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Staged Equity Financing*

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Abstract

We propose a rationale for why firms often return to the equity market shortly after their initial public offering (IPO). We argue that hard to value firms conduct smaller IPOs, and that they return to the equity market conditional on positive valuation signal from the stock market. Thus, information asymmetry is not a necessary condition for staged financing. We find strong support for these arguments in a sample of 2,143 U.S. IPOs between 1981-2014. Hard to value firms conduct smaller IPOs, and upon positive post-IPO returns, they tend to return to the equity market quickly, following the IPO.

JEL codes: G14, G24, G32
Keywords: IPOs, security issuance, sequential financing

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1. Introduction

A large number of firms return to equity market soon after their initial public offering (IPO). Hertzel, et al. (2012) report that such behavior is often premeditated, as witnessed by disclosures in the IPO prospectuses. We show that staged financing can be motivated when the firm's owner is faced with uncertainty, as she can learn from outside investors regarding the valuation of her firm. Our analysis suggests that using the IPO and the subsequent trading information as a learning channel for hard to value firms is sufficient to explain the observed sequential equity financing behavior of IPO firms.

Many of the existing explanations for staged financing rest upon information asymmetry. If management of the firm is better informed than outside investors, the firm may not initially fund all new positive net present value investments (Myers and Majluf, 1984; Strebulaev, et al., 2016). Firms with favorable future prospects may gain by incurring separate issuance costs and issuing equity in stages, as investors learn about quality and valuation of those prospects over time. Information asymmetry can also lead to capital rationing, due to investors' concern that firms use the funds that they raise inefficiently (Stiglitz and Weiss, 1981). For instance, Gompers (1995) reports that concerns for agency issues tend to affect the design of financing rounds by venture capital firms. Signaling models by Allen and Faulhaber (1989) and Welch (1989) also imply a sequence where an IPO is followed by a subsequent secondary equity offering (SEO). Their models suggest that good quality firms purposefully underprice their IPOs, in order to receive a more favorable valuation for their SEOs. Francis, et al. (2010) report that the signaling motive for IPO size determination is more relevant in segmented markets. We complement this avenue of research by showing that firms have a motive to raise their public equity in stages even in the absence of information asymmetry.

Inspired by Holmström (1982) and Aghion, et al. (2013), we develop a parsimonious model of two-sided learning regarding market value of the firm. First, depending on the initial valuation signal and uncertainty, the owner chooses both whether to conduct an IPO and the size of the IPO. If valuation uncertainty is low and the initial valuation is high (low), the manager conducts a large IPO (no IPO). In situations where the manager is faced with a high degree of uncertainty, she initially conducts a small IPO. If the post-IPO return is positive, the firm returns to the equity market to conduct an SEO to raise additional equity capital. In the model, the IPO process and subsequent trading activity transmit information, which motivates the firm's follow-on SEO issue. We test the implications of our model in a sample of 2,143 US firms that complete an IPO during 1.1.1981-31.12.2014.

As we hypothesize that uncertainty regarding firm valuation has an effect on the firm's likelihood to rely on sequential financing, we develop metrics for hard to value firms. We use the principal component analysis (PCA), which allows us to capture different aspects of challenges in firm valuation, as indicated by prior studies. Our first PCA metric is based on the three variables suggested by Gompers (1995), namely R&D expenses, firm age, and an indicator for high tech industries. For our second PCA metric, we add two additional variables, price revisions during the underwriting process, and an indicator for negative earnings. All of our PCA inputs are widely used as proxies for difficulty to value (see e.g. Lowry, et al., 2010; Hertzel, et al., 2012; Colak, et al., 2017). We observe each of the five variables at the end of the fiscal year prior to the IPO. In both PCA settings, we obtain the first principal component as our measure of hard to value. Each of the individual variables used in the PCA enters the first principal component with the expected sign: R&D expenses (+), Age (-), Absolute Revisions (+), Negative Earnings Indicator (+), and Hi Tech Indicator (+). It is notable that studies on financial slack relate some of these same variables to firms' need of additional slack. For instance, Leary and Roberts (2010) suggest that older firms have less demand for slack, and firms with greater investment opportunities (generated by R&D) require more slack. In our empirical analysis, these slack-related predictions generate a bias against findings, as additional need of slack should motivate larger IPO injections of capital, so that young and R&D intensive firms would prefer large IPOs. In contrast, our expectation is that as proxies of difficulty to value, the metrics above are connected to smaller IPO Size and subsequent SEOs

Consistent with our expectations, we find a strong negative connection between difficulty to value and the IPO size. A one standard deviation decrease in our main hard to value measure results in a 7.3% reduction in IPO size. We further report a positive relation between IPO size and the likelihood of a follow-on SEO within two years of the IPO, again with a large economic effect (19.4%). Both of these findings are consistent with the idea that firms with difficult to value projects fulfil their capital needs in stages. Furthermore, a hazard model analysis indicates that difficulty to value shortens the time to SEO for IPO firms. When we observe the connections between difficulty to value, IPO Size, and stock returns of IPO firms, we find that in support of our model's implications, firms with smaller IPOs and good outcomes following the IPO are more likely to follow with an SEO within two years. Our results regarding the likelihood of a follow-on SEO are robust to a setting following our model structure, where we consider the choice of relative IPO size to be endogenous, and thus model it separately. Due to the large difference in observable firm characteristics between hard to value and easy to value firms we also use an entropy balanced sample. Again, we find that valuation uncertainty drives the SEO likelihood through a smaller IPO.

Our analysis rests on the notion that also the manager faces a valuation uncertainty regarding her firm. While some of the information about the firm is likely to be asymmetric in practice, high degree of uncertainty surrounds the IPO. Our goal is to show that even if we assume perfectly symmetric information, a motivation exists for sequential issuance of equity. In line with our results, Brau and Fawcett's (2006) survey evidence indicates that one of the main reasons for a firm to go public is to resolve uncertainty about its valuation.

Our model is not unique in the sense that several IPO models build on two sided learning, where the managers learn about valuation of their firms from the market (see e.g., Benveniste and Spindt, 1989; Dow and Gorton, 1997; Chemmanur and Fulghieri, 1999; Benveniste et al., 2002; Alti, 2005; Hsieh et al., 2011). In a part of our empirical analysis, we exclude a fully asymmetric information structure in the IPO, and conduct an analysis on the participation of insiders in the IPO and follow-on offerings. Our findings on insider behavior during the IPO support the notion that asymmetric information does not drive our results.

Market timing plays a role in firms' security issuance decisions (Taggart, 1977). Market timing is therefore another potential motive for raising equity in stages, and we consider it as an alternative explanation for follow-on SEOs in our empirical tests. Alti (2006) shows that market timing is behind the observed clustering of IPOs into periods of "hot" IPO markets. During cold markets, potential IPO issuers need to consider not only the free cash flow implications of the funds raised in the IPO, but also the dilution of existing shareholders, due to low valuations. Concern for dilution may motivate the firm to postpone some of its current projects until a subsequent financing round (Myers and Majluf, 1984; Strebulaev, et al., 2016). While we include controls for IPO market cycles in all our regression tests, we further study whether market timing has an effect on the dynamics of the sequential equity financing pattern that we document and find no such pattern.

The paper empirically closest to ours is by Hertzel, et al. (2012), who observe financing injections within two years of the IPO. They motivate staging from the information asymmetry standpoint, and view it arising either from markets' reluctancy to provide capital due to agency concerns, or from the firm's incentive to time funding based on inside information about future prospects. They conclude that among these motives, agency issues seem to dominate, as they constrain availability of sufficient equity capital at the time of the IPO. Recently, Cole, et al. (2019) study firms that are listed on the over-the-counter market prior to their IPO. They find that post-IPO uncertainty, measured by both stock return volatility and textual content in corporate disclosures, is lower for firms that have a prior over-the-counter market listing. In a related empirical study, Derrien and Kecskes (2007) find in a UK setting that in the presence of valuation uncertainty, some firms conduct IPOs raising zero equity proceeds and subsequently return to raise funding from the market after a reduction in valuation uncertainty. Consistent with predictions of our study, pre-IPO listing thus appears to have a two-sided effect, as it reduces uncertainty both for the issuing firm and for the investors.

Our study is also related to a number of empirical papers on staged financing that concentrate on security issuers who set up a potential future financing sequence by using structures, such as convertible bonds (Mayers, 1998) or unit offerings (Schultz, 1993). The sequential nature of financing is easy to observe in such cases, as possible multiple financing stages are set within a single contract. Use of convertibles or warrants in staged financing economizes on flotation costs, while simultaneously limiting agency problems related to free cash flow (Jensen, 1986). With design of hybrid securities, incentives can be set for management to both invest first-stage proceeds efficiently, and provide more accurate information (Schultz, 1993; Cornelli and Yosha, 2003). Settings where firms match their investment options with optionality of their hybrid securities are consistent with our claim that hard to value projects are financed in stages, as they entail use of sequential financing to pursue uncertain future stages of firms' projects (see Korkeamaki and Moore, 2004).

The users of sequential financing identified by existing literature, namely convertible bond issuers and venture capital firms, tend to be characterized by amplified agency issues and high-risk projects. However, use of staged financing in such settings is also consistent with our model, as one of its predictions is that the likelihood of staged financing increases with difficulty to evaluate projects. Our study also offers solutions for how high risk firms can ease their access to staged equity financing. A key implication of our analysis is that an IPO process that transmits information more effectively is conductive for a subsequent equity offering.

2. A model of staged equity financing

2.1 Basic framework

Consider a privately-held firm whose controlling owner ("the owner") is contemplating a public equity offering. There are two periods, $t \in \{1, 2\}$. At the beginning of period 1, the owner decides first whether or not to sell a stake of the firm via a stock market and, upon the IPO decision, the size of the IPO. If the owner decides to make a small IPO, the owner will then at the beginning of period 2 decide whether or not to make a follow-on SEO. For simplicity, we normalize the total number of shares the owner is contemplating to offer to two, and denote the owner's equity offering decisions by a_t, with $a_1 \in \{0,1,2\}$ and $a_2 \in \{0,1\}$.

Following, e.g., Holmström (1982) and Aghion, et al. (2013), there is incomplete but symmetric information about the intrinsic value of the firm. The intrinsic value of the firm (per share) $\theta \in \mathbb{R}_+$ can be either high θ_H with probability $p \in (0,1)$ or low θ_L, $\theta_H > \theta_L$, with probability $1-p$. We may think of θ as representing talent of the firm's manager (to run a publicly listed company) as in Holmström (1982) and Aghion, et al. (2013). The parameter p reflects whether it is easy to value the firm or not: The firms with a very high or a very low p are easy to value whereas the firms with the intermediate values of p are difficult to value.

If the owner decides to go public, an IPO produces an imperfect signal S of the firm's intrinsic value θ during period 1. Here the term "IPO" can be interpreted loosely in the sense that includes both the preparation for the IPO and stock market trading in the immediate aftermath. More specifically, $S = h$ (respectively, $S = l$) with probability $q \in [1/2,1]$ when $\theta = \theta_H$ ($\theta = \theta_L$) i.e., the signal reveals correct information about the firm's intrinsic value with probability q and is misleading with probability $1-q$. The parameter q captures the information quality of the IPO. If $q = 1/2$, the IPO produces no additional information about the firm's intrinsic value and if $q = 1$, and the IPO is perfectly revealing.

Let us denote the value of the firm per share to the owner if the firm remains private by $\theta_0 \in \mathbb{R}_+$. For simplicity, we assume that θ_0 includes all opportunity costs of a public offering, including the transaction costs. Furthermore, to make notation more compact, we assume that θ_H = $\theta_0+\Delta$ and θ_L = $\theta_0-\Delta$ in which $\Delta \in (0, \theta_0]$. In words, the firm's intrinsic value is symmetrically distributed around the owner's private value of the firm. Therefore, if it were certain that the firm is of high (low) value, the owner would prefer (not) to go to public. Finally, $\delta \in [0,1]$ is the owner's discount factor, capturing the benefits of financial slack (the preference for having the cash in hand sooner rather than later). In the end of Section 2.2 we discuss the consequences of relaxing these (and some other) assumptions.

