Idiosyncratic Risk, Short-Sale Constraints, and Other Market Frictions in IPO Stocks*†

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Abstract

We analyze various market frictions and risk factors in IPO stocks for up to five years after issuance. We document the differences across IPO samples sorted by market heat, underpricing level, offer price, underwriter prestige, and VC backing. Relative to cold IPOs, on average, the hot-market IPOs are facing, higher liquidity frictions, higher information constraints, and higher idiosyncratic risk. Highly underpriced IPOs are more liquid, more recognized by analysts and institutional investors, but they have higher idiosyncratic risk, and higher percentage of them are short-sale constrained. IPOs with low offer price, low reputation underwriters, and no VC backing are more likely to encounter market frictions during their post-issuance trading years.

Keywords: idiosyncratic risk, incomplete information, initial public offerings, liquidity, short-sale constraints.

JEL Classification: G12, G14, G24, G30.

1 Introduction

While the long-run return performance of IPO stocks are heavily investigated area, our knowledge and understanding about the other trading-related characteristics of IPO stocks is limited. Our study fills this gap by presenting some stylized facts about IPO stocks' trading features. Specifically, we document how post-issuance trading characteristics of IPO stocks are related to five IPO features set at or before the time of issuance: market heat, underpricing, offer price, underwriter prestige, and venture capital involvement. Do the features of an IPO firm set (or known) in the primary market affect its trading characteristics in the secondary market?

To understand and characterize a stock's trading in the secondary market, we utilize various diagnostic measures. 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 an attention to this measure by documenting that it has been increasing steadily over time for individual firms. Many studies tried to explain this trend.[1] *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 usually smaller, neglected, and more volatile than the rest of the stocks. Other widely used *attention/neglect measures* include analyst coverage, and institutional ownership. Beside the more traditional *liquidity proxies*, such as turnover and price, new ones were recently 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. *Asymmetric information*

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

measures include analyst dispersion of opinion (Diether, Malloy, and Scherbina (2002)), idiosyncratic risk (Campbell and Taksler (2005)), size, and turnover (Dierkens (1991)).

How do the stocks of recent IPO firms differ from each other with regard to these measures? IPO stocks, after all, are unique equity securities in that they are issued recently, and they belong to firms that are not well known. This aspect distinguishes them from the rest of the stock universe and provides an opportunity to analyze, comparatively, the evolution of these new stock securities over time with regard to aforementioned market frictions and risk factors. The first goal of this study, thus, 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. Studies like Eckbo and Norli (2005) have opened some headway in this area, but they narrowed their scope by concentrating only on pricing the liquidity risk and the leverage of the IPO stocks.

Second, our goal is to determine whether and how the market friction and other trading characteristics of IPO stocks sorted by various issue features differ from each other. Many studies suggest, for example, that the composition of IPO firms issued during the hot markets is different than the one issued in the cold markets (see for example Yung, Colak, and Wang (2007), Lowry, Officer, and Schwert (2006), Helwege and Liang (2004), Cook, Jarrell, and Kieschnick (2001)). If there are such cross-sectional differences among the firms depending on their issuing environment, then we should expect the unobservable differences at the time of issuance to reflect in the stocks of these firms during secondary trading. These differences will show themselves not only in the long-run performance measures 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, Krishnamurthy, and Spindt (2004)), venture- vs. non-venture backed IPOs (Brav and Gompers (1997), Lerner 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. low-prestige underwriters (Carter, Dark, and Singh (1998)).

Our notable findings are that IPO stocks in general are somewhat different than the rest of the stocks, but not that much. On average, they are smaller in size and they have higher idiosyncratic risk, which stays persistently high for the first 5 years of being public. The other trading characteristics of IPO stocks does not seem to be noticeably different than the typical CRSP firms. The fact that on average IPOs are in a higher idiosyncratic risk vicile suggests that the market does not view the IPOs to have the same firm specific risk as the average CRSP firm. Therefore, in this regard IPO stocks in general seem to be segmented from the rest of the stocks during the first few years of their public life.

Our novel and more interesting findings, however, are obtained when we compare the IPO stocks within themselves. In comparison to cold IPOs, for example, a typical hot market IPO is facing significantly higher liquidity frictions and information constraints. There is also some evidence that hot IPOs are exposed to higher idiosyncratic risk and have higher chances of being short-sale constrained.[2]

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 by high reputation investment banks vs. low reputation ones. The relationship between underpricing and our friction and risk measures seems

[2]In this study we do not aim to provide economic explainations for our findings. However, we know that hot market IPOs are infested with low-quality, younger, and smaller firms (see Yung, Colak, and Wang (2007)), which can be one of the reasons behind these findings.

to be very strong. Highly underpriced IPOs are well recognized by analysts and institutional investors. However, they have significantly higher firm-specific risk, and 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 almost all five of our classifications schemes, we find significant differences in idiosyncratic risk, short-sale constraints, and other market frictions between each class of IPOs, which suggests that many trading characteristics of IPO stocks in the secondary markets are a function of their firm quality, their period of issuance, and/or their issue features set in the primary markets.

What are the implications of these findings? Our study provides yet another angle on a series of works that analyze the underperformance of IPO stocks. If there are major differences in liquidity, short-sale constraints, market frictions, and other risk factors between various IPO categories then the long-run IPO underperformance variation among IPO stocks is not so surprising. For example, these differences may explain the discrepancies between the performance of hot market IPOs relative to cold market ones. If hot IPOs are facing more severe market frictions associated with information absorption, then their return performance will be lower.[3] Studies like Loughran and Ritter (1995) and Cook, Jarrell, and Kieschnick (2003) find results consistent with this. Helwege and Liang (2004) in comparison of wealth relatives of hot and cold IPOs find the former ones underperforming for the first few years after issuance.

Furthermore, to the best of our knowledge, we are the first study that provides indirect evidence – inferred from IPO stocks' trading characteristics – of possible clientele

[3] This is consistent with Miller (1977)'s premise that higher uncertainty associated with a stock lead to lower long-run performance.

differences among various sorts of IPO stocks.[4] Our study allows such conclusions, because we have analyzed these stocks from many different trading dimensions. We have a very comprehensive picture of these stocks, that uses several trading-related diagnostic measures. However, in this study, we sufficed in just reporting these diagnostics. So, when it comes to clientele differences, our evidence is not direct and definitive, but it sheds some light on it, and opens the road for further analysis.

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 the results from our binary (or comparative) tests. *Section 5* provides concluding remarks.

2 Analysis Development

We aim to investigate short-sale constraints, market frictions related to liquidity and information, and idiosyncratic and other risk factors in 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 IPO categories according to various features set during the IPO process.

[4] It is important to mention that the clientele we are concerned with are the investors participating in trading of these IPO stocks after the immediate, and relatively more unstable, after-issuance period. The focus is not on investors that get allocated the shares on the day of issuance, and the flipping activity that follows immediately after that, but rather we take a longer term approach and we try to understand the behavior of the IPO stock after it is somewhat seasoned. That is, the period when the quality of the firm is revealed, and the true interest in the stock is observable.

2.1 IPO Categories

To better analyze the differences between various IPO firms we classify them into subsamples 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) the involvement of venture capital.

2.1.1 Hot vs. Cold Periods

We consider hot-market (cold-market) IPOs to be those that were issued during hot (cold) quarters. To determine the hot and cold quarters, we use a classification scheme similar to the one used in Yung, Colak, and Wang (2007). Our heat measure is number of IPOs per quarter, *NumIPO* (*Figure 1* plots this measures over time.). In obtaining the time series for this measure we rely on Jay Ritter's data, because it goes back all the way to 1960. 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.[5]

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 4^{th} quarter than in the 1^{st}), we use the average number of IPOs of the current and the previous three quarters as the heat level at that particular quarter (i.e. we use simple MA(4)). We compare the quarterly observation of this MA(4) for *NumIPO* to its historic average going back to 1960. If it is 50% above (below) the historic average, the quarter is

[5] If 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.

classified as hot (cold). The remaining quarters are considered 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.

The 50% cutoff is a round number chosen to provide a reasonable separation between hot and cold periods. It also assures that all heat groups – hot, normal, and cold – have a reasonable number of quarters in them. For example, a cutoff of 10% above (below) historic average would lead to hot (cold) classification that does not sufficiently distinguish between true hotness and true coldness in a given period, and there will be disproportionately fewer quarters classified as normal under such a classification. However, to avoid any ambiguity, we also checked our results when this cutoff point is chosen to be 33%, 40%, or 60%, and our qualitative conclusions are not significantly affected. These results are available upon request from the authors.

