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Learning and 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 a positive valuation signal. This is driven by two-way learning, as market information complements both corporate disclosure and internal information available to management. In contrast to prior studies, we find that information asymmetry is not a necessary condition for staged financing. Our arguments receive support in a sample of 3,625 U.S. IPOs between 1980-2018.

JEL codes: G14, G24, G32

Keywords: IPOs, security issuance, sequential financing

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Learning and 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 a positive valuation signal. This is driven by two-way learning, as market information complements both corporate disclosure and internal information available to management. In contrast to prior studies, we find that information asymmetry is not a necessary condition for staged financing. Our arguments receive support in a sample of 3,625 U.S. IPOs between 1980-2018.

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1. Introduction

A large number of firms return to equity market soon after their initial public offering (IPO). Hertz, et al. (2012) report that such behavior is often premeditated, as witnessed by disclosures in the IPO prospectuses. While many of the existing explanations for staged financing rest upon information asymmetry, we offer a simpler rationale for it. Our analysis suggests that using the IPO and the subsequent trading information as learning channels is sufficient to explain the observed sequential equity financing behavior of IPO firms, even in the absence of information asymmetry. The owner-manager deliberately undertakes a relatively small IPO, in order to gain information that will guide her subsequent capital raising decisions. This is consistent with Lowry and Schwert (2004), and Loughran and Ritter (2002), who find that the IPO process by itself fails to fully incorporate all public information.¹ Firms thus have an incentive to conduct their IPO in stages, especially when they operate in an environment with high uncertainty.

Our work is inspired by the literature on the feedback effects of stock prices.² This literature indicates that stock market trading provides valuable information that guides firm managers in taking actions that affect the value of their firms. New to the literature, we apply this argument in a setting where the firm raises equity through an IPO. As we note above, we posit that staging of equity offerings allows the firm's owner-manager to use the initial stock market information to learn about the valuation of the firm and then calibrate the size and the timing of a subsequent equity offering based on this information.

While our main contribution is an empirical one, we develop a parsimonious model that illustrates the idea behind our work. Inspired by Holmström (1982), Aghion, et al. (2013), and Dow et al. (2017), we build upon 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 faces a high degree of uncertainty, she initially conducts a small IPO.

¹ Also, several studies report substantial inefficiencies in IPO pricing. See e.g. Aussenegg, et al. (2006), Derrien (2005), Ljungqvist and Wilhelm (2003), Purnanandam and Swaminathan (2005).

² See, e.g. Edmans, et al. (2015), and Dow, et al. (2017) for theoretical arguments, and Edmans, et al. (2017) for empirical evidence. Also, Bond, et al. (2012) provide an early survey of the literature.

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, both the IPO process and the subsequent trading activity transmit information, which motivates the firm's follow-on SEO issue. 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; Alt, 2005; Hsieh et al., 2011). Our symmetric-but-incomplete information assumption is not only a simple way to explain follow-on SEOs but it is also plausible in the early stage trading where uncertainty about the firm value is high.

Many of the existing theories of SEOs, such as Allen and Faulhaber (1989) and Welch (1989), are based on the traditional perception (see Myers and Majluf (1984)) that a firm's owner-manager is better informed about the firm's market value than the market. While the owner-manager may well have private information about some internal aspects of the firm, it is equally conceivable that she faces uncertainty about the market valuation prior to an IPO. For information asymmetry to drive the sequential financing behavior, the owner-manager would essentially need to be better informed than the market about the value of her firm.

Much of the empirical literature on staged financing also relies on agency costs as a driver. Among venture capital firms, Gompers (1995) and Sahlman (1990) report that concerns for agency issues and subsequent credit rationing (Stiglitz and Weiss, 1981) tend to affect the design of financing rounds. Staged financing can also be carried out through security issues such as convertible bonds (Mayers, 1998) or unit offerings (Schultz, 1993). With design of hybrid securities, incentives can be set for management to both invest first-stage proceeds efficiently, and provide more accurate information (Korkeamäki and Moore, 2004; Cornelli and Yosha, 2003; Schultz, 1993).

