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Primary Market Characteristics and Secondary Market Frictions of Stocks

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Abstract

We analyze the relationship between the primary market characteristics and the secondary market trading frictions of new stocks. We identify major differences across portfolios of IPO stocks grouped by market heat, underpricing, offer price, underwriter prestige, and VC backing. IPOs issued in hot markets, IPOs with low offer price or low reputation underwriters or no VC backing face higher liquidity frictions, higher information constraints, worse short-sale constraints, and higher idiosyncratic risk. Highly underpriced IPO stocks are more liquid, more recognized by analysts and institutional investors, but they have higher idiosyncratic risk, and a higher percentage of them are short-sale constrained. Also, we find an interesting time trend in the evolution of the new stocks' secondary market trading frictions: the mean-reversion of an average IPO stock towards a typical seasoned stock is very slow, and it takes more than a few years. We propose a quality-based explanation for all of the above phenomena.

Keywords: idiosyncratic risk, information uncertainty, initial public offerings, liquidity, market frictions, short-sale constraints.

JEL Classification: G12, G14, G24, G30.

1. Introduction

How are the primary market (or IPO) characteristics of a firm related to its secondary market trading frictions (such as, idiosyncratic risk, illiquidity, incomplete information, short-sale constraints, etc.)? This important question is not fully addressed in the extant financial literature,¹ probably because of the rarely overlapping nature of the two major research areas in finance: corporate finance and asset pricing. However, it is important to establish whether there is a link between the IPO market and the secondary markets, and if there is, what is its nature? Our study fills this gap by showing that the IPO features we consider are good indicators of the trading frictions stocks face in the secondary markets. While we suggest that the primary driver behind these results is the issuing firm's risk (or quality), the stylized facts we report are open for further analysis and interpretation.

We select five IPO features that are shown to indicate meaningful economic variations across new public firms. For example, some studies suggest that the quality composition of IPO firms issued during the hot markets is different than the one issued in the cold markets (see for example Helwege and Liang, 2004; Lowry, et al., 2010; and Yung, et al., 2008). If there are such cross-sectional differences among firms, particularly with respect to quality, depending on their issuing environment, then we should expect these differences to be reflected in the secondary markets. Such discrepancies will manifest themselves not only in the long-run returns of these stocks, but also in other stock diagnostic measures. Similarly, there are studies reporting the existence of major differences between low- vs. high-issue-price IPOs (Fernando, et al., 2004), venture- vs. non-venture backed IPOs (Brav and Gompers, 1997; and Megginson and Weiss, 1991), highly-underpriced vs. not so underpriced IPOs (Loughran and Ritter, 2004; and Lowry and Schwert, 2002), and IPOs issued by high- vs.

¹The relationship that drew researchers' interest the most is the connection between an IPO's underpricing and its post-issuance liquidity. Ellul and Pagano (2006), for example, explain an IPO's underpricing with investors' expectation of its stock's illiquidity in the after-market. Hahn and Ligion (2004), Hanley (1993), Reese (1998), and Schultz and Zaman (1994) also document the positive relation between the underpricing and the liquidity of a stock. Gajewski and Greese (2008) investigate the same relationship for the Euronext IPOs. Cai, et al. (2007) investigate how underpricing of bond IPOs is related to their post-issuance liquidity. To the best of our knowledge, the analysis of the relationships between other primary market variables and secondary market measures are nonexistent.

low-prestige underwriters (Carter and Manaster, 1990; and Carter, et al., 1998).

To understand and characterize a new stock’s trading in the secondary market, we utilize various diagnostic measures. The asset pricing literature has yielded many such measures. *Idiosyncratic risk* has been in use since the development of CAPM. More recently Campbell, et al. (2001) drew attention to this measure by documenting that it has been increasing steadily over time for individual firms. Many studies have attempted to explain this trend.² *Price delay* is a new market friction metric developed by Hou and Moskowitz (2005), who suggest that it likely captures frictions associated with investor recognition. Most delayed firms are smaller, neglected, and more volatile than other stocks. Other widely used *attention/neglect measures* include analyst coverage, and institutional ownership. In addition to the more traditional *liquidity proxies*, such as turnover and price, new measures have recently been developed by Amihud (2002) (illiquidity factor) and Pastor and Stambaugh (2003) (aggregate liquidity risk), who claim that illiquidity is a risk factor incorporated into cross-sectional stock returns. *Measures of information constraints* include analyst dispersion of opinion (Diether, et al., 2002), idiosyncratic risk (Campbell and Taksler, 2003), and turnover (Dierkens, 1991). Finally, the *short-sale constraints* in stocks are shown to cause overvaluation in the short-run, and underperformance in the long-run (see Asquith, et al., 2005; Boehme, et al., 2006; Desai, et al., 2002; and Jones and Lamont, 2002).

When we compare the above trading frictions³ across stock portfolios sorted according to the five IPO attributes described earlier, we find several interesting linkages between the primary and the secondary markets. In comparison to cold IPOs, for example, a typical hot market issue faces significantly higher liquidity frictions and information constraints. There is also some evidence that hot issues are exposed to higher idiosyncratic risk. We perform similar comparative analysis for IPOs with high vs. low offer price; highly-underpriced vs. less-underpriced IPOs; venture-backed vs. non-venture backed IPOs; and IPOs underwritten

²Some explanations include presence of speculative episodes (Brandt, et al., 2010), rise in institutional holdings (Xu and Malkiel, 2003), rise in the number of younger and riskier IPOs (Brown and Kapadia, 2007; and Fink et al., 2005), and rise in volatility of earnings and cash flows (Wei and Zhang, 2006).

³Throughout the paper we use the concepts “trading frictions” and “trading constraints” interchangeably.

by high vs. low reputation investment banks. The relationship between underpricing and our friction and risk measures seems to be very strong. Highly underpriced IPOs are more liquid, and are better recognized by analysts and institutional investors; however, they also have significantly higher firm-specific risk, and a higher percentage of them are short-sale constrained. We also find that IPOs with low offer price, low reputation underwriters, and no VC backing are more exposed to such market frictions during their post-issuance trading years.

For all five of our IPO features, we find significant differences in idiosyncratic risk, short-sale constraints, and other market frictions across IPO firms. This suggests that many trading characteristics of IPO stocks in the secondary markets are predictable by their period of issuance and/or their issue features set in the primary market. We propose a quality-based hypothesis to explain these relationships. If an IPO's attributes and market frictions are both function of its underlying quality (or risk), then our results can be explained by this quality link that connects the primary market to the secondary market. Although, this quality-based explanation is intuitive, it has not been documented before in the literature.

In a further analysis, we point out that IPOs are unique equity securities in that, as a result of being recent issues, they are not well-known by investors. This aspect should distinguish them from the more seasoned common stocks, and thus provide an opportunity to analyze, comparatively, the evolution of these new stock securities over time with regard to aforementioned market frictions and risk factors. Another goal of this study, therefore, is to comparatively analyze these characteristics of IPO stocks relative to all other public firms, and observe the changes in these characteristics over time for several years after issuance.

Our notable findings from this analysis are that IPOs are distinguished from the other firms in several dimensions. On average, they have higher idiosyncratic risk and higher analysts' dispersion of opinion. Fewer analysts cover these firms, and they are more illiquid (using Amihud, 2002's measure). Similar, but lower in magnitude, differences exist for the other measures.

Furthermore, from a related analysis, we find an interesting time trend in the secondary-

market frictions of the IPO firms. It takes a long time (longer than five years) for a typical IPO firm to behave more like a typical seasoned firm with regards to the short-sale, liquidity, and information frictions. For most of the friction measures, there is a gradual reversion to the mean, but this mean-reversion process is quite slow. For liquidity frictions even the gradual mean-reversion is not there. Therefore, IPO stocks seem to be quite different from the seasoned stocks, which suggests that our trading-friction measures capture firm characteristics that are not much affected by the stock’s seasoning process.

What are the implications of these findings? Our study shows that there are strong connections between the primary and the secondary markets, and that a stock’s “fate” with regard to post-issuance trading frictions is mostly predictable by its five IPO attributes we consider. We suggest above that the common omitted variable that causes this link is the underlying firm quality of the new issue. In short, our findings demonstrate that the IPO market, on average, does a good job of signaling to the secondary market traders the risks and the frictions associated with a new issue. We should note, however, that even if the reader does not agree with our proposed quality-based explanation, our finding of strong connections between the primary-market characteristics and the secondary-market frictions on itself is an important contribution to the current literature.

The remainder of the paper is organized as follows. *Section 2* develops our analysis and relates it to the extant literature. *Section 3* describes the data, the sample selection, and the calculation of the asset-pricing measures used in the tests. *Section 4* reports and discusses the results from our tests. *Section 5* provides concluding remarks.

2. Analysis Development

We aim to investigate the post-issuance trading frictions related to short-selling, liquidity, and information in the IPO stocks. The motivation behind analyzing each one of these stock characteristics is explained below. First, however, to facilitate the exposition, the IPOs in our sample are grouped into categories according to various features set during the IPO

process.

2.1. IPO Categories

To better analyze the differences between various IPO firms we classify them into portfolios according to 1) the market’s heat level at the time of their public offering, 2) their level of underpricing, 3) their offer price, 4) their lead underwriter’s quality ranking, and 5) their association with venture capital.

2.1.1. Hot vs. Cold Periods

We consider hot-market (cold-market) IPOs to be those issued during hot (cold) quarters. To determine the hot and cold quarters, we use the classification scheme suggested in Yung, et al. (2008). Our heat measure is the number of IPOs per quarter, *NumIPO* (*Figure 1* plots this measures over time). In obtaining the time series of this measure we rely on Jay Ritter’s data about aggregate monthly IPO activity between 1960 and 2005 (obtained from his website), because it covers the 60s. As we will describe later, 60s are not included in our sample period, but we use that decade to obtain a more reliable historic average of this heat measure, which we use as a reference in classifying our quarters into hot, cold, and normal.⁴

To smooth out the seasonality effects that exist in the IPO markets (the time series data indicates that there are approximately 40% more IPOs issued in the 4th quarter than in the 1st), we use the average number of IPOs (*NumIPO*) during the past four quarters (current plus the previous three quarters) as the heat level at that particular quarter. Then, for each quarter, we compare the value of this 4-quarter average to the *NumIPO*’s historic average up to that quarter (i.e., average of all the quarters between the analyzed quarter and the first quarter of 1960). If it is 50% above (below) the historic average, the quarter is classified

⁴If we start measuring our historic average in 70s, almost all the following quarters would look “hotter” compared to early 70s. By using 60s as well, we obtain a more reasonable benchmark average to determine that indeed early 70s were very cold.

as hot (cold).⁵ The remaining quarters are normal.⁶ This method of separating quarters into heat groups conditions the classification only on the past, i.e. it considers how IPO market participants would have felt at that point in time given their knowledge of the past conditions.

We also construct a market heat measure, *HeatDegrees*, to be used in the regression analyses. It is a continuous variable measured as four-quarter average of the *NumIPO* divided by its historic average.

2.1.2. High- vs. Low-Underpricing and High- vs. Low-Offer-Price IPOs

In a different classification scheme, we divide the IPOs in our sample into most-underpriced, moderately-underpriced, and least-underpriced sub-samples. We rank them according to their return during the first day of trading: if they are in the top (bottom) tercile, they are included in the high-underpricing (low-underpricing) IPO sub-sample.

We apply a similar classification technique using the relative offer price of the IPO. First, we calculate the relative offer price as the IPO firm's offer price minus the contemporaneous median trading price of the CRSP firms.⁷ Then, we rank the firms according to their relative offer price. The firms in the top (bottom) tercile are the high-offer-price (low-offer-price) portfolio.

⁵Our qualitative conclusions are the same, if this cutoff point is chosen to be 33%, 40%, or 60%. These results are available upon request.

⁶One could classify the quarters into hot, cold, and normal by ranking them according to the number of IPOs in each quarter, and then consider the top (bottom) tercile of the ranked quarters as hot (cold). However, this classification scheme involves a look-ahead bias that will lead to misclassification of certain quarters. For example, anything compared to late 90s would look cold, and anything compared to early 70s would look hot.

⁷Average IPO offer price tends to stay in a certain dollar range, and all the other parameters might be changing with time. So, the best way to adjust the raw dollar price of an IPO seems to be by normalizing it by the contemporaneous median share price of the other stocks in CRSP. We should also note that our results are robust to not normalizing the offer price at all, or normalizing it with Consumer Price Index (CPI).

2.1.3. High- vs. Low-Prestige and Venture- vs. Non-Venture-Backed IPOs

Using updated Carter-Manaster underwriter prestige rankings obtained from Jay Ritter's website, we divide our IPOs into categories according to their lead underwriter's ranking.⁸ An IPO belongs to the high-prestige (low-prestige) group, if its lead underwriter has a reputation ranking ≥ 8 (ranking ≤ 5) at the time of the IPO date. The rest belong to the medium-prestige group.