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 offer price of the IPO. First, we

[6] One 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.

convert all the offer prices into year 2004 dollars using CPI.[7] Then, we rank the firms according to their offer price. The firms in the top (bottom) tercile are the high-offer-price (low-offer-price) sub-sample.

2.1.3 High- vs. Low-Prestige and Venture-Backed 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. 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 SEC and Ritter's data. If there is one or more venture capitalists involved with the IPO, then it is counted toward the venture-backed sub-sample. Otherwise it belongs to non-venture-backed sub-sample.

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. We review and present each constraint separately.

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

[7] CPI data is obtained from Bureau of Economic Statistics website.

we analyze how are the IPO stocks different among themselves with regard to market frictions related to short-sale constraints. These constraints could vary across IPOs. Documenting these differences will shed some light on other differences related to firm quality compositions between various IPO categories.

If the market heat, the level of underpricing, the offer price, the venture backing, and the lead underwriter's prestige of an IPO is indicative of the firm's quality and/or future performance (see *Introduction* for review of some related studies), then we should see some differences in the short-sale constraints measures across our IPO categories.

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, Loughran, Suchanek, and Yan (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. Related to this idea, we postulate that if there are more low quality firms in 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. This process is likely to last for years.

Majority of the literature, however, concentrates on all the short-sale constrained stocks, not only IPOs. Among others, Boehme, Danielsen, and Sorescu (2006), Asquith, Pathak, and Ritter (2006), Desai, Ramesh, Thiagarajan, and Balachandran (2002), and Jones and Lamonth (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, Hutton, Meulbroek, and Sloan (2001)), post-earnings announcement drift (Cao, Dhaliwal, and Kolasinski (2007)), and firm liquidity (D'Avolio (2002)).

To understand the short-sales constraints across our IPO groups, we use the method in Boehme, Danielson, and Sorescu (2006) to determine which IPOs are most likely to be affected by the short-sale constraints. 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 investors holding the shares of each IPO sub-sample are also likely to be different.

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 Pederson (2003), Amihud (2002), Brennan et al. (1998), Chordia et al. (2000), Easly et al. (2002), and Pastor and Stambaugh (2003). Specifically with regard to IPOs, Eckbo and Orli (2005) claim that liquidity is a relevant factor in IPO stocks.

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 and their clientele.

For that purpose, we use three measures of liquidity (or illiquidity) suggested by Amihud (2002), Eckbo and Orli (2005), and Pastor and Stambaugh (2003) to determine the degree of market frictions faced by the IPO classes we defined above. Amihud (2002) defines 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 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.

Most widely known market friction related to incomplete information is asymmetric information, however. It has been shown to affect variety of financial markets. Yung, et al (2007) show its effect on IPO firm composition in hot vs. cold markets. Some of the studies documenting its consequences on stock returns include Merton (1987), Hirshleifer (1988), Basak and Cuoco (1998), and Shapiro (2002).

Thus, we complement our price delay analysis with other recognition or asymmetric information related variables such as analysts dispersion of opinion, number of analysts covering the stock, and percentage of shares held by institutional investors. Although, only fraction of our sampled IPOs are covered by analysts or have institutional holdings data, we believe these measures provide auxiliary information about the degree of information constraints in various IPO classes, so we report their results.

2.3 Risk Factors and Momentum Effects in IPO Stocks

This sub-section analyzes the idiosyncratic and other risk factors faced by different classes of IPO stocks. We briefly review each factor.

2.3.1 Idiosyncratic Risk

Ever since the development of CAPM idiosyncratic risk has been a popular measure of firm-specific risk associated with holding a stock. It has been claimed that *idiosyncratic volatility (or sigma)* is an important determinant of a stocks's return. For example, Ang, Hodrick, Xing, and Zhang (2006) report a negative relation between idiosyncratic volatility and expected stock returns. Bali and Cakici (2006) find no such significant relation and Doran, Jiang, and Peterson (2007) find that it is seasonal. Campbell, et al (2001) find that this risk has increased in recent years.

Idiosyncratic risk has also been used as a measure of information asymmetry between the firm and the traders of its stock (He and Wang (1995), Campbell and Taksler (2003)), and as a market friction limiting the arbitrage (Shleifer and Vishny (1997) and Ali, Hwang, and Trombley (2003)).

Although the research on idiosyncratic volatility is aplenty, it is still unclear to what degree IPO stocks returns are affected by such firm-specific risks, and how does this effect compare to other, more seasoned, stocks. Typically, IPO firms are young and relatively unknown to investing public, which can lead to an elevated levels of firm-specific risks associated with their stocks (Fink, Fink, Grullon, and Weston (2006)). 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. The presence of IPO groups with different levels of firm-specific risk or asymmetric information risk should reflect in this measure. Thus, we use this variable to measure the cross-sectional variation in firm-specific and asymmetric information risks.

2.3.2 Market Risk

Overall (net) market exposure of a firm, as measured by its beta, has been used as a market risk measure since the invention of CAPM. It is a risk factor we need to consider when distinguishing IPO firms from the seasoned firms and within IPO stocks themselves. It is important to know whether IPO firms sorted by various pre-issuance characteristics show some variations in their exposure to the systematic risk. Although this risk is unavoidable, the degree of it can be predicted by potential investors, if indeed there are IPO characteristics that can be informative about this risk.

2.3.3 Momentum

Jegadeesh and Titman (1993) report that firms having high (low) prior three-to-twelve month returns continue to have high (low) abnormal returns over the subsequent year. In a more recent paper, Jegadeesh and Titman (2001) document that the profits to momentum strategies are robust, and continue to exist even after the publication of their first paper in 1993. They also report that post holding periods, i.e., months 13 to 60, consistently produce *negative* abnormal returns.

With regard to IPOs, Aggarwal et al. (2007) present a model in which managers strategically underprice new issues. The intentional underpricing creates information momentum concerning the new issue, resulting in higher prices at the lockup expiration. Given that average lock up expiration is within 6-months of issue, their predictions relate more to shorter-term momentum effects. Namely, the underpricing should be greater for hot IPOs than for cold ones, which can lead to a positive short-term momentum, but the momentum effects in the longer post-issue periods (1-to-5 year after issue) are unclear. Thus, our goal is to document these momentum effects in the IPO firms.

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 2004 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 10,670 common stock IPOs (i.e. we exclude REITs, closed-end funds, ADRs, unit offers, MLPs, etc.).[8] 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 9,373 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 360 firms to our sample that are not covered by the SDC data. Finally, we review Registered Offering Statistics (ROS)[9] dataset to uncover new IPOs not reported in the previous two

[8]We 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.

[9]This dataset is created by compiling the records of the Securities and Exchange Commission (SEC) from January 1970 through December 1988 in regards to the effective registrations of domestic business and foreign government securities under the Securities Act of 1933.

sources. We find 150 such firms. Thus, our combined initial sample is 9,883 IPOs.

In some instances CRSP does not immediately start recording the trading of a new public firm.[10] In extreme cases, the gap between the issue day and the day a stock's trading information is available can be more than a year. In those instances we require a minimum of 20 weeks of available returns data in order to calculate the price delay, idiosyncratic volatility, or the coefficients of the four Fama-French-Carhart factors. Otherwise we drop the firm from the sample when we calculate those particular measures.

The IPO data items we retrieve from SDC, Ritter, and ROS datafiles are the CUSIP of the new public firm, the date of the issue, its offer price, its lead underwriter's name, its age at the time of issuance, the percentage change in its stock's price on the first trading day (i.e. the underpricing), and the venture capital involvement. The daily 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 downloaded from the websites of these exchanges.[11] 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 our remaining sample sizes used in the tests.

[10] For example, CRSP NASDAQ only begins reporting returns in December, 1972.

[11] We thank Bartley Danielsen for this data.

3.2 Descriptive Statistics of the Sample

Table 1 describes various features of the IPO sample across our five different sorting 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, issue's offer price, the level of underpricing, issue's lead underwriter's prestige, and new issue's buy-and-hold abnormal return (BHAR) during the first 12 months of trading.[12]

These characteristics show significant differences when compared across various sorting groups. Notable observations from the table are: 1) hot IPO firms are, on average, younger, smaller, more underpriced, and deliver much lower 12-month returns than cold IPOs; 2) highly underpriced group of IPOs are younger, bigger, with higher offering price, and more poorly performing during the first 12-month of trading than less underpriced IPOs; 3) high offer price issues are older, much bigger, more underpriced, with more reputable underwriters, and better investment in the first 12-month of trading than the low offer price issues; 4) firms with more reputable underwriters are older, bigger, with much higher offer price, more underpriced, and better return performers than the firms underwritten by low reputation investment banks; 5) venture capital (VC) backed IPOs are younger, older, with high issue price, more highly underpriced, issued by higher reputation underwriter, and have higher 12-month BHAR return than non-VC backed IPOs.