As we hypothesize that uncertainty regarding firm valuation has an important effect on the firm's likelihood to rely on sequential financing, we develop metrics for hard to value (HTV) 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 main 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 robustness, we define a second PCA metric, that uses 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; Hertz, et al., 2012; Colak, et al., 2017). With the exception of the price revision indicator, we observe each of the other four 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. It is notable that studies on financial slack relate firms' need of additional slack to some of the same variables that are behind our PCA-based metric on hard-to-value. 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 (Denis and McKeon, 2020). 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.

We test the implications of our model in a sample of 3,625 US firms that complete an IPO during 1.1.1980-31.12.2018.³ Consistent with our expectations, we find a strong negative connection between difficulty to value and the 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. Both of these findings align 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 are consistent with several studies that argue that managers learn from stock prices (see e.g., Bond et al., 2012; Edmans et al., 2015; Edmans et al., 2017). Also, survey evidence

³ As in prior studies such as Baker and Wurgler (2002) and Alti (2006), we require availability of pre-IPO accounting data. This constrains our sample size, which is similar to that in the mentioned prior studies.

by Brau and Fawcett (2006) indicates that one of the main reasons for a firm to go public is to resolve uncertainty about its valuation.

We subject our findings to a number of robustness tests. In a part of our empirical analysis, we relax the assumption of fully asymmetric information structure in the IPO, and observe 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 (Baker and Wurgler, 2002; Taggart, 1977). Market timing and clustering of IPOs into periods of "hot" markets 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. Concern for dilution during cold markets 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 we find no such pattern. Furthermore, our empirical findings could arise from selection bias, as only a fraction of HTV firms may enter the IPO market and, as predicted by our model, poor quality easy-to-value firms may not get listed. To alleviate this concern, we use propensity score matching and study separately a sample of HTV and ETV firms with matched quality characteristics. HTV firms issue smaller IPOs and are more likely to return to the equity market in that setting as well. Our results are also robust to exclusion of VC-backed issues from the sample. This suggests that our findings are not driven by a bias arising from only a fraction of VC-backed firms going public.

In auxiliary tests, we explore how the market feedback channel holds up in relation to signaling models (Allen and Faulhaber, 1989; Welch, 1990) and negative cash flow explanations (Denis and McKeon, 2020; Huang and Ritter, 2020). According to the signaling models, high quality firms conduct smaller underpriced IPOs to subsequently issue an SEO. Our results remain intact after inclusion of underpricing in the IPO size regressions, which indicates that our results are not driven by signaling efforts. Also, recent evidence by Denis and McKeon (2020) suggests that staged equity financing is motivated by cash needs stemming from long-term negative cash flows. We are taking this potential explanation into

account, as our HTV measure includes a negative earnings indicator. Even though cash flows are negatively related to the SEO likelihood, our results remain intact after the inclusion of a cash flow variable.

Besides the information produced by their own market entry, IPO firms can also use the alternative learning channel of cross learning from industry peers (Aghamolla and Thakor, 2020; Foucault and Fresard, 2014; Kaustia and Rantala, 2015). Informative peers may thus aid high uncertainty peers to enter the market. This idea receives support in our tests, which suggests that the HTV firms with low peer informativeness and peer valuations stay out of the market. Our results may thus be biased downwards, as we do not observe firms that are the most difficult-to-value.

We are not the first ones to point out the market feedback channel as an explanation for staged equity financing as Jegadeesh, et al. (1993) suggest such channel in their early work. However, the channel has not received much research attention, as the literature has focused on the asymmetric information explanation. Jegadeesh, et al. (1993) interpret the positive relation between post-IPO stock returns and the SEO likelihood as staged financing that is driven by market feedback. However, their setting makes it very difficult to distinguish between pre-meditated staged financing and traditional market timing behavior. We explicitly test for how the level of valuation uncertainty combined with positive post-IPO return realizations increases the SEO likelihood, while we also exclude the market timing channel.