To determine whether a certain IPO was backed by a venture firm, we use the information provided in SDC and Ritter's data. If there is one or more venture capitalists involved with the IPO, then it is counted toward the venture-backed portfolio. Otherwise it belongs to the non-venture-backed one.

2.2. Market Frictions in IPO Stocks

We consider three main type of frictions faced by IPO stocks: short-sale constraints, liquidity constraints, and information dissemination constraints. In this section, we only review the literature on each friction, while leaving the more technical details on their calculation to Section 3.

2.2.1. IPO Stocks and Short-Sale Constraints

Recent developments in the short-sale constraints literature have yielded insightful suggestions on how to detect heavily short-sale constrained stocks. In light of these findings we analyze how IPO stocks differ among themselves with regard to market frictions related to short-sale constraints. If the market heat, the level of underpricing, the offer price, the venture backing, and the lead underwriter's prestige of an IPO are indicative of the firm's quality, then we should see some differences in the short-sale constraints measures across our IPO categories.

⁸Since this data is not available for the 1970s, we extrapolate an underwriter's reputation during 1980-1984 as its reputation for the earlier periods.

Miller (1977) suggests that the interaction between heterogeneous investor beliefs and short selling costs can lead to over-valuation in the short-run and under-performance in the long-run. Using this idea Houge, et al. (2001) attempt to explain the long-run underperformance of IPO stocks in terms of early market indicators of firm quality, uncertainty, and divergence in opinion among investors. They concentrate on the first few days after the IPO date. Similarly, Geczy et al. (2002) analyze the specialness of an IPO stock during its first month of trading. Related to Miller’s (1977) idea, we postulate that if there are more low quality firms in a certain IPO category, and due to recent cash injection these firms do not get delisted immediately, it is likely that upon revelation of their quality the investors will heavily short these stocks unless there are substantial short-sales constraints.

The majority of the literature, however, concentrates on all the short-sale constrained stocks, not only IPOs. Among others, Asquith, et al. (2005), Boehme, et al. (2006), Desai, et al. (2002), and Jones and Lamont (2002) report that short-sale constrained stocks are more overvalued, and thus underperform in the long-run, when compared to the rest of the stocks. Similarly, such stocks are different with regard to their price-to-earnings and book-to-market ratios (Dechow, et al., 2001) and firm liquidity (D’Avolio, 2002).

To understand the short-sales constraints across our IPO groups, we use the method in Asquith, et al. (2005) to determine which IPOs are most likely to be affected by the short-sale constraints (for more details on Asquith, et al. (2005) method see Section 3.3).⁹ Then, we compare what percentage of IPOs in each category are severely short-sale constrained. Presence of significant differences suggests not only that firm composition is different across our IPO categories, but that investors holding each IPO portfolio are also likely to be different.

⁹It is widely accepted that the best proxy for short-selling constraints is the short-stock-rebate rate, which provides a measure of the cost (fees) of borrowing shares (Jones and Lamont, 2002). Several studies have utilized the proprietary rebate data in examining short-selling constraints. D’Avolio (2002) ranks stocks into deciles based on Relative Short Interest (RSI), and finds that stocks in the highest RSI deciles have the highest average equity lending fees. While the relation between equity lending fees and RSI is mixed for low to medium levels of RSI, for high levels of RSI the shorting fees are strongly increasing with RSI. Boehme et al. (2002) replicate the results of D’Avolio (2002) in documenting that highly shorted stocks carry the highest average equity lending fees. Therefore, we feel confident that when lacking data on rebate rates, Asquith et al. (2005) measure (which utilizes RSI) would provide a good alternative to rebate rate.

2.2.2. Liquidity Constraints in IPO Stocks

Liquidity of a stock is an important determinant of its subsequent performance, as documented by, among others, Acharya and Pedersen (2003), Amihud (2002), Brennan et al. (1998), Chordia et al. (2000), and Pastor and Stambaugh (2003). Specifically with regard to IPOs, Eckbo and Norli (2005) claim that liquidity is a relevant factor in IPO stocks. Ellis, et al. (2000), on the other hand, show that an IPO stock's liquidity in the immediate post-issuance period is influenced by the market-making activities of the IPO's lead underwriter.

Furthermore, the degree of a stock's illiquidity is an important market friction that reflects the quality of the stock and the underlying firm. It is likely to influence the type of investors that are willing to trade in the stock. Thus, it is a useful characteristics to consider when analyzing the differences among various IPOs.

For that purpose, we use three measures of liquidity (or illiquidity), suggested by Amihud (2002), Eckbo and Norli (2005), and Pastor and Stambaugh (2003), to determine the degree of market frictions faced by the IPO classes we defined above. Amihud (2002) introduces an illiquidity measure that scales the stock's daily return by its daily trading volume. Eckbo and Norli (2005) use IPO stock's turnover as a liquidity factor in its pricing. Pastor and Stambaugh (2003) estimate a stock's response to an aggregate marketwide liquidity risk, and show that cross-sectionally stock returns are affected differently by it. Liquidity can be in varying forms. All three of these measures are capturing the liquidity in a different manner, thus reducing the chances of our results' dependence on a specific liquidity proxy.

2.2.3. Information and Recognition (Attention) Related Constraints

Price delay, defined as the average delay with which a stock's price responds to new information, is a market friction variable suggested by Hou and Moskowitz (2005). They claim it is a measure that is more likely to capture the degree of investors' recognition of the firm rather than any other friction. Thus, we use it as a proxy for constraints arising from incomplete information and lack of recognition.

The most widely known market friction related to incomplete information is information uncertainty, however. It has been shown to affect variety of financial markets (for example, Yung, et al. (2008) show its effect on IPO composition in hot vs. cold markets). Some of the studies documenting its consequences on stock returns include Basak and Cuoco (1998), Hirshleifer (1988), and Merton (1987). Thus, we complement our price delay analysis with other information uncertainty or recognition measures such as analysts' dispersion of opinion,¹⁰ number of analysts covering the stock,¹¹ and percentage of shares held by institutional investors.¹² Although, only fraction of our sampled IPOs are covered by analysts or have institutional holdings data, we believe these measures provide valuable information about the degree of information constraints in various IPO classes, so we report their results.

Another variable that has been used as an information frictions measure is *idiosyncratic risk* (or *idiosyncratic volatility*). It has been used both as a measure of information asymmetry between the firm and the traders of its stock (Campbell and Taksler, 2003; He and Wang, 1995), and as a market friction limiting the arbitrage (Ali, et al., 2003; Shleifer and Vishny, 1997).

It has been claimed also that idiosyncratic volatility is an important determinant of a stock's return. For example, Ang, et al. (2006) report a negative relation between idiosyncratic volatility and expected stock returns. Bali and Cakici (2008) find no such significant relation, and Doran, et al. (2007) find that it is seasonal. Campbell, et al. (2001) find that this risk has increased in recent years.

Although the research on idiosyncratic volatility is aplenty, it is still unclear to what degree IPO stock returns are affected by this volatility, and how this effect compares to

¹⁰Diether, et al. (2002) find that stocks with higher analyst earnings forecast dispersion have lower returns, which is associated with resolution of uncertainty and elimination of overvaluation over time.

¹¹Rajan and Servaes (1997) find that new stocks with higher underpricing are also covered by higher number of analysts. They also suggest that there may be a common omitted variable that leads to both higher analysts' following and higher underpricing, but they admit that it is not obvious what it is. As we explain below, a good candidate for this omitted common variable is issuing firm's underlying quality (or business risk).

¹²This measure represents a friction capturing the ability of large institutions to participate in the trading of the stock. The more they participate in researching and trading the stock, the more information is revealed about the stock. Thus, it can be considered an information friction metric. Like us, Boehme, et al. (2009) also use the institutional shareholdings as a measure of a firm's visibility or recognition.

other, more seasoned, stocks. Typically, IPO firms are young and relatively unknown to the investing public, which can lead to an elevated levels of firm-specific risks associated with their stocks (Fink, et al., 2005). Furthermore, IPO firms differ among themselves in their profitability, growth rates, and survival rates (Fama and French, 2004; Helwege and Liang, 2004), which suggests that idiosyncratic risk is also likely to vary across these stocks. Thus, the presence of information availability constraints in an IPO’s stock should be captured by this measure.

3. Sample and Variables

Some details about our data sources, our sample selection criteria, and our variable construction follows.

3.1. The Sample

We construct our sample of initial public offerings between 1970 and 2005¹³ using three sources: Securities Data Company (SDC)’s database, Jay Ritter’s hand-collected data, and Registered Offering Statistics (ROS) dataset. From the SDC sample we extract 10,328 common stock IPOs (i.e. we exclude REITs, closed-end funds, ADRs, unit offers, and MLPs).¹⁴ Our analysis is heavily dependent on market trading data, so we drop out any IPO that does not have any record in CRSP daily, weekly, or monthly files. There are 8,924 IPOs remaining in the SDC sample. We supplement this SDC sample with Jay Ritter’s sample, obtained from his webpage, for the period between 1975 to 1984. We select only CRSP listed, common stock, and firm-commitment IPOs. This adds 361 firms to our sample that are not in the SDC data. Finally, we review Registered Offering Statistics (ROS)¹⁵

¹³Our sample period stops at 2005, because we need several years after an IPO’s issuance to assess its post-issuance trading characteristics.

¹⁴We did not eliminate IPOs with offer price less than \$5, because price is an important variable in our analysis, and we did not want to truncate our offer price distribution.

¹⁵This dataset covers the period from January 1970 to December 1988, and it includes records of the Securities and Exchange Commission (SEC) in regards to the effective registrations of domestic business and

dataset to uncover new IPOs not reported in the previous two sources. We find 59 such firms, which brings our final sample to 9,344 IPOs.

In some cases there is a delay between the date of issue and the first trading day of a new public firm as recorded in CRSP.¹⁶ At the extreme, this gap can be more than a year long. In such instances we require a minimum of 20 weeks of available returns data for the first year following the IPO issuance in order to calculate the price delay, idiosyncratic volatility, or the coefficients of the four Fama-French-Carhart factors. Otherwise, the firm is eliminated from the sample when calculating those particular variables. Adapting more tighter filters for inclusion, like dropping any IPO firm that does not immediately show up in CRSP, would eliminate too many IPO firms from our sample, which can lead to serious sample selection biases.

We retrieve the following IPO data items from SDC, Ritter, and ROS datafiles: the CUSIP of the new public firm, the date of its issuance, its offer price, its lead underwriter’s name, the percentage change in its stock’s price on the first trading day (i.e. the underpricing),¹⁷ whether it is backed by venture capital, and its date of founding used in calculating its age (rounded to the nearest higher integer number)¹⁸ at the time of issuance.

The daily, weekly, and monthly trading data for all firms (IPO or seasoned) are extracted from CRSP. Institutional investors data is as reported in 13F filings with the Securities and Exchange Commission (SEC) and is obtained from Thomson Financial CDA Spectrum. I/B/E/S analyst coverage information and earnings estimates are also from Thomson Financial. Short interest data as reported by NYSE and Nasdaq on 15th of each month are

foreign government securities under the Securities Act of 1933.

¹⁶For instance, CRSP NASDAQ does not begin reporting returns until after December, 1972.

¹⁷When this variable is not available through SDC, Ritter, or ROS data, we use CRSP daily data to find the closing price for the first trading date of this firm. If the first trading date in CRSP is not the day of issuance as recorded in SDC, we check the dates that are at most three days separated from the issuing day, and use the earliest date for which price is available. This adds 520 more observations to the underpricing variable (Total = 8,318). If no price information is available within three days window of the issuing date, we do not calculate this variable.

¹⁸For this variable, we also use another datafile from Jay Ritter’s website: “Founding dates for 8,464 IPOs from 1975-2007.” In case of inconsistencies between this data and SDC data we rely on Ritter’s data.

downloaded from the websites of these exchanges.¹⁹ Accounting data is from COMPUSTAT. Matching with each of these data sources further decreases our sample size. In each step of our analysis, we provide further information about the number of observations used in the tests.

3.2. Descriptive Statistics of the Sample

Table 1 describes various features of the IPO sample across our five different classification criteria. The considered IPO characteristics are firm's age at the time of issuance, firm's ranked size vicile as of the end of the first month of trading,²⁰ issue's offer price, the level of underpricing, issue's lead underwriter's prestige, and new issue's buy-and-hold return (BHR) during the first 36 months of trading.²¹

These characteristics show significant differences when compared across various IPO groups. Notable observations from the table are: 1) hot IPO firms are, on average, younger, smaller, more underpriced, with lower offer price, with low reputation underwriter, and deliver much lower 36-month returns than cold IPOs; 2) highly underpriced group of IPOs are younger, bigger, with high offer price, and more poorly performing during the first three years of trading; 3) high offer price issues are older, bigger, more underpriced, with more reputable underwriters, and better investment in the first 36 months of trading than the low offer price issues; 4) firms with more reputable underwriters are older, bigger, with much higher offer price, and better return performers; 5) venture capital (VC) backed IPOs are younger, bigger, highly underpriced, issued by higher reputation underwriter, and have higher offer price and higher long-run returns than non-VC backed IPOs.