[12] We define buy-and-hold return (BHAR) as

$$BHAR_{i,12} = \prod_{t=1}^{12}(1+R_{i,t}) - \prod_{t=1}^{12}(1+R_{m,t})\,. \tag{1}$$

$R_{i,t}$ represents firm i's stock return (including dividends) for the month t. $R_{m,t}$ is the return on the CRSP equally-weighted market index (including dividends) for the same month.

3.3 The Variables

In this sub-section we describe the measures that characterize the market frictions and risk factors associated with public trading in stocks. The variables we use are: Amihud (2002)'s illiquidity factor, analysts' dispersion of opinion, idiosyncratic risk, institutional ownership, market risk, momentum, Pastor and Stambaugh (2003)'s liquidity measure, Hou and Moskowitz (2005)'s price delay (size orthogonalized), relative short interest, short-sale constraints measure, size, and turnover. We describe each one separately.

Amihud (2002) Illiquidity Measure

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:[13]

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

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, Malloy, and Scherbina (2002).

[13]Obviously, 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.

Due to nonstationarity and skewness, each calendar month we sort the dispersion into twenty categories or viciles. Firms having a forecast mean of zero are assigned to the highest vicile. We report only the ranked (in viciles for all CRSP firms) version of this variable. This database begins recording the analyst forecasts starting in January 1976.

Diether, Malloy, and Scherbina (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.

Idiosyncratic Risk

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

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + u_i UMD_t + \epsilon_{it} \tag{3}$$

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.[14]

For each month, the idiosyncratic risk (*sigma*) is computed over the prior 52 weeks (weekly return is defined as the holding period return of Thursday through Wednesday). Then, for each month, firms in CRSP are sorted into twenty categories or viciles according to their *sigma*. We use the vicile rankings at the end of each event period (one year after issuance, two years after issuance, etc.).

[14]The construction of these factors is discussed in detail in Fama-French (1993) and in Carhart (1997).

Institutional Ownership

The Institutional Ownership 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. This data item is available for the period after 1988.

Market Risk (or Beta)

Using *Equation (3)*, we estimate each firm's systematic risk, β_i, and then sort all betas into viciles in such a fashion that firms with highest beta go to the first vicile, and so on. Thus, the four-factor β_i estimate is our measure of market risk.

Momentum

For each firm in CRSP we calculate the raw holding period return over the prior twelve month period with monthly compounding. Next, we rank them into twenty groups (or viciles) according to their return, with 20^{th} vicile and 1^{st} vicile being the highest and lowest momentum groups, respectively. The missing returns are replaced with CRSP value-weighted index's returns. We start measuring an IPO firm's momentum after 12 complete calendar months of market listing.

Pastor and Stambaugh (2003)'s Return Reversal Measure

Pastor and Stambaugh (2003)'s liquidity measure (briefly PS liquidity 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:

$$R^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} R_{i,d,t} + \gamma_{i,t}[sign(R^e_{i,d,t}) \cdot \nu_{i,d,t}] + \epsilon_{i,d+1,t}, \qquad d = 1, \ldots, D, \tag{4}$$

where $R_{i,d,t}$ is the return on stock i on day d of the month t; $R^e_{i,d,t} = R_{i,d,t} - R_{m,d,t}$, 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.

Price Delay

We employ the market friction metric developed by Hou and Moskowitz (2005). They use 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:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \delta_{i,t-1} R_{m,t-1} + \delta_{i,t-2} R_{m,t-2} + \delta_{i,t-3} R_{m,t-3} + \delta_{i,t-4} R_{m,t-4} + \epsilon_{i,t}. \tag{5}$$

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:

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

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.

We orthogonalize this delay variable with size to eliminate any size effects that might be driving our results. For each calendar month, we estimate a cross-sectional regression of each firm's delay vicile on the size vicile. We then sort the regression residuals into viciles, with viciles 1 and 20 representing the lowest and highest orthogonalized delay viciles, respectively.

Relative Short Interest

The Relative Short Interest (*rsi*) is measured each month as the short interest (as reported by the NYSE or Nasdaq, beginning with January 1988) divided by the number of outstanding shares reported by CRSP. This variable is a proxy for the demand for shorting the stock, as well as asymmetric information. When this variables is extremely high for a stock (e.g. top vicile) it is indicative of poor subsequent stock performance i.e. low IPO quality (see Desai et. al. (2002), Boehme et. al. (2006), and Gopalan (2003)).

Short-Sale Constraint Friction (SSCF) Measure

Boehme, Danielson, and Sorescu (2006) document that either short-sale constraints or analyst earnings forecast dispersion of opinion, are separately insufficient to induce the Miller (1977) overvaluation. However, they do find that firms in the highest quartiles of both their (unitary) constraint and (unitary) dispersion proxies are strongly affected by the market frictions that induce the Miller (1977) overvaluation. Firms that are not included within this intersection of the highest quartiles of these two measures generally do not experience overvaluation. This latter result is intuitive, as firms that are difficult to short should not experience systematic misvaluation, if market participants do not possess large levels of disagreement concerning the stock's actual value.

Thus, following Boehme et al. (2006), we classify our IPO firms as being subject to the short-sale constraint market friction by using the interaction of two variables: a proxy for shorting demand (the short interest) and a proxy for heterogeneity in investor beliefs (the analysts' dispersion of opinion; when not available we use projected value as calculated in Boehme, at al. (2006)). A firm is short-sale constrained, if it is contained in the top quartile of each measure. Our SSCF measure can be calculated only after 1988, because that is when short interest data becomes electronically available.

Size

Size can also be used as attention variable: the smaller the firm, the less attention it gets from investors. We define size as market capitalization of the firm as of the end of each period specified in the analysis.

Turnover

The Volume of Trade (*turnover*) is used as liquidity measure or as information asymmetry 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. Trading volume for Nasdaq listed firms is unavailable before November 1982.

4 Results

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

4.1 IPOs vs. CRSP Firms

Are IPO firms' stocks systematically different than the seasoned firms with regard to liquidity constraints, information frictions, and risk factors? Most of our measures used in this study are pre-ranked into viciles using all the CRSP firms, where the firms with average observation of that particular measure are placed in viciles 10 and 11.[15] 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*). With regard to our vicile ranked liquidity measures (Amihud's illiquidity and turnover), our sampled IPOs' average vicile is 1 to 2 viciles above or below the typical CRSP firms. Similarly, our IPOs' average information constraint measures are almost always within half-a-vicile away from the 10^{th} or 11^{th} viciles. Finally, with regard to

[15]All the other variables that are not ranked into viciles are included in the table for descriptive purposes only.

two of our risk factors – market risk (or beta) and momentum risk – our IPOs are again not very different from seasoned firms. Only two of the vicile-ranked variables presented in the table show some visible deviations from the typical CRSP firm. Our IPOs are in a noticeably lower size vicile, and their average idiosyncratic risk vicile is somewhat higher than the other publicly trading firms. It is not surprising that new public firms have much smaller market capitalization than the seasoned public firms. Idiosyncratic risk difference is likely driven by their smaller relative size.

4.2 Short-Sale Constraints Across IPO Groups

As explained above, we divide our IPO sample into groups using the five classification variables described earlier. In this section our raw IPO sample between 1988 and 2004 is reduced to 6,172, because relative-short interest variable used to calculate our SSCF measure is not available before 1988. Then, we calculate our short-sale constraints friction (SSCF) measure for six post-IPO periods: 6-months, 1-year, 2-years, 3-years, 4-years, and 5-years.[16] This 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 used to obtain the results in this section.

4.2.1 Relationship Between Short-Sale Constraints and Market Heat

First, each quarter in the period between 1970 and 2004 is classified as hot, cold, and normal using the criteria described in Section 2.1, except here we use the $\pm 25\%$ cutoff

[16]We do not use periods shorter than 6 months, because those periods usually involve a lot of other constraints on IPO stock trading, such as lock-up periods. We use total of 6 post-IPO periods to get a sense of the changes in IPO stock's condition as the time progresses.

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 subsample 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 some weak evidence that hot IPOs are more likely to be short-sale constrained than cold ones for Years 1 and 2 (The rows named "Prob." in the table show the probability statistics from the nonparametric Wilcoxon test of equality of *SSCF Percentages* aross Hot and Cold IPO groups). The *SSCF Percentage* stays relatively steady between 5.68% and 8.85% over the years for both hot and cold sub-samples.