Our paper is empirically closest to Hertz, 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' reluctance to provide capital due to agency concerns, or from the firm's incentive to time their funding, based on inside information about future prospects. The results in Hertz, et al. (2012) are inconclusive as to whether supply- or demand-driven explanations dominate in motivating sequential financing, but they note the important role of agency issues, as they constrain availability of sufficient equity capital at the time of the IPO. Also, Cole, et al. (2019) address the effects of information learned from the market around the time of the IPO. They observe 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.

Furthermore, 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 the 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. We contribute by analyzing the relevance of this learning channel even at the point when firms consider going public. A key implication of our study is that an IPO process that transmits information effectively is conducive for a subsequent equity offering.

While Hertz et al. (2012) consider all financing injections subsequent to the IPO, our focus is on equity financing. This focus is motivated by equity valuation being more sensitive to information than debt valuation (see, e.g., Dang et al., 2017; McLean and Zhao, 2014). We thus exclude from our analysis any considerations where the initial IPO would be followed by increased leverage and more limited dilution, and concentrate on a two-sided learning effect under information symmetry, where the original desired level of equity financing (and dilution) is fixed. We further note that our exclusive focus on equity issuance may also bias our empirical tests against findings. Debt tends to be more accessible to firms that are easy to value, and furthermore, HTV firms with positive valuation signals after their IPOs should also enjoy an improved access to debt financing. Existence of debt would thus decrease the size of IPOs for easy-to-value firms, and make subsequent equity issues less appealing for HTV firms with good post IPO performance.

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 $a_2 \in \{0,1\}$. We denote by $\delta \in [0,1]$ the owner's discount factor between the periods, capturing the benefits of financial slack – the preference for having the cash in hand sooner rather than later.

Following, e.g., Holmström (1982), Aghion, et al. (2013), and Dow et al. (2017), there is incomplete but symmetric information about the intrinsic value of the firm as a public company. 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 the 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.

As in Zingales (1995), we assume that the firm produces a non-verifiable private benefit of $B \in \mathbb{R}_+$ to the owner. This benefit is lost if the owner decides to sell her share. There are a number of reasons for owners to waive the possibility of selling their stock to the public market, such as loss of the private benefits of control and freedom to operate without a pressure from external shareholders (Dyck and Zingales, 2004).

⁴ For simplicity we assume that the owner's private benefits are proportional to her control rights and hence

⁴ Other reasons for owners to stay private include the possibility of keeping business plans and financing sources confidential, and the desire to avoid laborious regulatory and reporting requirements of publicly listed companies. These opportunity costs of public listing are fully realized upon an IPO irrespective of its size. On the other hand, the private benefits of control might be lost only after the owner relinquishes a majority or all of her control rights. In this case, a small IPO would not realize these costs. We could allow for larger opportunity costs of public listing upon an IPO or only when the owner sells (the majority of) her company at the cost of complicating the notation. Yet one

B is measured per share. Under this assumption the owner's private value of the firm's share remains unchanged irrespective of chosen a_1 . Finally, the transaction cost of a public offering is $F \in \mathbb{R}_+$ irrespective of its size. We may think B captures all opportunity costs of a public offering that are proportional to the size of the offering and F captures fixed costs of the offering.

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. Upon the IPO, 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, $a_2(a_1 = 1, s) := a_2(s) \in \{0,1\}$.

2.2 Listing decisions

Prior to an IPO, the expected *market* valuation of a firm's stock is given by

$$(1) \quad E(V) = p\theta_H + (1 - p)\theta_L.$$

While we follow Zingales (1995) to assume that the firm's expected market valuation is independent of the owner's private benefits from her control rights, the desirability of a public offering depends on the relation between $E(V)$ and B . For example, if B is very large compared to $E(V)$, the owner will not conduct an IPO. A special case of our model is that $B = E(V)$, i.e., the expected market valuation of the firm's stock exactly equals the owner's private valuation of her control rights.