The owner's objective is to maximize the firm's value conditional on the information available to investors. The timing of events is as follows: In period 1, the owner chooses the size of an IPO, $a_1 \in \{0,1,2\}$. In the cases where $a_1 = 0$ (the owner decides to remain private) or $a_1 = 2$ (the owner decides to issue a single, large IPO), the owner's decision sequence ends. If $a_1 = 1$ or $a_1 = 2$, the signal S is generated, and the market updates its beliefs about the firm value. In period 2, which is relevant only if $a_1 = 1$, the owner, after observing the firm's post-IPO market value, chooses the size of a SEO, $a_2(a_1 = 1, s) \coloneqq a_2(s) \in \{0,1\}$.

2.2 Listing decisions

Prior to an IPO, the firm's expected market valuation is given by

$$\mathrm{E}(V) = p\theta_H + (1-p)\theta_L.$$

After the IPO the market updates its beliefs about the firm value using the signal realization $S = s$ and Bayes' rule. Let $\Pr(\theta|s)$ denote the probability that the firm's intrinsic value is $\theta \in \{\theta_L, \theta_H\}$, given a signal realization $s \in \{l, h\}$, and let V denote the firm's market valuation. Then, the firm's post-IPO market valuations are given by $V_h \coloneqq V|h = \Pr(\theta_H|h)\theta_H + \Pr(\theta_L|h)\theta_L$, and $V_l \coloneqq V|l = \Pr(\theta_H|l)\theta_H + \Pr(\theta_L|l)\theta_L$, which can be rewritten by using Bayes' rule as

(1) $$V_h = \frac{qp\theta_H + (1-q)(1-p)\theta_L}{qp + (1-q)(1-p)},$$

and

(2) $$V_l = \frac{(1-q)p\theta_H + q(1-p)\theta_L}{q(1-p) + (1-q)p}.$$

If the signal is informative $(q > 1/2)$, $V_h > \mathrm{E}(V) > V_L$.

To make the IPO decision meaningful, we impose the following assumption on the parameters:

Assumption 1. $V_h > \theta_0 > V_l$.

Assumption 1 implies that if the post-IPO market valuation is high (low) the owner will (not) sell another stake at the market. Since $\Pr(\theta|s) \in [0,1]$ for all θ and s, $\theta_H \geq V_h$ and $V_l \geq \theta_L$ (with the inequalities being strict unless $q = 1$). Hence, Assumption 1 is more stringent than assumption that $\theta_H > \theta_0 > \theta_L$ (which follows from $\Delta > 0$).

Write the firm's expected net value for the owner conditional on the IPO decision as $V(a_1)$. Our aim is to characterize the circumstances when a planning a staged equity offering is optimal for the owner, $V(1) \geq \max\{V(0), V(2)\}$. Let us first compare the expected net values of small and large IPOs, $V(1)$ and $V(2)$. The expected value of a single, large IPO is given by

(3) $$V(2) = 2[\Pr(h)V_h + \Pr(l)V_l - \theta_0],$$

in which the probabilities of high and low market valuations following the IPO are given by $\Pr(h) = qp+(1-q)(1-p)$ and $\Pr(l) = q(1-p)+p(1-q)$, respectively. The term in the square brackets gives the owner's expected net payoff per share from going to public. Using the fact that $\Pr(h)\,V_H + \Pr(l)\,V_L = E(V)$, equation (3) can be simplified to

$$V(2) = 2(E(V) - \theta_0).$$

Thus $V(2) \geq 0$ only if $E(V) \geq \theta_0$. In words, a large IPO profitable to the owner only if the expected market valuation is larger than the opportunity costs of going public. Since in our set up $\theta_H = \theta_0 + \Delta$ and $\theta_L = \theta_0 - \Delta$, the condition $E(V) = p\theta_H + (1-p)\theta_L \geq \theta_0$ is equivalent to $p \geq 1/2$.

The owner's expected payoff to a staged equity offering with two smaller rounds is

(4) $$V(1) = \Pr(h)\left(V_h + \delta V_2(h)\right) + \Pr(l)\left(V_l + \delta V_2(l)\right) - \theta_0,$$

in which $V_2(s) := V_2(a_S(s),s)$ gives the owner's expected net payoff from a SEO. Since Assumption 1 implies that the owner issues a SEO only upon a high signal ($a_S(l) = 0$ and $a_S(h) = 1$), we have $V_2(l) = 0$ and $V_2(h) = V_h - \theta_0$. We can thus simplify equation (4) to

(5) $$V(1) = \Pr(h)V_h + \Pr(l)V_l - \theta_0 + \Pr(h)\,\delta(V_h - \theta_0).$$

The first three terms in the right hand side of equation (6) capture the owner's expected net payoff from the IPO, and the last term captures the expected value of the option to the SEO in the case the firm's market valuation turns out to be high.

Planning a staged equity offering is optimal when $V(1) \geq V(2)$. After some algebra using equations (1)–(3) and (5), we get that the condition $V(1) \geq V(2)$ is equivalent to

(6) $$p \leq \bar{p} := \frac{1 - \delta(1-q)}{2-\delta}.$$

Note that $\bar{p} \in (0,1)$ (unless both $q = 1$ and $\delta = 1$ in which case $\bar{p} = 1$).

Next, for the owner, planning a staged equity offering is preferable to staying private if $V(1) \geq 0$. After substituting equations (1) and (2) for equation (5) we get that $V(1) \geq 0$ if

(7) $$p \geq \underline{p} := \frac{1 + \delta(1-q)}{2+\delta}.$$

Clearly, $\underline{p} \in (0,1/2]$. Therefore, the condition $p \geq 1/2$ implying $\mathrm{E}(V) \geq \theta_0$ is more stringent than inequality (7) implying $V(1) \geq 0$. When $p \in [\underline{p}, 1/2]$, it is profitable for the owner to plan a staged equity offering even if the firm's expected market valuation prior to the IPO is *less* than the value of the firm to the owner as a private company. A staged offering allows the owner to experiment – to learn about the market value of her firm – and gives the option to a SEO in the case the market valuation turns out to be high. The cost of that experimentation is the expected net loss from the IPO. Furthermore, from the definitions of $\bar{p}$ and $\underline{p}$ of inequalities (6) and (7) we observe that $\bar{p} \geq \underline{p}$, with the inequality being strict for $q > 1/2$.

We can summarize our results as follows:

Proposition 1. *i) If it is sufficiently likely that the firm's market valuation will be low* ($p < \underline{p}$)*, the owner remains private; ii) If it is sufficiently likely that the firm's market valuation will be high* ($p > \underline{p}$)*, the owner issues a single, large IPO; iii) If uncertainty about the firms' market valuation is sufficiently high,* $p \in (\underline{p}, \bar{p})$*, the owner plans a staged equity offering, where an IPO is followed by a SEO. The SEO will be implemented only if the post-IPO market valuation is high.*

Inequality (7) captures the tradeoffs associated with the owner's listing decision whereas inequality (6) captures the tradeoffs associated to the choice between a single, large IPO and a staged offering with two smaller rounds. Both inequalities only depend on three parameters, p, q and δ.

From the definitions of $\bar{p}$ and $\underline{p}$ of inequalities (6) and (7) we can establish that $\partial\bar{p}/\partial q \geq 0$ and $\partial\underline{p}/\partial q \leq 0$, with the inequalities being strict for $\delta > 0$. In words, a more revealing IPO process unambiguously makes a staged equity offering more attractive for the owner.

Similarly, the definitions of $\underline{p}$ and $\bar{p}$ also suggest that $\partial\bar{p}/\partial\delta \geq 0$ and $\delta\bar{p}/\partial\delta \leq 0$, with the inequalities being strict for $q > 1/2$. As is intuitive, a stronger need for financial slack (smaller δ) unambiguously makes a staged equity offering less attractive for the owner.

We summarize these comparative static results as follows.

Proposition 2. *A more informative IPO process (larger* q*) and a smaller need for financial slack (larger* δ*) make planning a staged equity offering more attractive.*

Before summing up the empirical implications that arise from these theoretical results, let us discuss some extensions. Our model assumes that θ_0 includes all opportunity costs of a public offering. Adding a fixed (transaction) cost of a public offering, say $F \in \mathbb{R}_+$, will change nothing if F is directly proportional to the size of the offering. However, if F is independent of the size of the offering, the attractiveness of the sequential offering will be decreasing in F.

We also assume that the intrinsic value of the firm is symmetrically distributed around θ_0 . This assumption can be relaxed at the cost of making exposition considerably messier in so far Assumption 1 – implying. e.g, that $\theta_H > \theta_0 > \theta_L$ – holds. For example, let us assume that $\theta_H = \theta_0 + \Delta_H$ and $\theta_L = \theta_0 - \Delta_L$ in which $\Delta_L \in (0, \theta_0]$ and $\Delta_H \neq \Delta_L$. It turns out that the public listing becomes more attractive the larger is Δ_H/Δ_L, since the expected market value of the firm is increasing in Δ_H/Δ_L. However, the attractiveness of a staged equity offering compared to a single, large IPO is inversely related to Δ_H/Δ_L since the smaller is Δ_H/Δ_L the more valuable is experimentation via a small IPO.

2.3 Implications for an empirical analysis

Our model does not (need to) take a stance on the pricing of IPOs. However, to operationalize our model, we assume that initial offering price is in the range of the lowest and highest possible post-IPO valuations (between $V_{l.}$ and $V_{h.}$). For example, a fair IPO price would be $\mathrm{E}(V) \in (V_{l.}, V_h)$. Under that assumption, our model predicts *an upward* (respectively, *downward*) *price revision* whenever an IPO produces the signal $S = h$ (respectively, $S = l$), leading to $V_{h.}$ (V_l) as the firm's post-IPO market valuation.[1]

[1] Focusing on price revisions that occur during the first trading day, our model would also provide an explanation for IPO underpricing (overpricing) without a need to resort to asymmetric information, behavioral biases or other even more complicated explanations (see, e.g., Ljungqvist, 2007, for a survey). In our empirical application, we use a price revision period of one moth.

The sample in our empirical analysis consists of the firms that have issued an IPO. Thus, our analysis focusses on the firms that satisfy inequality (7). Our model suggests that these IPO firms can be grouped into the following three categories: 1) Firms that plan and implement only an IPO; 2) Firms that plan and implement a staged equity offering where a SEO follows an IPO; 3) Firms that plan a staged equity offering but implement only an IPO.

The firms in categories 2 and 3 are similar to each other before their IPOs, but the firms in category 2 experience an upward price adjustment after the IPO, whereas the firms in category 3 have a downward price adjustment.

In comparison to the firms in categories in 2 and 3, the firms in category 1 implement a larger IPO, have more benefits from financial slack, and are easier to value prior to an IPO. Furthermore, the firms planning a single IPO benefit less from an informative IPO process. We hence expect that the IPOs of the firms in category 1 are less informative than the IPOs of the firms in categories 2 and 3.

3. Data and a hard to value metric

We follow Hertzel, et al., (2012) and use the IPO as a common reference point for our sample firms. We collect data on IPOs from 1981 to 2014 from Thomson SDC Platinum. Our original IPO sample includes 10,608 IPOs. We make several restrictions to our sample: (1) We require our sample firms to have accounting data in COMPUSTAT for the fiscal year end prior to the IPO. (2) We exclude spin offs, unit offerings, and issues by financial firms with the primary standard industrial classification (SIC) code between 6000–6999. (3) We exclude firms with total assets below $10 million in 2016 dollars. (4) We further follow Bradley and Jordan (2002), and exclude firms with offer price below $1 per share. After these restrictions, our remaining sample includes 2,143 IPOs, which is comparable to other studies that make use of pre-IPO accounting variables in COMPUSTAT, such as Baker and Wurgler (2002) and Alti (2006).