¹⁹We thank Bartley Danielsen for this data.

²⁰We define *size* as the market capitalization vicile of the firm (largest firms in CRSP are in vicile 20) as of the end of the considered period.

²¹We define buy-and-hold return (BHR) as

$$BHR_{i,36} = \prod_{t=1}^{36} (1 + R_{i,t}) - 1 \quad (1)$$

$R_{i,t}$ represents firm i 's stock return (including dividends) for the month t .

3.3. The Variables

In this sub-section we describe the measures that characterize the market frictions associated with public trading in stocks. We organize them according to the type of friction they represent: short-sale constraints, liquidity related frictions, and information frictions.

3.3.1. Short-Sale Constraints Measures

Our short-sale constraints measures are the relative short interest variable and the short-sale constraint friction (SSCF) measure.

Relative Short Interest (RSI): This variable is measured each month as the short interest (as reported by the NYSE or Nasdaq since January 1988) divided by the number of outstanding shares reported by CRSP. It is a proxy for the demand for shorting the stock. We sort the IPOs into viles according to their RSI. When this variable is extremely high for a stock (e.g. 20th vicle) it is indicative of poor subsequent stock performance i.e. low IPO quality (see Boehme et al., 2006 and Desai et al., 2002).²²

Short-Sale Constraint Friction (SSCF) Measure: As in Table 5 of Asquith, et al. (2005), we define a firm as short-sale constrained using a procedure that proxies for high demand for shorting (high RSI) and low supply of shares to short (low institutional ownership). We take only the firms that have short interest exceeding 2.5% of shares outstanding for a given month, and we sort them into terciles based on institutional ownership. Firms in the bottom tercile of institutional ownership are deemed to possess a high likelihood of being short-sale constrained.

Alternatively, we defined our SSCF measure as in Boehme, et al. (2006) (interaction of short interest and dispersion of opinion variables). The results were not significantly dependent on the way SSCF measure was defined. Both of these SSCF measure can be calculated only after 1988, because that is when short interest data becomes electronically available.

²²Occasionally, monthly short interest data is missing for some firms. As in Boehme, at al. (2006), we exclude such firm-month observations from the sample, as one cannot ascertain whether the missing observation indicates a zero level of short interest or a missing data problem.

3.3.2. Liquidity Constraints Measures

Our liquidity related friction measures are Amihud (2002)’s illiquidity factor, Pastor and Stambaugh (2003)’s liquidity measure, and the stock’s turnover.

Amihud (2002) Illiquidity Measure (IL): In order to calculate the Amihud (2002) illiquidity factor (IL), we estimate the following model over the past 250 trading days, where $|R_{i,d}|$ is the absolute value of the daily return per dollar of equity, $VOL_{i,d}$ is the total dollar trading volume (number of shares times price) in millions USD, and D_t equals the number of trading days of nonzero volume:²³

$$IL_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|R_{i,d}|}{VOL_{i,d}} \quad (2)$$

Stocks with large IL are less liquid. All the stocks in the CRSP universe are sorted into viciles according to their IL_{it} , with vicile 1 (vicile 20) representing most (least) liquid stocks.

Pastor and Stambaugh (2003)’s Return Reversal Measure (briefly PS Liquidity Measure): This measure relies on price impact or return-reversal due to order flow. More specifically, monthly return-reversal is extracted by running the following regression using daily data within a month:

$$R_{i,d+1,t}^e = \theta_{i,t} + \phi_{i,t}R_{i,d,t} + \gamma_{i,t}[\text{sign}(R_{i,d,t}^e) \cdot \nu_{i,d,t}] + \epsilon_{i,d+1,t}, \quad d = 1, \dots, D, \quad (3)$$

where $R_{i,d,t}$ is the return on stock i on day d of the month t ; $R_{i,d,t}^e = R_{i,d,t} - R_{m,d,t}$, where $R_{m,d,t}$ is the return on the CRSP value-weighted market return on day d in month t ; $\nu_{i,d,t}$ is the dollar volume for stock i on day d in month t . Firm months with more than 15 days of missing daily data are excluded.

The PS liquidity measure is the parameter $\gamma_{i,t}$, which captures the return reversal for given dollar volume. Low liquidity stocks should have higher expected return reversals per unit of volume. The large values of $|\gamma_{i,t}|$ are in higher viciles (less liquid stocks).

²³Obviously, this measure is flawed in the sense that it ignores the most illiquid days, those days when there is no trading whatsoever (like for some small Nasdaq stocks), because according to the measure one has to divide by zero volume.

Turnover: The volume of trade (*turnover*) is used as a liquidity measure or as an information uncertainty measure by various studies in the literature. It is defined as the average of the daily ratios of the number of shares traded to the total number of shares over the prior 250 days, as reported by CRSP. An IPO firm's turnover vicile is the vicile it falls into after sorting all CRSP firms according to their turnover. Trading volume for Nasdaq listed firms is unavailable before November 1982.

3.3.3. Information Constraints Measures

We rely on five different measure to capture various information related frictions: Hou and Moskowitz (2005)'s price delay measure, analysts' dispersion of opinion, number of analysts covering the stock, institutional holdings of the stock, and idiosyncratic risk.

Hou and Moskowitz's (2005) Price Delay Measure: We calculate this market friction metric using weekly returns for both the CRSP value-weighted market index (VWRETD) and for each individual firm in their study. Accordingly, from compounded CRSP daily returns we calculate one year (52 weeks) of ex-ante, weekly Thursday-to-Wednesday daily-compounded returns for all IPO firms. To give time for the stock to stabilize, we skip the month of issuance, as well as the month following the issuing month. For example, if the firm went public on January 11th, we skip the rest of January, as well as the whole month of February, and we start our first week on March 1st.

As shown in Hou and Moskowitz (2005), we regress each firm's weekly returns on the contemporaneous market index weekly return (CRSP VWRETD) and four lagged market weekly returns as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \delta_{i,t-1} R_{m,t-1} + \delta_{i,t-2} R_{m,t-2} + \delta_{i,t-3} R_{m,t-3} + \delta_{i,t-4} R_{m,t-4} + \epsilon_{i,t}. \quad (4)$$

A second constrained regression is then estimated by restricting $\delta_{i,t-1}$ through $\delta_{i,t-4}$ to be zero. The market friction measure (DELAY) is constructed as in Equation (2) of Hou and Moskowitz (2005), by dividing the R^2 of the restricted model by the R^2 of the full model and subtracting the result from one:

$$DELAY = 1 - [R_{restrictedmodel}^2 / R_{fullmodel}^2]$$

The larger the value of the DELAY variable, the more return variation is captured by the lagged returns. In other words, high values of DELAY indicate that there is a strong delay response in return innovations. Simply put, Hou and Moskowitz (2005) observe that firms with high DELAY values respond more slowly to new information. Alternatively, this measure may be capturing frictions like the attention level the stock receives or its trading costs. At the end of each analyzed period, we sort the price delay measures of all CRSP firms into viciles, with viciles 1 and 20 representing the least and the most delayed stocks, respectively.²⁴

Analysts' Dispersion of Opinion: The I/B/E/S Analyst Forecast Dispersion is the I/B/E/S standard deviation of earnings per share forecasts for the next fiscal year end scaled by the forecast mean. Our technique is identical to that employed by Diether, et al. (2002). Due to nonstationarity and skewness, each calendar month we sort the dispersion into viciles across all CRSP firms, with vicile 1 (vicile 20) representing the lowest (highest) values. Firms having a forecast mean of zero or less are assigned to the highest vicile. This database begins recording the analyst forecasts starting in January 1976.

Number of Analysts: It is calculated by counting the number of analysts covering the stock, as listed in I/B/E/S dataset.

Institutional Ownership: It is measured by dividing the reported number of shares held by institutions (SEC 13F filings) by the total number of outstanding shares reported by CRSP. This variable measures the degree of interest in the firm, and how widespread are the holdings in the stock. After vicile sorting is applied, firms in vicile 1 (20) have lowest (highest) institutional ownership. This data item is available after 1988.²⁵

²⁴To eliminate any size effects that might be driving our results related to price delay variable, we orthogonalized it with size by estimating a cross-sectional regression of each firm's delay vicile on the size vicile. Usage of size orthogonalized price delay variable has minimal effects on our results.

²⁵Dealing with missing observations of this variable is a tricky one. While most of these missing observations probably indicate zero (or almost zero) institutional ownership, we also observe many obvious errors with missing data. For example, we find that many of the firms with missing institutional ownership data are actually larger firms having coverage by 10 or more analysts on I/B/E/S. Since we cannot conclusively discern between firms lacking institutional ownership and errors in data reporting, we exclude those firm-month observations that are not listed in the database.

Idiosyncratic Risk: We extract the idiosyncratic volatility measure for each stock, ϵ_{it} , from the Fama-French-Carhart regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_iSMB_t + h_iHML_t + u_iUMD_t + \epsilon_{it} \quad (5)$$

where R_{it} is the return of the firm, R_{ft} is the return on three-month Treasury bills, R_{mt} is the return on a value-weighted market index, SMB_t is the difference in the returns of value-weighted portfolios of small stocks and big stocks, HML_t is the difference in the returns of value-weighted portfolios of high book-to-market stocks and low book-to-market stocks, and UMD_t is the difference in returns of value-weighted portfolios of firms with high and low prior momentum.²⁶

We use weekly returns for each of the Fama-French-Carhart independent variables in order to estimate the regression (weekly return is defined as the holding period return of Thursday through Wednesday). For each calendar month we estimate this regression, and record the resulting idiosyncratic risk (*sigma*) using the prior 52 weeks (or one year) of weekly returns.²⁷ Then, for each month, firms in CRSP are sorted into twenty categories or viciles according to their *sigma*. We use the vicile rankings (vicile 1=lowest values) at the end of each event period (one year after issuance, two years after issuance, etc.).

4. Results

We present our results in five different sub-sections: results comparing IPOs to the rest of the CRSP firms, results for short-sale constraints, results for liquidity constraints, and results for information related constraints.

4.1. IPOs vs. CRSP Firms

Are IPO firms' stocks systematically different than the seasoned firms with regard to short-sale constraints, liquidity constraints, and information frictions? Most of our measures used

²⁶The construction of these factors is discussed in detail in Carhart (1997) and in Fama and French (1993).

²⁷This estimation procedure is identical to that used in Kumar et al. (2008) and in Zhang (2006).

in this study are pre-ranked into viciles using all the CRSP firms, where the firms with average observation of that particular measure should be around 10.5th vicile. Therefore, just reporting the average vicile of our IPOs will provide a good description of where our sampled firms stand in comparison to the rest of the CRSP firms (see our *Table 2*). If a particular measure’s mean vicile is not statistically significantly different from 10.5, then the IPO firm is very similar to a typical CRSP firm with regard to that measure.

First observation from the table is that our IPOs are in a noticeably higher average vicile with regard to idiosyncratic risk and analysts’ dispersion of opinion, suggesting that investors and analysts consider them to be more uncertain than an average CRSP listed firm. With regard to two of our liquidity measures (Amihud’s illiquidity and turnover), our sampled IPOs’ average vicile is slightly above the typical CRSP firm. Similarly, our IPOs’ average short interest measure is slightly above of what is expected from CRSP firms. Only one of our measures (number of analysts covering the stock) has mean below the 9th vicile during the first year of post-issuance trading.

Second, with very few exceptions (like institutional ownership for years 4 and 5), the mean viciles of our IPO sample are significantly different from the CRSP mean of 10.5. That is, the IPO stocks are different than the seasoned stocks with regards to their trading frictions; they are more risky, less liquid, and less known to investors. While this result is expected for the first few months of trading, the fact that this phenomenon lasts for years (up to 5 years after issuance) is surprising to us. The finding that for years IPO stocks, on average, stay distinguishable from the seasoned stocks with regards to trading frictions is an interesting and novel result of this study. This persistence over time suggests that these measures are capturing certain firm characteristics that are not easily eliminated by the seasoning process.

In a related analysis, we try to determine whether there is a measurable time trend in these market-friction variables. We run a panel-data regression of each firm’s friction measure on the time trend variable, T , where T takes values of +1, +2, ..., +5, depending on the years passed after issuance. The results are presented in *Table 2* under the last two columns of

the table. The estimations suggest that there is a time trend in almost all of the friction measures, as indicated by the the sign and the significance of the “Slope” coefficient. Most of the variables behave as expected. For example, as the years pass, the IPO firms are moving up in the size vicile. Furthermore, as can be seen from the SSCF and RSI vicile means, the difficulty of shorting a recent-IPO stock is gradually alleviated over time, although the trend is not very steep (only a change of 0.0957 vicile per year for the RSI measure). That is, the mean convergence process is very slow.

With regards to the liquidity frictions, an interesting pattern emerges. Instead of becoming more liquid over time, the recently-issued firms are becoming *more illiquid* relative to the typical CRSP firm. This is confirmed by all three of our liquidity measures (the definitions of these measures presented in the previous section can help in interpreting the time patterns of the mean viciles). Thus, instead of converging to the mean, the relative liquidity of the IPOs is falling below the CRSP average as the time passes.