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

opportunity cost of a public offering is the possibility to sell out to a private buyer. This opportunity cost can be considered to be proportional to the size of the public offering – see Zingales (1995).

valuations are given by $V_h := V|h = \Pr(\theta_H|h)\theta_H + \Pr(\theta_L|h)\theta_L$, and $V_l := V|l = \Pr(\theta_H|l)\theta_H + \Pr(\theta_L|l)\theta_L$, which can be rewritten by using Bayes' rule as

$$(2) \quad V_h = \frac{qp\theta_H + (1-q)(1-p)\theta_L}{qp + (1-q)(1-p)},$$

and

$$(3) \quad V_l = \frac{(1-q)p\theta_H + q(1-p)\theta_L}{q(1-p) + (1-q)p}.$$

If the signal is informative ($q > 1/2$), $V_h > E(V) > V_l$.

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

Assumption 1. $V_h > B + F > V_l$.

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 also implies that $\theta_H > B + F > \theta_L$. In words, if it were certain that the firm is of high (low) value, the owner would prefer (not) to list publicly. To make notation more compact, we introduce the definitions $\Delta_H := \theta_H - B$ and $\Delta_L := B - \theta_L$ reflecting the relation of the firm's intrinsic value to the owner's private valuation of her control rights. Here our assumptions imply $\Delta_H \in (F, \infty)$ and $\Delta_L \in (-F, B]$. Finally, to establish analytic results compactly, we assume that F is "small" otherwise we would need to consider subcases where a large IPO or a staged equity offering is unprofitable.

We 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 planning a staged equity offering is optimal for the owner, $V(1) \geq \max\{V(2), V(0)\}$. The expected value of a single, large IPO is given by

$$(4) \quad V(2) = 2[\Pr(h)V_h + \Pr(l)V_l - B] - F,$$

in which the probabilities of high and low market valuations following the IPO are $\Pr(h) = qp + (1-q)(1-p)$ 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 (4) can be simplified to

$$(5) \quad V(2) = 2(E(V) - B) - F.$$

Thus, $V(2) \geq 0$ only if $E(V) \geq B + F/2$. Under this condition, a large IPO is more profitable for the owner than keeping her firm private. Note that the owner requires a premium to conduct a large IPO: A necessary condition for $V(2) \geq 0$ is that the expected market valuation of the firm's stock is strictly larger than the owner's private valuation of her control rights ($E(V) > B$). Using equation (1) we may rewrite the condition $E(V) \geq B + F/2$ as

$$(6) \quad p \geq \tilde{p} := \frac{F + 2 \Delta_L}{2(\Delta_H + \Delta_L)}$$

in which $\tilde{p} \in (0,1)$.

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

$$(7) \quad V(1) = \Pr(h) (V_h + \delta V_2(h)) + \Pr(l) (V_l + \delta V_2(l)) - B - F,$$

in which $V_2(s) := V_2(a_2(s), s)$ gives the owner's expected net payoff from a SEO. Since Assumption 1 implies that the owner issues an SEO only upon a high signal ($a_2(l) = 0$ and $a_2(h) = 1$), we have $V_2(l) = 0$ and $V_2(h) = V_h - B - F$. We can thus simplify equation (7) to

$$(8) \quad V(1) = E(V) - B - F + \Pr(h) \delta (V_h - B - F).$$

The first three terms in the right hand side of equation (8) 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 more profitable for the owner than a large IPO when $V(1) \geq V(2)$. After some algebra using equations (1), (2), (5) and (8), we get that the condition $V(1) \geq V(2)$ is equivalent to

$$(9) \quad p \leq \bar{p} := \frac{\Delta_L - \delta(1 - q)(\Delta_L + F)}{\Delta_H + \Delta_L - \delta[(1 - q)(\Delta_L + F) + q(\Delta_H - F)]}.$$

Our assumptions imply that $\bar{p} < 1$. (We have $\bar{p} = 1$ only if $\delta = q = 1$ and $F = 0$.)

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 (8) we get that $V(1) \geq 0$ if

$$(10) \quad p \geq \underline{p} := \frac{(\Delta_L + F)[1 + \delta(1 - q)]}{\Delta_H + \Delta_L + \delta[(1 - q)(\Delta_L + F) + q(\Delta_H - F)]}.$$

Under Assumption 1, $\underline{p} \in (0, 1)$.