We track the equity issuing behaviour of the firms in our IPO sample, and consider all SEOs that occur within two years of the IPO. Hertzel et al., (2012) argue that capital infusions that occur more than two years after the IPO are less likely to be sequential financing efforts that are planned at the time of the IPO. They report that 576 out of their 4054 sample IPO firms express in the prospectus their intent to return to the capital markets, and 95% of those 576 firms indicate that they will do so within two years. We further follow Hertzel et al. (2012) and exclude SEOs during the first month of trading[2].

We use Principal component analysis (PCA) to derive our metrics on difficulty to value. Our PCA input variables are suggested by prior literature. The value of firms with relatively high R&D expenses depends more on the future expectations related to their growth options, which makes them difficult to value (Hertzel, et al., 2012). Older firms are more established, and have a longer track record, which helps in their valuation (Lowry, et al., 2010). A greater uncertainty surrounding valuation of the firm can be reflected in the magnitude of price revisions, both negative and positive, during the IPO process (Lowry, et al., 2010). Finally, firms in high tech industries and firms with negative earnings are more difficult to value (Colak, et al., 2017), which motivates us to include an indicator for each of the two effects. Each of these variables focuses on different dimensions of difficulty to value a firm. As our main metric of hard to value (HTV1), we use the first component (with the highest eigenvalue) from the PCA that includes all five variables. Our metric explains 34.4% of the common variation amongst the five variables, and each of the five variables load with the expected sign on the first component, as follows: R&D/sales 0.5447,

[2] The one month time period coincides with our return (alpha) measurement period and thereby avoid look-ahead bias in the returns.

ln(Age) -0.4227, abs(Revisions) 0.0989, Negative Earnings 0.5866, and High Tech 0.4132. For robustness purposes, we utilize an alternative PCA-based component (HTV2), derived from those three of our five uncertainty-related variables that are used by Gompers (1995), namely R&D/Sales, Firm Age, and an indicator for High Tech industries. We also report results separately for individual variables that underlie the PCA component.

We include several control variables in our analysis, defined in appendix 1. In addition to standard controls explaining the IPO size and SEO likelihood (see e.g., Hertzel et al., 2012), we include a variable (UW Premium) capturing underwriter agency related problems as in Hoberg (2007) and Chang et al. (2017). Chang et al. (2017) argue that underwriter agency problems are exacerbated in firms with greater capital demand, and this may drive firms to sequential issuance. Firms accept to leave money on the table in the IPO due to planned follow on offerings. To control underwriter driven staged financing, we follow Hoberg (2007) and measure the UW Premium as the underwriter specific average underpricing. We further include an IPO market heat measure that builds on Yung et al. (2008) and Boehme and Colak (2012) classification of hot and cold markets. To calculate the measure, we start with the number of quarterly IPOs, gathered from Jay Ritter's web page.[3] To smooth out seasonality effects in our heat measure (4th quarter IPOs are more likely than 1st quarter IPOs), we calculate the measure using the average over the last four quarters. The market heat measure is the four-quarter average of the number of quarterly IPOs divided by the historical average.

We present the descriptive statistics of our sample in Table 1. Besides the full sample, Table 1 also provides information on subsamples, where we divide our full IPO sample into

[3] *http://bear.warrington.ufl.edu/ritter*

terciles, based on the HTV1 metric[4]. We label the extreme terciles in Table 1 as Easy to value (ETV) and Hard to value (HTV), respectively.

As Table 1 indicates, ETV firms deviate from HTV firms in a number of aspects. Deviations in Absolute Revisions, ln(age), R&D/Sales, Hi Tech, and Neg Earnings are to be expected, as those variables form the basis for the firm groupings. With respect to our model of sequential financing with equity, the most interesting statistics in Table 1 are related to subsequent SEO issuance and IPO size. Consistent with our expectations, hard to value firms are significantly more likely to issue follow-on SEOs within two years (35.11% vs. 23.08%). Hard to value firms also float smaller IPOs, which aligns well with the predictions of our model. The fact that means of nearly all of the variables listed in Table 1 deviate significantly between the HTV and the ETV group motivates us to consider the differences in a regression setting. It is noteworthy that the only variable with equal means for HTV and ETV firms is the IPO market heat, top underwriter and analyst following.

Insert Table 1

In Table 2, we test whether our pre-IPO hard to value metric is linked to more widely used post-IPO measures of valuation uncertainty, namely idiosyncratic volatility (see, e.g. Jiang, Lee, and Zhang 2005, Zhang, 2006; Kumar, 2009) and volatility. In panel A of Table 2, we sort the firms into terciles based on HTV1, and report that HTV firms have significantly higher idiosyncratic volatility and volatility both 1-month and 3-months following the IPO. In unreported sortings, HTV2 yields similar inferences.

Following proposition 1, the main hypothesis we pursue is that difficulty to value is negatively related to IPO size and positively related to the SEO likelihood. The increased SEO

[4] The number of observations deviate between the three terciles due to equal values of the sorting variable.

likelihood comes from two channels. Firstly, HTV firms conduct smaller IPOs, which should lead them to return to the equity market soon. However, conducting a small IPO is not sufficient to trigger a second round of equity issuance following the IPO. The small IPO needs to be coupled with a positive stock market return. Panel B in Table 2 considers two of those implications in a setting where we sort IPO firms both on our hard to value metric and on post-IPO alphas, calculated for the one-month period following the IPO.[5] To obtain the alphas, we use daily data and a Fama and French (2015) 5-factor model. We group both the HTV1 metric and the alphas into terciles, and compare the likelihood of an SEO within two years between the extreme terciles.

Panel B in Table 2 indicates that difficulty to value the firm has a significant effect on SEO likelihood, regardless of post-IPO alpha. While low alpha firms are less likely to issue an SEO within two years, even among low alpha firms, the hard to value ones are more likely to issue a follow on SEO. Similarly, post-IPO alphas have a positive effect on SEO likelihood in all difficult to value terciles. SEO likelihood increases across both HTV1 terciles and alpha terciles. Both findings are consistent with the predictions of our model.[6]

Insert Table 2

4. Regression results

In this section, we test the relation between HTV, IPO Size and post-IPO equity issuance in a regression setting. As we note above, our expectation is that firms with uncertainty surrounding their valuation conduct smaller IPOs and then engage in sequential equity financing, and further that firms in which the small IPO is followed by positive returns tend to return to the equity market shortly after their IPO.

[5] We obtain very similar results when we use either three-month or six-month post-IPO estimation period.
[6] In untabulated results we report that we find a similar pattern using the HTV2 metric

We begin our regression analysis by testing whether IPOs of difficult to value firms are smaller than those issued by easy to value firms, as smaller IPO size may indicate that only a portion of total equity needs is raised at the IPO stage. In Table 3, we run OLS regressions where the dependent variable is the IPO size (Shares offered in the IPO/Post-IPO shares outstanding). We employ year fixed effects to control for the annual variation in macroeconomic factors and market conditions. To further test whether our results regarding the effects of HTV on the IPO Size also hold within industries, we include industry fixed effects in columns (10) and (11). In the first two columns of Table 3, we employ the HTV1 and HTV2 versions of the PCA-based measures of valuation uncertainty, respectively. Both metrics exhibit a strong negative relation to IPO Size, suggesting that difficult to value firms issue IPOs with smaller relative proceeds. Columns (3) and (4) of Table 3 repeat the same analysis, with controls added for profitability [Returns on Assets (ROA)], size [ln(Sales)], indebtness (book leverage), and Cash/Assets, all measured at the fiscal year end prior to the IPO, and market to book at issuance. We also include controls for IPO Heat, VC Backing, Top Underwriter and Underwriter Premium. Our findings of the relation between valuation uncertainty and IPO Size are robust to including these controls. Our findings are also economically meaningful. In columns (3) and (4), a one standard deviation increase in valuation uncertainty corresponds to a 5.3% and 7.5% drop in IPO Size, respectively. In the remaining columns of Table 3, we use separately each of the five individual measures of valuation uncertainty included in the five-variable version of our PCA measure on valuation difficulty. The R&D metric in column (5) is accompanied by an indicator for firms that fail to report R&D expenses. Each of the five measures are statistically significant and enter with an expected sign, Results on our hard to value proxies are unaffected by inclusion of industry fixed effects in columns (10) and (11).[7] Interestingly, cash holdings are inversely related to IPO Size in all specifications of Table 3. This is in line with our prediction that firms with a greater degree of financial slack conduct a smaller IPO.

Staged financing that follows an IPO can take forms other than a follow-on SEO. Among the 1,922 firms that Hertzel, et al. (2012) observe to raise public financing within two years of their IPOs, 52% issue publicly traded debt within two years, and about 48% follow with an SEO. In our analysis, we focus on sequential equity financing, as our model does not provide predictions related to other forms of financing. However, adding a control for increase in debt/assets leaves the results in Table 3 intact (untabulated). To study whether our estimates are driven by omitted variables, we employ the partial identification methodology by Oster (2019). In the test, we create bounds for the betas of hard to value in specification (10) and (11). In unreported estimates, the intervals of the HTV betas is given by (R^2max = 1.3$\check{R}^2$ and delta =1) and the controlled betas where $\check{R}^2$ is the R-square from the model including controls. Our estimates indicate that no zeros exist within the intervals when using the solution that minimizes the distance to the estimate including controls[8]. Hence, our findings do not seem to be driven by omitted variables.

Insert Table 3

Next, we consider the determinants of the likelihood to return to the equity issuance market within two years of the IPO by running regressions where the dependent variable is a binary variable that takes the value of one for those IPO firms that conduct a follow-on SEO within two

[7] The number of observations differ between columns (1) to (9) and (10) to (11) due to the drop of singleton observations following Correia (2015). The number of observations further deviate from columns (1)-(9) and the descriptive statistics due to one singleton observations.
[8] As in e.g. Aktas et al. (2019) the coefficients move further away from zero when choosing the solution that minimizes the squared distance to the controlled coefficient.

years of the IPO. In this setting, our model predicts that IPO size is negatively related, our HTV measures and the alphas are positively related to the SEO likelihood. We estimate with OLS instead of Probit due to the large amount of fixed effects when including industry fixed effects, and the resulting inconsistency in the estimates.[9] The structure of Table 4 follows that of Table 3, as we employ both the five-variable and the three-variable version of the PCA-based metric of difficulty to value, and the individual variables behind the five-variable version. We further add several post-IPO controls to capture the firm's behavior during the first month of trading (First day return, 21-day return, volatility and ln(Analyst)). HTV1 enters with a positive and significant coefficient, both in Column (1) with the year fixed effects, in Column (3) with the additional controls, and in column (10) with year, industry fixed effects and the full set of controls. The economic effect is again substantial, as a one standard deviation increase in the HTV proxies increases the SEO likelihood by 19.4% in column (3) and 12% in column (4). In line with implications of our model, we further report that IPO Size is negatively related to the SEO likelihood. Increasing IPO size by one standard deviation changes the SEO likelihood by roughly 8.3% in column (4). Besides the controls in Table 3, we also include additional post-IPO controls related to analyst following, and initial returns (and their volatility).[10] Among the individual components of the PCA metric, only firm age and negative earnings reach statistical significance. Furthermore, our results are not driven by an underwriter agency problem explanation, even though Chang et al. (2017) argue that high underwriter premium is linked to a greater likelihood of a follow on offering. Together, Tables 3 and 4 support our model's implication that firms that are difficult to value use sequential equity financing, as they both issue smaller IPOs, and have a

[9] However, when we re-estimate all models with Probit, we obtain similar estimates. Angrist and Pischke (2009) further report that OLS and Probit yield similar estimates.
[10] While relevant for likelihood of follow-on SEO, such variables are not known prior to the IPO, which is why we exclude them from Table 3, where we study determinants of IPO size.

greater likelihood of returning to the equity market within two years. We again employ the Oster (2019) methodology to test the robustness of the coefficient estimates of our main independent variables from columns (3) and (4). Our findings remain robust to adjusting the coefficients for potential omitted variable bias.