4.2.2 Relationship Between Short-Sale Constraints and Underpricing

From our SSCF sample of 6,172 we drop the observations for which we have no underpricing information, which leaves us with a sample of 4,324 IPOs. Then, we rank them into terciles according to their underpricing level in hopes of searching for accurate signals about future market characteristics of IPOs by looking into their first day returns.[17] Highest (lowest) ones are in "High" ("Low") tercile.[18] *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 higher than the one

[17]Krigman, Shaw, and Womack (1999) find that highly undepriced IPOs have the lower long-run returns, for example.

[18]We do the ranking into terciles after eliminating the missing observations, because we want 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.

for the "Low" underpricing tercile. This effect is more pronounced during earlier years: difference between *SSCF Percentages* across underpricing groups is significant at 1% significance level for up to Year 2 and at 10% level for Years 3 and 4 using nonparametric Wilcoxon test.

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.[19]

In this study we are limiting ourselves to merely documenting this result for the first time in the literature – to the best of our knowledge. We have no economic explanation to what causes first day returns to be positively related to the future short-sale constraint likelihood of an IPO. However, the implications of such a finding is that the highly underpriced IPOs are short-sale constrained – and thus overvalued – during their earlier years, which leads to their return underperformance in the long-run as these constraints unwind down.

4.2.3 Relationship Between Short-Sale Constraints and Offer Price

Again, we rank our 6,172 IPOs into terciles according to their offer price. The ones with highest (lowest) 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 SSCF from Year 2 onward. At Year 3, for example, a typical low-offer priced IPO has approximately 50% higher chances of facing SSCF than the high-priced

[19]To 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.

one (11.65% vs. 6.97%). Appearently investors have difficulty shorting "penny stocks," because of low supply of loanable shares from institutions. Another notable result here is that *SSCF Percentage* increases with time, especially for "Low" tercile (from 6.49% to 11.65%). Thus, we conclude an IPOs offer price is negatively related to its probability of becoming severly short-sale constrained in the later years.[20] An interesting caveat: it appears that high priced IPOs are more likely to be SSCF during the first six months, but later on their constraints are aleviated.

4.2.4 Relationship Between Short-Sale Constraints and Underwriter Prestige

Of our 6,172 IPOs sample, only 4,318 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. Except, for the 6-month post-IPO period (where IPOs issued by highly prestigious lead underwriters are more likely to be SSCF!), it appears that there are no significant SSCF differences between the IPOs classified using this criteria. Thus, 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 8,957 IPOs in our original sample. Only 6,017 of them have nonmissing SSCF for at least one of our six post-IPO periods. As shown in *Table 3*, of the 2,284 VC supported IPOs 4% to 10% of them are SSCF during the first 5 years of public trading. The *SSCF Percentage* for VC backed IPOs

[20] Again, our unreported regression results from a simple logistic regressions predicting the likelihood of an IPO being a SSCF at Year 2 confirm that offer price has a significantly positive coefficient estimate.

is steadily declining with years, but the same statistics for non-VC backed ones stays roughly the same.[21] However, the most interesting result in this section is that VC backed IPOs have significantly higher probability of being SSCF when compared to non-VC backed ones! We do not have an explanation for this result, but it appears to be very pronounced across the years. To the degree that SSCF can be associated with IPO stock's risk, it probably indicates that some of the VC backed IPOs are quite risky and end up struggling after VC's support is pulled. It does not, however, indicate that VC backed IPOs are on average lower quality stocks, but rather that the left-tail of the quality distribution of VC backed IPOs (which is what SSCF captures) is thicker.

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

4.3 Liquidity Constraints Across IPO Groups

In this subsection we report the differences in our liquidity measures (Amihud (2002)'s illiquidity, stock's turnover rate, and Pastor and Stambaugh (2005)'s aggregate liquidity) across various IPO classes using a sample of 6,965 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 related frictions. One exception is for the Year 1 for the

[21] This result is likely contaminated by the survivorship bias, but eliminating the IPOs that did not survive for 5 years after the issue date would also bias our results towards high-quality IPOs. Most of the IPOs that did not survive for 5 years are those that failed to meet exchange requirements. That is they are low quality ones, and thus more likely candidates for being severely short-sale constrained.

turnover measure, which shows that in hot markets IPOs are more heavily traded early on (turnover is significantly higher for hot period). However, in the later years (probably after the issue's hotness resides) 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. Evidently underpricing attracts more trading in the stock. The results for offer price, prestige, and VC backing are as expected: higher offer price, better underwriter, and VC backing alleviate the future liquidity frictions of an IPO (see *Panels C-E*).

Our results for liquidity constraints reported in this section are quite strong and consistent. Almost all of them point to the same direction, and are significant at 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 7,054 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, and degree of institutional involvement in the trading of the stock. Each of these measures capture different aspects of information related frictions, thus they are helpful in obtaining the "big picture" about information constraints in general. In this section, we will also use the results about the idiosyncratic risk measure (originally presented in *Table 6*), because there are some studies that use this measure as an indicator of asymmetric information associated with a stock (see Campbell and

Taksler (2003)).[22]

4.4.1 Price Delay

According to *Table 5, Panel A* results 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 is in total support of Yung, Colak, and Wang (2007)'s findings of more bad IPO 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 Institutional Holdings

Although the information about these variables is lacking for majority of our IPOs, we believe analyzing these measures of asymmetric or 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. asymmetric information) is higher for hot IPOs; number of analysts covering the hot IPOs' stocks (i.e. information generation) is, on

[22]Size and turnover can also provide some insights about the information related frictions of a stock. The tests about size differences from *Table 1*, and turnover differences from *Table 4* also confirm our findings.

average, less than for cold IPOs; and institutions are more heavily involved with cold IPOs, again on average. Thus, the higher the market heat the greater the chances of facing information related frictions later on.

Similarly, under offer price, underwriter prestige, and VC backing classifications (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 less asymetric information. 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 from underwriter prestige–analysts' dispersion of opinion pair.

The tests across underpricing categories (shown in *Panel B*) are puzzling, however. High underpricing draws more analysts coverage and institutional investment, but there is a weak evidence that it also leads to higher asymmetric information (or dispersion of opinion). This result is also supported by idiosyncratic risk measure presented in *Table 6*. High underpricing again is associated with high asymmetric information, as captured by the idiosyncratic risk of a stock. Thus, underpricing helps generation of new information about the stock, but it also creates more disagreement about it. Such disagreement also reflects in the higher turnover of such IPO stocks, as documented earlier.

In short, underpricing creates more liquidity, more information generation by analysts and institutional investors, but it also increases the asymmetric information, 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 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. Our interpretation of these results is as follows. VC backing increases the stock's 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 illiquidity and PS' aggregate liquidity). However, apparently, such VC backing also increases the asymmetric information around the stock! VC backed stocks are also more likely to be severely short-sale constrained as reported in our *Table 2*.

4.5 Risk Factors and Momentum Effects Across IPO Groups

Table 6 presents the results for this subsection. In obtaining these results we can use 7,408 IPOs with nonmissing data for at least one of our measure-year grids.

4.5.1 Results for Idiosyncratic Risk

There is some weak evidence that IPOs issued in hot markets have higher firm-specific risk (in *Table 6, Panel A* the differences in vicile means of hot and cold IPOs is significant at 10% level for Years 1 and 2).

The results for other classification schemes is much more significant: for all the years and across all the groups the differences are significant at less than 1% level! Idiosyncratic risk associated with an IPO firm is likeley 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 negative relation between underpricing and idiosyncratic risk is worth noting here. Appearently, the factors (such as, not enough information) causing an issue to be underpriced are also captured by its idiosyncratic risk. The result of high firm-specific risk associated with VC backed IPOs is surprising to us! At this stage we will suffice with just reporting the result and leave the explanation for a more detailed study that concentrates only on VC backed analysis.

4.5.2 Results for Market Risk

The results for differences in beta coefficient estimates from 4-factor Fama-French-Carhart model are in general complementary to the above results of idiosyncratic risk. On average, IPOs that have high offer price and high underwriter prestige, and are issued in colder periods are in a higher beta-vicile, suggesting that they are more synchronized with the market. These results are as expected: they are symmetrical to our idiosyncratic findings above. However, the results for underpricing and VC backing classifications are again unexpected, because they suggest that the same group of firms (high underpricing and VC backed) have high betas and have, also, high idiosyncratic risk!

4.5.3 Momentum Results

When we compare the Jagadeesh and Titman (1993) type of momentum effects across our IPO categories, we find that, on average, IPOs that have prestigious underwriter, low underpricing, and high offer price exhibit higher momentum. The momentum results across heat and VC groups are mixed and inconclusive.

