	218	224	Significance	0.0000

Notes: This table illustrates the change that has happened in the U.S. IPO Markets from January 2005 to December of 2015. In April of 2012, the U.S. Government approved the JOBs Act which lifted some restrictions on smaller companies that may have led them to stay private. After this Act was enacted the number smaller firms that are going public are increasing at an economically and statistically significant rate.

A visual inspection of Table 1 will probably provide the reader with some indication that the JOBs Act had on the IPO market. Prior to its initiation in April of 2012, the percentage of companies that had an IPO on U.S. Exchanges that was classified as a 'Small' company was 27.55% and after the initiation of the JOBs Act that category increased to 39.43% of the new offerings listed from April 2012 to December 2015. We applied the Wilcoxon Signed Rank Test to determine if this change was statistically significant. The z value for the test was -3.57 with a sample size of 599 this generates a p-value of less than .001; therefore, the test illustrates that there is strong statistical evidence that there was an increase in small company issuance during this period and as such it seems as though the JOBs Act had an effect on IPO issuance.

2.2.2 Financial Collapse of 2007 to 2008

The financial collapse of 2007 to 2008 wreaked havoc on the financial markets and the U.S. Economy. The initial signs of the crisis occurred when, according to Elliott (2012), BNP Paribas "blocked withdraws from three hedge funds because of what it called a complete evaporation of liquidity". The crisis ensued as Merrill Lynch merged with Bank of America, Bear Stearns was bought by JP Morgan, Lehman Brothers collapsed, and AIG had to rely on the U.S. Federal Government to step in to pay claims on commitments that it had guaranteed. The purpose of this section is not to provide a summary of what happened in 2008, but to briefly illustrate the magnitude of that this effect had on the issuance of and performance of newly issued shares.

2.2.3 Structural Change in the Relationship Between Aggregate IPO Issuance and Performance

In Figure 3, the relationship between the 12-month rolling IPO issuance and the performance is illustrated and based on a visual inspection of the figure, it seems as though there is a positive relationship these two variables from 2005 and 2013. After 2013, the relationship between the issuance and the performance seems to diverge. The correlation coefficients between issuance and performance during these two periods were as follows: (a) from January 2005 to March 2013 the correlation between the average 12-month rolling performance and volume was 0.4151 and (b) from April 2013 to December 2015 the correlation between the average 12-month rolling performance and volume were -0.2759.

To further explore this structural change, we segmented the IPOs based upon the industry in which they were issued and the time period that they were issues. The three-time periods that we used were (a) From January 2005 to December 2015 (i.e. the entire sample), (b) From April 2012 to March 2014 (from the introduction of the JOBs Act to the change in the relationship, and (c) From April 2014 to December of 2015 (from the shift in the relationship between IPO volume and returns to the end of our sample). The change in the time horizon used was the result of moving from rolling 12-month performance and issuance to the actual performance and issuance. The results presented in Table 2 further support our conjecture that the relationships that we have previously identified have changed. In panels 2 and 3 of Table 2, we present a comparison of the industry affiliation of the firms that go public during the first window and the second window and summary statistics, which provide us with an idea about their performance and volatility. In the third panel, the variance of the entire sample picks up and is statistically different from the variance of returns identified in the second sample[1]. We describe this as potentially the second wave of IPOs that entered the market as a result of the introduction of the JOBs Act.

[1] $H_o\colon \sigma_1^2 = \sigma_2^2$ or $H_o\colon \sigma_1^2 \neq \sigma_2^2$; Critical value of F was 1.51. $F > F_{\alpha,N_1-1,N_2-1}$, where N_1 and N_2 were 373 and 360, respectively. Our results indicate that the test is significant using an α of .001.

Table 2 Comparison of the Composition of IPOs Issuing Shares Over Time

Panel 1: All IPOs from January 2005 to December 2015						
Industry	*Volume*	*%*	*MAAR*	*σ_{MAAR}*		*Average Issuance*
Basic Materials	55	4.13%	5.08%	12.11%	$	294,497,733.15
Communication Services	15	1.13%	-2.94%	20.05%	$	240,834,166.67
Consumer Cyclical	154	11.56%	23.40%	31.30%	$	478,378,656.45
Consumer Defensive	46	3.45%	16.21%	30.37%	$	230,218,899.36
Energy	133	9.98%	6.48%	11.57%	$	364,232,268.13
Financial	140	10.51%	8.13%	15.67%	$	538,808,345.61
Healthcare	307	23.05%	13.92%	31.42%	$	114,085,463.30
Industrials	135	10.14%	7.73%	15.90%	$	265,747,686.78
Real Estate	78	5.86%	2.59%	12.19%	$	260,035,717.12
Technology	257	19.29%	21.75%	29.77%	$	251,267,181.37
Utilities	12	0.90%	6.88%	15.46%	$	462,254,166.33
Total	1332	100.00%	13.35%	26.00%	$	292,437,347.20
Panel 2: IPO Performance from April 2012 to March 2014						
Industry	*Volume*	*%*	*MAAR*	*σ_{MAAR}*		*Average Issuance*
Basic Materials	11	3.06%	6.96%	9.38%	$	275,963,636.36
Communication Services	3	0.83%	-1.71%	8.04%	$	320,133,333.33
Consumer Cyclical	43	11.94%	26.52%	33.25%	$	270,817,495.25
Consumer Defensive	12	3.33%	19.23%	38.58%	$	302,651,388.42
Energy	42	11.67%	6.02%	10.91%	$	417,466,833.44
Financial	32	8.89%	7.53%	12.27%	$	347,889,586.47
Healthcare	89	24.72%	16.42%	25.64%	$	112,689,973.08
Industrials	19	5.28%	15.08%	23.43%	$	209,763,005.21
Real Estate	31	8.61%	2.19%	8.68%	$	255,631,451.39
Technology	75	20.83%	26.88%	33.41%	$	381,233,645.65
Utilities	3	0.83%	16.68%	9.21%	$	317,883,333.33
Total	360	100.00%	16.16%	26.61%	$	276,179,710.69
Panel 3: IPO Performance from April 2014 to December 2015						
Industry	*Volume*	*%*	*MAAR*	*σ_{MAAR}*		*Average Issuance*
Basic Materials	14	3.75%	5.20%	13.17%	$	313,965,678.36
Communication Services	3	0.80%	-16.10%	25.62%	$	47,750,000.00
Consumer Cyclical	41	10.99%	21.20%	33.59%	$	719,363,411.32
Consumer Defensive	9	2.41%	13.48%	40.46%	$	255,309,771.06
Energy	23	6.17%	12.87%	13.92%	$	485,465,311.04
Financial	46	12.33%	5.00%	12.58%	$	407,827,248.26
Healthcare	140	37.53%	16.81%	39.82%	$	89,460,449.64
Industrials	23	6.17%	-0.17%	20.75%	$	322,855,821.22
Real Estate	8	2.14%	2.37%	10.79%	$	159,212,500.00
Technology	60	16.09%	22.80%	34.35%	$	225,311,313.75
Utilities	6	1.61%	3.76%	19.07%	$	447,220,833.33
Total	373	100.00%	14.21%	32.67%	$	277,967,998.76

Notes: This table provides a comparison of the summary sample statistics from three time-periods (a) The entire sample from 2005 to 2015, (b) Post-Jobs Act, which lasted from 2012 to March 2014, and (c) Structural change, which lasted from 2014 to the end of the sample in 2015. This table illustrates that recently the type of firms and the volatility associated with those firms is increasing in the latest time period.

In this literature review, we have sampled the current state of on the IPO markets, the descriptions of the hot and cold IPO markets, and explanations of why these trends occur. It seems as though IPO performance emits cyclical patterns and that companies attempt to time their issuance based upon cyclicality in the process of IPO issuance (Helwege & Liang, 2004). Some researchers seem to suggest that certain factors need to be considered prior to constructing a model of IPO performance (i.e. Ritter, 1984) while others attempt to describe the patterns of performance as waves (Benninga et al. 2005); however, both of these veins of research indicate that patterns exist when it comes to examining both the rationale for IPO performance and the reasons that IPOs are issued.

2.3 Comparison Models

This section and its subsections provide models that have been previously developed and used in the past to examine and evaluate the cyclical nature of IPO performance and volume.

2.3.1 Modeling Volume

Helwege and Liang (2004) defined hot and cold IPO periods using a three-month centered moving average of the volume of IPOs issued in a given month to avoid "classifying seasonally low months as cold when they are actually neutral" (p. 549). We believe that there are a couple of issues with this classification. First, it relies on future data and current data to define the current period. Second, classification of a period being hot or cold tells us nothing about what caused this period to be hot or cold, just that it is hot or cold. Third, this categorization is useful if you are looking at a given time period, but it is period specific, and researchers cannot apply what Helwege et al. (2004) classified as hot and cold to a different period. For example, in Helwege et al. (2004) hot periods were classified as the three-month moving averages of more than 30 IPOs and those with 10.5 or fewer were cold. In the two sample periods that we obtained for our study, which lasted from April 1996 to January 2008 and January 2005 to December 2015, the cold periods would have been 13.38 and 6 issues or less, respectively, and 16.88 and 13 or more issues, respectively, for the hot periods. Furthermore, in the period lasting from January 2005 to December 2015, there was only one month that IPO issuance was in excess of 30 issues; therefore, based on the quartile cutoffs presented in Helwege et al. (2004) we would not have experienced a 'hot' period over this decade—the same was true for the April 1996 to January 2008 period.

