IPOs, Clustering, Indirect Learning and Filing Independently

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Abstract

IPO underpricing has been attributed to valuation uncertainty, which can be at least partially resolved by the indirect learning associated with IPO clustering (Beneveniste et al. [2003]). We examine motivations of firms that choose to issue IPOs as parts of clusters and exploit their indirect learning opportunities. In addition, we identify motives for the decision to file an IPO independently of clusters, foregoing the indirect learning opportunities they provide.

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1. Introduction

On February 3, 2006, www.marketwatch.com presented an article titled "Burger King IPO will likely top $300 million." The article stated "Burger King's planned IPO is expected to raise at least $300 million and be one of the largest restaurant deals in recent years as its investors take advantage of strong demand for franchise food offerings." Only weeks earlier, another food franchise, Chipotle, floated its IPO on January 26, 2006 issuing 7,878,788 shares at $22 per share. Chipotle's first day closing stock price was $44, reflecting a one-day 100% return. These events highlight certain key issues. First, at the time of the online article appeared, Burger King had not yet issued its IPO. Nevertheless, Burger King's anticipated IPO could have implications for other IPO candidates firms in the franchise food industry at that time.[1] Second, demand for franchise food offerings had been strong just prior to Burger King's IPO, suggesting that firms in a given industry may be influenced by other IPOs in that industry, causing them to cluster. Finally, the clustering need not occur only during "hot" IPO markets.[2]

Not surprisingly, clustering of IPOs has attracted much attention in the IPO literature. Studies have shown that IPOs tend to cluster because of high cash flows (Benninga, Helmantel and Sarig (2005)), prior underpricing (Ritter (1984), Lowry and Schwert (2002)), and industry characteristics (Jain and Kini (2006)). Another reason for IPO clustering is the underwriter's ability to bundle IPOs. Benveniste, Busaba and Wilhelm (2002) suggest that a firm reveals information through its IPO bookbuilding efforts, facilitating information production and bookbuilding efforts of firms subsequently issuing IPOs. To prevent market failures resulting from free-riding on these information production efforts, underwriters bundle IPOs to spread information production costs across many firms. Benveniste, Ljungqvist, Wilhelm and Yu (2003) find evidence that indirect learning from a prior IPO influences a firm's decision to complete or withdraw its own IPO and determines how the offer is priced relative to prior expectations.

In this study, we examine the IPO timing decision as a function of indirect learning from prior IPOs. Direct learning in the early stages of an IPO can be problematic, enhancing the relative importance of indirect learning or feedback from other firms' filings. Benveniste et al. (2003) argue that information spillovers from contemporaneous offerings (indirect learning or

[1] Burger King ultimately filed its S-1 registration statement with the Securities and Exchange Commission (SEC) on February 16, 2006, announcing a proposed maximum aggregate offer price of $400 million.

[2] 2005 (the most recent year prior to Burger King's announcement), only 161 IPOs were completed, compared to 476 and 382 during the hot IPO markets of 1999 and 2000 (see Professor Jay Ritter's website).

feedback) can reduce a firm's reliance on its own bookbuilding efforts (direct learning). However, the quality of indirect feedback varies across IPOs. Given that direct information from a firm's own IPO filing is not initially available, what motivates the firm to issue an IPO when indirect feedback is limited or non-existent? From a learning perspective, every firm should benefit from being part of an underwriter's bundle. Why are some IPOs not part of a bundle?

To address this question, we define a variable, the degree of independence, to capture the level of indirect learning available to a firm at the time of its IPO. The degree of independence is measured as the length of time between IPO filings of firms in the same industry. A relatively short (long) length of time between filings indicates greater (lower) indirect learning ability and, thus, a lower (greater) degree of independence. Contrasting Benveniste et al. (2003), we allow indirect feedback to occur from both prior and future firm IPO filings. Although there is more noise in the measure of learning from future filings, they still do allow for indirect learning.

Using a sample of IPOs from 1993 to 2002, we find that insiders' diversification needs and the firm's capital requirements are the key motivations for filing IPOs with lower indirect ability (i.e., higher degree of independence). Firm and offer characteristics also play an important role. However, the results are contingent on the measure of the degree of independence and specification of industry.

This study makes three contributions to the existing literature. First, we account for learning from future filings. Second, since the true functional form of learning is unknown, our study incorporates different measures of learning. Third, we focus on the initial filing to differentiate indirect from direct learning.

2. Literature Review

IPOs tend to cluster in time and industries. For example, Ibbotson and Jaffe (1975), examining IPOs in the 1960s, find that periods of high IPO volume are likely to be followed by further heavy IPO activity. Ritter (1984) finds that IPO waves can be attributed to certain industries. Lowry and Schwert (2002) argue that potential issuers learn from the experiences of other IPOs. They find that more firms go public after observing more underpriced IPOs. However, a survey of CFOs by Brau and Fawcett (2006) suggests that recent underpricing might not be an indicator of IPO timing.

Benveniste et al. (2002) argue that firms going public produce information influencing their own production decisions as well as the production decisions of their rivals. If information production costs are borne primarily by pioneering firms, market failures can occur in which firms remain private. Underwriters mitigate this free-rider problem by bundling IPOs within an industry, ensuring an equitable distribution of information production costs. Benveniste et al. (2003) empirically test the Benveniste et al. (2002) theoretical paper. Using a sample of 6181 IPOs from 1985 to 2000, they examine whether firms attempting IPOs learn from the filings of their industry peers (i.e., obtain indirect feedback). The authors posit that indirect feedback is a function of industry peers' withdrawal and pricing decisions, their underpricing experience and the rate of new registrations by related firms. Benveniste et al. (2003) account for indirect information both prior to a firm's (initial) filing and during the registration process, while examining how indirect learning influences the firm's decision to complete or withdraw the IPO. They find evidence that firms condition whether to proceed with IPO and the terms of those offerings on the experiences of their industry peers. In other words, indirect learning plays an important role in a firm's decision on whether to go public as well as the terms of the offering.

Benninga et al. (2005) argue that IPO activity begins when the firm with the largest cash flows in a given industry finds it optimal to go public. Since information is revealed during the bookbuilding process, potential investors gain valuable information regarding the firm's prospects as well as other industry opportunities. As a result, the benefits of remaining private in the industry are diminished, and the firm with the next highest cash flow is motivated to go public. This leads to a sequence of firms in the same industry going public within a relatively short period of time. Unlike earlier studies that consider going public a one-shot decision, Benninga et al. (2005) allow for the possibility that the publicly traded firm may choose to become private once again. Thus, their model suggests that the decision to go public reflects more than just the immediate costs and benefits.

Jain and Kini (2006) identify industry conditions that influence IPO clustering and analyze differences in characteristics of clustered and non-clustered IPOs. They find that IPO clustering is more likely to occur in high-growth and fragmented industries characterized by strong investment opportunities, favorable investor sentiment, and that require high levels of investment in research and development. The authors also find that clustered IPOs experience poorer long-run post-IPO performance compared to non-clustered IPOs. They argue that this is due to overinvestment in the industry.