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

5 Conclusion

We have analyzed liquidity, incomplete information, and short-sale constraints in IPO stocks, as well as, their exposure to momentum effects, and idiosyncratic and market risks. With regard to these trading characteristics we compared the IPO stocks among themselves when sorted across various categories formed according to market heat, issue price, underpricing level, underwriter prestige, and venture backing.

In this regard, for the first time in the literature we provide a comprehensive picture about post-issue trading features of IPO stock categories. We find that, on average, hot IPOs are facing higher market frictions, deeper asymmetric information problems, higher illiquidity hurdles, and lower recognition benefits than cold IPOs.

Further, we document that an IPO's first-day return is positively related to the asymmetric information and the shorting friction it will face in the future months and years. Underpricing improves an IPO stock's trading liquidity and investor recognition, however. An IPOs pre-issue features, such as its choice of underwriter, its offer price, and its involvement with venture capital, are also important determinants of its future exposure to various risks and frictions.

The implications of our findings can be consequential. First, higher market frictions and asymmetric information associated with IPOs that are issued in hot markets (or IPOs that have low offer price, high underpricing, low prestige underwriter, or no VC backing) are likely to drive up the expected stock returns required by the investors in these stocks, which can explain their long-run underperformance with regard to the other categories of IPO stocks.

Second implication is that these stocks will likely attract different clientele of investors. Stocks with different risk structure and different market-trading frictions have appeal to their own kind of investors. Thus, while not a definitive and a direct proof, our results suggest that the composition of participating investors 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 tolerance for idiosyncratic, momentum, and market risks. They are also likely to be different in their willingness to circumvent frictions related to illiquidity, incomplete information, and short-sale constraints.

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 the relationship between an IPO stock's underpricing, its risks, and its trading frictions are so strongly related? Our focus has mostly been at obtaining the bigger picture about differences in various IPO classes with regard to post-issue trading diagnostics. In such, our study avoided providing conclusive explanations to these differences, and instead sufficed in documenting these findings, and relating them to the existing literature.

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Figure 1: The Heat Measure Over Time

Number of IPOs per Quarter b/w 1970 and 2004

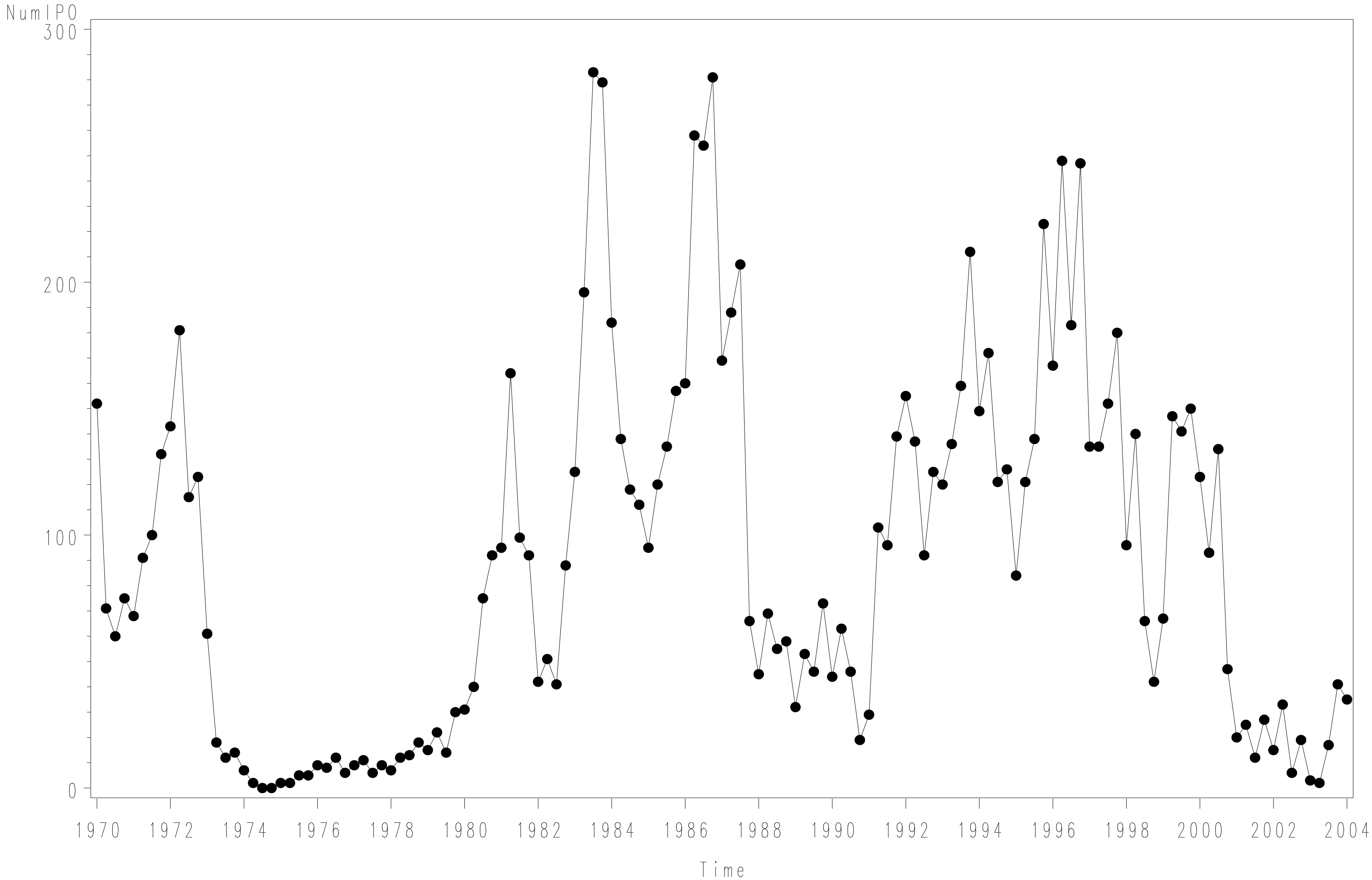

Table 1: Descriptive Statistics of the IPO Sample

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 as of the end of the 1^{st} month after issuance, IPO's offer price (in year 2004 dollars), IPO's underpricing level (in %), lead underwriter's Carter-Manaster reputation ranking or prestige, and IPO's 12-month 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 item "Prob." presents the probabilities that the test statistics of the nonparametric Wilcoxon two-sample test (equality of the means across the groups) are greater than their corresponding critical values ($Prob$ of $Z > |Z_a|$). 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.

Sorting Variable	IPO Categ.	**IPO Characteristics**												Num. of IPOs
		Age		**Size**		**Offer Price**		**Underpricing**		**UW Prestige**		**12-mo BHAR**		
		Numb.	Obs.	Vicile	Obs.	$	Obs.	Perc.	Obs.	Numb.	Obs.	Perc.	Obs.	
Market Heat	All	2.15	7085	3.87	7774	19.08	8978	16.31	7238	6.31	6744	-5.47	8177	8979
	Cold	2.38	683	4.32	756	21.95	856	11.26	721	6.87	615	+7.27	781	856
	Hot	2.12	5487	3.60	6022	18.41	6915	15.01	5584	6.18	5256	-10.54	6362	6916
	Prob.	0.0001		0.0001		0.0001		0.0018		0.0001		0.0001		
Underpricing Level	All	2.13	4553	4.49	4772	15.00	5051	23.35	5051	6.54	4141	-5.37	4935	5051
	Low	2.24	1466	3.23	1552	14.02	1684	-2.52	1684	6.39	1397	-4.61	1640	1684
	High	1.95	1548	6.09	1624	15.56	1684	61.65	1684	6.62	1384	-9.29	1649	1684
	Prob.	0.0001		0.0001		0.0001		0.0001		0.1635		0.0001		
Offer Price	All	2.14	7085	3.87	7773	19.08	8978	16.31	7238	6.31	6744	-5.47	8177	8978
	Low	1.85	2268	1.78	2746	7.73	2994	11.83	2457	4.23	2548	-11.93	2824	2994
	High	2.38	2058	6.13	2200	33.96	2993	20.18	2088	7.82	1773	-2.05	2444	2993
	Prob.	0.0001		0.0001		0.0001		0.0034		0.0001		0.0001		
Underwriter Prestige	All	2.11	5908	3.62	6328	15.61	6744	15.64	5980	6.31	6744	-5.78	6744	6744
	Low	1.69	1330	1.25	1722	8.28	1827	12.51	1554	2.60	1827	-13.04	1827	1827
	High	2.28	3024	5.47	3001	18.92	3218	20.70	2923	8.51	3218	-0.33	3218	3218
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		0.0001		
Venture Backing	All	2.14	7023	3.88	7500	16.93	8075	16.43	7019	6.32	6673	-5.29	8074	8075
	No	2.23	4423	3.33	4819	16.89	5338	11.49	4518	5.87	4391	-7.24	5337	5338
	Yes	1.98	2600	4.86	2681	17.02	2737	25.35	2501	7.19	2282	-1.50	2737	2737
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		0.0130		