Table 3 Hot or Cold Markets

	Panel I: 1996 to 2008			*Panel II: 2005 to 2015*		
	Model I	*Model II*	*Model III*	*Model III*	*Model IV*	*Model V*
β_0	14.00***	15.27***	12.81***	8.95***	12.73***	9.55***
Hot	7.46***			11.52***		
Cold	-6.60***			-5.89***		
$Heat_{Q1,T-20}$		12.11***			8.65***	
$Cool_{Q4,T-20}$		-10.11***			-8.60***	
$Heat_{Q1,T-10}$			9.74***			6.42***
$Cool_{Q4,T-10}$			-6.42***			-4.84***
N	141	22	131	131	112	121
R-square	0.5139	0.4417	0.505	0.6393	0.3077	0.2767

Notes: This table provides an in-sample (i.e. 2005 to 2015) and out of sample (1996 to 2008) comparison of the heat metric that was incorporated in this analysis compared to the heat metric that was applied in Helwege and Liang (2004). The heat metric used in this paper is constructed using trailing data and segmenting that data into quartiles; Helwege et al. (2004) used the entire sample to identify quartiles that were considered hot and cold based upon a centered moving average and a quartile ranking system.

As indicated in Table 3, categorizing IPO months as hot or cold using information from both the future and the current period is the best ex-post measure of the hotness or coldness of a particular period, but this metric is both a time-dependent estimate using data that is unavailable at any given time period. Lowry and Schwert (2002) found that past volume has a significantly positive effect on future IPO volume. Lowry et al. (2002) explain this effect narratively by concluding that abnormally high current IPO performance will signal companies that the market is willing to pay a premium for IPOs; therefore, those companies will be more likely to issue their shares to the market. As an alternative method to identify hot or cold periods, we used trailing data, separate the trailing data into quartiles to compare this against the volume issued in the current period, and classify that as hot or cold. In the above Table, we have provided a comparison of our measure for the relative 'hotness' or 'coldness' for the two subsamples that we have collected for this analysis. Sample 1 lasted from April 1996 to January 2008 and Sample 2 lasted from January 2005 to December 2015. For Sample 1, the change in the method to represent the heat associated with the current market conditions changed very little as we moved from estimation based on the Helwege et al. (2004) model to our model using a quartile ranking based upon the trailing 20 observations and then based upon the trailing 10 observations; the results were very different when we applied this technique to the second sample. Our conjecture is that this is because the effect of the changes in regulations associated with the issuance of IPOs, which has created a market environment that has long hot periods and cold periods, but we believe that when comparing the two models, the model that we have presented in this project provide a more useful and practical model that can be used to estimate IPO volume, which we will demonstrate in subsequent sections.

3. Data

We consider two samples of IPOs issues on U.S. Equity Exchanges. The primary sample was comprised of 1,572 IPOs issued during the period lasting from January 2005 to December 2015. We excluded 246 issues from the sample by imposing following filters: (a) 27 were ETFs, (b) 33 IPOs were under the value of $5.00, (c) there were 139 delisted IPOs, and (d) there were 47 five-letter symbols. After removing these issues, there were 1,326 IPOs left in the sample. To provide an out of sample comparison we, independently, gathered data for IPOs that went public from April of 1996 to January 2008. In the initial sample, we had data for the close of the issues on the first trading day; therefore, we used market adjusted returns. For the comparison sample, we obtained data from offer to the opening of trading on the first trading day; therefore, we used raw returns for the second sample when modeling the results of that sample. The purpose of this paper is to model the IPOs volume and performance for the January 2005 to December 2015 period; therefore, the April 1996 to January 2008 data will be used as out of sample data to compare against our general results.

Following the methodology has been employed by earlier studies[2], the underpricing for the IPOs in our sample was estimated for our main sample by adjusting raw return with market return. The market adjusted abnormal returns (MAAR) were computed as = $100 \times \left\{\left[\frac{(1+R_i)}{(1+R_m)} - 1\right]\right\}$. Raw return ($R_i$)[3] is measured as the difference between listing and closing price of stock i at the first trading day and market return (R_m)[4] is calculated as the difference between market index on the listing

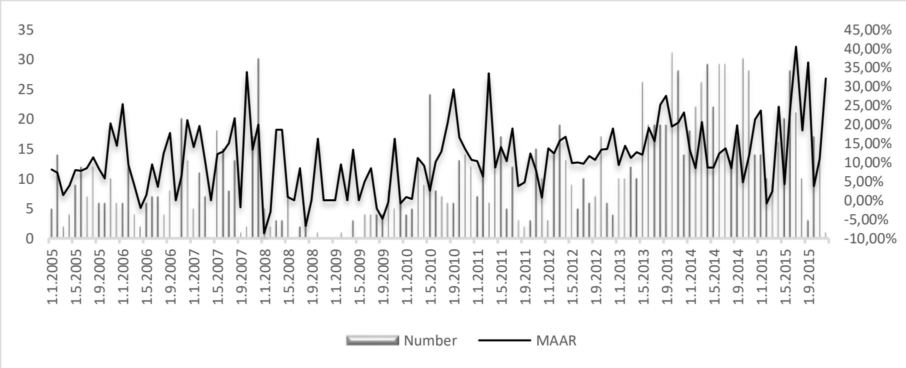
[2] Ljungqvist and Wilhelm (2003) and Agathee, Brooks, and Sannassee (2012).

[3] $R_i = \left(\frac{P_1}{P_0}\right) - 1$ where P_1 *is* price of stock *i* at the first trading day and P_0 = offer price of stock *i*.

[4] $R_m = \left(\frac{I_1}{I_0}\right) - 1$ where I_1 = market index (S&P 500) value at the first trading day of stock *i* and I_0 = market index value on the offering date of stock *i*.

and offering day of stock *i*. In this study, the S&P 500 Index is used as a proxy to measure market return.

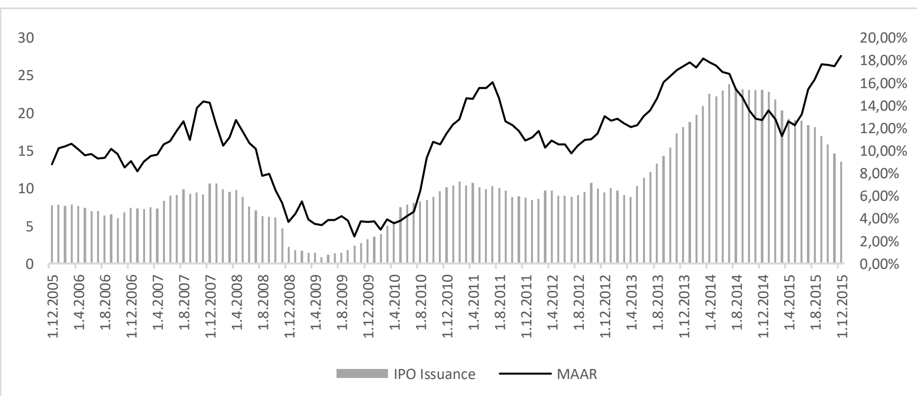
Figure 2 Number of Shares Issued in a Given Month and the MAAR



Notes: This figure illustrates the relationship between the monthly volume of IPOs issued in a given month and the average performance of those IPOs from January 2005 to December 2015.

Figure 2 provides a visual illustration of the relationship between the number of IPOs that were issued in a given month and the average MAAR generated from the IPOs issued in that particular month. Based on a visual inspection, it is difficult to make out any directional relationships between the two variables, but we will examine these relationships statistically in the Result's section of this document. The second way the data was grouped was by 12-month rolling periods. We grouped the data in this way to attempt to smooth the series and, by doing so, identify any more generalizable trends apparent in the data. The smoothed series for average initial IPO returns and average volume by monthly 12-month rolling periods are provided in Figure 3. The 'smoothed' and 'unsmoothed' relationships will be examined in the Result's section of this paper.

Figure 3 Relationship Between the Average 12-Month Rolling IPO Returns and Volume



Notes: This figure illustrates the relationship between the average IPO Issuance based upon a 12-month rolling average and the average monthly MAARs based upon a 12-month roll from January 2005 to December 2015.

4. Methodology

In this paper, we highlight the spline regression technique as a potential complement to studies that attempt to explore the dynamic relationship between IPO performance and volume, which leads us to answer deeper questions about the process of IPO issuance and what factors influence both their returns and volume. In this section, we will illustrate how the spline regression technique can be embedded in traditional models that seek to explore IPO performance and volume and how these additions help us to construct better models and, therefore, enhance our understanding of the relationship between events and IPO performance and issuance. We could have simply used dummy variables, as an alternative to using the spline regression approach, but they lack the flexibility of the spline regression approach. According to Marsh and Cormier (2002), the dummy variables are not continuous and they incorporate inappropriate jumps into the series, whereas the spline regression avoids any inappropriate jumps and incorporates any changes in the general trend into a continuous model. Moreover, there have been a number of studies that use regime switching models to attempt to model IPO performance and issuance; however, we believe that they may have overlooked the spline regression approach and that it provides us with a meaningful alternative estimation technique. According to Dai, Singleton, and Yang (2007) when applying regime switching models to estimate the behavior of complex return series at times you have to not only allow the regime to shift but in addition, have multiple regimes and price the risk for transitioning into those regimes differently. In their study Dai et al. (2007) found that single-regime models failed to accurately represent the expected returns in the U.S. Treasury markets and although a two-regime model tended to capture the behavior associated with the largest absolute returns, the model seems to be best specified when it is allowed to move between multiple regimes and priced regime-shift risk. We face similar problems when we attempted to model IPO performance and volume using methods like regime-switching models that have two or three states (Guo, Brooks, & Shami, 2010; Hu & Wang, 2013). This paper and the use of the spline regression provides an alternative to limiting the modeling process to two or three states and focuses on using the market forces that are driving these different states to model the return series.