From inequalities (6), (9) and (10) we observe that if F is sufficiently small, $0 < \underline{p} < \tilde{p} < \bar{p} < 1$. Hence, for $p \in (\underline{p}, \bar{p})$, it is optimal for the owner to plan a staged equity offering. Such a staged offering allows the owner to experiment – to learn about the market value of her firm – and gives the option to follow with an SEO in case the market valuation turns out to be high. The fixed cost of public offerings (F) needs to be sufficiently small to make experimentation profitable for the owner. Moreover, when $p \in [\underline{p}, \tilde{p})$, planning a staged offering is profitable for the owner, but launching a large IPO is not. It is also possible that planning a staged offering is profitable even if the expected market valuation of the firm's stock prior to the IPO is *less* than the owner's private valuation ($B > E(V)$).

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 ($p > \bar{p}$), 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 (9) captures the tradeoffs of the choice between a staged offering with two smaller rounds and a single, large IPO, and inequality (10) does the same for the choice between a staged offering and staying private. Both inequalities depend on a number of parameters (p , q , δ , F , B , θ_L and θ_H). From the definitions of \bar{p} and \underline{p} of inequalities (9) and (10) we can establish that $\partial \bar{p} / \partial q \geq 0$ and $\partial \underline{p} / \partial q \leq 0$,

with the inequalities being strict unless $\delta = 0$. In words, a more revealing IPO process unambiguously makes a staged equity offering more attractive for the owner. Similarly, a straightforward differentiation of the definitions of \bar{p} and \underline{p} suggests that $\partial\bar{p}/\partial\delta \geq 0$ and $\partial\underline{p}/\partial\delta \leq 0$, with the inequalities being strict unless $q = 1/2$, and that $\partial\bar{p}/\partial F \leq 0$ and $\partial\underline{p}/\partial F \geq 0$, with the inequalities being strict unless $q = 1/2$ or $\delta = 0$. Intuitively, a stronger need for financial slack (smaller δ) or larger fixed costs of public offerings (larger F) unambiguously make a staged equity offering less attractive for the owner.⁵

We summarize these comparative static results as follows.

Proposition 2. *A more informative IPO process (larger q), a smaller need for financial slack (larger δ) and a smaller fixed costs of public offerings (smaller F) make planning a staged equity offering more attractive.*

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 $E(V) \in (V_l, V_h)$. 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.⁶

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 (10). Our model suggests that these IPO firms can be

⁵ The analysis of the effects of B , θ_L and θ_H on the desirability of a staged equity offering is more complex as these parameters shift \bar{p} and \underline{p} into the same direction. However, it can be shown that the public listing becomes more attractive the larger is the ratio Δ_H/Δ_L , since the expected market value of the firm is increasing in Δ_H/Δ_L . 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.

⁶ 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 month.

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.

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. A difference between the firms in categories 2 and 3 is that the firms in category 2 experience an upward price adjustment after the IPO, whereas the firms in category 3 have a downward price adjustment.

3. Data and a hard to value metric

We follow Hertz et al., (2012) and use the IPO as a common reference point for our sample firms. We collect data on IPOs from 1980 to 2018 from Thomson SDC Platinum. Our original sample includes 19,674 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, we are left with 3,516 IPOs. The size of our final sample is comparable to other studies that make use of pre-IPO accounting variables in COMPUSTAT, such as Baker and Wurgler (2002) and Alti (2006).⁷

We track the equity issuing behavior of the firms in our IPO sample, and consider all SEOs that occur within two years of the IPO (until the end of 2020). Hertz et al. (2012) argue that capital infusions

⁷ Our sample size is smaller compared to Hertz et al. (2012) due to our restriction that firms need to have data available in COMPUSTAT for the year-end prior to the IPO. Also, their sample is partially hand-collected from 10K filings, whereas we rely on the SDC Platinum database.