Table 2: IPO vs. CRSP Firms Over Time

The table presents our market friction measures and our risk factors for 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 Boehme, Danielsen, and Sorescu (2006)'s indicator), illiquidity measure of Amihud (2002), aggregate liquidity measure of Pastor and Stambaugh (2003), stock's turnover rate, price delay (size orthogonalized), analysts's dispersion of opinion, number of analysts covering the stock, relative short interest, institutional holdings, idiosyncratic risk from 4 factor model, market risk (beta coefficient from 4 factor model). The details about the calculation of each measure is described in the text. These variables are calculated for each IPO firm separately, and whenever possible their mean is presented in two formats: the average of the continuous values for each IPO as they are calculated according to the appropriate formula, and the ranked (in viciles) version relative to the firms in the CRSP universe. The results for 6-months, Year 1-Year 5 (exactly n months or year(s) after the day of issuance) are shown. The rows named "N of obs." displays the number of IPO firms used in calculating the mean of each variable with nonmissing value for that period.

		Time After Issue Date					
Variables	Type	6-mo	Year 1	Year 2	Year 3	Year 4	Year 5
Size	vicile	3.7333	3.5609	3.4975	3.5749	3.6546	3.7267
	N of obs.	8029	8091	7309	6459	5678	4961
Short-Sale Const.	percent	8.4379	8.3963	9.1837	8.7490	8.3333	7.3300
(in %)	N of obs.	4319	4371	4214	3589	3036	2824
Illiquidity	vicile	N/A	10.6287	11.2532	11.3701	11.3107	11.2558
(Amihud)	contin.	N/A	3.3601	8.2667	12.1473	14.7357	16.3552
	N of obs.		6965	6581	5858	5163	4516
Liquidity x10^5	contin.	N/A	0.3489	0.7956	1.6078	2.4471	2.5276
(Pastor&Stamb.)	N of obs.	N/A	4009	5882	5387	4882	4369
Turnover	vicile	N/A	12.3259	11.6193	11.5772	11.4896	11.4682
	N of obs.	N/A	6851	6391	5664	4937	4287
Price Delay	vicile	8.7500	9.3768	9.9987	10.2382	10.0881	10.0195
(orthogonalized)	contin.	0.5418	0.5247	0.5628	0.5758	0.5564	0.5498
	N of obs.	4	4700	7054	6280	5562	4869
Analyst Dispers.	vicile	9.8385	10.3557	11.0674	11.5244	11.5769	11.4144
	N of obs.	3369	3852	3592	3101	2529	2133
Number of	number	3.3612	4.1327	5.1712	5.7459	6.2060	6.5326
Analysts	N of obs.	3369	3852	3592	3101	2529	2133
Short Interest	vicile	10.2445	10.7912	11.1074	11.1933	11.3090	11.1795
	N of obs.	4532	4597	4480	3849	3285	3098
Institutional	vicile	9.4898	9.9793	10.1348	10.3283	10.5646	10.7986
Holdings	contin.	0.2229	0.2513	0.2669	0.2781	0.2879	0.2941
	N of obs.	4367	4533	4586	4009	3507	3322
Idiosyncratic	vicile	15.7500	13.4893	13.4812	12.4484	13.2660	13.1353
Risk	contin.	0.0753	0.0844	0.0877	0.0897	0.0882	0.0873
	N of obs.	4	4703	7074	6300	5579	4878
Market Risk	vicile	8.0000	11.8159	11.0785	11.1473	11.1455	11.2050
(beta)	contin.	0.5007	1.1535	1.0141	1.0130	1.0174	1.0136
	N of obs.	4	4703	7074	6300	5579	4878
Momentum	vicile	9.3333	9.5563	9.1742	9.6781	9.9152	9.7230
	N of obs.	3	7408	7097	6284	5564	4874

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*). Our short-sales constraint measure is described in the text. The IPOs are grouped 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 results for 6-months, 1-year, 2-years, 3-years, 4-years, and 5-years after the IPO date are presented. The firms for which we can not calculate our short-sale constraint measure for at least one of these post-IPO periods are not included in the sample used to obtain this table's results. The item "Prob." presents the probabilities that the test statistics of the nonparametric Wilcoxon two-sample test (equality of the percentages across the groups) are greater than their corresponding critical values ($Prob$ of $Z > |Z_a|$). 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.

Sorting Variable	IPO Categ.	**Time After Issue Date** 6 Months Perc.	6 Months Num.	Year 1 Perc.	Year 1 Num.	Year 2 Perc.	Year 2 Num.	Year 3 Perc.	Year 3 Num.	Year 4 Perc.	Year 4 Num.	Year 5 Perc.	Year 5 Num.	Num. of IPOs
Market Heat	Cold	6.50%	492	5.68%	458	5.88%	408	6.53%	383	6.74%	356	8.43%	332	565
	Hot	6.75%	3501	7.84%	3608	8.68%	3581	8.85%	3051	8.22%	2676	7.51%	2504	4981
	Prob.	0.8442		0.0993		0.0532		0.1264		0.3350		0.5502		
Underpricing Level	Low	3.02%	1320	4.19%	1125	5.35%	1146	5.97%	963	5.08%	827	3.91%	702	1457
	High	16.35%	1093	13.99%	1301	11.83%	1179	7.17%	879	5.22%	624	3.06%	505	1437
	Prob.	0.0001		0.0001		0.0001		0.0588		0.0567		0.7138		
Offer Price	Low	6.49%	1464	8.41%	1511	10.80%	1408	11.65	1142	8.39%	1025	9.26%	1139	2055
	High	9.71%	1442	9.17%	1461	8.63%	1484	6.97	1320	6.68%	1093	6.23%	918	2057
	Prob.	0.0015		0.4604		0.0486		0.0001		0.0350		0.0100		
Underwriter Prestige	Low	5.03%	789	6.62%	817	6.96%	776	6.62%	641	4.27%	588	3.94%	547	1193
	High	8.13%	2207	7.51%	2211	7.40%	2114	5.57%	1793	4.29%	1410	3.70%	1258	2730
	Prob.	0.0428		0.7390		0.3622		0.1043		0.7828		0.6884		
Venture Backing	No	3.67%	2626	4.42%	2701	4.74%	2648	4.47%	2326	3.80%	1999	3.32%	1852	3733
	Yes	10.38%	1891	9.37%	1876	9.59%	1757	6.87%	1430	5.12%	1155	4.12%	1062	2284
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0029		0.0334		

Table 4: Liquidity Constraints in IPO Stocks

The table shows three liquidity measures across IPO categories sorted by market heat, underpricing, 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 viciles using all the CRSP firms, except for PS aggregate liquidity measure, which is the actual calculated value. 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 item "Prob." is the probability that the test statistics of the nonparametric Wilcoxon two-sample test (equality of the means) is greater than its critical value ($Prob$ of $Z > |Z_a|$). 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 Mean	Year 1 Num.	Year 2 Mean	Year 2 Num.	Year 3 Mean	Year 3 Num.	Year 4 Mean	Year 4 Num.	Year 5 Mean	Year 5 Num.	Total Numb.
		Panel A: Sorting According to Market Heat										
Amih. Illiq.	Cold	10.19	232	9.12	159	9.16	119	9.62	103	9.91	85	317
	Hot	11.19	4903	11.59	4732	11.56	4172	11.48	3662	11.45	3186	5265
	Prob.	0.0002		0.0001		0.0001		0.0004		0.0097		
Turnover	Cold	11.17	230	12.57	156	13.05	108	13.11	95	12.49	79	310
	Hot	11.97	4803	11.33	4606	11.46	4034	11.36	3493	11.27	3011	5208
	Prob.	0.0113		0.0064		0.0055		0.0039		0.0633		
PS Liquid. ($x10^5$)	Cold	0.20	147	1.09	223	0.36	155	0.81	99	0.76	76	442
	Hot	0.44	2683	0.97	4040	1.49	3808	2.32	3440	2.98	3060	6121
	Prob.	0.1623		0.1254		0.0001		0.0060		0.0106		
		Panel B: Sorting According to Underpricing Level										
Amih. Illiq.	Low	11.65	1550	11.88	1334	11.84	1160	11.74	1022	11.71	887	1563
	High	8.83	1553	9.89	1375	10.36	1155	10.36	990	10.25	851	1570
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Turnover	Low	11.47	1536	10.90	1312	11.15	1130	11.24	989	11.02	856	1556
	High	14.34	1553	13.54	1368	12.95	1147	12.91	983	12.94	842	1569
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
PS Liquid. ($x10^5$)	Low	0.55	1013	0.85	1346	2.38	1147	1.27	1016	3.64	889	1684
	High	0.19	1090	0.59	1425	1.61	1222	1.07	1021	1.66	886	1684
	Prob.	0.0001		0.0001		0.0013		0.0535		0.0001		