The spline regression analysis has been used in Horowitz, Loughran, and Savin (2000) to analyze the firm size premium in investments, Vasicek and Fong (1982) used exponential splines to model the term structure of interest rates, and Giordani, Jacobson, von Schedvin, and Villani (2014) used spline regression approach to predict firm bankruptcy and indicated that this model offers several advantages as compared to models traditionally applied to address this problem, continuity and flexibility being two of these benefits. Hu, Pan, and Wang (2013) applied the spline regression to construct a model of noise in the market and relate that to the level of arbitrage capital that is available and Dumas and Lyasoff (2012) used both regime change models and the spline regression approach alternative modeling techniques in their attempt to reconcile the differences between market models and financial data. According to Chun (2011) the U.S. Treasury uses the spline regression to estimate the CMT yields based on the yield curves of Treasury Securities that are traded in over-the-counter markets. We could have applied models that incorporate more flexibility into our estimation of IPO performance and volume, but we feel that the tradeoffs in terms of complexity and our ability to compare our results to previous studies might overcome any additional insights that we may be able to obtain from removing the restrictions that we have placed on the data using the spline regression approach. Additionally, we feel that the limiting features of the spline regression approach do not offer any meaningful disadvantage and they do a relatively good job of incorporating events (i.e. categorical variables) into our models.

According to Suits, Mason, and Chan (1978), a spline function can be fitted by a standard regression model as follows:

$$\begin{aligned} Y = {} & [a_1 + b_1(X - X_0)]D_1 + [a_2 + b_2(X - X_1)]D_2 + [a_3 + b_3(X - X_2)]D_3 \\ & + [a_4 + b_4(X - X_3)]D_4 + [a_5 + b_5(X - X_4)]D_5 + \epsilon \end{aligned} \tag{1}$$

where,

$$\begin{aligned} a_2 &= a_1 + b_1(X_1 - X_0) \\ a_3 &= a_2 + b_2(X_2 - X_1) \\ a_4 &= a_3 + b_3(X_3 - X_2) \\ a_5 &= a_4 + b_4(X_4 - X_3) \end{aligned} \tag{2}$$

therefore,

$$\begin{aligned} Y = a_1 + b_1[& (X - X_0)D_1 + (X_1 - X_0)D_2 + (X_2 - X_1)D_3 + (X_3 - X_2)D_4 \\ & + (X_4 - X_3)D_5] \\ & + b_2[(X - X_1)D_2 + (X_2 - X_1)D_3 + (X_3 - X_2)D_4 \\ & + (X_4 - X_3)D_5] \\ & + b_3[(X - X_2)D_3 + (X_3 - X_2)D_4 + (X_4 - X_3)D_5] \\ & + b_4[(X - X_3)D_4 + (X_4 - X_3)D_5] + b_5[(X - X_4)D_5] + \epsilon \end{aligned} \tag{3}$$

Marsh and Cormier (2002) simplified the representation that Suits, Mason, and Chan (1978) provided. Based on their model, we can apply the following model based on the knot positions that we define using the following form:

$$Y = a_0 + b_0X_t + b_1Z_{1t} + b_2Z_{2t} + b_3Z_{3t} + \epsilon \tag{4}$$

Interpret Z_{1t_1} as $D_{1t}(t - t_1)$ where t is the current period and t_1 is a fixed knot location (i.e. either a previous period or a future period). The knot location is activated once $t > t_1$. The same applies for Z_{2t} and Z_{3t}, Z_{2t} is defined as $D_{2t}(t - t_2)$ and is activated when $t > t_2$, and Z_{3t} is defined as $D_{3t}(t - t_3)$ and is activated when $t > t_3$ and so on and so forth.

According to Marsh et al. (2002), this same modeling process can be applied to generate quadratic spline and cubic spline regressions as follows:

Quadratic Spline Regression Model

$$Y = a_0 + b_0X_t + b_1Z_{1t} + b_2Z_{2t} + b_3Z_{3t} + \epsilon \tag{5}$$

In this case, interpret Z_{1t} as $D_{1t}(t-t_1)^2$, Z_{2t} as $D_{2t}(t-t_2)^2$, and Z_{3t} as $D_{3t}(t-t_3)^2$ and the Z variables are activated when $t > t_1$, $t > t_2$, $t > t_3$, and so on and so forth.

Cubic Spline Regression Model

$$Y = a_0 + b_0 X_t + b_1 Z_{1t} + b_2 Z_{2t} + b_3 Z_{3t} + \epsilon \tag{6}$$

According to Marsh et al. (2002), in the last case, interpret Z_{1t} as $D_{1t}(t-t_1)^3$, Z_{2t} as $D_{2t}(t-t_2)^3$, and Z_{3t} as $D_{3t}(t-t_3)^3$ and the Z variables are activated when $t > t_1$, $t > t_2$, $t > t_3$, and so on and so forth.

4.1 Volume

Initially, we applied a dependent lagged model to attempt to model the average monthly volume of IPO shares issued on U.S. Exchanges over the sample period based upon the lagged effect of the MAAR for the IPOs issued in previous periods. The research design in its general form as follows:

$$V_t^O = \mu + \beta_0^O \Lambda_t + \beta_1^O \Lambda_{t-1} + \cdots + \beta_k \Lambda_{t-k} + \epsilon_t \tag{7}$$

The model was adapted to meet our needs for the present study, which was to use in the initial distributed lag model.

$$V_t = \mu + \beta_0 MAAR_t + \beta_1 \mathrm{MAAR}_{t-1} + \cdots + \beta_3 \mathrm{MAAR}_{t-3} + \epsilon_t \tag{8}$$

Lowry and Schwert (2002) indicated that there is a statistically significant relationship between volume experienced in previous periods and the volume that we are likely to experience in the current period; therefore, we incorporated the lagged volume effect into our model and the lagged MAAR effect, while dropping the impact of the current periods MAAR on Volume. This model provides us with the following model:

$$V_t = \mu + \beta_1 \mathrm{MAAR}_{t-1} + \cdots + \beta_3 \mathrm{MAAR}_{t-3} + \beta_4 \mathrm{Vol}_{t-1} + \cdots + \beta_6 \mathrm{Vol}_{t-3} + \epsilon_t \tag{9}$$

Next, we integrated Dummy Variables (i.e. that take values of either 0 or 1) to represent (a) the effect of the structural change in the dynamic relationship between the average monthly IPO Volume and average monthly IPO performance, (b) the JOBs Act Effect, and (c) the effect of the Financial Crisis of 2007 to 2008; in addition, we include a market proxy (i.e. the S&P 500 Index):

$$\begin{aligned} V_t = \mu + \beta_0 MAAR_t + \beta_1 MAAR_{t-1} + \cdots + \beta_3 MAAR_{t-3} + \beta_4 D_{Structural} \\ + \beta_5 D_{JOBsAct} + \beta_6 D_{2008} + \beta_7 r_{S\&P\ 500} + \epsilon_t \end{aligned} \tag{10}$$

$D_{Structural}$: Is coded 0 from prior to April 2014 and a 1 from April 2014 to December 2015.

$D_{JobsAct}$: Is coded 0 prior to April of 2012 and a 1 after April 2012.

D_{2008}: Is coded 0 prior to January 2008 and a 1 from January 2008 until March 2009.

$r_{S\&P\ 500}$: Is a variable that tracks the performance of the S&P 500 Index (i.e. Market Performance).

In addition, we added a Dummy Variables to account for the hotness or coldness of the market using either Helwege et al. (2004) or our version of the heat variable and we placed spline knot into the equation to better account for the effects of the JOBs Act and the Structural Change variable.

$$\begin{aligned} V_t = \beta_0 + \beta_1 V_{t-1} + \cdots + \beta_3 V_{t-3} + \beta_4 MAAR_{t-1} + \cdots + \beta_6 MAAR_{t-3} \\ + \beta_7 D_{2008} + \beta_8 Z_{JOBs} + \beta_9 Z_{Structure} + \beta_{10} D_{Cold} \\ + \beta_{11} D_{Hot} + \epsilon_t \end{aligned} \tag{11}$$

Explanations of how the dummy variables associated with the heat of the IPO market were found in Section 2.3.1 and explanations of how the spline regression variables were integrated into this analysis can be found in the introduction to this section and Section 4.3.