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 original prospectus their intent to return to the capital markets, and 95% of those 576 firms indicate that they will do so within two years. As we observe SEOs that follow IPOs, we exclude SEOs during the first month of trading and consider SEOs taking place one month following the IPO.⁸

We use principal component analysis (PCA) to derive our metrics on difficulty to value. To identify our PCA input variables, we rely on prior literature as follows. R&D expenses is a relevant metric, as the value of research-intensive firms depends more on the future expectations arising from their growth options. This makes them difficult to value (Hertzel, et al., 2012). We include firm age, as more established firms have a longer track record, which eases 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). This motivates us to include a measure for price revisions. Finally, firms in high tech industries and firms with negative earnings are more difficult to value (Colak, et al., 2017), and we thus include indicators for both negative earnings and high tech firms. These variables each focus on different dimensions of difficulty to value a firm. As our main metric of hard to value (HTV), we use the first component (with the highest eigenvalue) from the PCA including the three of the variables mentioned above, also used by Gompers (1995), namely R&D/sales, ln(Age) and the High tech indicator. Our metric explains 44.2% of the common variation amongst the three variables, and each of the three variables load with the expected sign on the first component, as follows: R&D/sales 0.6225, ln(Age) -0.3536, and High Tech 0.6982. For robustness purposes, we utilize an alternative PCA-based component (HTV2), derived from all five uncertainty-related variables namely R&D/Sales, Firm Age, an indicator for High Tech industries, negative earnings indicator, and the absolute price revision. We note that due to missing data on absolute price revision observations, the sample size decreases from 3,516 to 1,929 observations when we use HTV2.

⁸ The one month time period coincides with our return measurement period and thereby we avoid look-ahead bias in the returns.

We include several control variables in our analysis, defined in Appendix 1. In addition to standard controls explaining the IPO size and the SEO likelihood (see, e.g., Hertz et al., 2012), we include a variable (UW Premium) capturing underwriter agency costs 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 for 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 Boehme and Colak (2012) and Yung et al. (2008) 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.⁹ 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 terciles, based on the HTV metric¹⁰. 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, $\ln(\text{Age})$, R&D/Sales and Hi Tech, 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 (43.6% vs. 31.5%). Hard to value firms also float smaller IPOs, which aligns well with the predictions generated by our model. The

⁹<http://bear.warrington.ufl.edu/ritter>

¹⁰ The number of observations deviate between the three terciles due to equal values of the sorting variable.

fact that means of 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.

< Table 1 about here>

In Panel A of 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, et al., 2005; Kumar, 2009; Zhang, 2006) and volatility. In panel A of Table 2, we sort the firms into terciles based on HTV, and report that HTV firms have significantly higher idiosyncratic volatility and volatility in both 1-month and 3-month periods following the IPO. In unreported sortings, HTV2 yields similar inferences. This supports validity of HTV as a measure of valuation uncertainty.

Following proposition 1, our main hypothesis is that difficulty to value is negatively related to IPO size and positively related to the SEO likelihood. The increased SEO 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 of 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 return, calculated for the one-month period following the IPO. We group both the HTV metric and the returns into terciles, and compare the likelihood of an SEO within two years between the extreme terciles.

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

<Table 2 about here>

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.

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 the first two columns of 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 Column (2). We add controls for profitability [Returns on Assets (ROA)], size [ln(Sales)], indebtiness (book leverage), and Cash/Assets, all measured at the fiscal year end prior to the IPO, and market to book at issuance. As issuance-specific controls, we further include IPO Heat, VC Backing, Top Underwriter and Underwriter Premium. The HTV metric exhibits a strong negative relation to IPO Size, suggesting that difficult to value firms issue IPOs with smaller relative proceeds. Results on our hard to value proxy are unaffected by inclusion of industry fixed effects in Column (2). Interestingly, cash holdings are inversely related to IPO Size in both specifications. This is consistent with the idea that firms with a greater degree of financial slack conduct a smaller IPO.

<Table 3 about here>

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 years of the IPO. In this setting, our model predicts that our HTV measures are positively related to the SEO likelihood. We estimate with OLS instead of Probit due to the large amount of fixed effects when we include industry fixed effects, and

the resulting inconsistency in the estimates.¹¹ The structure of Columns (3) and (4) follows those of Columns (1) and (2) of Table 3, but 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 $\ln(\text{Analyst})$], as mentioned below.¹²

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. For this reason, we include the number of analysts following the firm as a control for informativeness. 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. Chen, et al. (2020) provide support for the hypothesis that intermediaries and venture capitalists improve information production in IPOs. 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).