– **Continued on next page** –

Table 4 – Continued from previous page –

Liquidity Measure	IPO Categ.	Year 1 Mean	Year 1 Num.	Year 2 Mean	Year 2 Num.	Year 3 Mean	Year 3 Num.	Year 4 Mean	Year 4 Num.	Year 5 Mean	Year 5 Num.	Total Numb.
Panel C: Sorting According to Offer Price												
Amih. Illiq.	Low	13.24	2284	14.06	2110	13.96	1782	13.67	1550	13.40	1321	2551
	High	7.99	2215	8.73	2242	9.08	2089	9.26	1900	9.37	1709	2552
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Turnover	Low	11.96	2238	11.11	2038	11.22	1718	10.99	1479	11.06	1260	2518
	High	12.72	2188	12.18	2178	12.07	2027	12.03	1815	11.94	1625	2518
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
PS Liquid. ($x10^5$)	Low	0.90	1280	2.18	1840	3.04	1602	3.62	1418	3.36	1254	2994
	High	0.03	1028	-0.01	1651	0.95	1630	2.12	1550	0.79	1452	2993
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Panel D: Sorting According to Underwriter Prestige												
Amih. Illiq.	Low	13.63	1465	14.56	1399	14.51	1189	14.25	1046	14.09	881	1827
	High	8.90	2857	9.27	2590	9.56	2296	9.62	2006	9.65	1753	3218
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Turnover	Low	12.24	1636	11.22	1331	11.12	1137	10.67	988	10.89	824	1636
	High	12.85	2926	12.32	2577	12.15	2281	12.16	1976	12.05	1727	2926
	Prob.	0.0002		0.0001		0.0001		0.0001		0.0001		
PS Liquid. ($x10^5$)	Low	1.34	623	3.05	954	3.96	868	5.19	792	5.29	722	1827
	High	0.09	1926	0.25	2634	0.78	2342	0.87	2092	1.93	1843	3218
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Panel E: Sorting According to VC Backing												
Amih. Illiq.	No	11.06	4334	11.84	4110	11.92	3589	11.96	3132	12.01	2722	5338
	Yes	9.89	2461	10.06	2255	10.15	2018	9.88	1788	9.65	1573	2737
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Turnover	No	11.90	4242	10.87	3966	10.74	3452	10.36	2985	10.30	2566	4623
	Yes	13.09	2444	13.02	2231	13.14	2002	13.52	1760	13.53	1550	2598
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
PS Liquid. ($x10^5$)	No	0.47	2327	1.08	3535	2.04	3270	2.54	2938	3.63	2596	5338
	Yes	0.16	1593	0.49	2178	0.74	1945	1.43	1766	1.74	1593	2737
	Prob.	0.2360		0.0001		0.0008		0.0002		0.0001		

Table 5: Information Constraints in IPO Stocks

The table presents several measures of information constraints for our IPO categories sorted by market heat, underpricing, 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 (size orthogonalized), analysts's dispersion of opinion, number of analysts covering the stock, and institutional holdings. These variables are calculated for each firm in CRSP (IPO and seasoned) for each period separately. Then, in each period they are sorted into viciles using all the CRSP firms. The *mean* vicile for each IPO category are presented for Year 1 through Year 5, except for Number of Analysts measure, which is the actual number of analysts. The classification procedures applied to separate the IPOs in our sample into categories are detailed in the text. The item "Prob." is the probability that the test statistics of the nonparametric Wilcoxon two-sample test (equality of the means) is greater than its critical value ($Prob$ of $Z > |Z_a|$). 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.	Year 1 Mean	Year 1 Num.	Year 2 Mean	Year 2 Num.	Year 3 Mean	Year 3 Num.	Year 4 Mean	Year 4 Num.	Year 5 Mean	Year 5 Num.	Total Numb.
Panel A: Sorting According to Market Heat												
Price Delay	Cold	10.52	221	9.30	289	9.12	226	9.23	160	9.52	126	347
	Hot	9.64	3238	10.22	4975	10.31	4397	10.24	3920	10.08	3429	5411
	Prob.	0.0313		0.0085		0.0035		0.0398		0.2825		
Dispersion of Opinion	Cold	9.38	218	10.40	173	10.75	155	11.50	139	12.00	130	290
	Hot	10.40	3060	11.20	2898	11.50	2495	11.42	1969	11.22	1678	3972
	Prob.	0.0126		0.0206		0.0885		0.8252		0.1203		
Number of Analysts	Cold	4.71	218	5.57	173	6.10	155	6.68	139	7.08	130	290
	Hot	3.94	3060	5.00	2898	5.62	2495	6.07	1969	6.39	1678	3972
	Prob.	0.0001		0.0004		0.0095		0.0451		0.1876		
Instit. Holdings	Cold	11.10	275	11.04	226	11.27	216	11.32	199	11.46	180	333
	Hot	9.93	3531	10.14	3698	10.37	3068	10.59	2631	10.92	2168	4207
	Prob.	0.0001		0.0153		0.0196		0.0699		0.2123		

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Table 5 – Continued from previous page –

Information Constraints Measure	IPO Categ.	Year 1 Mean	Year 1 Num.	Year 2 Mean	Year 2 Num.	Year 3 Mean	Year 3 Num.	Year 4 Mean	Year 4 Num.	Year 5 Mean	Year 5 Num.	Total Numb.
Panel B: Sorting According to Underpricing Level												
Price Delay	Low	9.88	959	10.19	1342	10.50	1170	10.07	1031	10.18	892	1485
	High	8.31	975	9.48	1372	10.07	1153	9.86	988	9.37	849	1497
	Prob.	0.0001		0.0017		0.0887		0.4098		0.0039		
Dispersion of Opinion	Low	10.18	894	11.23	806	11.37	666	11.56	540	11.36	458	1151
	High	10.93	1019	11.75	857	12.25	653	12.17	446	11.85	339	1144
	Prob.	0.0058		0.0908		0.0056		0.0703		0.1544		
Number of Analysts	Low	3.60	894	4.53	806	5.14	666	5.62	540	5.90	458	1151
	High	5.03	1019	6.44	857	6.83	653	7.40	446	7.72	339	1144
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Instit. Holdings	Low	9.40	1163	9.73	1219	9.96	1046	10.17	902	10.40	770	1428
	High	10.41	1299	10.25	1234	10.26	947	10.56	682	10.83	556	1436
	Prob.	0.0001		0.0187		0.2582		0.1746		0.1587		
Panel C: Sorting According to Offer Price												
Price Delay	Low	10.79	1644	11.09	2299	10.75	1937	10.55	1684	10.32	1432	2612
	High	8.38	1358	9.21	2333	10.00	2204	9.70	2036	9.96	1843	2613
	Prob.	0.0001		0.0001		0.0001		0.0001		0.1041		
Dispersion of Opinion	Low	11.12	1151	11.99	1017	12.04	844	11.85	716	11.73	603	1661
	High	9.94	1334	10.63	1324	11.08	1175	11.45	979	11.26	818	1660
	Prob.	0.0012		0.0001		0.0001		0.0914		0.1214		
Number of Analysts	Low	3.28	1151	3.92	1017	4.32	844	4.69	716	4.95	603	1661
	High	4.97	1334	6.28	1324	7.02	1175	7.53	979	8.01	818	1660
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Instit. Holdings	Low	6.65	1409	6.77	1424	6.87	1216	7.42	1035	7.82	861	1776
	High	12.30	1511	12.49	1597	12.77	1321	13.04	1086	13.17	929	1775
	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.	Year 1 Mean	Year 1 Num.	Year 2 Mean	Year 2 Num.	Year 3 Mean	Year 3 Num.	Year 4 Mean	Year 4 Num.	Year 5 Mean	Year 5 Num.	Total Numb.
Panel D: Sorting According to Underwriter Prestige												
Price Delay	Low	11.20	1070	11.62	1466	11.14	1223	11.11	1064	10.74	894	1624
	High	8.32	1838	9.19	2619	9.82	2313	9.70	2016	9.54	1758	2823
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Dispersion of Opinnion	Low	10.85	99	12.12	160	12.24	167	11.90	168	12.28	150	346
	High	10.36	2269	11.20	1985	11.66	1633	11.64	1248	11.41	1002	2630
	Prob.	0.4064		0.0522		0.1766		0.4770		0.0632		
Number of Analysts	Low	2.55	99	3.00	160	3.49	167	3.63	168	3.83	150	346
	High	4.24	2269	5.46	301	6.06	228	6.55	1248	6.76	1002	2630
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Instit. Holdings	Low	4.41	708	4.80	769	5.07	689	5.54	603	6.01	488	986
	High	11.69	2198	11.97	2148	12.27	1753	12.68	1399	12.84	1161	2448
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Panel E: Sorting According to VC Backing												
Price Delay	No	9.78	2909	10.41	4321	10.59	3751	10.46	3261	10.31	2835	4660
	Yes	8.64	1654	9.14	2331	9.50	2063	9.30	1820	9.25	1598	2533
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Dispersion of Opinion	No	9.54	1966	10.38	1914	10.91	1655	11.09	1381	10.78	1140	2722
	Yes	11.16	1824	11.87	1608	12.30	1343	12.19	1029	12.22	869	2165
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Number of Analysts	No	3.94	1966	4.80	1914	5.35	1655	5.57	1381	5.93	1140	2722
	Yes	4.32	1824	5.59	1608	6.26	1343	7.09	1029	7.32	869	2165
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Instit. Holdings	No	9.10	2562	9.15	2720	9.38	2352	9.56	1996	9.90	1661	3148
	Yes	11.14	1908	11.64	1799	11.99	1440	12.56	1143	12.90	960	2077
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		