The SEC registration statement for the IPO is a key component of investors' information sets concerning company prospects. Studies of this information and its impact on underpricing include Beatty and Ritter (1986) who examine the number of uses of IPO proceeds, Leone, Rock and Willenborg (2006) who study intended uses of IPO proceeds, and Beatty and Welch (1996) who examine the number of IPO risk factors. Unlike the final prospectus that is issued at the end of the bookbuilding process, the initial SEC filing reflects only indirect learning occurring prior to starting the bookbuilding process. For example, insiders use concealing and confounding strategies to hide the true number of IPO shares (Ang and Brau [2003]) because insider sales raise concerns about the future prospects of the firm (Leland and Pyle [1977]). Filing of "obscure" amendments where insiders disclose the true number of shares that they wish to sell produces direct learning and impacts underpricing (Bradley and Jordan [2002]).

3. Learning and Measurement

Motivating the IPO and Degree of Independence

Since the decision to go public is endogenous, we examine the motivation for a firm to issue IPO shares when indirect learning is limited. Filings from other IPOs contain information (e.g., price, number of shares, risk factors, financial statements, etc.) that is useful to firm engaging in its own IPO, hence, firms should prefer to issue their own IPOs after indirectly learning from their peers. We define a variable, *the degree of independence*, to capture the level of indirect learning realized by a firm attempting an IPO. Firms with lower indirect learning are assumed to have a greater degree of independence. The degree of independence, in essence, captures the flexibility that a firm has in its IPO filing decision. Because of the presence of idiosyncratic factors, some firms should have greater flexibility in the filing decision than others. What motivates firms to issue IPOs at an indirect learning disadvantage?

Insiders reveal their knowledge of high future cash flows by retaining larger fractions of equity in the firm, that is, by selling fewer shares of the IPO (Leland and Pyle (1977) and Brau and Fawcett (2006). In fact, Aggarwal, Krigman and Womack (2002) find that only 26.4% of firms sell secondary shares in the IPO. Regardless, a key motivation for insider selling through the IPO is that they hold undiversified portfolios. Moskowitz and Vissing-Jorgensen (2002) find that households owning equity in private firms invest 41% of their net worth in private equity with approximately 73% of that investment in a single firm where the household has an active management interest. By selling shares in the IPO, the household diversifies its portfolio. Black and Gilson (1998) argue that the IPO is a tool for insiders to cash out. In their survey of CFOs, Brau and Fawcett (2006) find moderate support for the Black and Gilson (1998) argument.

When insiders need to diversify or when venture capitalists need to return capital to their investors, the limited learning from other IPOs may not deter a firm's decision to go public. As a result, we expect a positive relation between insider selling in the IPO and the degree of independence. Thus, a firm that issues an IPO at an indirect learning disadvantage is more likely to have increased insider selling of the IPO.

Using a sample of 16,958 IPOs from 38 countries, Kim and Weisbach (2005) find that the sale of primary shares is correlated with the firm's need for capital. Their univariate and multivariate tests show that primary offerings are significantly correlated with increases in inventory, net property, plant and equipment (PPE), capital expenditures and R&D expenditures for up to four years after the IPO. On the other hand, secondary offerings have little or no correlation with these company investments. They also find that primary offerings are more likely than secondary offerings to lead to reductions in debt levels and increases in cash.[3] Based on IPO prospectus details, Leone et al. (2006) find that firms use IPO proceeds for debt repayment, expansions and acquisitions, research and development, product development, advertising and other marketing related issues, and working capital.

Raising capital is certainly an important activity, though allowing for the possibility that some uses of IPO proceeds may be more important than others. A delay in raising necessary proceeds may result in the firm foregoing positive NPV projects, undermining share value. As a result, when a firm has greater capital requirements, it may choose to file for an IPO even when indirect learning from other IPOs is limited or non-existent. This suggests that there should be a positive relation between a firm's capital requirements and the degree of independence. That is, a firm floating an IPO at an indirect learning disadvantage is more likely to have significant need for IPO proceeds.

[3] Kim and Weisbach (2005) use two proxies; primary shares offered scaled by total shares offered and primary capital scaled by total assets. Results hold using both proxies.

Firm, Underwriter and IPO Characteristics and Degree of Independence

Venture capitalists (VCs) play a vital role in a firm's capital formation. Gompers (1995) finds that VCs concentrate investments in early stage companies and high technology industries, where informational asymmetries are significant and monitoring is valuable. VCs monitor the firm's progress and decide whether to continue to fund its projects. Firms going public receive more total financing and a greater number of financing rounds from VCs than firms that ultimately fail or become acquired.

On the other hand, VC-backed firms may be associated with a lower degree of independence through VC firms associations with underwriters. Like underwriters, VCs are powerful repeat players in the IPO market. They develop long-term relationships with other financial market participants. In fact, Brav and Gompers (1997) find that VC-backed firms are better able to attract higher quality underwriters and institutional investors as well as increased analyst followings. Note that VCs and underwriters are first associated with a firm before the IPO filing. The spinning hypothesis of Loughran and Ritter (2004) holds that key decision makers such as VC general partners and issuing firm executives received side payments by hiring high quality underwriters with histories of underpricing. If high-reputation underwriters have greater ability to bundle IPOs (Benveniste et al. [2003]), the positive relation between high quality underwriters and VC backing implies that VC-backed firms are more likely to float an IPO at an indirect learning advantage.

Lerner (1994) examines IPO timing decisions for a sample of VC-backed biotechnology firms, finding that VC-backed firms have the ability to time IPOs for market conditions.[4] Barry, Muscarella, Peavy and Vetsuypens (1990) find that successful IPO timing provides significant benefits to VC firms even though they rarely sell shares in IPOs. They argue that taking companies public when equity values are high minimizes dilution of VC ownership stakes. VCs also have several mechanisms such as board seats, control rights, and the right to put their shares to the firm's management to ensure that firms go public at optimal times, further suggesting that VCs have the ability to time IPOs to suit their needs. Despite the normal importance of indirect

[4] Lerner (1994) also finds that experienced VCs are more proficient in timing IPOs than their less experienced counterparts.

learning, we expect that VC-backed firms are less likely to be reliant on indirect learning, so that reduced degree of independence will be more likely to accompany VC presence.

Larger and older firms are generally considered to be more mature in their business experiences (Lowry and Schwert [2004]) and tend to have greater exposure to business processes, including more choices of suppliers and lenders and larger customer bases. Hence, larger and older firms should be less dependent on the learning from other firms, have greater flexibility with their IPOs and be more likely to float IPOs at a learning disadvantage. We expect that larger and older firms are more likely to float IPOs at an indirect learning disadvantage and a positive relation between firm maturity and the degree of independence.

The information asymmetry arguments of Beatty and Ritter (1986), Rock (1986), and Baron (1982) suggest a positive relation between risk and underpricing. We expect that riskier firms will be more dependent on indirect learning, with a negative relation between risk and the degree of independence.

High reputation underwriters seek to maintain their reputations. Habib and Ljungqvist (2001) find a negative relation between underwriter reputation and underpricing, suggesting that underwriters certify IPOs. Benveniste et al. (2003) argue that more reputable banks deal with less risky firms for which the likelihood of receiving substantial negative information during bookbuilding is low. In addition, underwriters tend to bundle IPOs in order to spread the costs of information production across IPOs, thus preventing free-rider market failures. Higher reputation underwriters are better able to bundle IPOs and be associated with greater indirect learning. Thus, a firm backed by a high reputation underwriter is more likely to float an IPO at a learning advantage and have lower degree of independence.