HTV enters with a positive and significant coefficient, both in Column (3) with the year fixed effects, and in Column (4) with year and industry fixed effects. In line with the implications of our model, we find that IPO Size is negatively related to the SEO likelihood.

Furthermore, in contrast to Chang, et al. (2017) argument that high underwriter premium is linked to a greater likelihood of a follow on offering, UW premium fails to reach conventional levels of statistical significance in our specifications. Together, our tests support our model's implication that firms that are

¹¹ However, consistent with Angrist and Pischke (2009), we obtain similar estimates in untabulated tests using Probit.

¹² We do not include this set of additional controls in Columns (1) and (2) of Table 3, as they are determined post-IPO. However, in our robustness tests we consider, First day return (Table 12), analyst following (Table 13) and volatility (Table 8) in IPO size regressions.

difficult to value use sequential equity financing, as they both issue smaller IPOs, and have a greater likelihood of returning to the equity market within two years.

To test the severity of a potential omitted variable bias, we employ the partial identification methodology by Oster (2019). In the test, we create bounds for the betas of HTV in specifications (1) and (3) of Table 3. In unreported estimates, the intervals of the HTV betas is given by $(R^2_{\max} = 1.3\check{R}^2 \text{ and } \Delta = 1)$ 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 controlled estimate. Hence, the observables in our model are likely to be at least as important as the unobservables in determining the IPO size and SEO likelihood.

In Columns (5) and (6) of Table 3, we consider the connection between sequential equity financing and difficulty to value in yet another setting. Hertz, et al. (2012) motivate studying sequential financing behaviour with a Cox 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.

The results of the Cox hazard model are consistent with those reported in Columns (3) and (4). The hazard rate exhibits a strong connection to our key variables, so that difficulty to value, IPO size 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 provide contrasting inferences between specifications. In both specifications, First day return, $\ln(\text{analyst})$, top underwriter, and leverage shortens and IPO market heat, profitability and market-to-book lengthens the time between the IPO and first SEO.

As a robustness exercise, we re-estimate the models of Table 3 using the five-variable HTV2 metric. The sample size decreases from 3,516 to 1,929 observations due to missing observations in the absolute price revision variable. Our findings in Table IA2 in the internet appendix remain qualitatively similar to the ones in Table 3. Again, our findings suggest that the hard to value metric is linked to smaller IPOs, increased SEO likelihood and a shorter duration to the first SEO.

Staged financing that follows an IPO can take forms other than a follow-on SEO. Among the 1,922 firms that Hertz et al. (2012) observe to raise public financing within two years of their IPOs, 52% issue 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, in Table IA1 (internet appendix) we test the effect of our HTV proxies on large debt increases (>5%) occurring within two years of the IPO. We report a negative relation between HTV and debt increases in one of the specifications. The other three specifications exhibit effects close to zero. Our findings support the notion that debt and equity issuance have different sensitivities to information uncertainty. However, as both cash holdings and ROA negatively relate to debt issuance, debt issuance is also an important source for post-IPO firms to fund financing deficits.

Next, we study the joint effects implied by our model. In Table 4, we focus on the triple interactions between post-IPO returns, HTV metrics, and IPO Size. In Columns (1) and (2) of Table 4, we interact small IPO Size with high one-month returns and a hard to value indicator (top tercile HTV1) with the SEO likelihood as the dependent variable. The positive and statistically significant coefficients for the triple interaction variable suggest that the likelihood of a follow-on SEO is elevated for firms with small IPOs, high post-IPO returns, and for firms that they are difficult to value. In Columns (3) and (4), we repeat our analysis focusing on the time to the SEO, using a Cox hazard model. Consistent with the predictions of our model, we find a triple interaction between IPO Size (conducting a small IPO), returns and HTV to have a positive effect on the likelihood of a follow-on issue.