The information friction variables appear to be slowly (but as noted above, may be too slowly) converging to the mean. With the exception of analysts’ dispersion of opinion, most of the information constraint measures are gradually moving towards the CRSP means. For example, the idiosyncratic risk of the IPOs is declining, but it never falls below 13th vicile even after 5 years of seasoning. So the seasoning process is observable, but it is quite slow. Similarly, as the time passes the number of analysts covering the stock rises, and the investor composition is gradually shifting towards institutional investors. Analysts’ dispersion show some unexpected trends towards more disagreement between the analysts, most likely due to rising coverage by analysts (which can increase the likelihood of disagreement among them). Price delay has insignificant time trend.

4.2. Short-Sale Constraints Across IPO Groups

We first divide our IPO sample into groups using the five IPO characteristics described earlier. Then, we report our short-sale constraints friction (SSCF) measure and the mean

RSI vicile for five post-IPO periods: 1-year, 2-years, 3-years, 4-years, and 5-years.²⁸ SSCF is essentially a dummy variable indicating whether the firm is short-sales constrained or not at the specific post-IPO date we consider. If for an IPO we can not calculate this SSCF measure for neither of these post-IPO periods, we drop that observation from the sample. In this section our raw IPO sample between 1988 and 2005 is reduced to 6,255, because relative-short interest variable is not available before 1988. It further declines to 5,974 when we calculate our SSCF measure, because this measure also requires institutional ownership data.

4.2.1. Relationship Between Short-Sale Constraints and Market Heat

First, each quarter in the period between 1970 and 2005 is classified as hot, cold, and normal using the criteria described in Section 2.1, except here we use the $\pm 25\%$ cutoff so that we have reasonable number of firms with non-missing SSCF in all groups. Then, using our SSCF measure we calculate the percentage of IPOs in each sub-sample that are short-sale constrained (from now on, we will refer to it as *SSCF Percentage*). The results are presented in *Table 3* (Market Heat Panel). There is no conclusive evidence here: the only significant difference is for Year 1 (the rows named “Prob.” in the table show the probability statistics from the nonparametric Wilcoxon test of equality of *SSCF Percentages* across Hot and Cold IPO groups).

4.2.2. Relationship Between Short-Sale Constraints and Underpricing

From our SSCF sample of 5,974 we drop the observations for which we have no underpricing information, which leaves us with a sample of 5,868 IPOs. Then, we rank them into terciles according to their underpricing level in order to find accurate signals about future market characteristics of IPOs by looking into their first day returns.²⁹ Highest (lowest) ones are

²⁸We do not use periods shorter than one year, because those periods usually involve other constraints on IPO stock trading, such as lock-up periods. We use total of 5 post-IPO periods to get a sense of the changes in IPO stock’s condition as the time progresses.

²⁹Krigman, et al. (1999) find that highly underpriced IPOs have lower long-run returns, and Purnanandam and Swaminathan (2004) find that they are overvalued at offer price relative to industry benchmarked price

in “High” (“Low”) tercile.³⁰ *Table 3* presents the *SSCF Percentage* for this classification. The main result from this analysis is that the *SSCF Percentage* for the firms in the “High” underpricing tercile is significantly higher than the one for the “Low” underpricing tercile. Highly underpriced IPOs seem to have very high levels of *SSCF Percentage*; the highest ones in the whole table.

Thus, an interesting conclusion emerges from this analysis: first day return (i.e. underpricing) has a significant predictive power on the probability of an IPO being short-sale constrained in the first few years after issuance; they are positively related.³¹

Geczy et al. (2002) find a similar relationship between an IPO’s underpricing and its specialness (how expensive it is to borrow the stock) during the first month of trading. They interpret this result as a support of Miller’s (1977) heterogeneous-beliefs argument. According to this argument the offer price is the mean valuation that incorporates the opinions of all the investors (trading and non-trading). The first day closing price, on the other hand, is the equilibrium price of all the investors that participated in the trading that day, which primarily includes the optimistic investors with valuation near or above the offer price, because of various difficulties of shorting. Thus, when the first day closing price reaches equilibrium at much higher levels than the offer price (i.e. high underpricing), it indicates higher dispersion of opinion. The higher the valuation dispersion, the higher the demand for shorting at those levels. Since these investors are unable to short (for reasons not totally known to us at the current stage of the literature), the more binding are the short-sale constraints.

multiples.

³⁰We do the ranking into terciles after eliminating the missing observations, because we aim to understand the relationship between underpricing and the probability of being SSCF. If we do the rankings first and then eliminate the missing observation, it is likely that some firms with missing data will be disproportionately represented in one of the terciles, which could bias the results. We want a clean and simple relationship between SSCF likelihood and underpricing, without any sample selection bias, survivorship bias, or ranking problems.

³¹To confirm this we run a logit regression predicting the odds of being SSCF at the end of the first year. The explanatory variable is underpricing level. The coefficient of underpricing is always significantly positive. The results are available upon request from the authors.

4.2.3. Relationship Between Short-Sale Constraints and Offer Price

Again, we rank our 5,974 IPOs into terciles according to their relative offer price. The ones with highest (lowest) relative offer price are grouped into “High” (“Low”) tercile. How does offer price predict an IPO’s chances of ending up short-sale constrained? According to the results presented in *Table 3*, low offer-price IPOs have a tendency to become significantly more short-sale constrained from Year 3 onward. At Year 5, for example, a typical low-offer priced IPO has approximately 52% higher chances of facing SSCF than the high-priced one (12.86% vs. 8.46%). Apparently, the low offer price IPOs later on end up with a price that is very low and investors have difficulty shorting “penny stocks,” because of low supply of loanable shares from institutions. For Year 1, however, the high priced IPOs seem to have higher *SSCF Percentage*. Another notable result here is that *SSCF Percentage* increases (decreases) with time for “Low” (“High”) tercile. Thus, we conclude that there is some evidence that IPOs offer price is negatively related to its probability of becoming severely short-sale constrained in the later years.

4.2.4. Relationship Between Short-Sale Constraints and Prestige

Of our 5,974 IPOs sample, only 4,757 IPOs also have underwriter information. After ranking them into prestige groups according to the scheme described earlier, we compare the *SSCF Percentage* across “High” and “Low” Prestige groups (see *Table 3*, Underwriter Prestige panel). The results here are mixed and inconclusive, which suggests to us that underwriter prestige is not a good indicator of how short-sales constrained an IPO could be after its issuance.

4.2.5. Relationship Between Short-Sale Constraints and Venture Backing

We have venture capital (VC) backing information for all of our original sample. As shown in *Table 3*, of the 2,312 VC supported IPOs 10.09% to 11.63% of them are short-sale constrained during the first 5 years of public trading. The most interesting result here is that during their first year of trading, the VC backed IPOs have significantly higher probability of being

short-sale constrained in comparison to non-VC backed ones! To the degree that shorting constraints can be associated with IPO stock’s risk, this result indicates that some of the VC backed IPOs are quite risky and end up struggling after VC’s support is pulled. That is, the left-tail of the quality distribution of VC backed IPOs (which is what *SSCF Percentage* captures) is thicker (Lowry, et al., 2010 also reach similar conclusion). VC support itself may indicate higher average quality for the overall sample of VC-backed IPOs, but apparently there are enough bad VC-backed firms to cause an increase in the *SSCF Percentage* relative to non-VC backed sample. This result certainly merits further investigation. We will briefly discuss it at the end of this section.

In summary, the results from this sub-section suggest that the underpricing level, the relative offer price, and the VC backing, are useful indicators of an IPOs potential to be severely short-sale constrained.³²

4.2.6. Relationship Between RSI and IPO Attributes

Panel B of *Table 3* describes the relationship between relative short interest (RSI) and our five IPO attributes. Insightful results emerge from this panel of the table. IPOs are shorted more, if they are issued in a cold market, have high underpricing,³³ high offer price, more reputable underwriter, and a VC backing.

How are the results from this RSI panel related to the results from the previous panel?

³²It can be claimed that SSCF represents a special type of a liquidity-related trading friction, so there is no need to investigate it separately than the liquidity constraints. However, the asset-pricing literature has put enough importance on the short-sale constraints to investigate it separately than the liquidity frictions (see our literature review on the short-sale constraints in section 2.2.1). Most of these papers find results suggesting that short-sale constraints capture different aspects than the typical liquidity measures. For example, D’Avolio (2002) finds that a liquidity measure (turnover) is positively correlated with short-sale constraints; a result driven by heavy trading in stocks with information uncertainty. To check whether SSCF and our liquidity measures capture the same underlying trading constraints, we estimate how closely they are correlated for our IPO stocks. We find that SSCF is highly negatively correlated with Amihud’s illiquidity and Pastor and Stambaugh’s aggregate liquidity, and significantly positively correlated with stock’s turnover for each of the five years after issuance. The correlation coefficients for year 1 are: -0.2416, -0.0366, and 0.2249, correspondingly. All are significant at 5% level (to save space we do not report the results for every year). This negative correlation between short-sale constraints and our illiquidity measures suggest that these measures do not necessarily capture the same type of frictions. Thus, these two frictions deserve to be investigated separately, which is what we do in this paper.

³³Butler, et al. (2005) reach similar conclusions.

Our mean RSI viciles just indicate the actual amount of shorting that is going on with certain group of IPOs. The *SSCF Percentage* measure is obtained through intersecting the RSI and the institutional ownership variables. Combining the information from the RSI table and the ownership table (see *Table 5*), we can easily interpret the results for offer price: for low offer price firms simply there is not enough institutional holdings to satisfy the demand for shortable shares. The short-sale constraints results for market heat and underwriter prestige are inconclusive, therefore they do not require any interpretation.

The results that need further discussion are related to underpricing and VC support. For both of these IPO features we have high RSI and high institutional ownership associated with the same sub-samples (highly underpriced IPOs and VC supported IPOs). Yet, the same sub-samples have more short-sale constrained stocks in them? These findings can be explained along the lines of the above interpretation we provided for the high *SSCF Percentage* of VC related IPOs. The left tail of the quality distribution within VC backed and highly underpriced IPOs is thicker, as captured by our *SSCF Percentage*. Thus, while the average viciles of both measures, RSI and institutional holdings, is high for VC backed and underpriced IPOs, there could still be a higher percentage of them that are facing shorting constraints.

4.3. Liquidity Constraints Across IPO Groups

In this subsection we report the differences in our liquidity measures across various IPO classes using a sample of 7,919 IPO firms with available data for at least one of these measures. The results are presented in *Table 4*. *Panel A* of that table reports that hot market IPOs are more illiquid, are in a lower average turnover vicile, and have higher return reversal per unit of volume. In short, hot IPOs are, on average, facing more severe liquidity frictions. The exception is for the Year 1 for the turnover, which shows that in hot markets IPOs are more heavily traded early on. In later years (probably after the issue's hotness recedes) this result is reversed, and cold market IPOs end up being in a significantly higher turnover vicile.

With regard to underpricing, in *Panel B* of the same table, all of our liquidity measures suggest that highly underpriced IPOs are more liquid, again on average. Ellul and Pagano (2006), Gajewski and Grasse (2008), and Reese (1998) find similar results. Miller and Reilly (1987) and Schultz and Zaman (1994) find the same relationship, but only for the immediate days after issuance. The results for offer price and VC backing are as expected: higher offer price and VC backing alleviate the future liquidity frictions of an IPO (see *Panels C&E*).

We also find that better underwriting is associated with more liquidity in the years following the IPO (*Panel D* of the table). In a related study, Ellis, et al. (2000) show that in the immediate period following the IPO date, the lead underwriter assumes the role of a market maker in the stock, and provides price stability and trading liquidity to the stock. Their finding suggests that the lead underwriter who is more prestigious is also probably more capable liquidity provider in the after-market; which is consistent with what we document in *Panel D*.

In short, the results for liquidity constraints reported here are quite strong and consistent with each other. Almost all of them point to the same direction, and are significant at the 1% level.

4.4. Information Related Constraints Across IPO Groups

How are the IPOs different from each other with regard to information constraints? To answer this question we worked with a sample of 8,414 IPOs with nonmissing data in at least one of the five years for at least one of the four measures we use in this subsection: Hou and Moskowitz (2002)'s price delay, dispersion of opinion, number of analysts covering the stock, degree of institutional involvement in the trading of the stock, and the idiosyncratic volatility of the stock. Each of these measures captures a different aspect of information related frictions, thus they all contribute in getting the global view on information constraints.³⁴

³⁴In this section, we will also use the results about turnover (see *Table 4*), because we believe high values of this measure can indicate presence of disagreement between investors due to information uncertainty.