Insert Table 4

In Table 5, we consider the connection between sequential equity financing and difficulty to value in yet another setting. Hertzel, et al. (2012) motivate studying sequential financing behaviour with a hazard model, where the dependent variable is the time period between the IPO and the subsequent capital injection. For this analysis, we observe equity issuance of the IPO firms for the two years or 730 days following the IPO, so for those firms that do not issue a follow on SEO, the dependent variable receives its maximum value of two years.[11] Table 5 reports results of Cox Hazard models. We use the same specification in Columns (1) to (4), and (5) and (8), respectively, with the difference that in Columns (5) to (8), the independent variables are updated every six months, whereas in Columns (1) to (4), we use the pre-IPO values (except for Alphas). We further include year fixed effects in all specifications and industry plus year fixed effects in columns (3), (4), (7) and (8). The variables of interest are our HTV metrics, and Alphas, as we test whether difficulty to value, IPO size and post-IPO returns have an effect on the time between the IPO and the SEO.

Insert Table 5

The results of the Cox hazard model are consistent with those reported in our earlier tables. Both difficulty to value and post-IPO returns have a strong effect in shortening the time between the IPO and the SEO, and IPO size lengthens the time to first SEO. Some of our control variables

[11] Our findings are robust to extending the hazard analysis to a longer time period.

provide contrasting inferences between specifications. In Columns (1) to (4), where we use the pre-IPO values of the covariates, the coefficients for ROA, first day return and ln(Analyst) are negative and significant. When we allow the accounting variables to be time-varying in columns (5) to (8) they play a greater role in determining the time to the SEO. In all specifications, first day return and ln(analyst) shortens and IPO market heat lengthens the time between the IPO and first SEO.

If information production is essential in allowing the second stage follow-on SEO, then the issuing firm would have an incentive to improve information production during the IPO process, and immediately after it. This is why we include the number of analysts following the firm as a control for informativeness in Tables 4 and 5. Prior studies suggest two other variables that can function as pre-certification devices, by improving information production of a newly-listed firm. Megginson and Weiss (1991) and Megginson, et al. (2017) report that VC Backing of the IPO enhances information dissemination during the IPO process. Francis and Hasan (2001), and Francis, et al. (2010) forward the "analyst coverage purchase hypothesis", which posits that firms engage top-ranked underwriters to improve information production in the secondary market. In untabulated tests, we find that firms that are more difficult to value (according to our HTV measures) are significantly more likely both to have VC Backing and to employ Top Underwriters, defined as in Loughran and Ritter (2004).

Next, we study the joint effects implied by our model. In Table 6, we focus on the triple interactions between post-IPO Alphas, HTV metrics, and IPO Size. In Column (1) and (2) of Table 6, we interact small IPO Size with high one-month Alphas and hard to value (top tercile of HTV1 and HTV2 measures). The positive and statistically significant coefficient for the triple interaction variable in column (2) suggests that firms with follow-on SEOs are ones that have small IPOs, high post-IPO returns, and that are difficult to value. Similar results emerge from Column (1) of Table 6, where we employ the 3-variable PCA metric on HTV, albeit not statistically significant. In columns (3) and (4), we repeat our analysis by studying the within industry variation. The triple interactions are statistically significant in both specifications. Consistent with the predictions of our model, we find a triple interaction between IPO Size (conducting a small IPO), Alpha and hard to value have a positive effect on the likelihood of a follow-on issue.

Insert Table 6

In Tables 3 and 4, we establish that HTV is correlated with IPO size and SEO likelihood, in accordance with our model. However, the interplay between the firm's choice of IPO Size, and the decision to raise equity in stages is likely to be plagued by endogeneity. We address this concern as follows. Proposition 1 in our model predicts that the HTV measure only affects the SEO likelihood through the IPO Size (see also the illustration of proposition 1 in Figure 1). Hence, using the HTV as an instrument theoretically satisfies the exclusion restriction, and thus a good instrument if the relation to IPO Size is strong. In our specifications, we first determine the IPO Size with our hard to value measures in Table 7. Besides valuation uncertainty, we further include Industry Misvaluation (measured as in Rhodes-Kropf, et al., 2005) as an additional instrument. We argue that misvaluation works well as an instrument since firms in general aim to time the market, by issuing overvalued shares (Alti, 2006; Baker and Wurgler, 2002). Misvaluation is also temporary and should shortly revert to the correct valuation and thereby not significantly positively affect future issuance. Furthermore, industry conditions such as valuation are an important determinant of the going public decision, Brau and Fawcett (2006) report from survey evidence that industry conditions is the second most important factor in determining the timing of the IPO. Hence, in line with Alti (2006) IPO firms are likely to conduct larger IPOs when equity capital is cheap. Following proposition 1 we argue that valuation uncertainty affects future equity issuance only through the IPO Size, firms conducting larger IPOs might not have the same needs for external financing during the following two years.

In Tables 7 and 8, we account for endogeneity by using the 2SLS methodology, where on the first stage (Table 7), we test for determinants of IPO Size, which is then one of the determinants of SEO likelihood in Table 8. All our excluded instruments in the first stage have a strong impact on IPO Size (minimum F-stat = 14.87 in specification 3). Hence, our excluded instruments satisfy the inclusion restrictions. The setup for the first stage resembles that used in Table 3, and it is therefore not surprising that the results are also very similar to Table 3. The second stage results in Table 8 indicate that even in the 2SLS setting, IPO Size has a strong inverse relation to the likelihood that a firm issues a follow-on SEO within two years.

Insert Table 7

Insert Table 8

In an attempt to separate between asymmetric and imperfect but symmetric information structures, we analyze the insiders' participation in the IPO. In an asymmetric information structure, insiders are better informed than outsiders, and can thereby make better informed decisions. In the IPO, this takes the form of market timing of their secondary share sales. If insiders act in accordance with asymmetric information, their sales of IPO shares should be positively related to valuation uncertainty (or degree of asymmetric information) and negatively related to post-IPO abnormal returns[12]. In a symmetric but incomplete information structure the value of the

[12] The asymmetric information and market timing behaviour is prevalent in the literature. For example, Bergstrasser and Philippon (2006) find that the management manipulates earnings prior to share sales with a resulting fall in stock prices. Also the employee stock option literature, e.g. Bartov and Mohanran (2004) report that firms share prices drops following employ stock option exercises. However, it is plausible to argue that even insiders do not know the true valuation of their firm prior to the listing [See, e.g., Brau and Fawcett (2006)].

option to sell shares at a later time should increase with uncertainty causing an either staged offering of secondary shares or postponing of secondary shares issues until information is more complete (see e.g., Damaraju et al., 2015). Hence, in a symmetric information setting we expect that the participation ratio and secondary share sales decreases with valuation uncertainty. We conduct three different tests: 1.) We analyze the link between the HTV proxy and the sale of secondary shares in the IPO. 2.) We test the link between insider participation and post-IPO performance[13]. 3.) We test if the sale of secondary shares in the IPO and valuation uncertainty is linked to a follow-ons offering consisting of 100% secondary shares. In our tests, participation ratio is defined as the fraction of secondary shares offered in the IPO (Chanine et al., 2020). We also include a second measure of sales of secondary shares (Secondary/Total) defined as secondary shares scaled by total post-IPO shares outstanding.

Table 9 reports the findings on the secondary share sales. In columns (1) and (2), we study the effect of the HTV1 measure on the participation ratio and Secondary/Total measures. In column (1) we report a negative albeit non-significant effect. Meanwhile, the HTV proxy is inversely linked to the Secondary/Total at the 10% level. In columns (3) to (6) we study the effect of insider participation in the IPO on post-IPO performance measured by the 1-month and 6-month alpha from a Fama-French 5-factor model. We do not find any link between insider participation and higher post-IPO stock market performance[14]. In column (7) but not in column (8), we report a positive link between valuation uncertainty and conducting a 100% secondary share SEO. We further find a link between secondary sales in the IPO and subsequent secondary SEO. To summarize, our results do not support the notion that insiders take advantage of an asymmetric

[13] E.g. Jordan and Riley (2015) use a similar framework with alpha as left hand side variable.
[14] Our results are in line with Brau et al., (2007), who report no-relation between insider participation and post-IPO performance.

information structure to maximize their own profits. Even though we cannot totally rule out that our results are driven by information asymmetry, we instead find evidence that insiders act upon uncertain information and postpone issuing their own shares. To further rule out an insider market timing explanation we do not find that future returns are related to insider IPO participation.

Insert Table 9

In our next set of empirical tests, we pursue an alternative explanation, in which firms would time the market for their subsequent SEO issuance, and such timing would correlate with our measures for valuation uncertainty. Our model predicts that positive post-IPO returns trigger firms to conduct an SEO. However, seasoned equity offerings that follow high returns can also be driven by market timing (Taggart, 1977; Baker and Wurgler, 2002), which is thus another possible explanation to the findings we report above. However, market timing would also imply that the SEO is followed by low returns, as firms optimize to take advantage of high valuations. In Table 9, we report the Post-SEO Alphas, along with the coefficients for the factors of the Fama-French five-factor model, for portfolios that are formed based on terciles of valuation uncertainty. The first three columns use the HTV2 metric, while the remaining three columns show the results when the HTV1 metric is used to sort the uncertainty terciles. The sample includes firms that follow their IPOs with SEOs within two years, and their returns are observed either for the 12-month period following the SEO (Panel A) or for the 24-month post-IPO period (Panel B). In case the main motive for SEO issuance is market timing based on firm-specific information, the alphas should be negative in the period following the SEO. However, none of the portfolios exhibit statistically significant alphas, which suggests that market timing is not a major consideration when firms make their decision to float a follow-on SEO.

Insert Table 10

In a final set of tests, we use an entropy balanced sample to re-estimate the two-stage models in Table 7 and 8. Given the large differences in means between the extreme terciles (HTV and ETV in Table 1), we use entropy balancing to ensure similar means of the treated (HTV firms) and control group (ETV firms). Entropy balancing weighs the covariates in the control group to have the same means as the ones in the treated group (Hainmueller, 2012). Entropy balancing also provides advantages over other data pre-processing methods. First, unlike nearest neighbor matching it reweighs all units to prevent a loss of information. Second, Harvey et al. (2017) report that entropy balancing achieves higher estimation accuracy and effectively mitigate selection bias. When applying the entropy balancing, eight pre-IPO covariates are included to balance the sample in Table 11 panel B.

In Table 12, we re-estimate the two-stage analysis using a balanced sample (excluding the mid tercile). Our results from column (1) and (2) show that valuation uncertainty is negatively related to the IPO size. However, industry misvaluation does not remain a significant determinant of IPO size using the matched sample. This is also observable when analyzing the F-stats of the excluded instruments in column 2 (F-stat= 8.21). Meanwhile, the F-stat remains high in column (1) (F-stat=15.63). The second stage models are reported in columns (3) and (4), instrumented IPO-size remains a statistically significant determinant of the SEO likelihood.