Benveniste et al. (2003) find that a firm is more likely to complete an IPO during periods of strong industry performance. For example, during the late 1990s, strong investor demand for technology sector firms influenced many firms to float IPOs. More generally, the late 1990s bubble period saw a surge in the number of IPO filings. Nonetheless, Helwege and Liang (2004), find that industry clustering occurs in both hot and cold IPO markets. Regardless, IPO filing decisions are affected by both recent industry performance and the strength of IPO markets.

Measuring Degree of Independence

The degree of independence captures the level of indirect learning available to a firm attempting an IPO. Suppose that firm IPOs within an industry are chronologically ordered from i =1 to n.[5] The degree of independence for firm i is measured as the sum of days from firm i-1's initial IPO filing to firm i+1's initial filing.[6] The value of information from a firm's filing should be a decreasing function of time. Thus, a greater length of time between firm i-1's initial filing and firm i+1's initial filing suggests a reduced level of indirect learning.[7]

Firm i has an obvious indirect learning advantage if it files its IPO only shortly after the filing of firm i-1, whose own filing would incorporate learning from prior filings. Learning also occurs from future filings of other firms. Widespread media coverage typically precedes a firm's initial filing for an IPO. Consider, for example, the intense media coverage and speculation preceding the Google IPO. In fact, on October 23, 2003, *Financial Times* reported that Google was planning its IPO the following year. Google eventually filed its S-1 form with the SEC on April 29, 2004, and floated its new issue on August 18, 2004. Even though complete information about Google's initial filing was unavailable prior to April 29, 2004, there would still be substantial learning opportunities for peer firms filing IPO forms prior to April 29, 2004.[8]

Similarly, on February 3, 2006, Burger King announced its intent to float its IPO on February 16, 2006. Suppose that a peer firm in the franchise food industry planned to file its IPO between February 3rd and 16th 2006, say on February 6th. Given Burger King's announcement on February 3, this firm can learn from Burger King's forthcoming filing and incorporate revealed information into its own decisions. In addition, Benveniste et al. (2003) argue that underwriters bundle IPOs, producing peer information for competitor bookbuilding efforts. Formation of underwriter syndicates with overlapping members enhances this information flow, particularly when bundles contain firms from the same industry. The length of time from firm i's initial filing to firm i+1's initial filing captures this future learning.

Unfortunately, measuring learning as the time from firm i's initial filing to firm i+1's initial filing presents some problems. For example, the degree of independence captures the time ex-post. Suppose that at the time of firm i's initial filing, firm i+2 was expected to file before

[5] See Fama (1997) for 48 industry classifications used here.
[6] Other variations of the degree of independence are discussed later.
[7] Sometimes, two or more firms in the same industry file for an IPO on the same date. In this case, it is hard to determine which firm learns from the other. To counter this, we assume that the minimum period of learning is one day. Thus, the degree of independence has a lower bound of 2.
[8] News reports by *Financial Times* and *Dowjones Newswires* on October 23, 2003 mentioned that the Google IPO would be around $15 billion and that an auction would be used to sell the shares.

firm i+1. But, if firm i+1 files before i+2, firm i+1 is captured in the degree of independence measure.[9] There is also an implicit assumption that information from only one future filing is available at the time of firm i's filing, regardless of the number of future filings. Finally, some firms disclose more information about an anticipated filing than others. The degree of independence measure does not capture different levels of disclosure. Hence, the time taken from firm i's initial filing to firm i+1's initial filing should be viewed only as an approximation of learning from future filings.

4. Data and Methodology

Sample

Data used in this study is drawn from IPOs that were completed, withdrawn or postponed from 1993 to 2002. While this study focuses on completed IPOs, learning does occur from withdrawn and postponed IPOs as well. As with many previous studies of IPOs, unit offers, closed end funds, real estate investment trusts (REITs), American Depository Receipts (ADRs), and issues with an offer price less than $5 are excluded because their characteristics are significantly different from other (more traditional) IPOs. In addition, we removed 25 firms because their SIC codes were unavailable and could not be allocated to a particular Fama and French (1997) industry. Ten more firms were excluded because they had SIC codes not listed in Fama and French (1997). Another 258 firms in five industries (Agriculture, Finance, Miscellaneous, Toys, and Utililities) were removed because their industry returns were not available. This was because the SIC codes of the firms in these industries were not the same as those listed in French (2006), from which industry returns were obtained and Fama and French (1997), the source of industry classifications.[10] Information on the prior and follower firms (required to calculate the degree of independence) was not available for another 59 firms. Finally, 793 firms are excluded because of missing information, including 468 because firm ages were not available from Ritter (2006). Due to missing information, two more industries, Coal and Soda, were also excluded. Thus, our final sample consists of 2935 completed IPOs and 1158 withdrawn and postponed IPOs in 41 of 48 Fama and French (1997) industries.[11, 12] Table 1

[9] This problem is mitigated in Section 6.1.2, where we assume an upper bound for the time from firm i's initial filing to firm i+1's initial filing.
[10] An alternative industry classification is used later, mitigating this issue.
[11] 18 firms were excluded because information on underpricing and stock exchange listing was not available.

categorizes completed and withdrawn/postponed IPOs by year, revealing that the largest number, 16% of the total, of IPO filings was in 1996. The smallest numbers of IPO filings were in 2001 and 2002. These periods also had the largest proportions of withdrawn to total IPOs (77% and 66%, respectively), suggesting that IPO timing decisions may be affected by sample periods.

Table 2 displays summary statistics of the lengths of time between initial filings for the 41 industries. Column 1 shows the number of firms in each industry. Mean and median number of days from firm i-1's initial filing to firm i's initial filing in each industry (Days Prior) are in Column 2. The Business Services industry has the largest number of filings (857), resulting in the lowest mean (3.49 days) and median (2 days) Days Prior. On the other hand, Aero, Gold, and Guns have only one filing each. By construction, summary statistics of the number of days from firm i's initial filing to firm i+1's initial filing (Days Following) are the same as those for Days Prior. For example, if firms i-1 and firm i are in the Autos industry, Days Prior for firm i equals Days Following for firm i-1. Finally, Column 3 shows the mean and median of the degree of independence (i.e., the sum of Days Prior and Days Following).

Variable Descriptions and Definitions

Insider diversification needs are proxied by secondary shares offered, measured as the percentage of total IPO shares represented by secondary IPO shares. Similarly, the firm's capital requirements are proxied by primary shares offered, measured as the percentage of total outstanding shares after the IPO reflected by primary shares offered in the IPO. A firm that does not offer primary (secondary) shares is assumed to have offered zero primary (secondary) shares. Primary and secondary shares are accounted for at the offer rather than at the initial filing because Ang and Brau (2003) find that insiders engage in concealing and confounding strategies in the initial filing. Thus, the actual offer is a more truthful representation of insider issuing firm intentions. Our tests include dummy variable that equals one if the IPO firm is backed by a venture capital firm and zero otherwise. The book value of total assets just prior to the IPO and firm age are proxies for firm maturity. Firm age is obtained from Ritter (2006). The offer price

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[12] From the initial sample of 1246 withdrawn/postponed IPOs from 1993-2002, the following exclusions occur: no SIC codes (21 firms), SIC codes not listed in Fama and French (1997) (2 firms), and SIC codes in Agric, Fin, Misc, Toys, and Util industries from French (2006) and Fama and French (1997) don't tally (61 firms). Further, 4 firms from the Coal and Soda industries are removed since these industries no longer exist in the completed IPOs sample. Thus, 1158 firms remain. Some learned from and contributed to learning of the 2935 completed IPOs.

range listed on the preliminary prospectus proxies for the IPO valuation uncertainty (risk), and is computed as the high minus low of the preliminary offer price divided by the range midpoint.