4.4.1. Price Delay

According to the results in *Table 5, Panel A* hot market IPOs are substantially more price delayed, suggesting that, on average, it takes a longer time for the information to be incorporated into these stocks in comparison to cold IPOs. Since we present the averages for each IPO group here, we can interpret this result to indicate that there are more firms issued during hot periods that lack sufficient recognition by the investors. Not necessarily that all hot IPOs are associated with incomplete information frictions. This results supports Yung, et al. (2008)’s findings that negative-NPV firms tend to issue equity in overheated periods. Similarly, IPOs with low offer price, less underpricing, low underwriter prestige, and no VC backing are exhibiting longer price delays.

4.4.2. Dispersion of Opinion, Number of Analysts, and Ownership

Although the information about these variables is lacking for a majority of our IPOs, we believe analyzing these measures of incomplete information will help in obtaining better picture of information frictions across various IPO groups. Briefly, the results for hot and cold IPOs for all three variables are consistently leading to the same qualitative conclusions: dispersion (i.e. information uncertainty) is higher for hot IPOs; number of analysts covering the hot IPOs’ stocks (i.e. information generation) are, on average, less than for cold IPOs; and institutions are more heavily involved with cold IPOs, again on average. Thus, the higher the market heat at the time of issuance, the greater the chances of facing information related frictions later on.

Similarly, for classifications with offer price, underwriter prestige, and VC backing (shown in *Panels C through E*), the results for all three information measures are consistent, in the sense that more information generation by analysts is associated with lower information frictions. In general, IPO stocks have higher dispersion of analysts’ opinion, less analysts coverage, and less institutional involvement, if they have low offer price, low reputation underwriter, and no venture capital backing. The exception is the result for underwriter prestige-analysts’ dispersion of opinion pair.

The tests across underpricing categories (shown in *Panel B*) are puzzling, however. High underpricing draws more analysts coverage³⁵ and institutional investment, but there is a weak evidence that it also leads to more information frictions, as captured by idiosyncratic risk and dispersion of opinion measures in *Table 5*. High underpricing again is associated with higher information uncertainty, as captured by the idiosyncratic risk of a stock. Underpricing may help in generating new information about the stock, but it also brings more disagreement about it. This disagreement also reflects in the higher turnover of such IPO stocks, as documented earlier. In short, underpricing leads to more liquidity and more information generation by analysts and institutional investors, but it also indicates higher information constraints, as measured by dispersion of opinion and idiosyncratic risk of the stock. It is also associated with more severe short-sale constraints, as documented in Section 4.2.

Another surprising result is associated with the VC backing categorization scheme. Our findings indicate that dispersion of opinion is significantly higher for IPOs backed by VCs! This finding is supported by higher average idiosyncratic risk for VC backed IPOs, we report in the next section. Our interpretation of these results is as follows. VC backing increases the stock’s exposure (higher analysts’ coverage and institutional holdings), thus more information is generated much faster (as captured by price delay), which increases stock’s liquidity (as measured by turnover and Amihud’s illiquidity and PS’ aggregate liquidity). However, apparently, such VC backing is also associated with higher information frictions around the firm. VC backed stocks are also more likely to be severely short-sale constrained, as reported in our *Table 3*. Heightened information frictions of VC backed firms are likely due to their younger average issuance age (see *Table 1*).

4.4.3. Idiosyncratic Risk

There is some weak evidence that IPOs issued in hot markets have higher firm-specific risk (in *Table 5, Panel A* the differences in vicile means of hot and cold IPOs is significant at 5% level for Years 3 and 4, and at 10% for Year 2).

³⁵This conclusion is also supported by the findings of Rajan and Servaes (1997).

The results for other classification schemes are much more significant: for all the years and across all the groups the differences are significant at better than 1% level! Idiosyncratic risk associated with an IPO firm is likely to be higher, if that firm has high underpricing, low offer price, low underwriter prestige, and it was backed by a VC. The result of positive relation between underpricing and idiosyncratic risk is worth noting here. Apparently, the factors (such as information uncertainty) that are causing an issue to be underpriced are also captured by its idiosyncratic risk.

Our finding that prestigious underwriters are issuing IPOs with less idiosyncratic risk, is a refinement to Carter and Manaster (1990)'s claim that relates total risk of an IPO to its underwriter's prestige. The result of high firm-specific risk associated with VC backed IPOs is surprising to us, because IPOs associated with reputable intermediaries, such as investment banks and venture capital firms, are generally thought to have low risk and less *ex ante* uncertainty. At the end of this section we will provide a plausible explanation for this result.

For a quick reference, *Table 7, Panel A* provides a succinct presentation of all the results from this section in a simple summary-chart format.

4.5. Multivariate Analysis

The above results are based on comparisons of the means of various IPO sub-samples. To complement the above analyses, we test these connections in a multivariate setting. We, essentially, check whether the IPO features have explanatory power over the considered secondary-market trading frictions in a regression setting. We should note that, the conclusions derived from such an analysis are limited, and thus should be approached with caution. For the most part, the asset-pricing literature is unclear on what is the complete set of factors affecting the market-trading frictions. For example, can we say that we know all the right-hand-side variables explaining the idiosyncratic risk? So, in our analysis we incorporate only the obvious IPO features as the explanatory variables. Our goal is restricted to showing the effect of these IPO variables on the friction measures, without claiming that we have

controlled for everything. In such, our multivariate analysis serves as an auxiliary result to the above-documented bivariate relationships.

In our regressions, the dependent variables are the market frictions variables we use in the previous subsection (again ranked into viciles, for consistency with the previous analyses). All the friction variables are as of the end of the first year.³⁶ The regressors are the five IPO features we used in the bivariate analysis, plus the obvious control variables, such as the size of the IPO firm at the end of the first year (sorted into CRSP viciles) and the IPO firm’s age at the time of issuance.

Table 6 shows the results from such regressions. For substantial majority of these regressions, the signs and significances of the explanatory variables are consistent with our findings in the previous tables. It is reassuring that our main results are confirmed by these multivariate regressions. So, the above-analyzed links between the primary and the secondary markets are quite robust.

In the next subsection, we propose an explanation for these links. While we do not claim it is the only one, we believe it is a highly plausible one. It is important to mention that, the above documented stylized facts are valuable to the literature, even if the reader does not agree with the explanation below.

4.6. Discussion: What Explains Our Findings?

We have documented several stylized facts that relate the primary markets to the secondary markets with an aim to obtain the “big picture” about the connection between the two markets. These stylized facts have not been reported or analyzed before. Next, we propose an explanation for our findings. It can be called *quality-based explanation*. The primary-market features we have considered are indicative of IPO quality (or firm’s general business risk). That is, we postulate that more uncertainty about firm quality is present in 1) IPOs

³⁶As we saw above, the secondary-market frictions of the recently issued stocks are quite persistent over time. So, to save space, we report only the results for the first year after IPO, and we do not present the results when the dependent variables are measured as of the year 2, 3, 4, or 5. They are similar to the ones presented here and are available upon request.

issued in hot markets, 2) IPOs with higher first trading day returns, 3) IPOs with lower offer price, 4) IPOs with lower UW prestige, and 5) IPOs without VC backing.³⁷ Stocks of the lower quality firms should also face more serious trading frictions during the post-issuance period. Thus, firm quality is the unobservable link connecting the primary market attributes of an IPO to its stock’s trading frictions observed in the secondary markets.

Based on our quality-based explanation, we create a panel showing what are the expected signs for each relationship if our hypothesis is true (see *Table 7, Panel B*). Using this table, we find that out of 50 relationships we document in that panel only seven (or 14%) are contradicting our hypothesis. Six of those seven results are related to underpricing, which is a notoriously difficult-to-interpret IPO feature whose causes are still debated. See also the literature review below on the connection between underpricing and quality.

In a further analysis of the quality-based explanation, we construct a direct measure of IPO firm’s quality. It approximates quality by assuming that high-quality IPO firms have post-issuance cash flows (CFs)³⁸ that are large, positive, and with lower volatility. Namely, we define quality as the average annual CFs over the Years 1 through 5, divided by standard deviation of CFs over the same period ($QM = \text{Mean CFs} / \text{Standard Deviation of CFs}$). The larger this value, the higher the quality of the IPO firm. This measure should capture the invisible link between the primary and the secondary markets. If our quality-based hypothesis is true, we would expect QM to be highly correlated with both the five primary-market features we consider and the secondary-market frictions we analyze.

Table 8 shows the correlation coefficients between QM and the five primary market characteristics (*Panel A*) and the ten trading friction measures we consider (*Panel B*). In this

³⁷The effect of VC support reducing uncertainty about the IPO may be convoluted by our findings in *Table 1* that IPOs with VC backing are younger. Also, in unreported results we find that about 73% of the VC backed IPOs are also in a high-tech industry. Thus, we have two opposing effects at play: VC support may signal higher firm quality, but the youth and the industry of the VC backed firms can cause enough uncertainty to offset some of this effect. Lerner (1994) also claims that VC support can sometimes indicate lower post-issuance performance. These observations can explain our findings of higher idiosyncratic risk, higher dispersion of opinion, more severe short-sale constraints, and more underpricing associated with VC backed firms.

³⁸The cash flow of each firm is defined as the $(\text{income before extraordinary items} + \text{depreciation and amortization} - \text{preferred dividends} - \text{common dividends}) / \text{total assets}$. All the data items are annual data.

analysis, we use the continuous version of the friction variables instead of the CRSP vicile rankings (except for the SSCF measure, which is a dummy variable). Similarly, for the IPO feature, we use the continuous versions of the market heat indicator (*HeatDegrees*), the actual underpricing, relative offer price, and underwriter ranking of the firm, and the dummy indicator for venture capital. It is clear from the table that QM is significantly correlated with the IPO characteristics and the stocks' trading frictions. For the overwhelming majority of our results, the signs of the correlation coefficients are as expected (see above for clarification on expected signs). Therefore, we conclude that significant majority of our findings from this table support the quality-based hypothesis. While further research on this hypothesis could be done, we believe that the stylized facts we report in this paper are best explained by such a quality-based hypothesis.

Our quality-based explanation is in accordance with various signaling models and empirical findings reported in the IPO literature. Numerous studies claim that the issuing firm, its underwriter, or its venture capitalist do try to signal the quality of the issue through various IPO features. For example, the level of IPO's offer price is considered a reliable signal of the firm's quality. Stoughton and Zechner (1998) show that firms seeking to attract sophisticated institutional investors, who can monitor the management, do so by signaling through higher IPO offer price; if such monitoring is successful, these IPOs are likely to perform better in the long run. Institutional investors, on the other hand, are likely to avoid investing in low-priced IPOs due to prudent-man laws (Falkenstein, 1996; and Gompers and Metrick, 2001). Empirical studies by Fernando, et al. (2006) and Seguin and Smaller (1986) show that the offer price of an IPO can predict the likelihood of a firm experiencing a delisting from the exchange due to financial distress. The results of all of these papers is consistent with our claim that IPO firm's quality is driving the negative correlation between offer price and post-issuance market frictions. High offer price signals high quality to the investors, whose opinions, in turn, manifest themselves in the secondary market trading frictions of the stocks.

Similarly, certification through VC presence or through more reputable underwriters is

shown to indicate better firm-quality. Reputable underwriters have an incentive to protect their reputation by being associated with high quality IPOs (Seguin and Smaller, 1997; and Carter, et al., 1998). Formal models of VCs signaling their IPO's quality are proposed by Allen and Faulhaber (1989) and Gompers (1996). Brav and Gompers (1997) claim that small, non-venture backed IPOs' stocks underperform more than a typical IPO in the years following the IPO event. Megginson and Weiss (1991) report that venture capitalists are known to credibly stake their reputation on the issuer's quality. Thus, the certification efforts by VCs and underwriters reported by these studies are consistent with our quality based explanation.

Based on the signaling theories of Allen and Faulhaber (1989), Grinblatt and Hwang (1989) and Welch (1989), and the empirical findings of Jain and Kini (1994), one can claim that low-value firms are unlikely to incur the cost of underpricing in order to look like high-value firms, and thus in the resulting separating equilibrium the high quality firms end up underpricing at the offering. Alternative signaling role of underpricing is provided by behavioral finance theories. For instance, high underpricing is taken as a signal of investor exuberance (Krigman, et al., 1999). Therefore, in such situations higher initial returns will foreshadow declines in subsequent operating performance. Also, underpricing is shown to be larger for small priced (and thus lower quality) IPOs (Chalk and Peavy, 1987; and Ibbotson, et al., 1988) and for stocks that are in high demand for shorting (Geczy, et al., 2002). Thus, while the signaling power of underpricing is quite convoluted, it does carry some valuable information about the IPO firm's nature.

Finally, the fact that an IPO issues during hot markets can signal lower post-issuance performance (see Ljungqvist, et al. 2004). Similarly, Ljungqvist and Wilhelm (2003) show a dramatic decline in earnings quality of US IPOs during the hot market period of 1997 and 1999. Yung, et al. (2008) find that the delisting rates from exchanges is higher among hot-market IPOs. The theoretical model of Benninga et al. (2005) suggests that firms are taken public when the market valuation of the expected cash flows is high. The insiders have private information on their firms' prospects, and only propose to float them on the public

markets when their profitability is about to decline.