Insert Table 11

Insert Table 12

5. Conclusions

We examine the impact of valuation uncertainty on staged equity financing. Our aim is to explain why a number firms choose to return to the equity market shortly after their IPOs. We develop a simple model that indicates that even under valuation uncertainty, firms may stage their equity issuance. We obtain a predictions that hard to value firms choose to conduct smaller IPOs and that they thereafter return to the equity if they experience a positive post-IPO return. We test the implications of our model using a sample of 2,143 U.S. IPOs between 1.1.1981–31.12.2014. Our results provide support for our model, as we find a strong effect of both post-IPO alphas and firm level valuation uncertainty on the likelihood that the firm returns to the equity markets. New to the literature, we provide both rationale and empirical support for the idea that information asymmetry is not a necessary criterion for raising equity financing in stages.

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Figure 1: Illustration of proposition 1

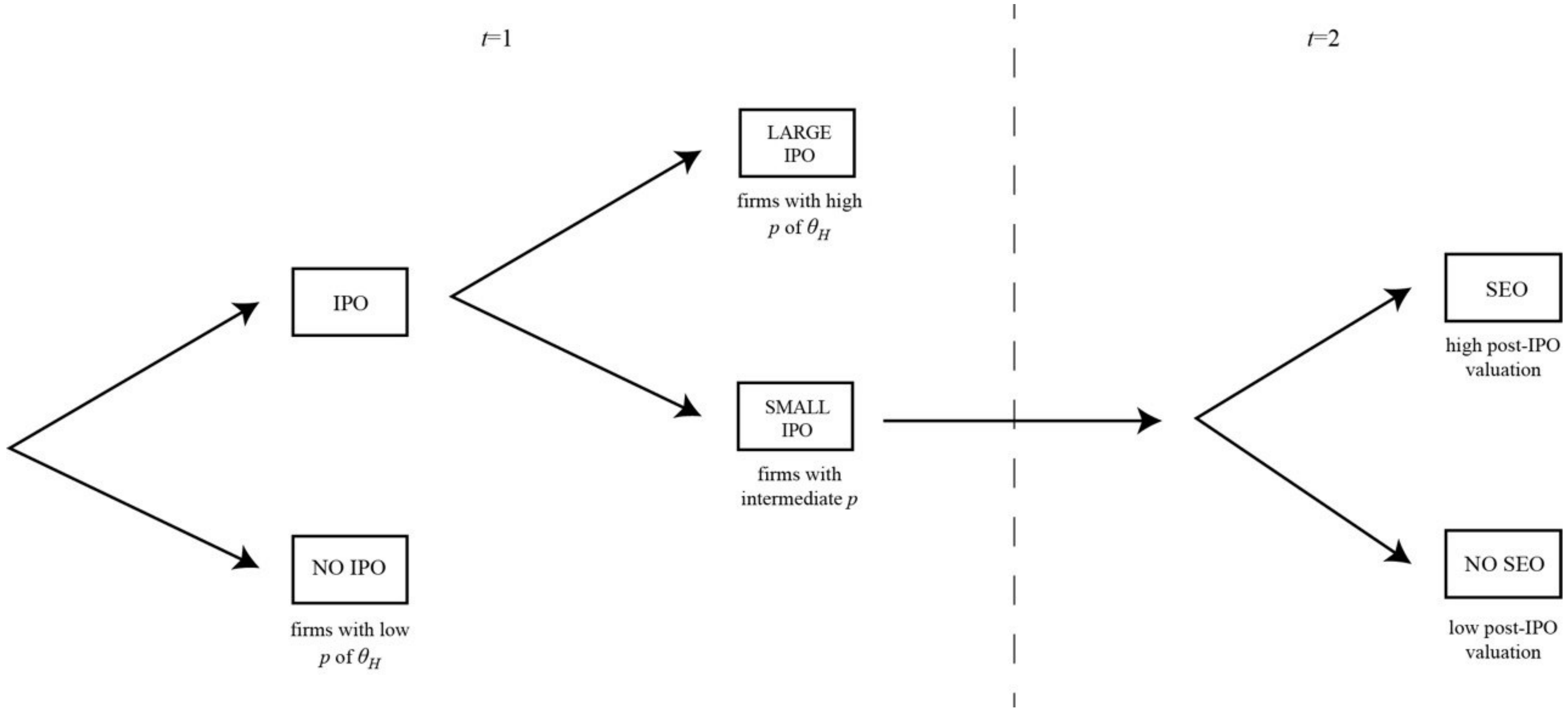

Table 1: Descriptive statistics

The table below reports descriptive statistics for our sample firms. Our sample consists of 2,143 U.S. IPOs between 1.1.1981–31.11.2014. We sort the firms on difficulty to value. We measure the difficulty to value with the first principal component from revision in offer price, a negative earnings indicator, R&D scaled by sales, firm age and a high tech indictor. For variable definitions see appendix 1. ***, **,* denotes 1%, 5%, 10% significance, respectively.

	FULL SAMPLE					Easy to value firms, ETV			Mid			Hard to value firms, HTV			
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	t-stat ETV - HTV
IPO Size	2143	0.311	0.154	0.0755	0.983	715	0.3371	0.1664	716	0.3262	0.1544	712	0.2692	0.1295	8.599***
SEO 1/0	2143	0.2809	0.4496	0.0000	1.0000	715	0.2308	0.4216	716	0.2612	0.4396	712	0.3511	0.4777	-5.001***
SEO w.o./ Secondary	2143	0.2380	0.4259	0.0000	1.0000	715	0.1650	0.3715	716	0.2235	0.4169	712	0.3258	0.4690	-7.059***
SEO 100% Secondary	2143	0.0429	0.2027	0.0000	1.0000	715	0.0657	0.2480	716	0.0377	0.1906	712	0.0253	0.1571	3.664***
Participation Ratio	2143	0.1640	0.2396	0.0000	1.0000	715	0.2161	0.2922	716	0.1677	0.2282	712	0.1078	0.1702	8.554***
Secondary/Total	2143	0.0594	0.1185	0.0000	1.0000	715	0.0857	0.1592	716	0.0592	0.1030	712	0.0333	0.0693	8.058***
R&D	2143	0.2408	1.2094	0.0000	13.0629	715	0.0116	0.0345	716	0.0301	0.0686	712	0.6829	2.0266	-8.856***
Missing R&D	2143	0.4447	0.4970	0.0000	1.0000	715	0.5413	0.4986	716	0.5475	0.4981	712	0.2444	0.4300	11.480***
Ln(Age)	2143	2.3846	1.0666	0.0000	5.1059	715	3.4738	0.6344	716	2.0148	0.5482	712	1.6629	0.9320	42.921***
Abs(Revision)	2143	0.0988	0.1291	0.0000	1.7273	715	0.0706	0.0841	716	0.1075	0.1164	712	0.1182	0.1680	-6.774***
Earnings <0	2143	0.1479	0.3551	0.0000	1.0000	715	0.0000	0.0000	716	0.0000	0.0000	712	0.4452	0.4973	-23.937***
Hi Tech	2143	0.1969	0.3978	0.0000	1.0000	715	0.0000	0.0000	716	0.0251	0.1567	712	0.5674	0.4958	-23.789***
ROA	2143	0.1217	0.2286	-0.8544	0.4711	715	0.1864	0.0990	716	0.1995	0.1216	712	-0.0216	0.3191	16.638***
M/B	2143	4.0598	3.0459	0.1072	10.0000	715	2.5994	1.9290	716	3.9695	2.9445	712	5.6171	3.3035	-21.081***
Ln(Sales)	2143	4.4151	1.6438	-4.6377	10.6438	715	5.3640	1.3928	716	4.4900	1.2478	712	3.3868	1.6299	24.636***
Leverage	2143	0.3008	0.2395	0.0000	0.9678	715	0.3661	0.2312	716	0.3233	0.2431	712	0.2125	0.2170	12.941***
Cash Holdings	2143	0.1580	0.2166	0.0000	0.9930	715	0.0736	0.1120	716	0.1099	0.1446	712	0.2912	0.2837	-19.071***
IPO Heat	2143	1.2167	0.5305	0.1385	2.5785	715	1.2309	0.5499	716	1.2051	0.5440	712	1.2141	0.4961	0.605
Top Underwriter	2143	0.4545	0.4980	0.0000	1.0000	715	0.4671	0.4993	716	0.4581	0.4986	712	0.4382	0.4965	1.097
UW Premium	2143	0.2126	0.1976	-0.0571	1.0430	715	0.1955	0.1736	716	0.1949	0.1840	712	0.2476	0.2268	-4.880***
VC backing	2143	0.3257	0.4687	0.0000	1.0000	715	0.1021	0.3030	716	0.3212	0.4673	712	0.5548	0.4973	-20.773***
Ln(Analyst)	2143	0.4376	0.6497	0.0000	3.1355	715	0.4120	0.6642	716	0.4562	0.6671	712	0.4446	0.6165	-0.960
First Day Return	2143	0.1945	0.5555	-1.0000	11.8333	715	0.0992	0.3202	716	0.1642	0.3953	712	0.3206	0.8023	-6.851***
1-Month Return	2143	0.0350	0.1998	-0.8356	1.5587	715	0.0240	0.1456	716	0.0377	0.1767	712	0.0433	0.2596	-1.730*
1-Month Std Dev	2143	0.0374	0.0241	0.0048	0.2052	715	0.0294	0.0158	716	0.0347	0.0189	712	0.0482	0.0309	-14.551***

Table 2: Average SEO likelihood sorted by post-IPO alpha and difficulty to value

The table shows sorting on the difficulty to value. We measure the difficulty to value with the first principal component (HTV1) from absolute revision in offer price, a negative earnings indicator, R&D scaled by sales, firm age and a high tech indictor. ETV denotes easy to value, mid is the mid tercile and HTV is the most difficult to value tercile. Panel A reports the 1-month idiosyncratic volatility from a Fama-French 5-factor model (IVOL) and 1-month return volatility (VOL) over the three terciles. Panel B reports the SEO likelihood between 1–24 months following the IPO. In addition to sort on valuation uncertainty, we further sort the firms on their 1-month alpha obtained from a Fama-French 5-factor regression model. ***, **,* denotes 1%, 5%, 10% significance, respectively.

Panel A: IVOL and VOL sorted over the valuation uncertainty terciles

	1-month		3-month	
	IVOL	VOL	IVOL	VOL
ETV	2.866	2.940	3.126	3.265
mid	3.358	3.469	3.534	3.671
HTV	4.570	4.804	4.490	4.741
T-stat	-14.315***	-14.238***	-12.181***	-11.769***

Panel B: SEO Likelihood sorted on Alpha and and Valuation Uncertainty

	Low alpha	mid	High alpha	Z-stat
ETV	0.164	0.220	0.301	-3.451***
mid	0.191	0.281	0.325	-3.3417***
HTV	0.332	0.296	0.409	-1.6622*
Z-stat	-4.1919***	-2.0431**	-2.447**	-5.7981***