4.2 MAAR

To model the *MAAR*, we used the equation built to estimate the volume which was Equation 10 and used the *MAAR* as the dependent variable.

$$\begin{aligned} MAAR_t = \beta_0 + \beta_1 V_{t-1} + \cdots + \beta_3 V_{t-3} + \beta_4 MAAR_{t-1} + \cdots + \beta_6 MAAR_{t-3} \\ + \beta_7 D_{2008} + \beta_8 Z_{JOBs} + \beta_9 Z_{Structure} + \beta_{10} D_{Cold} \\ + \beta_{11} D_{Hot} + \epsilon_t \end{aligned} \tag{12}$$

4.3 Spline Regression Technique (Volume and MAAR)

For our examination of the average 12-month rolling performance and volume, we have provided a detailed explanation of how the knot positions were constructed and have represented them using formulas. In our estimation of the monthly issuance and volume of IPOs, we used two variables that had knot locations and those were the JOBs Act and the Structural Change in the relationship between the performance and volume occurring as the dynamics of the market changed, after April 2013. A Knot location for the JOBs Act was placed in our regression at March 2012 and, therefore, it took a value of 1 on April 2012, 2 on May 2012 and so on and so forth. Another Knot location for the Structure Change was placed in August of 2014 and, therefore, it took a value of 1 on September 2014, 2 on October 2014, and so on and so forth. These spline variables were only applied when estimating the actual volume and performance of IPOs in this paper.

When we estimated the average 12-month rolling performance and volume, we found it necessary to clarify just how the spline variables would be incorporated into our analysis and when they would be incorporated. The Knot positions for the variables are as follows: (a) Month 21 in the series, which was August 2007, in which according to Elliott (2012) BNP Paribas “blocked withdraws from three hedge funds because of what it called a complete evaporation of liquidity”, (b) Month 49 in the series, which was December 2009, at this point it seemed as though volume started coming back into the market, but returns remained repressed, (c) Month 59 in the series, which was October 2010, was a point that seemed to suggest that IPO volume return to its 'normal' volume of issuance after the financial collapse, (d) Month 88, which was March 2013, this month was approximately one-year after the JOBs Act was enacted, and, according to Dambra, Field, and Gustafson (2015), when the effect of the act started to be felt in the data, and (e) Month 105, which was August 2014 and this was approximately six months from the structural shift that we uncovered in the relationship between the volume of IPO issuance and the performance of IPOs.

We felt that a description of both the average performance and the average volume of shares issued in the U.S. during the period could be explained better by partitioning the sample into a few distinct periods. Moreover, it was important to note that these periods should not be described as cold or hot or cold, normal, or hot periods, we endeavored to find reasons, something that explained what seems to be a cyclical relationship between the return and the volume of IPOs issued and time. The following paragraph will outline the position that we felt were important positions to consider allowing the variables to transition from one state to another.

In addition to the aforementioned models, we integrated a dummy variable lasting from December 2008 to November of 2009. This variable will serve as a proxy for the relatively depressed period of IPO issuance and performance resulting from the financial collapse of 2007 to 2008. Therefore, the final models in this segment include an additional dummy variable to incorporate the prolonged impact of the financial crisis.

Time Series Model

$$Y_t = a_0 + b_0 X_t + \epsilon_t \tag{13}$$

Linear Spline Model

$$\begin{aligned} Y = a_0 + b_0 X_t + b_1[(X_t - 21)D_{21}] + b_2[(X_t - 48)D_{48}] \\ + b_3[(X_t - 59)D_{59}] + b_4[(X_t - 88)D_{88}] \\ + b_5[(X_t - 105)D_{105}] + b_6 D_{2008} + \epsilon \end{aligned} \tag{14}$$

Quadratic Spline Regression Model

$$\begin{aligned} Y = a_0 + b_0 X_t + b_1[(X_t - 21)^2 D_{21}] + b_2[(X_t - 48)^2 D_{48}] \\ + b_3[(X_t - 59)^2 D_{59}] + b_4[(X_t - 88)^2 D_{88}] \\ + b_5[(X_t - 105)^2 D_{105}] + b_6 D_{2008} + \epsilon \end{aligned} \tag{15}$$

Cubic Spline Regression Model

$$\begin{aligned} Y = a_0 + b_0 X_t + b_1[(X_t - 21)^3 D_{21}] + b_2[(X_t - 48)^3 D_{48}] \\ + b_3[(X_t - 59)^3 D_{59}] + b_4[(X_t - 88)^3 D_{88}] \\ + b_5[(X_t - 105)^3 D_{105}] + b_6 D_{2008} + \epsilon \end{aligned} \tag{16}$$

where

X_t: Is a time variable that starts in month 1 and continues to Month 121

D_{20} (X – $07/2007$): Is a Dummy Variable or a Knot Location that indicates the beginning of the financial crisis of 2008. It is initiated at 1 in time period 21 and increases by 1 each month until time period 121 at which its value is 101.

D_{48} (X – $11/2009$): Is a Dummy Variable or a Knot Location that indicates the 'start' of the end of the effect that the financial crisis had on the rolling average volume of issuance of IPOs. It is initiated at month 49 or December 2009 with a value of 1 and has a value of 73 at month 121.

D_{59} (X – $10/2010$): Is a Dummy Variable of a Knot Location that indicates that the average month volume of IPO issuance seemed to have reached its normal issuance (i.e. recovered from the financial crisis of 2008). It is initiated at month 60 or November of 2010 with a value of 1 and has a value of 62 on month 121.

D_{88} (X – $03/2013$): Is a Dummy Variable or a Knot Location that indicates the beginning of the effect of the implementation of the JOBs Act on the IPO market. This variable is initiated on month 89, which was April 2013, with a value of 1 and has a value of 33 on month 121.

D_{105} (X – $03/2014$): Is a Dummy Variable or a Knot Location that indicates there seem to be a structural breakdown in the relationship between IPO issuance and the MAAR Variable (i.e. the correlation between the two variables was .4151 prior to March of 2014 and it change to -.2759 from then on). The variable was initiated at 1 on September 2014 to allow for the moving average to reflect the changing trend and it had a value of 16 on month 121.

D_{2008}: Is a traditional Dummy Variable that takes on a value of 1 if activated and a value of 0 if not activated. Based upon a visual inspection of Figure 2, it seems as though the effect of the financial crisis of 2008 had its most severe influence over the issuance and performance of IPOs during the period lasting from December 2008 to November 2009; therefore, the variable is 1 if the month variable is greater than or equal to 37 (i.e. December 2008) and less than or equal to 48 (i.e. November 2009).

We expect the parameter estimate attached to the D_{20} (X – $07/2007$) variable to be negative because it is an indication that the market was entering into the 2007 to 2008 financial crisis and the parameter estimate attached to the D_{48} (X – $11/2009$) variable to be positive because the market was exiting the crisis. We do not have an indication of whether the parameter estimate attached to the D_{59} (X – $10/2010$) variable should be positive or negative; if anything, the economic significance attached to this variable should be muted. The D_{88} (X – $03/2013$) variable is anticipated to generate an increase in the volume of shares that are issued, but we are unclear as to how it should affect the average performance of IPOs since smaller, relatively unproven, companies are more likely to issue their shares as a result of the JOBs Act. The D_{105} (X – $03/2014$) variable is expected to generate a negative response in terms of issuance and omit a positive signal in terms of performance.

At this point, it is worth noting that the knot locations were applied in the same manner when evaluating both of the series (i.e. the month volume and performance of IPOs). We could have attempted to fit them both based on estimates of when the financial crisis effect wore off on both series (i.e. the average monthly volume of IPO issuance increases faster than the average monthly performance of the IPOs coming out of the 2007 to 2008 financial crisis); however, we felt that it was better to apply the rules governing the series equivalently to both of the series.

In the preceding section, we introduced distributed lag model, which will be applied to model the rolling volume of IPO issuance in a given month, dummy variables that take on a value of 1 if a particular criterion is met and 0 otherwise, and the linear, quadratic, and cubic spline regression models. In the following section, we will apply these models to attempt to explain the process of aggregate IPO issuance and performance.

5. Results

5.1 Average IPO Performance

We found that IPOs, on average, produced a return of 13.36% (t-statistics = 17.72) from issue to the close on the first day of trading using 1,326 unseasoned issues listed in the U.S. Equity Exchanges during the 2005 to 2015 period. This finding is in line with earlier studies (e.g. on average, IPOs generated performance of 13.30% in US market during the 2001 to 2013 period based on the data contained on Jay Ritter's website). Historically, initial IPO performance ranged from between 10% and 15% across different time periods. The median initial abnormal returns are 5.74% and standard deviation of the sample is 26.00%, which represents large variations in IPO returns.

Table 4 Sample Distribution, Total Proceeds, and Initial Returns by the Calendar Year

Year	*N*	*Total proceeds ($ million)*	*Average first day*	
			Raw returns	*Market-adjusted returns*
2005	93	19,725.86	9.72%	9.64%
2006	89	22,135.53	11.00%	10.91%
2007	127	28,741.80	16.11%	16.22%
2008	26	25,153.81	3.38%	3.11%
2009	39	19,257.78	3.98%	3.76%
2010	121	33,292.22	10.53%	10.73%
2011	105	32,839.10	11.03%	11.00%
2012	113	40,830.76	13.35%	13.22%
2013	217	54,399.29	18.40%	18.27%
2014	277	83,618.84	12.10%	12.22%
2015	162	29,594.42	17.82%	17.81%
2005-2015	1369	389,526.55	13.40%	13.40%

Notes: The table covers 1369 IPOs issued by U.S. equity exchange from January 2005 to December 2015. *N* represents the number of IPOs in a year. Total proceeds show the total amount generated by the issues in a given year. Market-adjusted abnormal returns are computed as $100 \times \left\{\left[\frac{(1+R_{x,d})}{(1+R_{m,d})} - 1\right]\right\}$ where R_i is the raw return and measured as $R_i = \left(\frac{P_i}{P_{,0}}\right) - 1$ where P_1 is the first-day closing prices and P_0 is the offer price of stock *i*. R_m is the market return and estimated as $R_m = \left(\frac{I_1}{I_{m,0}}\right) - 1$ where I_1 = market index (Wilshire 5000) value at the first trading day of stock i and I_0 = market index value on the offering date of stock *i*.