5. Conclusion

While the long-run return performance of IPO stocks is a heavily investigated area, our knowledge and understanding about the other trading-related attributes of IPO stocks is limited. This study analyzes the liquidity, information, and short-sale constraints in IPO stocks. With regard to these trading characteristics we compare the IPO stocks among themselves when grouped into portfolios based on their market heat, issue price, underpricing level, underwriter prestige, and venture backing. We also compare the IPO stocks to more seasoned stocks in CRSP. Thus, for the first time in the literature we provide a comprehensive picture of the post-issue trading features of IPO stocks.

The implications of our findings can be consequential. We demonstrate that there are strong links between the primary and the secondary markets that are likely driven by the IPO's underlying business quality. The primary market features of an IPO can be interpreted as a reliable signal of its trading risks to the secondary market participants.

Our results further imply that different groups of IPO stocks will likely attract different clientels of investors. Stocks with different market-trading frictions have appeal to their own kind of investors. Thus, our results suggest that the composition of participating investors (institutional vs. individual) is changing during the hot IPO markets. Market participants invested in IPOs with different underpricing, substantially different issue price, different reputation underwriters, and different VC support are also likely to be very different in their willingness to tolerate frictions related to illiquidity, information, and short-sale constraints.

Our focus has mostly been at obtaining a broad overview of differences across various IPO classes with regard to post-issue trading frictions. Relationship to other trading diagnostics, such as momentum (Jagadeesh and Titman, 1993) and market risk (or beta), can be considered as well. More direct and more detailed tests are required to demonstratively prove that indeed the type of traders invested in IPO stocks in the immediate months and

years (not the immediate days) after issuance are not the same. Further analysis, empirical and theoretical, can be done in explaining each individual relationship between a certain market friction and a specific IPO issuance feature. For example, why are underpricing and short-sale constraints so strongly related?

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Figure 1: The Heat Measure Over Time
 Number of IPOs per Quarter between 1970 and 2005

Table 1: Descriptive Statistics of the IPO Sample

Some descriptive statistics about our IPO sample are presented in this table. The included IPO characteristics are the IPO's age at the time of issuance, the IPO firm's size vicile (in CRSP) as of the end of the 1st month after issuance, IPO's offer price (in year 2000 dollars), IPO's underpricing level (in %), lead underwriter's Carter-Manaster reputation ranking or prestige, and IPO's 3-year buy-and-hold return (in %). The IPO categories are formed by grouping them into sub-samples according to 1) market heat, 2) underpricing level, 3) offer price, 4) underwriter prestige, and 5) venture backing. Detailed explanation of each classification scheme is provided in the text. The row "Prob." provides the p -values from the nonparametric Wilcoxon two-sample test (equality of the means across the groups). # next to the p -value indicates caution in interpreting the significance from the test. The z -statistic used to generate that p -value is not reliable according to the 90% confidence intervals obtained through bootstrap sampling (with 5000 repetitions) that controls for clustering within issuance quarter. That is, the z -statistic is not significantly different from zero (which in turn indicates that the means are not significantly different from each other). The column named "Obs." under each characteristics shows the number of IPOs in each group with nonmissing data for that variable. The last column presents the total sample size in each group.

	IPO Categ.	IPO Characteristics										Num. of IPOs	
		Age		Size		Offer Price		Underpricing		UW Prestige		36-mo BHR	
		Numb.	Obs.	Vicile	Obs.	\$	Obs.	Perc.	Obs.	Numb.	Obs.	Perc.	Obs.
Market Heat	All	15.27	7889	10.44	7956	11.09	9344	20.26	8318	6.30	6721	21.51	7657
	Cold	18.95	389	11.13	390	15.03	447	15.00	409	6.88	282	88.89	307
	Hot	15.48	5229	9.91	5340	10.51	6250	35.92	5550	6.07	4613	25.77	5343
	Prob.	0.0001		0.0001		0.0001		0.0797#		0.0001		0.0001	
Underpricing Level	All	15.36	7742	10.55	7730	11.15	8318	20.26	8318	6.39	6499	22.66	7430
	Low	16.78	2524	9.46	2533	10.42	2769	-8.46	2769	6.34	2203	37.67	2428
	High	11.31	2599	11.62	2609	11.83	2773	62.92	2773	6.50	2127	3.03	2512
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0642#		0.0001	
Offer Price	All	15.27	7889	10.44	7956	11.09	9344	20.26	8318	6.30	6721	21.51	7657
	Low	9.94	2538	6.57	2761	5.21	3273	24.84	2783	3.98	2426	10.45	2707
	High	18.54	2910	14.10	2766	17.40	3288	26.29	3014	8.03	2216	24.47	2604
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		0.0001	
Underwriter Prestige	All	14.55	6177	10.27	6244	10.65	6721	17.19	6499	6.30	6721	19.51	6134
	Low	8.59	1503	5.87	1699	5.31	1826	15.91	1678	2.59	1826	0.16	1694
	High	17.56	3083	13.11	2949	13.70	3192	21.71	3173	8.51	3192	27.99	2878
	Prob.	0.0001		0.0001		0.0001		0.0795#		0.0001		0.0001	
Venture Backing	All	15.27	7889	10.44	7956	11.09	9344	20.26	8318	6.30	6721	21.51	7657
	No	17.95	5140	9.67	5188	10.76	6429	17.51	5533	5.85	4466	18.66	5019
	Yes	10.25	2749	11.87	2768	11.82	2915	25.72	2785	7.18	2255	26.94	2638
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		0.0011	

Table 2: IPO vs. CRSP Firms Over Time

The table presents our market friction measures for the IPO firms in comparison to all the CRSP firms. The considered variables are size rank of the IPO firm, percentage of firms that are severely short-sales constrained (as measured by Asquith, et al. (2005)'s indicator), illiquidity measure of Amihud (2002), aggregate liquidity measure of Pastor and Stambaugh (2003), stock's turnover rate, price delay, analysts' dispersion of opinion, number of analysts covering the stock, relative short interest, institutional holdings, and idiosyncratic risk from 4 factor model. The details about the calculation of each measure is described in the text. These variables are calculated for each firm in the CRSP universe (IPOs plus seasoned firms) separately, and then the firms are ranked into viciles. This ranking is repeated for each of the five years after the corresponding IPO firm's issuance date; Year 1 through Year 5 (exactly n years after the day of issuance). The shown values are the mean vicile ranking of the IPO firms in our sample for each post-issuance period. The rows named " p -values" show the results from the nonparametric (sign rank) test, where the null hypothesis is that the IPO sample's mean vicile for the corresponding measure is equal to expected CRSP mean of 10.5 viciles. # next to the p -value indicates caution in interpreting the significances from the test. The z -statistic used to generate that p -value is not reliable according to the 90% confidence intervals obtained through bootstrap sampling (with 5000 repetitions) that controls for clustering within issuance quarter. That is, the z -statistic is not significantly different from zero (which in turn indicates that the mean is not significantly different from 10.5). The rows named "N of obs." display the number of IPO firms with nonmissing data that are used in calculating the mean of each variable. The columns under "Time Trend" show the estimated slope and its significance ("Prob.") from the univariate regression of an IPO firm's vicile on the time trend, over the five-year period after issuance. The number under the slope estimates shows the number of observations used in these panel data regressions.

Variables	Type	Time After Issue Date					Time Trend	
		Year 1	Year 2	Year 3	Year 4	Year 5	Slope	Prob.
Size	vicile	9.7117	9.3900	9.3757	9.3673	9.4015	0.0625	0.0001
	p-values	0.0001	0.0001	0.0001	0.0001	0.0001		
	N of obs.	8,241	7,398	6,415	5,603	4,911	32,567	
SSCF	vicile	9.9359	10.6171	10.9837	10.9777	11.0421	0.2521	0.0001
	p-values	0.0001	0.0001	0.0001	0.0001	0.0001		
	N of obs.	4,102	5,602	5,081	4,609	4,112	20,165	
RSI	vicile	10.7139	11.0597	11.0905	11.1989	11.0929	0.0957	0.0008
	p-values	0.0072	0.0001	0.0001	0.0001	0.0001		
	N of obs.	4,952	4,724	4,199	3,725	3,585	21,184	
Amihud Illiquidity	vicile	10.8813	11.4699	11.5370	11.5140	11.3816	0.1212	0.0001
	p-values	0.0001	0.0001	0.0001	0.0001	0.0001		
	N of obs.	7,151	6,776	5,912	5,187	4,536	29,561	
PS Liquidity	vicile	9.7036	10.3345	10.8250	10.9633	11.0321	0.3265	0.0001
	p-values	0.0001	0.0012	0.0001	0.0001	0.0001		
	N of obs.	4,102	5,602	5,081	4,609	4,112	23,505	
Turnover	vicile	12.1509	11.5215	11.4978	11.4177	11.4214	-0.1704	0.0001
	p-values	0.0001	0.0001	0.0001	0.0001	0.0001		
	N of obs.	7,025	6,581	5,713	4,960	4,307	28,585	
Price Delay	vicile	10.2945	10.8651	11.0608	10.8585	10.7841	0.0887	0.1018
	p-values	0.0105	0.0001	0.0001	0.0001	0.0004		
	N of obs.	4,842	7,255	6,348	5,604	4,895	28,943	
Analyst Dispersion	vicile	10.4418	11.1611	11.5600	11.6290	11.6259	0.3096	0.0001
	p-values	0.5196 [#]	0.0001	0.0001	0.0001	0.0001		
	N of obs.	4,144	3,800	3,232	2,752	2,398	16,081	
Number of Analysts	vicile	8.4888	9.1859	9.4861	9.6277	9.9130	0.3372	0.0001
	p-values	0.0001	0.0001	0.0001	0.0001	0.0001		
	N of obs.	5,080	4,729	4,055	3,481	2,999	20,039	
Institutional Holdings	vicile	9.6600	10.0052	10.1449	10.4101	10.5718	0.2385	0.0001
	p-values	0.0001	0.0001	0.0001	0.2298 [#]	0.3699 [#]		
	N of obs.	6,808	6,382	5,626	4,975	4,380	22,069	
Idiosyncratic Risk	vicile	13.5748	13.6320	13.5305	13.3496	13.1860	-0.1091	0.0001
	p-values	0.0001	0.0001	0.0001	0.0001	0.0001		
	N of obs.	4,840	7,253	6,347	5,603	4,897	28,939	

Table 3: Short-Sale Constraints in IPO Stocks

The table presents the percentage of IPO firms in each sub-sample that are short-sale constrained (*SSCF Percentage*), and their mean relative short interest (*RSI*) vicile. Our short-sale constraint measure is described in the text. The IPOs are grouped into sub-samples according to 1) market heat, 2) underpricing level, 3) relative offer price, 4) underwriter prestige, and 5) venture backing. Detailed explanation of each classification scheme is provided in the text. The results for 1, 2, 3, 4, and 5-years after the IPO date are presented. The firms for which we can not calculate our short-sale constraint measure for neither of these post-IPO periods are not included in the sample used to obtain this table's results. The row "Prob." provides the p -values from the nonparametric Wilcoxon two-sample test (equality of the means across the groups). # next to the p -value indicates caution in interpreting the significance from the test. The z -statistic used to generate that p -value is not reliable according to the 90% confidence intervals obtained through bootstrap sampling (with 5000 repetitions) that controls for clustering within issuance quarter. That is, the z -statistic is not significantly different from zero (which in turn indicates that the means are not significantly different from each other). The column named "Num." under each post-IPO period shows the number of IPOs in each group with nonmissing data. The last column presents the total number of IPOs in each category.