Table 6: Risk Factors and Momentum Effects in IPO Stocks

The table displays our risk factors across IPO categories sorted by market heat, underpricing, offer price, underwriter prestige, and venture capital support (presented in Panels A through E, correspondingly). The risk measures are idiosyncratic risk from 4 factor model, market risk (or beta coefficient from 4 factor model), and stock's momentum. These variables are calculated for each firm in CRSP (IPO and seasoned) for each period separately. Then, in each period they are sorted into viciles 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 item "Prob." is the probability that the test statistics of the nonparametric Wilcoxon two-sample test (equality of the means) is greater than its critical value (*Prob* of $Z > |Z_a|$). 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.

Risk Factors	IPO Categ.	**Time After Issue Date** Year 1 Mean	Year 1 Num.	Year 2 Mean	Year 2 Num.	Year 3 Mean	Year 3 Num.	Year 4 Mean	Year 4 Num.	Year 5 Mean	Year 5 Num.	Total Numb.
						Panel A: Sorting According to Market Heat						
Idiosync.	Cold	13.36	221	12.95	290	12.68	226	12.25	162	13.04	126	347
Risk	Hot	13.27	3241	13.29	4994	13.37	4408	13.17	3929	12.99	3435	5418
	Prob.	0.8944		0.0617		0.0204		0.0270		0.9885		
Market	Cold	11.61	221	12.03	290	11.63	226	12.16	162	12.17	126	347
Risk	Hot	11.53	3241	10.85	4994	11.16	4408	10.95	3929	11.04	3435	5418
	Prob.	0.9752		0.0022		0.3079		0.0116		0.0479		
Momentum	Cold	10.09	365	10.48	301	9.92	228	10.45	165	9.42	129	395
	Hot	9.63	5076	9.55	5000	9.77	4391	9.87	3920	9.82	3440	5601
	Prob.	0.2719		0.0297		0.7980		0.3438		0.4814		
						Panel B: Sorting According to Underpricing Level						
Idiosync.	Low	13.20	961	13.23	1343	13.24	1172	13.17	1031	12.96	893	1485
Risk	High	15.15	975	14.93	1372	14.68	1153	14.48	988	14.13	849	1497
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Market	Low	11.60	961	11.16	1343	11.01	1172	11.32	1031	11.38	893	1485
Risk	High	12.54	975	11.47	1372	11.43	1153	11.87	988	11.81	849	1497
	Prob.	0.0004		0.1132		0.0721		0.0235		0.1123		
Momentum	Low	9.62	1549	9.54	1342	10.18	1166	9.75	1029	9.88	892	1570
	High	8.65	1540	7.87	1382	9.17	1170	10.19	999	9.82	852	1578
	Prob.	0.0001		0.0001		0.0001		0.2325		0.6571		

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Table 6 – Continued from previous page –

Risk Factors	IPO Categ.	Year 1 Mean	Year 1 Num.	Year 2 Mean	Year 2 Num.	Year 3 Mean	Year 3 Num.	Year 4 Mean	Year 4 Num.	Year 5 Mean	Year 5 Num.	Total Numb.
Panel C: Sorting According to Offer Price												
Idiosync. Risk	Low	15.04	1649	15.59	2304	15.63	1942	15.17	1690	14.92	1438	2616
	High	11.87	1355	11.80	2344	11.90	2215	11.89	2047	11.99	1847	2617
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Market Risk	Low	10.59	1649	10.33	2304	10.71	1942	10.72	1690	10.73	1438	2616
	High	12.78	1355	11.72	2344	11.23	2215	11.52	2048	11.50	1847	2617
	Prob.	0.0001		0.0001		0.0332		0.0008		0.0020		
Momentum	Low	8.86	2518	8.37	2287	9.08	1922	9.58	1658	9.18	1410	2731
	High	9.94	2218	9.69	2381	10.07	2226	10.10	2057	9.88	1863	2732
	Prob.	0.0001		0.0001		0.0001		0.0082		0.0002		
Panel D: Sorting According to Underwriter Prestige												
Idiosync. Risk	Low	15.05	1072	15.77	1469	15.73	1223	15.28	1065	15.17	896	1625
	High	13.25	1838	12.82	2621	12.84	2316	12.78	2017	12.67	1758	2823
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Market Risk	Low	10.21	1072	9.92	1469	10.33	1223	10.41	1065	10.50	896	1625
	High	12.93	1838	11.93	2621	11.70	2316	11.70	2017	12.16	1758	2823
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Momentum	Low	8.61	1603	8.15	1477	8.93	1227	9.17	1061	8.93	898	1720
	High	10.04	2914	9.40	2637	10.03	2325	10.29	2041	9.85	1776	2965
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Panel E: Sorting According to VC Backing												
Idiosync. Risk	No	12.82	2912	12.91	4333	12.85	3753	12.69	3264	12.56	2839	4660
	Yes	14.69	1654	14.46	2334	14.53	2066	14.27	1820	14.09	1598	2534
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Market Risk	No	11.38	2912	10.76	4333	10.83	3753	10.81	3264	10.93	2839	4660
	Yes	12.61	1654	11.85	2334	11.87	2066	11.89	1820	12.05	1598	2534
	Prob.	0.0001		0.0001		0.0001		0.0001		0.0001		
Momentum	No	9.75	4595	9.20	4352	9.75	3761	9.73	3271	9.77	2852	4879
	Yes	9.27	2590	9.21	2344	9.71	2072	10.33	1829	9.69	1603	2660
	Prob.	0.0005		0.7096		0.5501		0.0034		0.4926		

Table 7: Summary Chart of our Results

The table summarizes the results for each of our constraint/risk measure–IPO category pair. The considered measures are percentage of firms that are severely short-sale constrained (as measured by Boehme, Danielsen, and Sorescu (2006)'s indicator), illiquidity measure of Amihud (2002), aggregate liquidity measure of Pastor and Stambaugh (2003), stock's turnover rate, Hou and Moskowitz (2005)'s price delay (size orthogonalized), analysts's dispersion of opinion, number of analysts covering the stock, institutional holdings, idiosyncratic risk from 4 factor model, market risk (beta coefficient from 4 factor model), and momentum. The details about the calculation of each measure is described in the text. The sorting variables are market heat, underpricing, offer price, underwriter prestige, and venture capital backing. "+" ("–") indicates strong positive (negative) relationship between the measure and the classification variable. "?" indicates that the results are mixed or not significant.

	Sorting Variable				
Measures	Market Heat	Underpricing	Offer Price	UW Prestige	VC Backing
Short-Sale Const.	?	+	−	?	+
Amihud Illiquid.	+	−	−	−	−
Turnover	−	+	+	+	+
PS Liquidity	+	−	−	−	−
Price Delay	+	−	−	−	−
Analyst Dispersion	+	+	−	?	+
Number of Analysts	−	+	+	+	+
Instit. Holdings	−	+	+	+	+
Idiosyncratic Risk	+	+	−	−	+
Market Risk (beta)	−	+	+	+	+
Momentum	?	−	+	+	?