Table 4 presents year-wise sample distribution, total proceeds, and average first day raw and market adjusted abnormal returns. The results illustrate that IPO performance was at its highest point in 2013 (18.40%) followed by 2015 (17.82%) and 2007 (16.11%). This reflects that IPOs outperformed the market. The lowest level of performance was observed during the 2008 and 2009 period due to the financial crisis that affected the US market in 2007 and 2008.

5.2 Average IPO Underpricing by Sector

Using the same data as the previous section, we explored the sector level performances. Our sample shrunk from 1369 to 1332 because some of the IPOs were delisted or the information on the industry affiliation was unavailable. In aggregate, after the sample was reduced, the average return across all IPOs was the same as the 13.36% obtained when the entire sample was used. Table 5 illustrates that firms in the Healthcare, Technology, and Consumer Cyclical Industries had over 53.90% of the IPOs issued during this time period. If we were to combine these industries, we would obtain an average performance of 18.76% with a standard deviation of 30.81% (718 IPOs) and the remaining industries' average performance was 7.04% with about half of the standard deviation or 15.28% (614 IPOs). We understand that it is important to point out that certain industries seem to dominate the issuance of and the performance obtained by the IPOs during this time period. Questions pertaining to what impact this had on the aggregate performance data are interesting, but not a subject that we intend to focus on in this research project.

Table 5 Illustrates the Relationship Between Industry and Return

Industry	*Average Return*	*Standard Deviation*	*t Stat*	*P Value*	*N*
Basic Materials	5.30%	12.14%	1.801	0.045	54
Communication Services	-2.94%	20.05%	-0.568	0.711	15
Consumer Cyclical	23.40%	31.30%	9.278	0.000	154
Consumer Defensive	16.21%	30.37%	3.619	0.000	46
Energy	6.48%	11.57%	6.458	0.000	133
Financial	8.13%	15.67%	6.140	0.000	140
Healthcare	13.92%	31.42%	7.748	0.000	307
Industrials	7.73%	15.90%	5.670	0.000	136
Real Estate	2.59%	12.19%	1.876	0.032	78
Technology	21.75%	29.77%	11.713	0.000	257
Utilities	6.88%	15.46%	1.541	0.076	12

Notes: The preceding table provides the average return, the standard deviation of returns, a test of whether we obtained evidence of positive returns for the IPOs, and how many IPOs were issued from each industry in the U.S. from January 2005 to December 2015.

5.3 Evaluation of Volume

Prior to using the different spline techniques and events to describe the pattern of IPO issuance, we used prior performance and the events listed and techniques highlighted in previous sections to attempt to explain changes to the average volume of shares issued on the U.S. Markets. The results of these tests are presented in the first panel of Table 6 and 7. In Panel 1 of Table 6, we illustrate that there is was a small, but statistically significant lead-lag effect in the relationship between both the current MAAR and the Volume of IPO issuance and previous MAARs and the Volume of IPO issuance. We were able to generate an r_{adj}^2 value of approximately 0.176 using three monthly lags of IPO performance to explain the volume of IPO shares issued in a given month. In Model II, our goal was to determine whether the bulk of the MAAR's explanatory power over volume was contained in the current period's MAAR or if there was a lead-lag effect. It seems, judging from the small loss in predictive power, that a great deal of the MAAR's explanatory power over the Volume variable is contained in previous periods.

In the second panel of our analysis, we evaluate the difference between the general results that we obtained using the data that we collected for this analysis and a previous data set that we had on IPOs during the period lasting from August 1996 to January 2008. We wanted to illustrate how the change in our heat variable, from the Helwege and Liang (2004) to our methodology, influenced our estimation results. In Table 6, we compared the two sample periods and the estimated changes in the relationships between these variables as we changed our heat metric. First, within the August 1996 to January 2008 sample, the overall predictive power of the model falls when using the newer version of the hotness or coldness of a market, but it also highlights the idea outlined in Lowry and Schwert (2002), which is that a previous periods' volume is also an indicator of current volume; so, our interpretation of this finding is that in addition to the relative heat of the market, the volume of shares issued in previous periods also impacts the volume issued in the current period. Moving to the January 2005 to December 2015 period, as we changed our heat metric the results of our general regression improved. In addition, we found similar relationships to the relationships identified in the April 1996 to January 2008 period. These were that the previous volume of shares issued had an influence on the current volume and the previous returns have some influence over current IPO volume. Unlike the April 1996 to January 2008 period, the new heat metric paired with the other explanatory variables provided a better description of IPO volume.

Table 6 IPO Volume Through Time

	Panel 1: Returns & Volume			***Panel 2: Comparison through Time***			
	1/2005 to 12/2015			*8/1996 to 1/2008*		*1/2005 to 12/2015*	
Statistic	***Model I***	***Model II***	***Model III***	***Model IV***	***Model V***	***Model VI***	***Model VII***
Intercept	3.82***	5.08***	7.38***	11.76***	4.35***	7.08***	0.55
$MAAR_t$	19.23**		27.02***				
$MAAR_{t-1}$	20.45***	23.58***				3.70	1.76
$MAAR_{t-2}$	17.45**	27.47***				8.86*	11.83**
$MAAR_{t-3}$	2.21					-5.57	-1.26
Vol_t	Dependent	Dependent	Dependent	Dependent	Dependent	Dependent	Dependent
Vol_{t-1}				0.10**	0.23***	0.03	0.37***
Vol_{t-2}				-0.01	0.21***	-0.09	0.09
Vol_{t-3}				0.01	0.17***	0.16**	0.27***
R_{t-1}				4.64*	7.80**		
R_{t-2}				-2.75	-3.21		
R_{t-3}				0.24	1.16		
Hot_{Old}				11.27***		10.79***	
$Cold_{Old}$				-8.28***		-4.94***	
Hot_{New}					9.10***		6.67***
$Cold_{New}$					-6.90***		-5.29***
r^2_{adj}	0.1760	0.1415	0.0872	0.8589	0.7683	0.6516	0.7084
n	129	129	129	139	132	129	122

Notes: The data obtained for this comparison includes the period lasting from April 2005 to December 2015. The $MAAR_t$, $MAAR_{t-1}$, $MAAR_{t-2}$, $MAAR_{t-3}$ variables are the average Market Adjusted Abnormal Returns for IPOs issued in month t through month t-3. Volume is the dependent variable across all regressions. Notes: *, **, and *** are significant at .10, .05, and .01.

In summary, Table 6 provides two descriptive results. First, we illustrate the relationship between the returns obtained by IPOs and the volume of IPOs in the current period. The results indicate that in the January 2005 to December 2015 period, there was a lagged relationship between IPO volume and IPO returns and that there was a positive relationship between the current IPO performance the volume of shares issued, which seems to provide general support to the idea that hot markets and cold markets exist. In the next analysis, we compared the results of our sample using the Helwege et al. (2004) model to identify hot and cold markets with our model and compared the differences in our models using two different time horizons. In general, for the January 2005 to December 2015 sample our model's predictive power improved after incorporating our heat variable, but it did not as we incorporated it into the April 1996 to January 2008 period. As we compared these results to the results obtained in the previous table comparing the two heat variables, we believe that our new heat variable allows us to gain further insights on the true determinates of IPO volume. The results from our model incorporate, what we believe is, an improvement in the heat variable presented in Helwege et al. (2004) and identifies the determinates that are very similar to the estimation results presented in Lowry et al. (2002) in which they used three independent samples that span the 1960 to 1997 period (i.e. positive lagged influence of the first and third lag of volume on itself and some relationship between IPO returns and volume).

Table 7 IPO Volume Comparison of Results

	Panel 1: 1/2005 to 12/2015				***Panel 2: 4/1996 to 1/2008***		
	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
Intercept	8.93***	12.73***	9.06***	5.95***	4.32***	15.46***	7.44***
V_{Lag1}				0.23***	0.34***		0.18**
V_{Lag2}				-0.08	0.20**		0.19***
V_{Lag3}				0.13*	0.09		0.07**
$MAAR_{Lag1}$				3.79			
$MAAR_{Lag2}$				4.91			
$MAAR_{Lag3}$				-1.9			
R_{Lag1}					20.15***		17.01***
R_{Lag2}					-13.42*		-13.70**
R_{Lag3}					0.15		1.55
D_{2008}	-7.17***		-3.26**	-1.72			
Z_{JOBS}	0.53***		0.61***	0.42***			
$Z_{structure}$	-0.06***		-0.97***	-0.67***			
$Cold_{New}$		-8.60***	-6.86***	-6.53***		-10.85***	-9.12***
Hot_{New}		8.65***	9.64***	9.76***		11.91***	11.35***
r^2_{adj}	0.5150	0.3077	0.7189	0.7429	0.3243	0.4501	0.6604
N	109	112	109	109	119	119	119

Notes: The data obtained for this comparison includes the period lasting from April 2005 to December 2015 and August 1996 to January 2008. The $MAAR_t$, $MAAR_{t-1}$, $MAAR_{t-2}$, $MAAR_{t-3}$ variables are the average Market Adjusted Abnormal Returns for IPOs issued in month t through month t-3 and were obtained calculated as the market adjusted returns from issue to close on the first day of trading using the sample lasting from January 2005 to December 2015. The R_{Lag1}, R_{Lag2}, and R_{Lag3} are the raw performance results obtained for the period lasting from August 1996 to January 2008 because the data that we collect for this sample was from the issue to the first day of trading. Volume is the dependent variable across all regressions. Notes: *, **, and *** are significant at .10, .05, and .01.