The expected offer price (i.e. midpoint of the initial price range) might be expected to reflect earnings from assets in place and future growth opportunities. Following Benveniste et al. (2003), the extent to which the expected offer price reflects the present value of growth opportunities (PVGO) rather than the earnings from assets in place is measured with the following index:

$$PVGO\ index = \frac{Midpoint\ of\ preliminary\ offer\ price\ range - \dfrac{Fully\ diluted\ EPS}{Industry\ cost\ of\ capital}}{Midpoint\ of\ preliminary\ offer\ price\ range}$$

where *Midpoint of preliminary offer price r*ange is the mean of the high and low prices listed on the IPO preliminary prospectus.*Fully diluted EPS* is capitalized at the CAPM risk-adjusted *Industry cost of capital*.[13] The PVGO index proxies anticipated growth prospects and serves as an additional risk variable.

We use Loughran and Ritter (2004) updated measures of the Carter and Manaster (1990) underwriter reputation to rank each lead underwriter. Ranks range from 0 to 9.1, with higher ranks representing higher-reputation lead underwriters. If there is more than one lead underwriter, we use the average underwriter rank. Our relative return measure follows Benveniste et al. (2003), focusing on recent industry scaled by market returns. Industry returns are obtained from French (1997).[14] We use three-month equally-weighted industry buy-and-hold returns ending in the month prior to the month of the IPO filing date. For example, if a firm in the Banks industry files for an IPO on March 10, 2000, the industry return is based on the months of December 1999 along with January and February 2000. The market return is the CRSP equally-weighted 3-month buy-and-hold return, also ending in the month prior to the firm's initial filing date. Finally, dummy variables are included to account for hot and cold IPO markets. The hot IPO market period dummy equals one if the IPO is completed during 1999 or 2000 and zero otherwise. Similarly, the cold IPO market period dummy equals one if the IPO is withdrawn or postponed during 2001 and 2002 and zero otherwise.

[13] Inputs are the 3-Month T-Bill rate (the Secondary Market Rate obtained from the Federal Bank of St. Louis and Fama and French (1997) Capital Asset Pricing Model (CAPM) risk premium estimates of the given industry.
[14] The "Old Specification" is used.

5. Results

Univariate Results

Table 3 Panel A shows the distribution of key variables when the degree of independence is sorted by decile. Decile 1 contains firms with the lowest degree of independence, while Decile 10 consists of firms with the highest. Columns 4-11 contain variable means in each decile. The average total asset level of firms filing IPOs exceeds $250m. This variable is positively skewed with a median value of almost $26m. The median age of firms in the sample is 7 years, and shows an upward trend, indicating that firms that file for an IPO at a learning disadvantage are older and more mature. The size of initial price range, a proxy for risk, is 16% on average and shows a downward trend as expected, indicating that less risky firms are more likely to file for an IPO at a learning disadvantage. PVGO index has a median of 0.94, indicating that 94% of the expected offer price comes from growth opportunities and only 6% comes from the current earnings capacity of the firm's assets. This shows the highly speculative nature of the average IPO filing. The median underwriter rank is 8.10.

Table 3 Panel B compares differences between the bottom deciles (Deciles 1, 2 - firms with the lowest degree of independence) and top deciles for each of our key variables. Panel B indicates that most variables are significantly different from each other in the top and bottom deciles at the 5% level of significance. *Primary shares offered* is significantly lower for firms in the bottom deciles than for firms in the top deciles. This suggests that the desire for capital is a key motivation for firms to file for an IPO at a learning disadvantage. In the case of insider selling, the difference in means is significant for Decile 1 vs. Decile 10, and Deciles 1&2 vs. Deciles 9&10.

Firm/Offer characteristics also differ between firms in the top and bottom deciles. The VC dummy is highly significant using all three decile comparisons. VC-backed firms are less likely to file for an IPO at a learning disadvantage. Total assets and age (both proxies for firm maturity) are significantly higher for firms in the top deciles (greater degree of independence). That is, older firms and firms with greater assets are less dependent on learning, so they are more likely to file at a learning disadvantage. Both proxies for risk, size of initial price range and PVGO index are significantly different based on the top and bottom deciles. Finally, underwriter rank is significantly higher for firms in the bottom decile than the top decile. This suggests that, because of reputation concerns, more reputable underwriters are more likely to be associated with firms with a greater learning advantage, i.e., a lower degree of independence.

Table 4 shows the Pearson correlation matrix of the variables. The positive correlations between natural logs of secondary shares offered, firm age (rho=0.12) and total assets (rho=0.13) indicate that insider selling is greater when the firms are more mature. This may be because greater firm maturity somewhat counters the negative signal of insider selling, thus allowing insiders to sell more shares. VC-backed firms are more likely to choose more reputable underwriters (rho=0.23). This result is consistent with Brav and Gompers (1997) and Lee and Wahal (2004). Also, larger firms tend to be older (rho=0.22), have lower risk (proxied by size of initial price range (rho=-0.07) and PVGO index (rho=-0.23)), and are more likely to choose a highly reputable underwriter (rho=0.39). Finally, as expected, VCs are more likely to be associated with firms with greater growth opportunities (rho=0.32).

By construction, the degree of independence dependent variable is discrete and bounded from below by two.[15] Cameron and Trivedi (1998) suggest that count data regressions are useful for studying distributions of inter-arrival times conditional on covariates. The problem with using ordinary least squares (OLS) is that it ignores the restricted support for the dependent variable. This, according to Cameron and Trivedi (1998), "leads to significant deficiencies unless the mean of the counts is high, in which case normal approximation and related regression methods may be satisfactory." Long (1997) concurs that OLS estimates for count data are biased and inefficient.

Poisson regressions, nonlinear models, have been widely used to study count data. However, "[t]he assumed equality of the conditional mean and variance functions is typically taken to be the major shortcoming of the Poisson regression model" (Greene (2000), p. 886). In this study, the mean and variance of the degree of independence are not equal. Specifically, the mean degree of independence is 43.49 (Table 2 Column 3) while the variance is 7540.06 (not reported on the table). When the conditional variance exceeds the conditional mean, it is referred to as "over-dispersion." An alternative to the Poisson regression model is the negative binomial regression model, a standard generalization of the Poisson model and accounts for over-dispersion. We use the negative binomial regression to estimate the degree of independence.[16]

[15] In some of the later regressions, the lower bound is one because an alternative definition of the degree of independence is used.
[16] OLS is used in regressions where the degree of independence variable is transformed.

In addition, the standard errors are adjusted for industry clustering by assuming that observations are independent across industries, but not necessarily for firms that file for an IPO in the same industry. These standard errors are more conservative than White (1980) standard errors.