Table 3: Regressions on IPO size

This table reports regressions on IPO size measured as total proceeds scaled by total market value of equity. We use the two principal components as our main explanatory variables. First, a five component PCA (HTV1) including revision in offer price, a negative earnings indicator, R&D scaled by sales, firm age and a high tech indictor. The second PCA (HTV2) we use includes three variables: a negative earnings indicator, a high tech indicator and firm age. We further include the components of the PCA and regress them on IPO size in columns five to eight. All our models include year effects and the last 2 models also include 3-digit SIC code industry effects. All variables are defined as in appendix 1. Clustered robust standard errors on industry and year are reported in parentheses. ***, **,* denotes 1%, 5%, 10% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	IPO Size	IPO Size	IPO Size	IPO Size	IPO Size	IPO Size	IPO Size	IPO Size	IPO Size	IPO Size	IPO Size
HTV1	-0.0188***		-0.0180***							-0.0172***	
	(-6.036)		(-5.618)							(-3.761)	
HTV2		-0.0190***		-0.0144***							-0.0141***
		(-5.670)		(-5.691)							(-3.239)
R&D/Sales					-0.0048**						
					(-2.426)						
Missing R&D					0.0057						
					(0.678)						
Hi Tech Indicator						-0.0264***					
						(-2.814)					
ln(Age)							0.0080**				
							(2.224)				
abs(Revision)								-0.0444			
								(-1.679)			
Earnings <0									-0.0307***		
									(-2.970)		
ROA			-0.0065	0.0239	0.0289**	0.0361**	0.0344**	0.0359**		-0.0034	0.0250
			(-0.404)	(1.664)	(2.065)	(2.743)	(2.657)	(2.632)		(-0.222)	(1.683)
M/B			-0.0200***	-0.0205***	-0.0206***	-0.0205***	-0.0204***	-0.0204***	-0.0202***	-0.0209***	-0.0213***
			(-14.611)	(-14.619)	(-13.651)	(-14.410)	(-14.304)	(-13.898)	(-14.803)	(-14.675)	(-14.436)
ln(Sales)			-0.0251***	-0.0239***	-0.0212***	-0.0206***	-0.0223***	-0.0204***	-0.0210***	-0.0286***	-0.0275***
			(-9.452)	(-9.828)	(-8.003)	(-8.837)	(-10.709)	(-8.492)	(-7.947)	(-7.726)	(-7.960)
Leverage			-0.0122	-0.0124	-0.0119	-0.0147	-0.0103	-0.0118	-0.0126	-0.0465***	-0.0452**
			(-0.602)	(-0.613)	(-0.581)	(-0.726)	(-0.535)	(-0.601)	(-0.638)	(-2.810)	(-2.661)
Cash/Assets			-0.0470**	-0.0530**	-0.0598***	-0.0589***	-0.0677***	-0.0676***	-0.0626***	-0.0469**	-0.0512***
			(-2.234)	(-2.545)	(-2.812)	(-2.813)	(-3.068)	(-3.073)	(-3.031)	(-2.504)	(-2.780)
IPO Heat			-0.0122	-0.0139	-0.0110	-0.0133	-0.0112	-0.0109	-0.0086	-0.0259	-0.0276
			(-0.424)	(-0.476)	(-0.371)	(-0.450)	(-0.379)	(-0.377)	(-0.298)	(-0.792)	(-0.832)
Top Underwriter			-0.0033	-0.0036	-0.0040	-0.0047	-0.0045	-0.0040	-0.0049	-0.0036	-0.0037
			(-0.923)	(-1.049)	(-1.023)	(-1.386)	(-1.396)	(-1.024)	(-1.420)	(-0.636)	(-0.677)
UW Premium			0.0056	0.0052	0.0042	0.0010	0.0047	0.0010	0.0027	0.0095	0.0094
			(0.409)	(0.365)	(0.290)	(0.072)	(0.333)	(0.064)	(0.197)	(0.459)	(0.448)
VCB			-0.0040	-0.0038	-0.0070	-0.0032	-0.0057	-0.0066	-0.0075	-0.0008	-0.0008
			(-0.583)	(-0.543)	(-0.917)	(-0.444)	(-0.831)	(-0.955)	(-1.096)	(-0.114)	(-0.111)
Constant	0.3106***	0.3106***	0.5306***	0.5272***	0.5126***	0.5188***	0.4989***	0.5147***	0.5180***	0.5748***	0.5706***
	(53.524)	(49.786)	(13.559)	(13.542)	(13.005)	(13.039)	(12.754)	(13.216)	(12.886)	(13.500)	(13.320)
Observations	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,108	2,108
R-squared	0.093	0.088	0.223	0.222	0.216	0.219	0.217	0.216	0.216	0.311	0.310
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES

Table 4: Regressions on SEO likelihood

This table reports regressions on an indicator variable taking value one if the firm conducts an SEO within 24 months following the IPO. We use the principal component as our main explanatory variables. First, a five component PCA (HTV1) including revision in offer price, a negative earnings indicator, R&D scaled by sales, firm age and a high tech indictor. Second, a three component PCA (HTV2) including R&D scaled by sales, firm age and a high tech indictor. All our models include year fixed effects and models (10) and (11) also include 3-digit SIC code industry effects. All variables are defined as in appendix 1. Clustered robust standard errors on industry and year are reported in parentheses. ***, **,* denotes 1%, 5%, 10% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0
HTV1	0.0454***		0.0403**							0.0444**	
	(3.427)		(2.568)							(2.444)	
HTV2		0.0436***		0.0283**							0.0297
		(2.825)		(2.147)							(1.375)
R&D/Sales					0.0015						
					(0.084)						
Missing R&D					0.0091						
					(0.409)						
Hi Tech Indicator						0.0371					
						(1.126)					
ln(Age)							-0.0341***				
							(-3.395)				
abs(revision)								0.0751			
								(0.815)			
Earnings <0									0.1017*		
									(2.015)		
IPO Size			-0.1592**	-0.1660**	-0.1829**	-0.1761**	-0.1699**	-0.1802**	-0.1777**	-0.1770**	-0.1846**
			(-2.330)	(-2.463)	(-2.640)	(-2.536)	(-2.554)	(-2.566)	(-2.519)	(-2.500)	(-2.647)
ROA			-0.0186	-0.0895	-0.1138	-0.1135*	-0.1068*	-0.1135*		0.0136	-0.0637
			(-0.288)	(-1.449)	(-1.635)	(-1.891)	(-1.863)	(-1.886)		(0.164)	(-0.825)
M/B			0.0052	0.0062	0.0067	0.0063	0.0058	0.0062	0.0049	0.0053	0.0063
			(0.741)	(0.872)	(0.895)	(0.848)	(0.792)	(0.828)	(0.652)	(0.724)	(0.845)
ln(Sales)			0.0116	0.0080	0.0013	0.0010	0.0094	0.0007	0.0030	0.0114	0.0068
			(1.393)	(1.083)	(0.178)	(0.133)	(1.130)	(0.083)	(0.364)	(1.328)	(0.849)
Leverage			0.1798***	0.1800***	0.1763***	0.1830***	0.1735***	0.1789***	0.1811***	0.1510***	0.1478***
			(3.678)	(3.608)	(3.555)	(3.539)	(3.285)	(3.528)	(3.753)	(2.877)	(2.803)
Cash/Assets			0.0683	0.0853	0.1131	0.1011	0.1178	0.1135	0.0955	0.0188	0.0318
			(0.999)	(1.116)	(1.413)	(1.192)	(1.227)	(1.217)	(1.113)	(0.475)	(0.686)
IPO Heat			-0.0101	-0.0068	-0.0155	-0.0099	-0.0099	-0.0132	-0.0201	-0.0593	-0.0550
			(-0.172)	(-0.115)	(-0.254)	(-0.160)	(-0.166)	(-0.215)	(-0.330)	(-1.014)	(-0.924)
Ln(Analyst)			0.0841***	0.0842***	0.0841***	0.0853***	0.0828***	0.0843***	0.0848***	0.0804***	0.0809***
			(3.834)	(3.831)	(3.821)	(3.929)	(3.758)	(3.803)	(3.875)	(3.366)	(3.395)

First Day Return			0.0166	0.0167	0.0134	0.0152	0.0113	0.0128	0.0133	0.0195	0.0202
			(1.016)	(1.060)	(0.862)	(0.936)	(0.669)	(0.744)	(0.742)	(1.225)	(1.318)
1-Month Return			0.2484***	0.2423***	0.2430***	0.2434***	0.2427***	0.2446***	0.2523***	0.2475***	0.2400***
			(4.323)	(4.185)	(4.104)	(4.244)	(4.274)	(4.327)	(4.320)	(4.776)	(4.540)
1-Month Std Dev			-0.0604	-0.0728	-0.0800	-0.0890	-0.1835	-0.1034	-0.0750	0.3949	0.3834
			(-0.102)	(-0.125)	(-0.147)	(-0.158)	(-0.325)	(-0.183)	(-0.139)	(0.622)	(0.619)
Top Underwriter			0.0044	0.0053	0.0075	0.0073	0.0062	0.0061	0.0078	0.0041	0.0048
			(0.144)	(0.175)	(0.258)	(0.242)	(0.206)	(0.199)	(0.260)	(0.126)	(0.148)
UW Premium			0.0560	0.0578	0.0657	0.0661	0.0586	0.0685	0.0642	0.0613	0.0634
			(1.205)	(1.265)	(1.426)	(1.398)	(1.211)	(1.346)	(1.377)	(1.159)	(1.198)
VCB			0.0522**	0.0528**	0.0611**	0.0537**	0.0534**	0.0584**	0.0598***	0.0504***	0.0504***
			(2.387)	(2.379)	(2.700)	(2.713)	(2.443)	(2.720)	(2.923)	(3.257)	(3.222)
Constant	0.2806***	0.2806***	0.1299	0.1453	0.1799	0.1723	0.2310*	0.1789	0.1601	0.1909*	0.2122**
	(53.706)	(44.073)	(1.098)	(1.247)	(1.480)	(1.429)	(1.840)	(1.414)	(1.336)	(1.813)	(2.067)
Observations	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,108	2,108
R-squared	0.053	0.048	0.097	0.095	0.092	0.093	0.097	0.093	0.094	0.179	0.177
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES

Table 5: Cox regressions explaining time to first SEO

In the table below we report the results from a proportional hazard model. Time to first SEO is the dependent variable. A negative coefficient estimate indicates a shorter time to failure. We track the firms for two years following the IPO. Hence, our distributions is truncated at 730 days. Our model updates the alpha every 6 months in all models. Models (5) to (8) further updates all accounting variables. We measure the difficulty to value with the first principal component (PCA) from revision in offer price, a negative earnings indicator, R&D scaled by sales, firm age and a high tech indictor. The variable definitions is as in appendix 1. The model includes year fixed effects and clustering on firm. ***, **,* denotes 1%, 5%, 10% significance, respectively.

	(1) Time to SEO	(2) Time to SEO	(3) Time to SEO	(4) Time to SEO	(5) Time to SEO	(6) Time to SEO	(7) Time to SEO	(8) Time to SEO
Alpha	-0.3399***	-0.3447***	-0.3514***	-0.3589***	-0.3337***	-0.3299***	-0.3401***	-0.3362***
	(-8.043)	(-8.186)	(-7.610)	(-7.839)	(-7.568)	(-7.324)	(-7.199)	(-7.010)
PCA (5 variables)	-0.1501***		-0.1967***		-0.1724***		-0.2040***	
	(-3.992)		(-4.481)		(-4.398)		(-4.676)	
PCA (3 variables)		-0.0897**		-0.1304***		-0.1237***		-0.1464***
		(-2.384)		(-2.802)		(-3.509)		(-3.545)
IPO Size	0.8518***	0.9223***	0.9146***	1.0117***	0.8074**	0.8338**	0.6726*	0.6986**
	(2.680)	(2.855)	(2.660)	(2.880)	(2.503)	(2.570)	(1.942)	(1.998)
ln(Sales)	-0.0095	0.0195	-0.0364	0.0013	-0.1223***	-0.1138***	-0.1869***	-0.1769***
	(-0.268)	(0.562)	(-0.821)	(0.029)	(-3.827)	(-3.525)	(-4.833)	(-4.514)
Leverage	0.1639	0.1309	0.3007	0.2908	-0.6537***	-0.6531***	-0.6014**	-0.5874**
	(0.693)	(0.556)	(1.146)	(1.110)	(-3.211)	(-3.207)	(-2.522)	(-2.453)
M/B	0.0112	0.0084	0.0007	-0.0005	-0.0167	-0.0232	-0.0347*	-0.0417**
	(0.663)	(0.498)	(0.040)	(-0.030)	(-0.865)	(-1.204)	(-1.770)	(-2.134)
ROA	-0.4961**	-0.2472	-0.7908***	-0.5171**	0.1150	0.4426**	-0.1164	0.2643
	(-2.156)	(-1.134)	(-3.045)	(-2.065)	(0.514)	(2.275)	(-0.476)	(1.257)
Cash/Assets	-0.1669	-0.2265	-0.3611	-0.3751	-0.1369	-0.2243	-0.2134	-0.2973
	(-0.760)	(-1.031)	(-1.439)	(-1.499)	(-0.523)	(-0.857)	(-0.762)	(-1.058)
IPO Heat	1.2227***	1.1664***	0.5260**	0.4833*	1.5373***	1.5086***	0.6758**	0.6593**
	(10.512)	(10.108)	(1.988)	(1.828)	(12.004)	(11.748)	(2.530)	(2.456)
First Day Return	-0.1503**	-0.1501**	-0.1802***	-0.1860***	-0.1374**	-0.1307*	-0.1464**	-0.1427**
	(-2.293)	(-2.273)	(-2.866)	(-2.967)	(-2.016)	(-1.869)	(-2.212)	(-2.116)
Ln(Analyst)	-0.3156***	-0.3197***	-0.2955***	-0.3045***	-0.3066***	-0.3056***	-0.2713***	-0.2720***
	(-5.472)	(-5.511)	(-4.664)	(-4.797)	(-5.396)	(-5.359)	(-4.396)	(-4.396)
VCB	-0.1512	-0.1650*	-0.2287**	-0.2398**	-0.2482**	-0.2474**	-0.2948***	-0.2932***
	(-1.566)	(-1.716)	(-2.149)	(-2.259)	(-2.540)	(-2.514)	(-2.767)	(-2.737)
Top Underwriter	-0.0669	-0.0803	-0.0541	-0.0670	0.0161	0.0151	0.0351	0.0375