In Table 7, we have reported on both the January 2005 to December 2015 and the August 1996 to January 2008 samples and highlighted how incorporating the heat variable and the spline, dummy, and control variables provide a better model of IPO Volume. Models I through IV use the sample data from January 2005 to December 2015 and Models V, VI, and VII use data from April 1996 to January 2008. Model I provided the estimation results using only the dummy variable for the financial collapse and the spline variables for the introduction of the JOBs Act and the structural change in the relationship between volume and returns. In Model II, we provide the results of a regression using only the heat variables. It is important to note that Model I provides a direct comparison of the result generated using the dummy and spline variables against Model II, which presents results generated solely based upon the heat metric. Models III and IV integrates the dummy variables, spline variables, and the heat variable and incorporates the control variables which are the lags of the MAARs and the Volume. Comparing the results presented in Model IV to the results presented in Model VII, there is a marginal improvement in the model's fit; however, the results presented in Models I and II indicate that the dummy and spline variables provide a more prescriptive representation of volume and we believe that the combined model provides a more accurate description of IPO volume. It is important to note the first and third lags of volume still have a positive effect on volume similar to the results presented in Lowry et al. (2002); however, the impact of the dummy variable associated with the financial collapse becomes insignificant; we believe that the heat variable is compensating for this effect in the model. In Panel 2, we provide the estimation results from April 1996 to January 2008. Model V presents the estimation results using the control variables, Model VI provides the output from the heat variables, and Model VII incorporates the two models. The parameter estimates are relatively stable and the only thing that seems a little bit outside of our expectation is the negative coefficient attached to the second lag of the return variable.

5.3.1 Examining the Average 12-month rolling MAARs

In this section, we attempt to model the average 12-month rolling MAARs. In Table 8, we have presented five models. Model I applied a simple linear regression and, in this model, we regress time on the 12-month rolling MAARs to attempt to describe its performance. This model is used as a benchmark for the other models. Model II uses the methodology that was presented to identify hot and cold IPO markets as illustrated previously in this research project and outlined in Helwege et al. (2004). Models III, IV, and V use the spline regression technique (i.e. linear, quadratic, and cubic, respectively) with the Knot locations identified in Section 4.3 to attempt to model the 12-month rolling MAARs

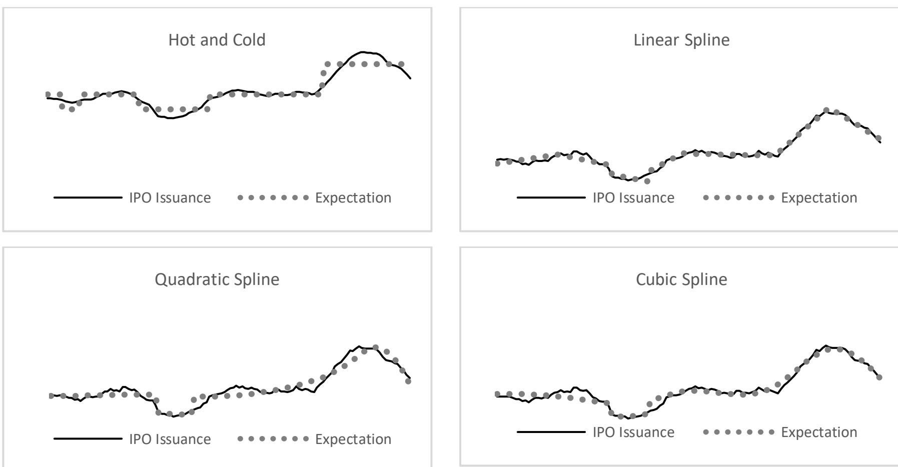
Table 8 Modeling the IPO Trends

	Model I	***Model II***	***Model III***	***Model IV***	***Model V***
Intercept	2.99***	9.119***	6.189***	7.620***	8.625***
Hot_{Old}		10.273***			
$Cold_{Old}$		-5.006***			
Month	0.122***		0.162***	0.001	-0.000***
D_{2008}			-3.063***	-6.107***	-4.058***
X - 07/2007			-0.370***	-0.002	0.000***
X - 11/2009			0.772***	0.006	-0.002***
X - 10/2010			-0.586***	-0.000	0.002***
X - 03/2013			0.955***	0.0112**	-0.003***
X - 08/2014			-1.59***	-0.107***	0.003***
N	121	119	121	121	121
r^2_{adj}	0.521	0.871	0.975	0.911	0.946

Notes: This table provides a comparison of the models used to illustrate the rolling returns generated by IPOs over the 2005 to 2015 time-period. *, **, and *** are significant at .15, .10, .05, and .01.

In Table 8, we compared the spline regression approach to estimating the volume of IPOs issued in a given month against a linear approximation and against a model that uses dummy variables as proxies for hot and cold markets as outlined in Helwege & Liang (2004). As illustrated in Table 8, the spline regression approach to estimating 12-month rolling volume offers a better fit when comparing this approach against the two alternative approaches (i.e. a linear relationship and applying the Helwege et al., 2004 methodology). The magnitude of the differences between the Helwege et al. (2004) model and the spline regression approach are not obvious when looking at the goodness of fit or the parameter estimates associated with the models; therefore, we provided a visual comparison of the Helwege et al. (2004) model and our application of the spline regression approach using events and policy initiatives to explain the rolling 12-month IPO volume. Figure 4 outlines the differences between the two estimation techniques and the major benefit of the spline regression approach. In the first portion of Figure 4, we illustrate the estimation results presented by the model provided in Helwege et al. (2004), which use dummy variables that fluctuate between hot and cold market indicators and, what seems to be obvious is the jumpiness estimation line as the expectation moves from the cold state to the normal state and then to the hot state. This, to us, is a fundamental problem with the current state of the literature on IPO markets and based on the results presented in this paper, we show that the spline regression analysis helps us to avoid the jumpiness of the state transition process and provides a rationale for why the transition might be occurring in the first place.

Figure 4 Comparison of Estimation Results



Notes: This figure provides a comparison of the actual 12-month rolling average volume against the expectation obtained using: Hot and Cold binary dummy variables and Linear, Quadratic, and Cubic Spline Regression Models.

5.3.2 Evaluation of the MAAR

In Tables 9 and 10, we begin to develop our general model for returns for our period of interest, which was the January 2005 to December 2015 period found in Table 10, and our comparison period, which lasted from April 1996 to January 2008, which is presented in Table 9. In Models I and II and Models VI and VII, we compare our metric for the heat of the market, which takes the trailing 10 monthly observations, ranks them in quartiles, and classifies the current period as a hot period if it is in the upper quartile and a cold period if it is in the lower quartile, against measures of hot and cold presented in Helwege et al. (2004). In the comparison sample the two measures of heat perform similarly and in the current sample, the new metric seems to do a much better job of explaining IPO returns when compared against the former metric; in addition, the estimated parameters for the hot and cold markets and the intercept seem to be marginally more stable over time.

Table 9 Monthly Returns: April 1996 to January 2008

	Model I	*Model II*	*Model III*	*Model IV*	*Model V*
Intercept	0.0737***	0.0724***	0.0154	0.0299	-0.0037
Hot_{Old}	0.1246***			0.0699***	
$Cold_{Old}$	-0.0639***			-0.0374	
Hot_{New}		0.1211***			0.1000***
$Cold_{New}$		-0.0893***			-0.0564**
v_{t-1}			-0.0004	-0.0006	-0.0006
v_{t-2}			-0.0012	-0.0017	-0.0006
v_{t-3}			0.0032**	0.0034***	0.0033***
R_{lag1}			0.7784***	0.6464***	0.6793***
R_{lag2}			-0.3987***	-0.3859***	-0.3151***
R_{lag3}			0.2402***	0.1754**	0.1506*
DV_{2008}					
DV_{JOBS}					
DV_{Change}					
n	140	132	132	132	132
r^2_{adj}	0.2503	0.2524	0.4359	0.4835	0.5832

Notes: This table reports the results of estimation of MAARs and raw returns for April 1996 to 2008 time-period. This table presents the estimation results associated with our comparison sample. Models I and VI use the Helwege and Liang (2004) methodology to identify hot and cold markets and Models II and IV use the method developed in this paper. The lagged volume of IPOs and MAARs and Returns are used as control variables in Models III through V to determine whether the Hot and Cold Variables are stable and whether the dummy and spline variables have predictive power over IPO returns. Notes: *, **, and *** are significant at .10, .05, and .01.