Multivariate Results

New information can come from an offer or withdrawal announcement of a firm that filed for an IPO prior to firm i-1's initial filing. It could also come from the offer or withdrawal of firm i-1 itself. Thus, this information would be even more recent than that in firm i-1's initial filing. To account for withdrawals, a withdrawal dummy variable is included. The withdrawal dummy equals one if a withdrawal occurs in between firm i-1's initial filing and firm i's initial filing, and zero otherwise. Similarly, an offer dummy is included, which equals one if an offer occurs between firm i-1's initial filing and firm i's initial filing, and zero otherwise.

To account for significant information in the offer, a price update dummy variable is included, which equals one if the percent change between the midpoint of the preliminary price range and offer price exceeds 20%, and zero otherwise.[17] This would capture any significant positive information in the offer. We also require that there be a minimum period of one day between the withdrawal or offer date (if either occurs in between firm i-1's initial filing and firm i's initial filing) and firm i's initial filing date.[18] The following empirical model is tested (the expected signs of the coefficients are in parentheses):

Degree of independence = f [Secondary shares offered (+), Primary shares offered (+), VC dummy (-), Ln Total Assets (+), Ln Age (+), Size of initial price range (-), PVGO index (-), Underwriter rank (-), Relative return, Hot IPO market dummy, Cold IPO market dummy, Withdrawal dummy, Offer dummy, Price Update dummy]

Table 5 displays multivariate results. Degree of independence is represented by Days Prior in Column 1 and Days Following in Column 2. Column 1 shows that secondary shares offered and primary shares offered are not significant. This suggests that insider diversification

[17] See Bradley and Jordan (2002) (pp. 605-606) and Loughran and Ritter (2002) (p. 426) for discussions on the SEC's 20% rule.
[18] For sake of consistency, the offer and price update dummies are based on pricing date rather than the offer date. This is because some firms go public on the same day as the pricing date while others go public a day later.

needs and the firm's desire for capital do not influence a firm's decision to float an IPO at a learning disadvantage. However, the VC dummy variable is significantly negative as expected, indicating that VC backed firms prefer to file for an IPO at a learning advantage. This is because the VC can provide additional funding if necessary to the firm in the interim period. A firm's decision to file for an IPO at a learning disadvantage is influenced by its characteristics. Total assets has a significantly positive coefficient as expected, indicating that larger firms are more likely to file for an IPO at a learning disadvantage because they are more mature. Age is not significant. Both risk proxies are significant. While size of initial price range is negatively significant at the 10% level, there is strong evidence that less growth-oriented firms (where growth is associated with speculation) are more likely to file at a learning disadvantage. Underwriter rank is not significant in this regression.

When the degree of independence is defined as Days Following (Table 5 Column 2), secondary shares offered is weakly significant at the 10% level, while primary shares offered is not significant. These results suggest that, once again, the motivations to file for an IPO at a learning disadvantage do not appear to play a significant role. The VC dummy variable is not significant. Total assets and PVGO index are again significant, while age and size of initial price range do not appear to influence a firm's decision to file at a learning disadvantage. The underwriter rank variable is now significantly negative as expected, indicating that more reputable underwriters prefer IPOs with greater learning advantages.

Since learning is expected to occur from both past and future filings, the sum of Days Prior and Days Following is used to measure degree of independence. This specification is used in Columns 3-6 in a stepwise regression framework. In Table 5 Column 3, industry and market characteristics are ignored so that the focus is on the key variables of interest. Secondary shares offered and primary shares offered are again insignificant. In fact, they continue to be insignificant as additional variables are included in Columns 4-6. However, VC dummy, total assets, age, PVGO index and underwriter rank are all significant with the expected signs. In Column 4, a control variable for recent industry performance is added. The results are very similar to those in Column 3. In Column 5, hot and cold market dummy variables are introduced. Total assets, size of initial price range, PVGO index, and underwriter rank are all significant with expected signs. Finally, in Column 6, variables are added to control for withdrawals, offers and large price updates that occur between firm i-1's initial filing and firm i's initial filing. The overall results are similar to those in Column 5, except that the VC dummy is now significant.[19]

We summarize our results as follows. There is overall no evidence that insider selling and the firm's desire for capital influences a firm to file for an IPO at a learning disadvantage. There is some evidence that firms floating IPOs at a learning disadvantage are less likely to be VC backed. There is strong evidence that firm size plays a role, but weak evidence that firm age influences a firm's decision to file with an indirect learning disadvantage. There is some evidence that the size of initial price range, and strong evidence that growth firms prefer to file for an IPO when they are at a learning advantage. This is probably due to the speculative nature of growth firms. Finally, more reputable underwriters prefer to be associated with IPOs with greater indirect learning, probably since their reputations are at stake. This result is consistent with the Benveniste et al. (2003) argument that highly reputed underwriters find it easier to bundle IPOs than lower reputed underwriters. The overall conclusion is that firm/offer characteristics do influence decisions to file for an IPO at an indirect learning disadvantage.

6. Robustness Checks

Alternative Specifications of Degree of Independence

We have assumed that indirect learning for firm i occurs from firm i-1 (Table 5 Column 1), firm i+1 (Column 2), and firms i-1 and i+1 (Columns 3-6). However, greater learning may be realized from the filing of the closest in date firm to firm i. For example, if firm i-1 filed its IPO 300 days prior to firm i's filing, but firm i+1 was expected to file for the IPO 30 following firm i days, firm i may garner more information from firm i+1 since it is more relevant. To allow for this type of learning, the degree of independence is now assumed to be the minimum of Days Prior or Days Following. We use the negative binomial regression again because of the count dependent variable. In Table 6 Column 1, primary shares offered is highly significant, while secondary shares offered is not. In addition, VC dummy, total assets, age, size of initial price range, and PVGO index continue to be significant with the expected signs. Of the key variables, only underwriter rank is insignificant. Overall, the evidence still suggests that the firm's capital

[19] Underpricing from recent IPOs is not used as an explanatory variable because, as mentioned earlier, Brau and Fawcett (2006) find low support that CFOs use recent underpricing as an indicator of IPO timing.

requirements are the key motivation to file an IPO at a learning disadvantage, though firm/offer characteristics also influence the firm's decision.

Table 3 indicated that the first decile consists of firms where the degree of independence (measured as the sum of Days Prior and Days Following) ranges from 2-4 days. The assumption is that learning is greater for a firm with a degree of independence of 2 than for a firm with a degree of independence of 4. However, there may not be a significant difference in learning between two days and four days. Thus, we may overestimate measuring learning for some firms (i.e. those with a degree of independence of 2) and underestimate others (those with a degree of independence of 4). Similarly, the tenth decile consists of firms in the 104-1607 range. There may not be a significant difference in learning for a firm with a degree of independence of 200 days than for another firm with a degree of independence of 300 days. To account for this, the median degree of independence in each decile is assumed to be the representative degree of independence for all firms in that decile. For example, the median degree of independence of firms in the first decile is 3, which is the value used to represent the degree of independence for all firms in the first decile. In this framework, the degree of independence used to represent all firms in each decile are 3, 5, 7, 9, 14, 20, 29, 45, 74, and 173 respectively. We use the negative binomial regression model for our tests. The results are displayed in Table 6 Column 2. All the key variables are significant, with the expected signs, except for secondary shares offered.