	(-0.774)	(-0.931)	(-0.580)	(-0.717)	(0.188)	(0.175)	(0.383)	(0.407)
UW Premium	-0.0542	-0.0846	-0.0148	-0.0528	0.0137	0.0048	0.0248	0.0190
	(-0.288)	(-0.454)	(-0.078)	(-0.282)	(0.067)	(0.023)	(0.123)	(0.093)
Observations	6,939	6,939	6,939	6,939	6,931	6,931	6,931	6,931
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	NO	NO	YES	YES	NO	NO	YES	YES
Time Varying Covariates	NO	NO	NO	NO	YES	YES	YES	YES

Table 6: Interaction models

The table below studies the interactions between IPO Size, post-IPO alpha and information uncertainty. We include indi of being in the bottom tercile of IPO Size, top tercile of 1-month post-IPO alpha from a Fama-French 5-factor model a terciles of the hard to value PCAs (HTV1 and HTV2). All variables defined as in appendix 1. The model includes year effects and standard errors clustered on both industry and year. ***, **,* denotes 1%, 5%, 10% significance, respectivel

	(1)	(2)	(3)	(4)
	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0
Top Tercile 1-Month Alpha	0.0966**	0.0931**	0.0680	0.0688*
	(2.480)	(2.392)	(1.688)	(1.799)
Bottom Tercile IPO Size	0.0598*	0.0418	0.0766**	0.0631*
	(1.936)	(1.475)	(2.351)	(1.932)
Top Tercile 1-Month Alpha x Bottom Tercile IPO Size	-0.0142	-0.0323	-0.0124	-0.0401
	(-0.303)	(-0.816)	(-0.229)	(-0.863)
Top Tercile HTV2	0.0663***		0.0537	
	(2.882)		(1.659)	
Top Tercile 1-Month Alpha x Top Tercile HTV2	-0.1468***		-0.1120*	
	(-2.899)		(-1.928)	
Bottom Tercile IPO Size x Top Tercile HTV2	-0.0460		-0.0598	
	(-0.845)		(-0.981)	
Top Tercile 1-Month Alpha x Top Tercile HTV2 x Bottim Tercile IPO Size	0.1491		0.1497*	
	(1.599)		(1.766)	
Top Tercile HTV1		0.0843**		0.1035***
		(2.648)		(3.613)
Top Tercile 1-Month Alpha x Top Tercile HTV1		-0.1333***		-0.1090**
		(-3.497)		(-2.710)
Bottom Tercile IPO Size x Top Tercile HTV1		-0.0015		-0.0251
		(-0.024)		(-0.349)
Top Tercile 1-Month Alpha x Top Tercile HTV1 x Bottom Tercile IPO size		0.1910*		0.2066**
		(2.036)		(2.348)
Observations	2,142	2,142	2,108	2,108
R-squared	0.089	0.092	0.171	0.175

Controls	YES	YES	YES	YES
Industry FE	NO	NO	YES	YES
Year FE	YES	YES	YES	YES
F-stat for Interaction and Main Effects	4.42***	4.14***	3.40***	6.12***

Table 7: First stage regression models

The table below reports the first stage regressions in the 2SLS models. The excluded instruments are HTV1, HTV2 and industry misvaluation as in Rhodes-Kropf et al., (2005). All variables are defined as in appendix A1. All models include year fixed effects and the standard errors are clustered on year. ***, **,* denotes 1%, 5%, 10% significance, respectively.

	(1)	(2)	(3)	(4)
	IPO Size	IPO Size	IPO Size	IPO Size
HTV2	-0.0144***		-0.0142***	
	(-5.826)		(-5.394)	
HTV1		-0.0180***		-0.0180***
		(-6.094)		(-5.813)
Industry Misvaluation			0.0257	0.0268*
			(1.637)	(1.717)
ROA	0.0239*	-0.0065	0.0253*	-0.0051
	(1.876)	(-0.465)	(1.889)	(-0.346)
M/B	-0.0205***	-0.0200***	-0.0203***	-0.0199***
	(-17.737)	(-17.105)	(-17.190)	(-16.555)
ln(Sales)	-0.0239***	-0.0251***	-0.0247***	-0.0259***
	(-10.063)	(-9.965)	(-10.610)	(-10.524)
Leverage	-0.0124	-0.0122	-0.0136	-0.0134
	(-0.624)	(-0.620)	(-0.669)	(-0.666)
Cash/Assets	-0.0530***	-0.0470**	-0.0545***	-0.0483**
	(-3.055)	(-2.660)	(-3.176)	(-2.755)
IPO Heat	-0.0139	-0.0122	-0.0177	-0.0161
	(-0.469)	(-0.421)	(-0.588)	(-0.547)
Top Underwriter	-0.0036	-0.0033	-0.0026	-0.0023
	(-0.817)	(-0.739)	(-0.596)	(-0.517)
UW Premium	0.0052	0.0056	0.0036	0.0041
	(0.295)	(0.325)	(0.212)	(0.246)
VCB	-0.0038	-0.0040	-0.0029	-0.0031
	(-0.495)	(-0.528)	(-0.378)	(-0.402)
Constant	0.5272***	0.5306***	0.5297***	0.5333***
	(14.149)	(14.473)	(14.111)	(14.435)
Observations	2,142	2,142	2,129	2,129
Year FE	YES	YES	YES	YES
Industry FE	NO	NO	NO	NO
F-Stat of Excluded Instruments	33.94***	37.14***	14.61***	16.93***

Table 8: Second stage regressions

The table below reports the second stage regressions in the 2SLS models. The excluded instruments are the five variable PCA measuring valuation uncertainty and industry misvaluation as in Rhodes-Kropf et al., (2005). All variables are defined as in appendix A1. All models include year fixed effects and the standard errors are clustered on year. ***, **,* denotes 1%, 5%, 10% significance, respectively.

	(1)	(2)	(3)	(4)
	SEO 1/0	SEO 1/0	SEO 1/0	SEO 1/0
IPO Size (first stage)	-2.1076**	-2.2469**	-1.6440**	-1.7794**
	(-2.398)	(-2.542)	(-2.361)	(-2.414)
ROA	-0.0426	-0.0375	-0.0590	-0.0540
	(-0.979)	(-0.863)	(-1.554)	(-1.411)
M/B	-0.0299	-0.0328*	-0.0205	-0.0233
	(-1.654)	(-1.873)	(-1.368)	(-1.534)
ln(Sales)	-0.0298	-0.0327	-0.0209	-0.0237
	(-1.476)	(-1.636)	(-1.213)	(-1.343)
Leverage	0.1418*	0.1402*	0.1507**	0.1493**
	(1.760)	(1.746)	(2.090)	(2.059)
Cash/Assets	-0.0129	-0.0222	0.0188	0.0097
	(-0.137)	(-0.261)	(0.204)	(0.112)
IPO Heat	-0.0143	-0.0157	-0.0124	-0.0141
	(-0.240)	(-0.253)	(-0.243)	(-0.268)
Top Underwriter	0.0061	0.0055	0.0076	0.0070
	(0.263)	(0.238)	(0.310)	(0.288)
UW Premium	0.1001**	0.1004**	0.0937**	0.0936*
	(2.145)	(2.077)	(2.091)	(2.045)
VCB	0.0594*	0.0584*	0.0616**	0.0606**
	(1.897)	(1.840)	(2.180)	(2.119)
Observations	2,142	2,142	2,129	2,129
Model	2SLS	2SLS	2SLS	2SLS
Year FE	YES	YES	YES	YES
HTV Measure	3 var	5 var	3 var	5 var
Excluded Instruments	1	1	2	2

Table 9: Secondary shares

The table below reports OLS models using secondary share sales in the IPO (models 1 to 4), post IPO-alpha (models 5 to 8) and a 100% secondary share SEO indicator (9 to 10) as dependent variables. All variables are defined as in appendix A1. All models include year fixed effects and the standard errors are clustered on year. ***, **,* denotes 1%, 5%, 10% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Participation Ratio	Secondary/Total	1-Month Alpha		3-Month Alpha		SEO 100% Secondary	Secondary/Total
HTV1	-0.0098	-0.0050*	-0.0431	-0.0430	0.0036	0.0035	0.0083*	0.0077
	(-1.639)	(-1.855)	(-1.155)	(-1.157)	(0.374)	(0.368)	(1.847)	(1.695)
Participation Ratio			0.0540		0.0191		0.1044***	
			(0.703)		(0.633)		(3.238)	
Secondary/Total				0.1169		0.0238		0.0869
				(0.829)		(0.515)		(1.666)
ROA	0.1073**	0.0156	0.1330	0.1370	0.0608	0.0625	0.0105	0.0198
	(2.522)	(0.910)	(0.732)	(0.764)	(0.994)	(1.036)	(0.510)	(0.872)
M/B	0.0033*	-0.0031***	0.0234**	0.0240**	0.0013	0.0014	0.0070***	0.0077***
	(1.983)	(-3.217)	(2.520)	(2.543)	(0.615)	(0.695)	(2.903)	(3.185)
ln(Sales)	0.0301***	0.0086***	0.0279	0.0285	0.0041	0.0044	0.0214***	0.0237***
	(5.528)	(3.505)	(1.204)	(1.245)	(0.581)	(0.639)	(3.485)	(3.783)
Leverage	-0.2303***	-0.1138***	0.0988	0.0997	-0.0036	-0.0053	0.0595***	0.0456**
	(-10.529)	(-5.880)	(1.091)	(1.065)	(-0.106)	(-0.153)	(3.300)	(2.557)
Cash/Assets	-0.0623**	-0.0420***	0.3345	0.3361	0.0815	0.0813	0.0390*	0.0368
	(-2.139)	(-3.246)	(1.418)	(1.418)	(1.221)	(1.217)	(1.773)	(1.670)
IPO Heat	-0.0410	-0.0136	0.2335	0.2329	0.0012	0.0008	0.0347	0.0311
	(-1.056)	(-0.662)	(1.018)	(1.016)	(0.014)	(0.009)	(0.990)	(0.840)
Top Underwriter	0.0163*	0.0056	0.0334	0.0336	0.0155	0.0157	0.0229**	0.0240**
	(1.769)	(1.338)	(0.632)	(0.633)	(1.041)	(1.058)	(2.498)	(2.610)
UW Premium	0.0294	0.0100	0.0806	0.0810	0.1480***	0.1484***	-0.0052	-0.0054
	(0.749)	(0.728)	(0.664)	(0.667)	(3.597)	(3.631)	(-0.837)	(-0.840)
VCB	0.0139	-0.0013	0.1357***	0.1366***	-0.0106	-0.0103	0.0069	0.0102
	(1.527)	(-0.344)	(3.400)	(3.385)	(-0.581)	(-0.562)	(0.320)	(0.470)
Ln(Analyst)							-0.1665	-0.2218
							(-0.707)	(-0.956)
First Day Return							-0.0096	-0.0085
							(-0.903)	(-0.800)
1-Month Return							0.0415	0.0441
							(1.597)	(1.589)
1-Month Std Dev							-0.0163**	-0.0149**
							(-2.235)	(-2.099)
Constant	0.1152**	0.0849***	-0.5235*	-0.5273*	-0.0310	-0.0308	-0.1672***	-0.1602***
	(2.323)	(3.137)	(-1.830)	(-1.834)	(-0.296)	(-0.294)	(-2.980)	(-2.780)
Observations	2,142	2,142	2,142	2,142	2,142	2,142	2,142	2,142
R-squared	0.173	0.120	0.059	0.059	0.024	0.024	0.095	0.085
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	NO	NO	NO	NO	NO	NO	NO	NO

Table 10: Market timing models

This table study the 6 months post-SEO returns for calendar time portfolios based on the valuation uncertainty measures. Columns (1) to (3) sorts on the 3 variable PCA measure (HTV2) and columns (4) to (6) is sorted on the 5 variable measure (HTV1). All calendar time models are estimated on monthly data using Fama-French 5-benchmark factors. ***, **,* denotes 1%, 5%, 10% significance, respectively.