Continuing with our analysis of Table 9 and moving on to exploring the determinates of returns in the comparison period, which fits neatly as a comparison to the estimation results presented in Lowry et al. (2002), we will now discuss Models III, IV, and V. Model III aims at providing a direct comparison to the estimation results presented in Lowry et al. (2002) in which the researchers explore the predictive power of the lagged returns and volume on the current periods returns covering a period lasting from 1960 to 1997 using three independent samples. The evidence presented in the 1996 to 2008 sample has some similarities with Lowry et al. (2002) estimation results: (a) the first lag of returns has a positive and significant effect on current returns and (b) there is some evidence of negative serial correlation between the returns experienced in the present month and in past months (i.e. Lowry et al., 2002, find statistically significant evidence that the third lag of returns had a negative impact on the current performance results and we find that the second lag has a negative effect). There are some inconsistencies between the two studies: (a) We find that the third lag of volume has a positive effect on the returns experienced in the current period, which could indicate that the previous volume could be indicative of current returns, but their evidence does not support this finding and (b) the predictive power of the Lowry et al. (2002) three samples range from 0.072 to 0.373 as judged by the R^2 value associated with their models and our R^2 seems to be higher with a value of 0.4359 during this sample period when using only the descriptive variables used in Lowry et al. (2002). Next, we incorporated the hot and cold indicator variables presented in Helwege et al. (2004) but used monthly performance instead of the volume as an indicator of the hotness or coldness of returns. When we incorporated the heat variables presented in Helwege et al. (2004) into our model based upon Lowry et al. (2002) the estimated parameter estimates remained relatively stable, but the statistical significance associated with the cold market variable changed to insignificant. We created a new set of heat variables, which were not sample dependent, and applied them to this analysis in Model V and both of our heat variables were statistically significant, the parameter estimates remained relatively stable and the predictive power of our model increased.

Table 10 Monthly Returns: January 2005 to December 2015

	Model VI	*Model VII*	*Model VIII*	*Model VIV*	*Model X*	*Model XI*	*Model XII*
Intercept	0.1122***	0.0846***	0.1099***	0.0518***	0.1187***	0.0361***	0.0526***
Hot_{Old}	0.0747***				0.0866***		
$Cold_{Old}$	-0.0804***				-0.0809***		
Hot_{New}		0.1153***				0.1133***	0.1084***
$Cold_{New}$		-0.1006***				-0.0901***	-0.0925***
v_{t-1}				0.0011	0.0002	0.0003	0.0002
v_{t-2}				0.0017	0.0011	0.0004	0.0005
v_{t-3}				0.0046	0.0004	0.0019**	0.0018**
R_{lag1}				0.0689	-0.2190**	0.0523	0.024
R_{lag2}				0.0194	-0.0891	0.0292	-0.0008
R_{lag3}				0.0662	0.0882	0.1043*	0.0798
DV_{2008}			-0.0704***				-0.0338**
DV_{JOBS}			0.0018				-0.0008
DV_{Change}			0.0002				0.0036
n	130	122	122	122	122	122	122
r^2_{adj}	0.3717	0.5799	0.1538	0.108	0.332	0.6459	0.6646

Notes: This table presents the estimation results associated with our sample of interest. Models VI and X use the Helwege and Liang (2004) methodology to identify hot and cold markets and Models VII, XI, and XII use the method developed in this paper. The lagged volume of IPOs and MAARs and Returns are used as control variables in Models VIV through XII to determine whether the Hot and Cold Variables are stable and whether the dummy and spline variables have predictive power over IPO returns. Notes: *, **, and *** are significant at .10, .05, and .01.

In Models VI through XII found in Table 10, we apply our application of the Helwege et al. (2004) hot and cold variables, our new heat variable, the descriptive variables presented in Lowry et al. (2002), and both our dummy variable for 2008 and our two spline variables for the introduction of the JOBs Act in 2012 and the structural change variable to estimate IPO returns from 2005 to 2015. Over the entire sample, we find that the only additional variable that we added to estimate returns which were a significant predictor of returns was the dummy variable incorporated to illustrate the effect of the financial collapse; therefore, our two spline variables did not have a statistically significant relationship with returns. Our model, using the new heat variable, was able to provide a much more accurate representation of the heat of the market as compared to the Helwege et al. (2004) model of hot and cold markets. In addition, the third lag of volume had a similarly positive and statistically significant association with IPO performance in this period, which supports the finding that is presented in the April 1996 to January 2008 period and provides a contrast to the results presented in Lowry et al. (2002). The statistical significance of the lagged market returns on the current market returns in the 2005 to 2015 sample fades to insignificant, which provides a counterpoint to both the 1996 to 2008 data analyzed in this research project and the 1960 to 1997 findings presented in Lowry et al. (2002). In summary, using our model of heat to capture the hotness and coldness of the IPO market and predict returns provide a more prescriptive model of IPO performance and we have some evidence in our two samples that the lagged volume of IPOs may impact returns in the current period and the results are statistically significant from 1996 to 2015.

5.3.2 Examining the Average 12-month rolling MAARs

As we attempt to provide a more general description of IPO performance, we are going to move to an analysis of the 12-month rolling average MAARs. This stage of the analysis is conducted to obtain a general idea of the breadth of the MAARs and to model the general trends that are occurring within the market. In this portion of the analysis, we will use our competing definitions of hot and cold markets, dummy variables, and spline knot locations to explore how well the competing models do at describing the 12-month rolling MAARs.

Initially, we used a similar approach to the method that was used when we examined the relationship between performance and volume and questioned whether there was a lagged relationship between the MAAR and the volume. Throughout our analysis we found that this was not the case; therefore, it was excluded from this paper. In Table 11, Model I used the entire sample starting in December 2005 and ending in December 2015 and regresses the 12-month rolling average returns on the 12-month rolling volume. Model II uses data from December 2005 to April 2014 and Model III uses data from April 2014 to December 2015. Models IV, V, and VI illustrate that the binary dummy variables help to explain the MAARs during this sample period. Models IV through VI uses a dummy variable to indicate a structural break in the data from 4/2014 to 12/2015 as indicated in Section 2.2.3. Models V and VI use a dummy variable as a proxy for the effect of the financial crises of 2008 to 2009. This dummy variable is coded as one from a year after January 2008 to 14 months later; so, from January 2009 to February 2010 because we are using 12-month rolling average returns. Model VI incorporates a dummy variable to act as a proxy for the impact that the JOBs act had on the volume of IPOs issued on the U.S. Equity Markets since April of 2012. The variable is coded as 1 six months after the initiation of the JOBs act in April of 2012 since it will take some time for the effect to be integrated into the average returns; therefore, from October 2012 to December 2015 the dummy variable is coded as 1 and 0 otherwise. Model VII uses the Helwege et al. (2004) definition of hot and cold markets, which takes the centered moving average of each month’s returns and classifies the returns into hot and cold periods based upon that month's return and Model VIII uses the current research project's method of defining hot and cold markets based on an observation falling in the first quartile (i.e. hot market) or the fourth quartile (cold market) and classifying the remaining observations as normal or not hot or cold.

In Model I, we indicate that volume does a good job of explaining returns, but in Models II and III, we illustrate that this description has broken down recently and it has created both a statistically significant positive influence and a statistically significant negative influence over the MAAR for which a potential explanation was provided in Section 2.2.3 of this paper. To attempt to adjust for that change, we included a the DV_{Change} variable in Models IV through VI and we expected this variable to be negative, which it is, and it is statistically significant and relatively stable as we move from Model IV to Model VI. The DV_{2008} variable used in Models V and VI were used as a proxy for the impact that the financial collapse had on the MAARs of IPO during this time horizon. We expected that this variable would have a negative effect on the MAAR and it was negative and statistically significant. In Model VI, we incorporated the DV_{JOBS} variable and, in line with our expectation, the variable had a positive effect on the MAAR and that effect was statistically significant. As indicated previously, Models VII and VIII are presented to compare the Helwege et al. (2004) definition of hot and cold markets against our definition of hot and cold markets. Given that we are using a rolling average or smoothed return series as a proxy for the market sentiment in general, it is almost intuitive that Model VII does a better job at explaining when this return series and the new estimate seems to do a better job of explaining the actual MAARs.

Table 11 An Examination of MAARs, Volume, Hot & Cold Markets, & Events

	Model I	*Model II*	*Model III*	*Model IV*	*Model V*	*Model VI*	*Model VII*	*Model VIII*
Intercept	0.052***	0.028***	0.211***	0.037***	0.053***	0.059***	0.117***	0.091***
Volume	0.006***	0.009***	-0.003*	0.008***	0.006***	0.005***		
DV_{Change}				-0.043***	-0.030***	-0.030***		
DV_{2008}					-0.028***	-0.032***		
DV_{JOBS}						0.015**		
$Cold_{Old}$							-0.078***	
Hot_{Old}							0.016***	
$Cold_{New}$								0.006
Hot_{New}								0.0422***
n	121	101	19	121	121	121	119	112
r^2_{adj}	0.617	0.780	0.144	0.677	0.702	0.710	0.599	0.182

Notes: This table covers 1,369 IPO issued on U.S. Equity Exchanges from January 2005 to December 2015. The returns of the IPOs are calculated as the holding period return from issuance to the close of trade on the first day of trading. The returns are then averaged, and a monthly average return is generated. The rolling returns are then calculated using a 12-month rolling average. The volume of shares was calculated as the 12-month rolling average issuance (i.e. the average number of shares issued in a given month over a 12-month rolling period). Levels of significance: *, **, and *** are significant at .10, .05, and .01.