Until now, we have assumed that prior and future learning are equally important to the degree of independence variable. Suppose, for example, there were ten days between firm i-1's initial filing and firm i's initial filing, along with a ten day period between firm i's initial filing and firm i+1's initial filing. Our degree of independence variable is consistent with learning for firm i is to be the same from firm i-1 as from firm i+1, since each firm's filing is ten days removed from firm i. However, the true functional form of learning is unknown. Since the terms of firm i+1's filing are, at best, an estimation when firm i files, the learning ability from firm i+1 may be significantly less than that from firm i-1, whose actual filing is publicly available. Thus, because of different levels of disclosure, learning from firm i-1 may be relatively more valuable. To account for this, we use two different functional forms of learning. First, Days Following is squared to indicate the greater learning disadvantage from future filings while Days Prior remains unchanged. These two variables are summed for each firm to create an alternative measure of the degree of independence. However, now the negative binomial regression cannot be used since the dependent variable has been transformed and is no longer a count variable. Instead, the natural logarithm is taken and we perform an OLS regression. The results presented in Table 6 Column 3. All key variables, with the exception of secondary shares offered, are significant with the expected signs.

Another variation of the degree of independence is defined as the sum of the square root of Days Prior and the square of Days Following. This accounts for even greater learning from the prior IPO than the following IPO. Again, we perform an OLS regression on natural logarithms. The results are similar (Column 4). In summary, all the key variables except for secondary shares offered are now significant using these alternative specifications.[20]

Alternative Industry Specification

Degree of independence is sensitive to the definition of an industry. We used the 48 industry classifications from Fama and French (1997). These Fama and French industry classifications account for functional and vertical relationships among firms (Benveniste et al. [2003]). As a robustness check, all firms in our original expanded sample are reclassified based on 38 industry classifications from French [2006]. However, 3 industries (Ptrlm, Steam, and Stone) are lost because they have only 2, 1 and 1 firm respectively. Thus, we cannot compute degree of independence since both Days Prior and Days Following are required for each firm. In addition, the new sample has no firms in the Water and Other industries. Thus, the final sample is based on 3090 firms in 33 industries.[21]

We performed again several of our earlier regressions using this alternative industry specification, and presented results in Table 7. Note that relative return, withdrawal dummy, offer dummy and price update dummy all take on different values because of the new industry specification. The Table 7 Column 1 regression (based on 33 industries) can be compared with the Table 5 Column 1 regression (based on 41 industries). Primary shares offered is now significant (earlier it was insignificant). Secondary shares offered continues to be insignificant. Of the firm/offer characteristics, venture capital dummy is highly negatively significant once again. Total assets and PVGO index are still significant while size of initial price range is not,

[20] As another robustness check, the Table 5 Column 6 regression was run for only firms in the Business Services industry (N=857). This is an attempt to examine whether the results hold within a specific industry as opposed to across all industries. Of the key variables, only VC dummy is significant (not reported). The results may be driven by the fact that this is a highly clustered industry (see Table 2) and, therefore, not representative of the entire dataset.
[21] As opposed to the earlier sample, the industry returns of all industries are available.

using the new specification. Age and underwriter rank continue to be insignificant. Similarly, the Table 7 Column 2 regression can be compared with the Table 5 Column 2 regression. Secondary shares offered continues to be significant, while primary shares offered, VC dummy, and age are now significant. PVGO index is now insignificant. The other results are unchanged. Next, the Table 7 Column 3 regression is compared with the Table 5 Column 6 regression. As mentioned earlier, this specification incorporates both past and future learning. Primary shares offered, secondary shares offered, and age are now significant. Size of initial price range and underwriter rank are insignificant in the new specification.

Alternative specifications of the degree of independence are examined next. Table 7 Column 4 is compared with Table 6 Column 1. Based on 33 industries, secondary shares offered is now significant. Size of initial price range and PVGO index are now insignificant, while underwriter rank continues to be insignificant. The other key variables continue to be significant with the expected signs. The next comparison is of Table 7 Column 5 with Table 6 Column 3. Secondary shares offered is now significant using the new industry definition. Of the key variables, total assets, size of initial price range, PVGO index, and underwriter rank are now insignificant. Finally, Table 7 Column 6 is compared with Table 6 Column 4. The results are similar to the previous comparison. We conclude that degree of independence is influenced by how industry is defined.

7. Summary and Conclusions

There are two primary sources of learning for a firm filing its IPO, prospective investors and other IPO filings. When a firm files its IPO, information from prospective investors (direct learning) is not available since the bookbuilding process has not yet begun, rendering the issuing firm dependent on learning from other firms' filings (indirect learning). If indirect learning is important, then firms should file for an IPO relatively close to each other, so that they can take advantage of the indirect learning. However, many firms do not take advantage of this indirect learning, but choose to file for an IPO at a learning disadvantage. Our paper has focused on why firms file for IPOs when they are at a learning disadvantage. Two key motives are identified; insiders' diversification needs and the firm's desire for capital. In addition, firm/offer characteristics are expected to play a vital role in a firm's decision to file for an IPO at a learning disadvantage. Indirect learning occurs from firm filings in the same industry. The length of time between filings is used as a measure of the level of indirect learning, proxied as the degree of independence. A higher degree of independence is associated with lower indirect learning ability. We argue that firms with a higher degree of independence have greater flexibility in their filing decision, which allows them to file for an IPO at a learning disadvantage.

The results show that secondary shares offered (proxy for insiders diversification needs) and primary shares offered (proxy for the firm's capital requirements) are positively correlated with the degree of independence. Firm/offer characteristics also play an important role in the filing decision. However, the results are contingent on how learning is defined and how industry is specified. This study makes the following contributions. First, it accounts for the learning from future filings. Second, since the true functional form of learning is unknown, this study incorporates different measures of learning. Third, by focusing on the initial filing, indirect learning is isolated from direct learning.

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TABLE 1

NUMBER OF COMPLETED AND WITHDRAWN IPOS SORTED BY YEAR

The sample includes IPOs from 1993-2002 after excluding unit offers, closed end funds, REITs, ADRs, and issues with an offer price less than $5.

Year	Number of Completed IPOs	Number of Withdrawn IPOs	Total	Ratio of Total IPOs by year to Total IPOs	Ratio of Completed IPOs to Total IPOs
1993	371	63	434	0.11	0.85
1994	338	113	451	0.11	0.75
1995	399	67	466	0.11	0.86
1996	554	95	649	0.16	0.85
1997	367	104	471	0.12	0.78
1998	219	162	381	0.09	0.57
1999	359	106	465	0.11	0.77
2000	253	235	488	0.12	0.52
2001	48	160	208	0.05	0.23
2002	27	53	80	0.02	0.34
Total	2935	1158	4093	1.00	0.72

TABLE 2

NUMBERS OF DAYS BETWEEN INITIAL FILINGS

The sample includes 2935 IPOs from 1993-2002 after exclusions. Days Prior is the number of days from firm i-1's initial filing to firm i's. Days Following is the number from firm i's initial filing to firm i+1's.