IPO Categ.	Time After Issue Date											Total Number
	Year 1		Year 2		Year 3		Year 4		Year 5			
	Percent	Num.	Percent	Num.	Percent	Num.	Percent	Num.	Percent	Num.		
Panel A: SSCF Percentage												
Market Heat	Cold	14.07%	668	8.91%	517	8.92%	437	9.29%	355	5.84%	291	738
	Hot	7.05%	3332	11.03%	3456	9.04%	3162	11.55%	2843	9.22%	2831	4628
	Prob.	0.0001		0.1208#		0.9344#		0.1711#		0.0541		
Underpricing Level	Low	5.41%	1312	6.81%	1322	7.77%	1249	8.13%	1144	8.33%	1213	1950
	High	14.77%	1686	14.64%	1591	12.37%	1374	13.67%	1178	12.49%	1057	1958
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0011		
Relative Offer Price	Low	8.06%	1439	10.35%	1362	11.04%	1169	12.22%	1039	12.86%	980	1990
	High	11.06%	1564	10.98%	1558	9.11%	1460	9.77%	1300	8.46%	1289	1993
	Prob.	0.0054		0.5866#		0.1015#		0.0581		0.0007		
Underwriter Prestige	Low	7.27%	880	9.21%	923	11.70%	812	11.33%	750	9.68%	754	1360
	High	9.81%	2191	10.57%	2071	9.28%	1865	10.25%	1629	9.59%	1512	2583
	Prob.	0.0268		0.2534#		0.0549		0.4258#		0.9444#		
Venture Backing	No	7.27%	2600	8.67%	2677	9.05%	2432	8.82%	2165	8.11%	2134	3662
	Yes	10.87%	1978	11.63%	1806	10.09%	1606	11.56%	1427	11.34%	1340	2312

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Table 3 – Continued from previous page –

IPO Categ.	Time After Issue Date												Total Number
	Year 1		Year 2		Year 3		Year 4		Year 5				
	Percent	Num.	Percent	Num.	Percent	Num.	Percent	Num.	Percent	Num.			
Prob.	0.0001		0.0011		0.2686#			0.0072		0.0014			
Panel B: Relative Short Interest (RSI) Vicile													
Market	Cold	11.37	723	12.09	547	11.67	446	11.64	360	11.15	298	765	
Heat	Hot	10.37	3622	10.80	3655	10.94	3302	11.05	2964	10.99	2931	4863	
Prob.		0.0001		0.0001		0.0147		0.0789#		0.6471#			
Underpricing Level	Low	9.17	1425	10.02	1403	10.46	1299	10.74	1192	10.71	1256	2043	
	High	12.77	1821	12.60	1672	12.17	1414	12.14	1199	11.85	1072	2041	
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001			
Relative Offer Price	Low	9.23	1677	9.63	1486	9.68	1207	9.84	1064	9.87	987	2096	
	High	12.48	1653	12.81	1641	12.61	1540	12.58	1372	12.27	1360	2102	
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001			
Underwriter Prestige	Low	9.54	1156	9.76	1083	9.77	899	9.62	822	9.59	821	1539	
	High	11.57	2202	12.01	2075	12.05	1873	12.27	1645	12.11	1522	2598	
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001			
Venture Backing	No	9.98	2932	10.20	2893	10.34	2581	10.29	2282	10.14	2231	3911	
	Yes	11.78	2020	12.43	1831	12.29	1618	12.63	1443	12.66	1354	2344	
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001			

Table 4: Liquidity Constraints in IPO Stocks

The table shows three liquidity measures across IPO categories sorted by market heat, underpricing, relative offer price, underwriter prestige, and venture capital support (presented in Panels A through E, correspondingly). The liquidity variables are illiquidity measure of Amihud (2002), Pastor and Stambaugh (2003)'s aggregate liquidity measure, and stock's turnover rate. These variables are calculated for each firm in CRSP (IPO and seasoned) for each period separately. Then, in each period they are sorted into viles using all the CRSP firms. The *mean* vicile for each IPO category are presented for Year 1 through Year 5. The classification procedures applied to separate the IPOs in our sample into categories are detailed in the text. The row "Prob." shows the *p*-values from the nonparametric Wilcoxon two-sample test (equality of the means across the groups). # next to the *p*-value indicates caution in interpreting the significance from the test. The *z*-statistic used to generate that *p*-value is not reliable according to the 90% confidence intervals obtained through bootstrap sampling (with 5000 repetitions) that controls for clustering within issuance quarter. That is, the *z*-statistic is not significantly different from zero (which in turn indicates that the means are not significantly different from each other). The column named "Num." under each post-IPO period shows the number of IPOs in each group with nonmissing data. The last column presents the total number of IPOs in each category.

Liquidity Measure	IPO Categ.	Time After Issue Date									
		Year 1		Year 2		Year 3		Year 4		Year 5	
		Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.
Panel A: Categorization by Market Heat											
Amih. Illiq.	Cold	10.64	234	10.12	226	9.73	169	9.62	144	9.43	108
	Hot	11.37	4926	11.82	4754	11.76	4169	11.48	3647	11.52	3162
	Prob.	0.0063		0.0001		0.0001		0.0001		0.0001	
Turnover	Cold	10.94	232	11.90	223	12.41	159	12.97	135	12.25	102
	Hot	11.89	4815	11.06	4622	11.38	4025	11.28	3478	11.26	2988
	Prob.	0.0031		0.0524		0.0307		0.0007		0.0876#	
PS Liquid.	Cold	10.24	148	9.59	220	9.37	150	8.95	96	9.60	73
	Hot	10.11	2679	10.76	3848	11.06	3581	11.13	3238	11.13	2863
	Prob.	0.7526#		0.0005		0.0001		0.0001		0.0170	
Panel B: Categorization by Underpricing Level											
Amih. Illiq.	Low	11.86	2317	12.13	2150	12.03	1900	11.95	1679	11.76	1471
	High	9.69	2368	10.57	2183	10.76	1842	10.72	1572	10.61	1360
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001	
Turnover	Low	11.15	2242	10.61	2068	10.90	1825	10.84	1600	10.94	1387
	High	13.53	2344	12.83	2144	12.48	1809	12.42	1543	12.37	1329
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001	
PS Liquid.	Low	10.78	1219	11.19	1734	11.52	1630	11.44	1512	11.56	1354
	High	8.46	1456	9.14	1881	9.84	1638	10.21	1433	10.23	1263
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001	

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Table 4 – Continued from previous page –

Liquidity Measure	IPO Categ.	Time After Issue Date										Total Number
		Year 1		Year 2		Year 3		Year 4		Year 5		
		Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	
Panel C: Categorization by Relative Offer Price												
Amih. Illiq.	Low	13.67	2342	14.27	2131	14.25	1710	14.03	1453	13.74	1219	2637
	High	7.94	2365	8.71	2346	8.98	2149	9.16	1943	9.19	1746	2623
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Turnover	Low	11.39	2286	10.86	2057	10.93	1638	10.75	1375	10.76	1155	2594
	High	12.92	2330	12.19	2287	12.07	2102	12.07	1878	11.92	1680	2588
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
PS Liquid.	Low	12.43	1431	12.84	1893	13.31	1501	13.11	1340	12.90	1175	2285
	High	7.02	1322	8.01	1804	9.61	1811	9.03	1686	9.19	1540	2296
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Panel D: Categorization by Underwriter Prestige												
Amih. Illiq.	Low	13.62	1873	14.42	1800	14.32	1536	14.14	1352	13.89	1142	2131
	High	9.09	2804	9.50	2602	9.74	2268	9.89	1977	9.87	1734	2879
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Turnover	Low	11.88	1803	10.99	1714	10.98	1466	10.59	1276	10.77	1065	2089
	High	12.78	2795	12.23	2589	12.10	2254	12.08	1949	11.93	1710	2874
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
PS Liquid.	Low	12.98	808	13.72	1173	13.98	1069	13.70	999	13.77	901	1573
	High	8.23	1874	8.72	2463	9.36	2183	9.61	1939	9.71	1710	2798
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Panel E: Categorization by VC Backing												
Amih. Illiq.	No	11.26	4620	12.08	4416	12.16	3857	12.23	3368	12.19	2922	5166
	Yes	10.19	2531	10.33	2368	10.38	2055	10.19	1819	9.93	1614	2704
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Turnover	No	11.74	4512	10.78	4245	10.66	3677	10.30	3174	10.27	2717	5067
	Yes	12.88	2513	12.87	2336	13.01	2036	13.40	1786	13.38	1590	2695
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
PS Liquid.	No	10.26	2483	10.95	3502	11.50	3221	11.62	2917	11.83	2590	4339
	Yes	8.86	1619	9.30	2100	9.66	1860	9.82	1692	9.67	1522	2518
	Prob.	0.0104		0.0001		0.0033		0.0024		0.0002		

Table 5: Information Constraints in IPO Stocks

The table presents several measures of information constraints for our IPO categories sorted by market heat, underpricing, relative offer price, underwriter prestige, and venture capital support (presented in Panels A through E, correspondingly). The measures are Hou and Moskowitz (2005)'s price delay measure, analysts's dispersion of opinion, number of analysts covering the stock, institutional holdings, and idiosyncratic risk from 4 factor model. These variables are calculated for each firm in CRSP (IPO and seasoned) for each period separately. Then, in each period they are sorted into viciies using all the CRSP firms. The *mean* vicile for each IPO category are presented for Year 1 through Year 5. The classification procedures applied to separate the IPOs in our sample into categories are detailed in the text. The row "Prob." displays the p -values from the nonparametric Wilcoxon two-sample test (equality of the means across the groups). # next to the p -value indicates caution in interpreting the significance from the test. The z -statistic used to generate that p -value is not reliable according to the 90% confidence intervals obtained through bootstrap sampling (with 5000 repetitions) that controls for clustering within issuance quarter. That is, the z -statistic is not significantly different from zero (which in turn indicates that the means are not significantly different from each other). The column named "Num." under each post-IPO period shows the number of IPOs in each group with nonmissing data. The last column presents the total number of IPOs in each category.

Information Constraints Measures	IPO Categ.	Time After Issue Date										Total Number
		Year 1		Year 2		Year 3		Year 4		Year 5		
		Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	
Panel A: Categorization by Market Heat												
Price Delay	Cold	11.04	225	10.07	366	9.82	270	9.54	204	9.77	144	386
	Hot	10.66	3262	11.12	5017	11.15	4406	11.06	3915	10.92	3411	5459
	Prob.	0.3338#		0.0007		0.0001		0.0002		0.0173		
Dispersion of Opinion	Cold	10.03	189	10.87	176	10.44	108	9.48	58	9.83	23	290
	Hot	10.30	2562	11.83	2491	11.42	2175	11.43	1823	11.15	1570	3299
	Prob.	0.5388#		0.0420		0.0687#		0.0132		0.0218		
Number of Analysts	Cold	9.79	200	11.01	188	11.55	119	12.26	62	12.46	24	208
	Hot	7.93	3305	8.75	3191	9.17	2810	9.44	2363	9.83	1993	3971
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0150		
Instit. Holdings	Cold	11.20	222	11.96	204	12.76	129	13.54	67	13.74	23	224
	Hot	9.68	3546	9.99	3360	10.29	2981	10.52	2611	10.72	2272	3799
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0102		
Idiosync. Risk	Cold	13.35	223	13.02	365	12.81	270	12.42	204	12.66	144	384
	Hot	13.36	3262	13.45	5016	13.46	4406	13.26	3915	13.04	3412	5458
	Prob.	0.8425#		0.0913#		0.0138		0.0124		0.3230#		

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Information Constraints Measure	IPO Categ.	Time After Issue Date										Total Number
		Year 1		Year 2		Year 3		Year 4		Year 5		
		Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	
Panel B: Categorization by Underpricing Level												
Price Delay	Low	11.15	1594	11.10	2222	11.09	1942	11.01	1705	10.98	1491	2434
	High	9.36	1577	10.26	2226	10.63	1863	10.47	1586	10.05	1365	2433
	Prob.	0.0001		0.0001		0.0124		0.0064		0.0001		
Dispersion of Opinion	Low	10.03	1264	11.07	1174	11.12	1025	11.62	880	11.74	771	1696
	High	10.75	1500	11.51	1311	11.84	1053	11.79	872	12.08	759	1699
	Prob.	0.0148		0.0803#		0.0399		0.5795#		0.1793#		
Number of Analysts	Low	7.36	1591	8.05	1501	8.62	1304	8.95	1114	9.29	950	1971
	High	9.93	1747	10.49	1586	10.59	1293	10.45	1096	10.51	952	1963
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Instit. Holdings	Low	9.51	1821	9.83	1629	10.04	1408	10.30	1235	10.44	1078	1927
	High	10.05	1801	10.23	1675	10.22	1429	10.52	1205	10.80	1048	1921
	Prob.	0.0001		0.0238		0.4009#		0.2802#		0.0900#		
Idiosync. Risk	Low	13.22	1593	13.26	2222	13.22	1942	13.07	1705	12.95	1492	2433
	High	14.68	1577	14.69	2226	14.30	1862	14.10	1586	14.84	1365	2433
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Panel C: Categorization by Relative Offer Price												
Price Delay	Low	12.60	1608	12.75	2284	12.41	1837	12.13	1588	12.01	1338	2688
	High	8.11	1610	9.07	2513	9.86	2304	9.65	2081	9.61	1861	2706
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Dispersion of Opinion	Low	11.45	1276	12.07	1069	12.18	803	11.99	692	11.89	608	1702
	High	9.86	1483	10.61	1424	11.09	1248	11.47	1064	11.43	928	1721
	Prob.	0.0001		0.0001		0.0001		0.0359		0.0887#		
Number of Analysts	Low	7.03	1529	7.43	1343	7.39	1057	7.64	890	7.99	757	1989
	High	10.06	1806	10.88	1735	11.21	1533	11.20	1333	11.40	1155	1989
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Instit. Holdings	Low	6.76	1672	6.83	1533	6.84	1264	7.29	1073	7.70	906	1956
	High	12.07	1945	12.49	1797	12.57	1585	12.66	1397	12.81	1222	1956
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Idiosync. Risk	Low	15.31	1607	15.86	2285	15.76	1837	15.30	1588	15.11	1339	2687
	High	12.15	1610	11.96	2512	11.95	2303	11.95	2081	11.88	1861	2705
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		

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Table 5 – Continued from previous page –