Panel A: 12 months Post SEO	(1)	(2)	(3)	(4)	(5)	(6)
Uncertainty Tercile	1	2	3	1	2	3
Market	1.1755***	0.9380***	1.0797***	1.0461***	0.6417*	1.3805***
	(5.557)	(3.645)	(2.859)	(5.558)	(1.992)	(6.176)
SMB	0.5612	0.8349**	0.4715	0.6475**	1.5349**	0.5170
	(1.537)	(1.989)	(0.793)	(2.015)	(2.636)	(1.010)
HML	-0.4757	-0.2205	-0.2171	-0.4044	-0.6430	-0.1756
	(-1.396)	(-0.490)	(-0.194)	(-1.327)	(-0.993)	(-0.263)
RMW	-1.0528**	-0.9791	-0.2959	-0.9359**	0.2686	-0.4735
	(-2.017)	(-1.457)	(-0.281)	(-2.005)	(0.305)	(-0.668)
CMA	0.3416	-0.5219	-1.3880	0.1472	-1.2136	-0.3787
	(0.544)	(-0.604)	(-0.839)	(0.247)	(-1.302)	(-0.413)
Constant	-0.0428	1.4008	-0.7184	0.0192	0.4432	-0.0968
	(-0.057)	(1.496)	(-0.440)	(0.027)	(0.391)	(-0.093)
Observations	115	107	84	114	69	98
R-squared	0.472	0.288	0.154	0.480	0.259	0.373

Panel B: 24 months Post SEO	(1)	(2)	(3)	(4)	(5)	(6)
Uncerctainty Tercile	1	2	3	1	2	3
Market	1.1209***	1.1223***	1.2579***	1.0211***	1.0529***	1.3348***
	(8.382)	(7.987)	(4.794)	(7.813)	(6.085)	(7.310)
SMB	0.5901**	0.8690***	-0.4187	0.5587**	1.0788***	0.2105
	(2.434)	(3.219)	(-0.777)	(2.220)	(2.766)	(0.481)
HML	-0.2036	-0.3868	-0.3727	-0.1896	-0.3631	-0.4551
	(-0.737)	(-1.328)	(-0.718)	(-0.698)	(-0.962)	(-1.007)
RMW	-0.5014	-0.6852	-1.5591**	-0.4953	-0.3171	-1.3573**
	(-1.556)	(-1.645)	(-2.049)	(-1.456)	(-0.524)	(-2.615)
CMA	0.3464	0.2317	-1.6534*	0.1275	-0.3835	-0.0531
	(0.832)	(0.368)	(-1.672)	(0.289)	(-0.618)	(-0.072)
Constant	0.0909	0.5714	-0.4264	0.2175	-0.4271	0.1088
	(0.195)	(0.855)	(-0.383)	(0.471)	(-0.459)	(0.135)
Observations	136	124	130	136	107	130
R-squared	0.556	0.422	0.286	0.508	0.408	0.403

Table 11: Entropy balanced sample

The table below reports pre- and post-balanced samples using the Hainmueller (2012) entropy-balancing algorithm. We match firms in the top valuation uncertainty tercile (HTV) with firms from the lowest tercile (ETV) using the 5-variable PCA (HTV1). All variables are defined as in appendix A1.

Panel A: Pre-Matching

	HTV		ETV	
	Mean	Std. Dev.	Mean	Std. Dev.
M/B	5.617	10.910	2.599	3.721
ln(Sales)	3.387	2.657	5.364	1.940
Leverage	0.213	0.047	0.366	0.053
Cash/Assets	0.291	0.080	0.074	0.013
IPO Heat	1.214	0.246	1.231	0.302
Top Underwriter	0.438	0.247	0.467	0.249
UW Premium	0.248	0.051	0.196	0.030
VCB	0.555	0.247	0.102	0.092

Panel B: Post-Matching

	HTV		ETV	
	Mean	Std. Dev.	Mean	Std. Dev.
M/B	5.617	10.910	5.617	9.370
ln(Sales)	3.387	2.657	3.387	0.349
Leverage	0.213	0.047	0.213	0.059
Cash/Assets	0.291	0.080	0.291	0.050
IPO Heat	1.214	0.246	1.214	0.235
Top Underwriter	0.438	0.247	0.438	0.247
UW Premium	0.248	0.051	0.248	0.048
VCB	0.555	0.247	0.555	0.247

Table 12: 2-stage models with entropy balanced sample

The table below reports the first and second stage regressions from 2SLS models with the entropy balanced sample in table 11. The first two columns shows the first stage regressions using IPO size as dependent variable and the two latter columns the second stage models. The excluded instruments are the five variable PCA measuring valuation uncertainty and industry misvaluation as in Rhodes-Kropf et al., (2005). All variables are defined as in appendix A1. The constant term is not reported. All models include year fixed effects and the standard errors are clustered on year. ***, **,* denotes 1%, 5%, 10% significance, respectively.

	(1)	(2)	(3)	(4)
	IPO Size	IPO Size	SEO 1/0	SEO 1/0
HTV1	-0.0254***	-0.0255***		
	(-3.954)	(-4.050)		
Industry Misvaluation		-0.0118		
		(-0.735)		
IPO Size (first stage)			-1.5589**	-1.5611**
			(-2.067)	(-2.151)
ROA	-0.0224	-0.0234	-0.1366	-0.1335
	(-1.204)	(-1.246)	(-1.670)	(-1.639)
M/B	-0.0135***	-0.0136***	-0.0243*	-0.0242*
	(-6.074)	(-6.140)	(-1.739)	(-1.741)
ln(Sales)	-0.0268***	-0.0266***	-0.0141	-0.0147
	(-8.978)	(-9.227)	(-0.726)	(-0.766)
Leverage	-0.0292	-0.0295	-0.0953	-0.0927
	(-0.951)	(-0.951)	(-0.669)	(-0.646)
Cash/Assets	-0.0471*	-0.0472*	-0.0874	-0.0864
	(-1.801)	(-1.810)	(-0.555)	(-0.542)
IPO Heat	-0.0262	-0.0262	0.0782	0.0772
	(-0.819)	(-0.816)	(0.604)	(0.597)
Top Underwriter	0.0004	0.0001	0.0156	0.0148
	(0.042)	(0.014)	(0.353)	(0.331)
UW Premium	-0.0589**	-0.0601**	-0.0078	-0.0085
	(-2.395)	(-2.441)	(-0.088)	(-0.096)
VCB	-0.0064	-0.0070	0.0315	0.0311
	(-0.580)	(-0.625)	(0.553)	(0.545)
Observations	1,426	1,419	1,426	1,419
2SLS stage	1st stage	1st stage	2nd Stage	2nd stage
Year FE	YES	YES	YES	YES
HTV measure	5 var	5 var	5 var	5 var
Excluded Instruments	1	2	1	2

Appendix 1: Variable definitions

Variable	Formula	Description	Source
SEO 1/0		Indicator variable taking the value of 1 if the firm conducts an SEO within 24 months following the IPO	SDC
SEO 100% Secondary		Indicator variable taking value 1 if the firm conducts an SEO within 24 months following the IPO (Excluding 100% secondary offerings)	SDC
IPO Size	Shares Offered in IPO/Post-IPO Shares Outstanding		SDC/CRSP
Participation Ratio	Secondary Shares in the IPO/Total shares in the IPO	Proportion of secondary shares in the IPO	
Secondary/Total	Secondary Shares in the IPO/Post-IPO Shares outstanding	Proportion of secondary shares offered in the IPO scaled by total shares	
R&D	R&D/Sales	Pre-IPO R&D expenses scaled by Pre-IPO sales	COMPUSTAT
Firm Age	ln(1+IPO Year-Founding year)		SDC/Jay Ritter
High Tech Indicator		Following COMPUSTAT description, industries with the following three-digit SIC codes are considered high tech industries: 283, 357, 366, 367, 381, 382, 383, 384, 737, 873, and 874.	COMPUSTAT
abs(Revision)	Abs(Offerprice/Midrange filing price-1)		SDC
Earnings <0		Indicator variable taking value 1 if the firm has negative pre-IPO earnings	COMPUSTAT
ROA	EBITDA/Total Assets	Pre-IPO EBITDA scaled by Pre-IPO Total Assets, winsorized at 1%	COMPUSTAT
M/B	(MV(equity)+total assets-BV(equity))/total assets	Market value of equity at the IPO day, post-IPO total assets, post-IPO Book equity. Following Alti (2005), all values above 10 is given the value 10	CRSP/COMPUSTAT
ln(Sales)	ln(Sales)	the natural logarithm of pre-IPO sales	COMPUSTAT
Leverage	(Long term+Short Term debt)/Total Assets	Pre-IPO long term and short term debt scaled by pre-IPO total assets	COMPUSTAT
IPO heat		Measured as in Yung et al. (2008) from Jay Ritter's IPO data	Ritter
VC Backing		Indicator variable taking the value of one if the firm is VC backed	SDC
Top Underwriter		Indicator variable taking the value of 1 if the firm has at least one lead underwriter with score	SDC/Jay Ritter

		of 8 or 9 according to the Carter and Manaster Ranking	
UW Premium		Average underwriter specidic premium as in (Hoberg, 2007)	SDC
First Day Return	First day Close/Offer price–1		SDC
1-Month Return		Return of the stock during the first 21 days of trading (excluding the first day of trading)	CRSP
1-Month Std Dev		Standard deviation of the first 21 days stock return trading (excluding the first day of trading)	CRSP
Secondary	Secondary shares/total shares	percentage of secondary shares offered in the IPO	SDC
Ln(Analyst)	ln(1+nr. of analysts)	Number of analysts measured at 60 days following the IPO as in Rajan and Servaes (1995)	IBES
HTV2		PCA constructed from R&D/Sales, high tech indicator and ln(+1firm age)	CRSP/ COMPUSTAT
HTV1		The variables from the 3 variable PCA plus absolute offerprice revision and a negative earnings indicator	CRSP/ COMPUSTAT/SDC
Industry Misvaluation		Industry misvaluation calculated as in Rhodes Kropft et al., (2005)	CRSP/ COMPUSTAT

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