	(1)	(2)		(3)	
Industry Name	Number of firms	Days Prior		Days Prior + Days Following	
		Mean	Median	Mean	Median
Aero	1	25.00	25.00	64.00	64.00
Autos	28	43.14	27.50	86.39	70.50
Banks	78	17.09	8.50	35.85	21.00
Beer	10	110.60	28.50	195.00	59.50
BldMt	18	57.11	46.50	143.94	133.00
Books	18	90.28	82.50	183.28	145.00
Boxes	4	214.00	112.50	512.00	507.50
BusSv	857	3.49	2.00	7.18	5.00
Chem	14	88.14	89.00	181.79	147.50
Chips	247	11.21	7.00	20.37	15.00
Clths	23	60.65	38.00	110.35	111.00
Cnstr	27	60.41	38.00	117.26	88.00
Comps	170	15.42	7.00	29.94	17.00
Drugs	124	16.71	9.00	32.53	21.00
ElcEq	24	53.71	40.50	112.92	97.50
Enrgy	51	39.78	19.00	75.59	57.00
FabPr	8	222.63	152.00	439.13	427.00
Food	22	95.55	46.00	146.32	90.50
Fun	62	25.00	17.00	48.39	40.00
Gold	1	183.00	183.00	405.00	405.00
Guns	1	547.00	547.00	887.00	887.00
Hlth	97	23.73	14.00	45.36	30.00
Hshld	28	58.00	44.50	133.11	97.50
Insur	52	35.42	17.50	73.54	47.50
LabEq	59	44.02	19.00	73.14	48.00
Mach	56	31.41	12.00	58.07	40.00
Meals	68	36.47	18.50	70.68	52.00
MedEq	95	20.37	7.00	43.15	25.00
Mines	2	131.50	131.50	174.00	174.00
Paper	13	100.31	85.00	215.15	187.00
PerSv	49	41.47	31.00	80.53	73.00
RlEst	10	129.00	65.50	224.40	190.00
Rtail	149	16.98	8.00	29.12	18.00
Rubbr	12	65.42	48.00	153.17	116.00
Ships	7	233.29	174.00	647.43	477.00
Smoke	3	71.33	56.00	192.67	181.00
Steel	39	38.00	28.00	96.28	62.00
Telcm	168	11.19	7.00	20.89	14.00
Trans	61	34.21	16.00	56.62	49.00
Txtls	9	71.22	48.00	244.67	173.00
Whlsl	170	13.46	7.00	25.61	16.00
Total	2935	21.92	7.00	43.49	16.00

TABLE 3

DESCRIPTIVE STATISTICS BASED ON DEGREE OF INDEPENDENCE DECILES

The sample includes IPOs from 1993-2002 after. The deciles are formed from lowest (Decile 1) to highest (Decile 10) based on Degree of Independence. Means of key variables are shown in Columns 4-11. The median of each variable is shown in parentheses.

PANEL A: KEY VARIABLES SORTED BY DECILES

(1) Decile	(2) Number of firms	(3) Days Prior + Days Following	(4) Secondary shares offered	(5) Primary shares offered	(6) Venture capital dummy	(7) Total Assets	(8) Age	(9) Size of initial price range	(10) PVGO index	(11) Underwriter rank
1	374	2-4	3.28	23.16	0.64	73.41	8.36	0.17	0.90	7.60
2	331	5-6	3.03	24.59	0.62	107.54	8.94	0.17	0.86	7.50
3	199	7-7	3.03	24.46	0.57	178.11	8.69	0.16	0.87	7.92
4	283	8-11	4.10	25.81	0.44	235.14	11.54	0.16	0.78	7.47
5	295	12-16	3.96	27.06	0.41	257.19	12.49	0.15	0.81	7.38
6	294	17-23	3.02	27.48	0.35	235.41	11.40	0.15	0.75	7.25
7	308	24-35	3.69	28.37	0.36	394.06	10.51	0.15	0.78	7.07
8	273	36-56	5.43	28.81	0.35	182.12	14.83	0.15	0.76	7.39
9	285	57-103	4.01	30.54	0.28	299.12	14.84	0.15	0.69	7.10
10	293	104-1607	5.15	27.84	0.31	593.67	20.15	0.15	0.67	7.14
Total	2935		3.86	26.75	0.44	252.27	12.11	0.16	0.79	7.37
			(0.00)	(25.13)	(0.00)	(25.50)	(7.00)	(0.15)	(0.94)	(8.10)

PANEL B: P VALUES OF T-TEST FOR DIFFERENCE IN MEANS AND WILCOXON RANK SUM TEST (IN PARENTHESES)

Variables	Decile 1 vs. Decile 10	Decile 2 vs. Decile 9	Deciles 1 & 2 vs. Deciles 9 & 10
Secondary shares offered	0.05	0.18	0.02
	(0.62)	(0.87)	(0.79)
Primary shares offered	<0.001	<0.001	<0.001
	(<0.001)	(<0.001)	(<0.001)
Venture capital dummy	<0.001	<0.001	<0.001
	(<0.001)	(<0.001)	(<0.001)
Total Assets	0.01	0.03	<0.001
	(<0.001)	(<0.001)	(<0.001)
Age	<0.001	<0.001	<0.001
	(<0.001)	(0.01)	(<0.001)
Size of initial price range	<0.001	0.002	<0.001
	(<0.001)	(<0.001)	(<0.001)
PVGO index	<0.001	<0.001	<0.001
	(<0.001)	(<0.001)	(<0.001)
Underwriter rank	0.01	0.03	<0.001
	(0.02)	(0.04)	(0.002)

TABLE 4

PEARSON CORRELATION MATRIX

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Days Prior + Days Following (1)	1.00								
Secondary shares offered (2)	0.07	1.00							
Primary shares offered (3)	0.03	-0.26	1.00						
Venture capital dummy (4)	-0.11	-0.12	-0.20	1.00					
Ln Total Assets (5)	0.13	0.13	-0.12	-0.07	1.00				
Ln Age (6)	0.12	0.12	-0.03	-0.10	0.22	1.00			
Size of initial price range (7)	-0.04	-0.02	-0.05	0.10	-0.07	-0.02	1.00		
PVGO index (8)	-0.14	-0.17	-0.08	0.32	-0.23	-0.21	0.04	1.00	
Underwriter rank (9)	-0.03	0.10	-0.30	0.23	0.39	0.08	0.10	0.11	1.00

TABLE 5

DETERMINANTS OF DEGREE OF INDEPENDENCE

Relative return is (1+industry return) / (1+market return). Standard errors are adjusted for industry clustering by assuming that observations are independent for companies across industries, but not necessarily for companies in the same industry. They are more conservative than the standard errors in White (1980). Neg Bin refers to Negative Binomial regression.