To continue our analysis, we used the results and illustrate how the spline regression technique could be used to improve our model of the 12-month rolling MAARs, we compared the performance of using linear regression, dummy variables, and the spline regression technique to estimate the MAARs. Model I, in Table 12, illustrates the effectiveness of a simple linear regression, which uses time as a predictive variable and provides us with a comparison benchmark. Model II uses the methodology presented in Helwege et al. (2004) for identifying hot and cold markets and uses dummy variables to account for those hot and cold markets. In Model III, we incorporate the DV_{JOBS}, DV_{Change}, and DV_{2008} variables as a comparison to the model that uses dummy variables and hot and cold markets and the two models offer similar predictive power over the MAAR. Model IV uses the spline knot locations identified in Section 4.3 and applies the spline regression technique to model the MAARs. There is evidence of a significant improvement in the model's predictive power as compared against Models II and III, which were constructed using dummy variables. Model V incorporates the hot and cold dummy variables using the Helwege et al. (2004) methodology and of the two heat variables, only the impact of the Hot_{Old} variable on the MAAR remains statistically significant.

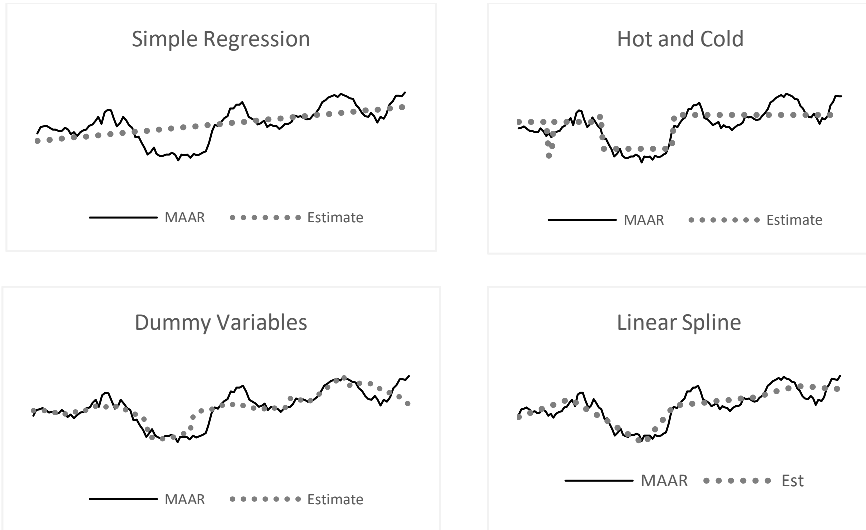
Table 12 Modeling the Effects of 'Events' on IPO MAAR

	Model I	*Model II*	*Model III*	*Model IV*	*Model V*
Intercept	6.909***	0.117***	0.103***	8.021***	7.560***
Month	0.067***			0.233***	0.232***
Hot_{Old}		0.016***			1.267**
$Cold_{Old}$		-0.078***			0.095
Volume					
DV_{2008}			-0.065***	-0.233	-0.367
DV_{2008}			0.041***		
DV_{JOBS}			0.007		
X - 07/2007				-0.615***	-0.639***
X - 11/2009				1.208***	1.341***
X - 10/2010				-0.758***	-0.872***
X - 03/2013				0.097	0.215
X - 08/2014				-0.205	-0.225
n	121	120	121	121	121
R^2adj	0.307	0.599	0.621	0.753	0.759

Notes: ^, *, **, and *** are significant at .20, .10, .05, and .01.

In Figure 5, we provided a visual illustration of some of the main models presented in Table 12. The first illustration presents a simple linear regression, which does not seem flexible enough to incorporate the changes that we experience in the MAARs. The second illustration provides a visual representation of the what an estimation using hot and cold dummy variables looks like. The dummy variable moves between two states, similar to Markov chain and regime switching models, but it does not pick up on some of the micro-level changes occurring in the data. In the third illustration, we provide the model that uses dummy variables associated with the events that we suggested impact both the volume and MAARs produced by IPOs. This approach, using events to explain changes in the MAARs does a better job of explaining the MAARs when compared against the previous two models. In the last illustration, we provide a visual representation of how we could apply the linear spline regression approach to improve our description of the MAARs. Based upon our visual and statistical examination of the spline regression technique paired with actual events that affect the MAARs, we believe that this modeling technique does a better job estimating MAARs as compared against either using hot and cold variables or using dummy variables to account for the effect of an event on the MAAR.

Figure 5 Description of MAAR (Simple, Hot / Cold, Dummy Variables, & Linear Spline)



Notes: Figure 7: Illustrates the MAAR against four different models: (a) Hot and Cold, (b) Linear Spline Model, (c) Quadratic Spline Model, and (d) Cubic Spline Model.

6. Summary and Conclusion

The objective of this paper was to explore the relationship between IPO returns and performance on the U.S. Equity Exchanges from 2005 to 2015. The reason that this research is important is that today's IPO markets are different from IPO markets in the past and as the underlying dynamics of the market changes, it is important to update and improve our understanding of those markets. In this section, we will highlight the key points that we believe distinguish our paper from the current state of the literature and therefore, add some additional insights on what drives the performance and volume of IPOs.

Our first objective was to highlight that IPO markets today are reliant on policy decisions that create hot and cold markets. Unfortunately, the current body of research on IPO volume and performance seems to use either hot or cold markets or regime changing models to illustrate the different states of the IPO market, but those states seem to move between two extreme states (i.e. hot and cold) or at best three regimes, which are typically hot, normal, and cold. This definition of the different states of the world is too restrictive and more importantly a hot market last decade may not feel like a hot market this decade and the coldness of the market changes drastically as well. To improve our understanding of the hotness or coolness of the markets we integrated a new measure of categorizing the hotness and coldness of the market based on a trailing return series, which we believe provides a more realistic and practical measure of market heat. We believe that this method provides a number of improvements over the alternative proxies that have been used in the literature to explain the hotness or coldness of the market and we believe that this is a strength of this paper. In addition, when reviewing the state of the literature, it seemed as though initial studies of hot and cold markets classified the markets as hot or cold, but other researchers would, in subsequent studies, explain the hotness or coolness of the markets by industry-specific phenomena or events that were outside of the market and so, upon reflection, it seemed that there were better explanations of what was going on in the market rather than its heat. In this paper, we identified three specific events (i.e. the financial collapse of 2008, the introduction of the JOBs Act, and the more recent change in the type of IPOs that are entering the market causing a change in the relationship between volume and returns) that we believe influenced the market to behave in a hot or cold manner or had a significant impact on the market for U.S. IPOs. This final point, that we should explain the variables that cause the hot or cold markets, is, from our perspective, an important point, one that has not received adequate attention in the literature, and we believe this is another strength of this paper.

The second objective of this research project was to use the events (i.e. policy changes and or changes in the regulatory environment) that we had previously identified and the heat variable to explain the volume and performance of IPOs during the 2005 to 2015 period. In addition to accomplishing this objective we wanted to provide an out of sample test of our main model; therefore, we used a sample of previously collected data on IPOs that went public from August 1996 to December of 2005 as our out of sample test and to validate or provide a comparison of our general findings. With this in mind, we used lag performance variables, return variables, and market variables along with our measure of heat and old measures of heat and the events that we suggested that affect the performance and volume of IPO performance and ran a battery of test to determine if our model was well defined. While working with the data and attempting to describe the patterns emitted by the volume and returns of the IPOs we found that we needed some additional flexibility to properly model the return series. After considering regime shifting models and models that jump from one state to another, we identified the spline regression technique and applied it in a few ways throughout the paper to help explain the changes in the series that we were attempting to model (i.e. avoiding the jumpiness as we moved from one state to the next). In our opinion, introducing this methodology to examine IPO volume and returns is another contribution to the literature.

It may seem evident, but the data that researchers use to evaluate performance and returns really matters. For example, we illustrate that when we attempted to model the actual volume and returns for IPOs in these two samples, in both our analysis of performance and volume, that our new method of estimating the hotness or coldness of the market seemed to work better than a previous method of classifying hot and cold markets; however, when we looked at the average 12-month rolling volume and returns the previous method of classifying hot and cold markets provided better-estimated results (we reported the old method throughout the paper to compare against our use of the spline regression technique). The old estimate required the entire sample and based on that entire sample it ranked each observation as hot or cold, but the new method examines heat; therefore, if a market is hot for more than 10 months then it must become increasingly hot for the next observation to be considered hot, because the determination of heat is based on the previous 10 months and not the entire sample. We believe that this is an important distinction and it should be considered when evaluating the findings and results of studies.

In conclusion, we used two independently drawn samples, a primary sample, which ran from 2005 to 2015 and, an out of sample comparison, which ran from 1996 to 2008, to examine the determinates of IPO issuance and performance on U.S. Equity Exchanges. While conducting our analyses we incorporated a new heat variable and compare its ability to describe aggregate issuance and performance against a standard heat variable, we illustrated how events can affect IPO issuance and performance and incorporated those events into a model of performance and volume. To incorporate these events into our models we integrated the spline regression technique into our model, which improved the fit of our model substantially over methods that could be seen as alternative modeling techniques such as applying dummy variables or using regime switching models to capture changes from one market environment to the next. We believe that our use of events in the modeling process provides a more accurate representation of the underlying dynamics of the processes that are causing changes in IPO performance and issuance. In addition, we feel that our application of the spline regression technique to model IPO performance and issuance provides researchers with an important tool that could help us to better estimate, model, and understand the true determinates of IPO Performance and issuance.

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