Information Constraints Measure	IPO Categ.	Time After Issue Date										Total Number
		Year 1		Year 2		Year 3		Year 4		Year 5		
		Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	Mean	Num.	
Panel D: Categorization by Underwriter Prestige												
Price Delay	Low	12.61	1335	12.75	1913	12.42	1595	12.30	1389	11.96	1173	2103
	High	8.59	1815	9.53	2626	10.09	2286	9.99	1990	9.82	1743	2804
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Dispersion of Opinion	Low	10.42	279	11.61	345	11.64	322	11.74	298	11.52	257	615
	High	10.44	2323	11.27	2056	11.76	1682	11.80	1379	11.71	1168	2581
	Prob.	0.9835 [#]		0.2867 [#]		0.8481 [#]		0.9797 [#]		0.7570 [#]		
Number of Analysts	Low	5.00	568	5.84	602	6.36	550	6.62	498	6.96	429	990
	High	9.37	2594	10.18	2353	10.40	1953	10.51	1631	12.30	1374	2751
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Instit. Holdings	Low	5.85	1082	6.08	1065	6.32	930	6.76	811	7.16	683	1907
	High	11.45	2531	11.92	2318	11.96	1989	12.17	1726	12.26	1507	2901
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Idiosync. Risk	Low	14.70	1334	15.29	1912	15.27	1595	14.91	1389	14.72	1175	2102
	High	13.40	1815	12.97	2626	12.96	2286	12.92	1990	12.78	1742	2803
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Panel E: Categorization by VC Backing												
Price Delay	No	10.82	3147	11.37	4801	11.50	4219	11.40	3722	11.30	3227	5392
	Yes	9.32	1695	9.89	2454	10.18	2129	9.81	1882	9.79	1668	2680
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Dispersion of Opinion	No	9.70	2176	10.48	2056	10.97	1775	11.08	1505	10.84	1272	2882
	Yes	11.27	1963	11.97	1721	12.32	1404	12.33	1173	12.61	1037	2232
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Number of Analysts	No	7.95	2858	8.60	2699	8.95	2342	9.07	1977	9.36	1652	3538
	Yes	9.18	2217	9.97	2000	10.21	1647	10.40	1412	10.59	1236	2422
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Instit. Holdings	No	8.93	4234	9.16	4020	9.31	3567	9.54	3154	9.66	2771	4789
	Yes	10.85	2574	11.44	2362	11.59	2059	11.92	1821	12.14	1609	2688
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Idiosync. Risk	No	12.89	3145	13.11	4799	12.97	4218	12.80	3721	12.66	3229	5389
	Yes	14.84	1695	14.66	2454	14.65	2129	14.44	1882	14.21	1668	2680
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		

Table 6: Multivariate Analysis

The table presents the results from our multivariate analysis (OLS regression). Each market friction measure is regressed on the issuing firm's IPO characteristics. The dependent variable is the viciile the firm is ranked into at the end of the first year of public trading; ranking is done for each friction measure separately. Our friction measures are: the percentage of firms that are severely short-sale constrained (*SSCF*), relative short interest (*RSI*), Amihud (2002)'s illiquidity measure, Pastor and Stambaugh (2003)'s aggregate liquidity measure (*PS Liquidity*), stock's turnover rate, Hou and Moskowitz (2005)'s price delay, analysts's dispersion of opinion, number of analysts covering the stock, institutional holdings, and idiosyncratic risk from the Fama-French-Carhart's four factor model. The independent variables (the IPO features) are: the IPO's age at the time of issuance, the IPO firm's size viciile (in CRSP) as of the end of the 1st year after issuance, IPO's relative offer price, IPO's underpricing level (in %), lead underwriter's Carter-Manaster reputation ranking, IPO market's heat as measured by *HeatDegrees* variable, and VC indicator. The details about the calculation of each variable is described in the text. The coefficients' *p*-values (presented in the parantheses under each coefficient's estimate) are adjusted for heteroskedasticity and for clustering by issuing quarter. The adjusted R^2 from the regressions are also presented. The last row shows the number of IPOs in each estimation with nonmissing observations for the regressors.

Independent Variables	Dependent Variable (Friction Measures)									
	SSCF	RSI	Amihud Illiquidity	Turnover	PS Liquidity	Price Delay	Dispersion of Opinion	Number of Analysts	Institutional Holdings	Idiosyncratic Risk
Intercept	01285 (0.0001)	10.77 (0.0001)	14.15 (0.0001)	13.72 (0.0001)	13.27 (0.0001)	13.42 (0.0001)	10.14 (0.0001)	2.69 (0.0001)	3.69 (0.0001)	14.47 (0.0001)
MarketHeat	-0.0369 (0.0049)	-0.6039 (0.0010)	0.1968 (0.0471)	-0.7468 (0.0001)	0.4296 (0.0176)	0.2789 (0.0478)	-0.0648 (0.6162)	-0.4038 (0.0014)	-0.091 (0.5790)	-0.2914 (0.0081)
Underpricing	0.0008 (0.0001)	0.0110 (0.0089)	-0.0057 (0.0011)	0.0149 (0.0001)	-0.0118 (0.0001)	-0.0091 (0.0001)	0.0122 (0.0001)	0.0071 (0.0001)	-0.0100 (0.0001)	0.0204 (0.0001)
OfferPrice	0.0006 (0.7230)	0.1360 (0.0001)	-0.1927 (0.00010)	0.1017 (0.0053)	-0.2042 (0.0001)	-0.1409 (0.0001)	-0.1127 (0.0001)	-0.0101 (0.5840)	0.1290 (0.0001)	-0.2267 (0.0001)
UW Prestige	-0.0004 (0.9010)	-0.1972 (0.0001)	-0.1162 (0.0001)	-0.1865 (0.0007)	-0.2730 (0.0001)	-0.3094 (0.0001)	0.1332 (0.0745)	0.4711 (0.0001)	0.6123 (0.0001)	0.0229 (0.5902)
VC	0.0005 (0.9650)	1.2491 (0.0001)	-0.1952 (0.0207)	0.9747 (0.0001)	-0.5978 (0.0001)	-0.4173 (0.0460)	1.1003 (0.0001)	0.6327 (0.0001)	1.3648 (0.0001)	1.5560 (0.0001)
Age	-0.0014 (0.0001)	-0.0323 (0.0001)	-0.0115 (0.0001)	0.0185 (0.0033)	-0.0065 (0.0517)	0.0004 (0.9369)	-0.0175 (0.0016)	-0.0039 (0.1842)	0.0206 (0.0004)	-0.0440 (0.0001)
Size	0.0044 (0.0770)	0.4184 (0.0001)	-0.6032 (0.0001)	0.0405 (0.0880)	-0.3647 (0.0001)	-0.3325 (0.0001)	-0.1442 (0.0038)	0.5566 (0.0001)	0.2673 (0.0001)	-0.0659 (0.0035)
<i>Adj. R²</i>	0.0451	0.1569	0.5806	0.0625	0.4076	0.1751	0.0503	0.4264	0.3160	0.2413
Observations	3,562	3,788	5,381	5,310	3,058	3,629	3,160	3,912	5,135	3,629

Table 7: Summary of Our Results and the Predictions of the Quality-Based Hypothesis

The table summarizes the results for each of our friction measure–IPO feature relationship (Panel A). It also shows these same relationships as they should be according to our quality-based hypothesis (Panel B). The considered measures are: the percentage of firms that are severely short-sale constrained (as measured by Asquith, et al. (2005)’s indicator), relative short interest, illiquidity measure of Amihud (2002), aggregate liquidity measure of Pastor and Stambaugh (2003), stock’s turnover rate, Hou and Moskowitz (2005)’s price delay, analysts’s dispersion of opinion, number of analysts covering the stock, institutional holdings, and idiosyncratic risk from 4 factor model. The details about the calculation of each measure is described in the text. The IPO related variables are market heat, underpricing, offer price, underwriter prestige, and venture capital backing. “+” (“−”) indicates strong positive (negative) relationship between the measure and the IPO variable. “?” indicates that the results are mixed or not significant.

Measures	IPO Attributes				
	Market Heat	Underpricing	Rel. Offer Pr.	UW Prestige	VC Backing
Panel A: Summary of Our Results					
Short-Sale Constraint	?	+	−	?	+
Relative Short Inter.	−	−	+	+	+
Amihud Illiquidity	+	−	−	−	−
Turnover	−	+	+	+	+
PS Liquidity	+	−	−	−	−
Price Delay	+	−	−	−	−
Analysts’ Dispersion	+	+	−	?	+
Number of Analysts	−	+	+	+	+
Instit. Holdings	−	+	+	+	+
Idiosyncratic Risk	+	+	−	−	+
Panel B: Relationships as Predicted by the Quality-Based Hypothesis					
Short-Sale Constraint	+	+	−	−	−
Relative Short Inter.	−	−	+	+	+
Amihud Illiquidity	+	+	−	−	−
Turnover	−	−	+	+	+
PS Liquidity	+	+	−	−	−
Price Delay	+	+	−	−	−
Analysts’ Dispersion	+	+	−	−	−
Number of Analysts	−	−	+	+	+
Instit. Holdings	−	−	+	+	+
Idiosyncratic Risk	+	+	−	−	−

Table 8: Correlations Between The Quality Measure and Our Variables

The table presents the Spearman correlation coefficients between the quality measure (QM) and the primary- and secondary-market variables of the IPO firms. The considered primary-market variables are: the IPO market's hotness at the time of issuance (*HeatDegrees*), IPO firm's underpricing, the relative offer price of the issue, the underwriter's reputation ranking, and the indicator of presence of venture capital. The results for primary market variables are shown in *Panel A*. *Panel B* shows the results for the secondary-market friction measures. These measures are: the percentage of firms that are severely short-sales constrained (*SSCF*), relative short interest (*RSI*), Amihud's illiquidity measure (*Amihud Illiquidity*), Pastor and Stambaugh (2003)'s aggregate liquidity measure (*PS Liquidity*), stock's turnover rate, price delay, analysts' dispersion of opinion, number of analysts covering the stock, institutional holdings, and idiosyncratic risk from 4 factor model. The details about the calculation of each variable is described in the text. These variables are calculated for each firm for each of the five years after the issuance date. Then, the cross-sectional correlation between QM and each variable is taken to assess whether the strong link between the primary and the secondary variables is driven by the unobservable quality component, as predicted by our quality-based hypothesis. The rows named "*p*-values" show the significances of the coefficients. The rows named "Obs." display the number of IPO firms with nonmissing data that are used in calculating each coefficient.

Panel A: Correlation Coefficients b/w QM and the IPO Characteristics						
		HeatDegrees	Underpricing	Offer Price	Reputation	VC
	Coeff.	0.0380	-0.1151	0.3479	0.1506	-0.1749
	p-value	0.0034	0.0001	0.0001	0.0001	0.0001
	Obs.	5,929	5,518	5,929	4,362	5,929

Panel B: Correlation Coefficients b/w QM and the Market Frictions						
Friction Measures	Time After Issue Date					
		Year 1	Year 2	Year 3	Year 4	Year 5
SSCF	Coeff.	-0.1574	-0.1501	-0.1252	-0.1324	-0.1849
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	Obs.	3,528	3,214	2,826	2,482	2,358
RSI	Coeff.	-0.0967	-0.0424	-0.0365	-0.0626	-0.0735
	p-value	0.0001	0.0142	0.0488	0.0015	0.0003
	Obs.	3,465	3,351	2,918	2,559	2,417
Amihud Illiquidity	Coeff.	-0.1105	-0.1523	-0.1855	-0.1472	-0.0947
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	Obs.	4,897	4,802	4,113	3,546	3,068
PS Liquidity	Coeff.	0.0151	-0.0339	-0.0649	-0.0784	-0.0448
	p-value	0.4205	0.0315	0.0001	0.0001	0.0174
	Obs.	2,836	4,024	3,591	3,217	2,814
Turnover	Coeff.	-0.0893	-0.0535	-0.0450	-0.0804	-0.0887
	p-value	0.0001	0.0002	0.0044	0.0001	0.0001
	Obs.	4,829	4,694	4,003	3,428	2,941
Price Delay	Coeff.	-0.1209	-0.1115	-0.1357	-0.1086	-0.0840
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	Obs.	3,300	5,025	4,312	3,736	3,235
Analysts' Dispersion	Coeff.	-0.2756	-0.3006	-0.2613	-0.2875	-0.2565
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	Obs.	3,151	2,954	2,409	1,996	1,697
Number of Analysts	Coeff.	0.0231	0.1216	0.1802	0.1799	0.1664
	p-value	0.1587	0.0001	0.0001	0.0001	0.0001
	Obs.	3,724	3,545	2,939	2,449	2,070
Institutional Holdings	Coeff.	0.2286	0.2547	0.2897	0.2905	0.2653
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001
	Obs.	3,855	3,639	3,061	2,599	2,218
Idiosyncratic Risk	Coeff.	-0.5010	-0.5518	-0.5560	-0.5198	-0.4506
	p-value	0.0001	53 0.0001	0.0001	0.0001	0.0001
	Obs.	3,298	5,022	4,311	3,735	3,236