	(1) Days Prior Neg Bin	(2) Days Following Neg Bin	(3) Days Prior + Days Following Neg Bin	(4) Days Prior + Days Following Neg Bin	(5) Days Prior + Days Following Neg Bin	(6) Days Prior + Days Following Neg Bin
Secondary shares offered	0.002	0.006*	0.007	0.007	0.006	0.004
	[0.598]	[0.083]	[0.106]	[0.106]	[0.133]	[0.213]
Primary shares offered	0.005	0.007	0.008	0.007	0.006	0.006
	[0.177]	[0.145]	[0.144]	[0.152]	[0.164]	[0.131]
Venture capital dummy	-0.260***	-0.12	-0.226*	-0.190*	-0.117	-0.165*
	[0.002]	[0.249]	[0.061]	[0.092]	[0.220]	[0.064]
Ln Total Assets	0.077**	0.105**	0.142***	0.141***	0.128***	0.091**
	[0.048]	[0.020]	[0.001]	[0.001]	[0.003]	[0.023]
Ln Age	0.082	0.067	0.101*	0.095*	0.075	0.072
	[0.112]	[0.300]	[0.057]	[0.069]	[0.149]	[0.172]
Size of initial price range	-1.322*	-0.961	-1.046	-1.01	-1.342**	-1.157*
	[0.087]	[0.194]	[0.157]	[0.177]	[0.045]	[0.079]
PVGO index	-0.706***	-0.550***	-0.602***	-0.608***	-0.628***	-0.618***
	[0.000]	[0.002]	[0.009]	[0.008]	[0.001]	[0.000]
Underwriter rank	-0.01	-0.055**	-0.058**	-0.060**	-0.055**	-0.037*
	[0.670]	[0.024]	[0.016]	[0.014]	[0.017]	[0.091]
Relative return	-1.610***	-0.781		-1.091*	-1.079**	-1.082**
	[0.001]	[0.150]		[0.053]	[0.036]	[0.034]
Hot IPO market dummy	-0.105	-0.318**			-0.296*	-0.228
	[0.428]	[0.031]			[0.066]	[0.101]
Cold IPO market dummy	0.706***	0.579***			0.941***	0.656***
	[0.000]	[0.001]			[0.000]	[0.000]
Withdrawal dummy	1.187***	0.769***				0.985***
	[0.000]	[0.000]				[0.000]

Offer dummy	1.036***	0.273*				0.640***
	[0.000]	[0.064]				[0.000]
Price Update dummy	-0.227*	-0.547***				-0.341***
	[0.063]	[0.000]				[0.004]
Constant	4.236***	3.940***	3.910***	4.996***	5.128***	4.731***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	2935	2935	2935	2935	2935	2935

Robust p values in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE 6

OTHER SPECIFICATIONS OF DEGREE OF INDEPENDENCE

	(1) Min (Days Prior, Days Following) Neg Bin	(2) Days Prior + Days Following (based on median of each decile) Neg Bin	(3) Ln (Days Prior + Days Following^2) OLS	(4) Ln (Days Prior^0.5 + Days Following^2) OLS
Secondary shares offered	0.006	0.003	0.005	0.006
	[0.128]	[0.295]	[0.329]	[0.275]
Primary shares offered	0.008**	0.008**	0.015***	0.015***
	[0.038]	[0.029]	[0.001]	[0.002]
Venture capital dummy	-0.174**	-0.183**	-0.368***	-0.376***
	[0.034]	[0.016]	[0.000]	[0.001]
Ln Total Assets	0.093**	0.086**	0.202***	0.206***
	[0.014]	[0.025]	[0.003]	[0.003]
Ln Age	0.093**	0.085**	0.118*	0.122*
	[0.043]	[0.019]	[0.067]	[0.072]
Size of initial price range	-1.200**	-1.079**	-2.018***	-1.970***
	[0.049]	[0.043]	[0.002]	[0.003]
PVGO index	-0.528***	-0.541***	-0.885***	-0.862***
	[0.000]	[0.000]	[0.004]	[0.006]
Underwriter rank	-0.023	-0.036**	-0.051*	-0.052*
	[0.300]	[0.047]	[0.074]	[0.088]
Relative return	-1.226**	-1.313***	-1.193	-1.173
	[0.012]	[0.006]	[0.101]	[0.115]
Hot IPO market dummy	-0.092	-0.109	-0.489***	-0.462***
	[0.482]	[0.361]	[0.000]	[0.000]
Cold IPO market dummy	0.742***	0.627***	1.445***	1.451***
	[0.000]	[0.000]	[0.000]	[0.000]
Withdrawal dummy	0.887***	0.742***	1.064***	0.937***
	[0.000]	[0.000]	[0.000]	[0.000]
Offer dummy	0.856***	0.657***	0.820***	0.679***
	[0.000]	[0.000]	[0.002]	[0.009]
Price Update dummy	-0.433***	-0.250**	-0.541**	-0.617**
	[0.002]	[0.016]	[0.014]	[0.012]
Constant	3.101***	4.748***	5.520***	5.313***
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	2935	2935	2935	2935
R-squared			0.186	0.155

Robust p values in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE 7

ALTERNATIVE INDUSTRY SPECIFICATION

	(1)	(2)	(3)	(4)	(5)	(6)
	Days Prior	Days Following	Days Prior + Days Following	Min (Days Prior, Days Following)	Ln (Days Prior + Days Following^2)	Ln (Days Prior^0.5 + Days Following^2)
	Neg Bin	Neg Bin	Neg Bin	Neg Bin	OLS	OLS
Secondary shares offered	0.001	0.007**	0.004*	0.007***	0.010**	0.010**
	[0.795]	[0.018]	[0.096]	[0.007]	[0.041]	[0.044]
Primary shares offered	0.008***	0.011**	0.010***	0.011***	0.014***	0.014***
	[0.009]	[0.020]	[0.004]	[0.001]	[0.000]	[0.001]
Venture capital dummy	-0.252***	-0.217*	-0.234**	-0.187*	-0.340***	-0.347***
	[0.002]	[0.093]	[0.026]	[0.062]	[0.006]	[0.007]
Ln Total Assets	0.081*	0.100*	0.091*	0.082*	0.133	0.131
	[0.073]	[0.073]	[0.061]	[0.068]	[0.110]	[0.122]
Ln Age	0.063	0.145***	0.102***	0.088**	0.167***	0.175***
	[0.138]	[0.001]	[0.007]	[0.030]	[0.007]	[0.009]
Size of initial price range	-1.139	-0.066	-0.513	-0.762	-0.751	-0.715
	[0.174]	[0.919]	[0.400]	[0.353]	[0.256]	[0.326]
PVGO index	-0.446*	-0.501	-0.458*	-0.35	-0.548	-0.518
	[0.086]	[0.102]	[0.095]	[0.154]	[0.179]	[0.210]
Underwriter rank	-0.024	-0.060*	-0.043	-0.034	-0.044	-0.044
	[0.439]	[0.086]	[0.169]	[0.280]	[0.177]	[0.190]
Relative return	-0.587	-0.918	-0.79	-0.917	-0.029	-0.102
	[0.374]	[0.201]	[0.231]	[0.158]	[0.973]	[0.904]
Hot IPO market dummy	-0.067	0.056	0.006	-0.036	-0.181	-0.151
	[0.613]	[0.760]	[0.967]	[0.795]	[0.133]	[0.234]
Cold IPO market dummy	0.373*	0.31	0.346**	0.438**	0.937***	0.963***
	[0.051]	[0.117]	[0.042]	[0.029]	[0.003]	[0.003]
Withdrawal dummy	1.338***	1.299***	1.294***	1.272***	1.234***	1.136***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Offer dummy	1.147***	0.369*	0.752***	0.879***	0.930***	0.777***
	[0.000]	[0.068]	[0.000]	[0.000]	[0.002]	[0.007]
Price Update dummy	-0.342**	-0.484**	-0.400**	-0.369*	-0.625**	-0.676**
	[0.033]	[0.044]	[0.025]	[0.085]	[0.019]	[0.015]

Constant	2.702***	3.267***	3.703***	2.310***	3.279***	3.167***
	[0.001]	[0.000]	[0.000]	[0.003]	[0.007]	[0.008]
Observations	3090	3090	3090	3090	3090	3090
R-squared					0.145	0.118

Robust p values in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%