<Table 4 about here>

5. Further analysis and alternative explanations

This section begins with an analysis of whether our HTV proxy captures valuation uncertainty or asymmetric information. Second, we consider the potential selection bias present in empirical tests. Third,

we test whether our results can be explained by alternative explanations of sequential equity financing. Fourth, we study the role of the IPO in the two-sided learning process about firm valuation.

5.1 Asymmetric or imperfect information

In an attempt to separate between asymmetric and imperfect but symmetric information structures, we analyze the insiders' participation in the IPO. By studying the insiders' actions we can gain understanding of the informational wedge between the insiders and the outsiders (Chen, et al., 2007; Focault Fresard, 2014). In an asymmetric information structure, insiders are better informed than outsiders, and can thereby make better-informed decisions. In the IPO, this can be reflected for instance in market timing of their secondary share sales. If insiders act on 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 returns.¹³ In a symmetric but incomplete information structure, the value of the option to sell shares at a later stage should increase with uncertainty, causing either a staged offering of secondary shares or postponing of secondary shares issues until information is more complete (see, e.g., Damaraju, et al., 2015). Hence, we expect that participation ratio and secondary share sales decrease with valuation uncertainty. We conduct two different tests: 1.) We analyze the link between the HTV proxy and the sale of secondary shares in the IPO. 2.) We acknowledge that in asymmetric information structures, insiders can better forecast future returns and test the link between insider participation and post-IPO performance. If insiders are better informed about the firm's future prospects, they will sell a larger fraction of shares in the IPO given that the expected future returns are low.¹⁴ In our tests, the participation ratio is defined as the fraction of secondary shares offered in the IPO (Chanine, et al., 2020). We also include a second measure

¹³ The role of asymmetric information and market timing behaviour is prevalent in the literature. For example, Bergstrasser and Philippon (2006) find that management manipulates earnings prior to share sales with a resulting post sell off decrease in stock prices. Also, Bartov and Mohanran (2004) report that firm's share price drops following employee stock option exercises. However, in the IPO setting, 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).

¹⁴ E.g. Jordan and Riley (2015) use a similar framework with alpha as the left hand side variable.

of secondary share sales defined as secondary shares scaled by total post-IPO shares outstanding (Secondary/Total).

<Table 5 about here>

Table 5 reports our findings on secondary share sale. In Columns (1) and (2), we study the effect of the HTV measure on the participation ratio and Secondary/Total measures. In both Columns, we report a negative relation to the HTV proxy. In Columns (3) to (6) of Table 5, we study the effect of insider participation in the IPO on post-IPO performance, measured by the 1-month and 6-month return. At the month horizon, the participation ratio is positively related to future returns. We fail to find consistent evidence of a link between insider participation and higher post-IPO stock market performance in the other three specifications.¹⁵ To summarize, our results fail to support the notion that insiders take advantage of an asymmetric information structure to maximize their own profits. Even though we cannot completely rule out the effect of information asymmetry on our results, our evidence suggests that insiders act upon uncertain information and postpone issuing their own shares. As further evidence against the insider market timing explanation, future returns are not inversely related to insider IPO participation. Our results are consistent with McLean (2011), who studies cash savings from IPO issues and finds that firms are increasingly precautionary in use of their IPO proceeds and that this trend is unaffected by market timing.

<Table 6 about here>

In Table 6 we study the robustness of our HTV proxy against commonly used measures of asymmetric information. In both the IPO size and SEO likelihood regressions, we include the Amihud (2002) illiquidity measure, idiosyncratic volatility and volatility as right-hand-side variables (all measured up to one month following the IPO). Since, it is possible that the post-IPO measures convey information not contained in our proxy, we include the post-IPO variables as controls in the IPO size regressions. Our findings remain intact following the inclusion of the post-IPO asymmetric information measures in both specifications.

¹⁵ Our results are in line with Brau, et al. (2007), who report no-relation between insider participation and post-IPO performance.

5.2 Selection bias

Our model predicts that some firms will stay out of the market, creating an unobservable counterfactual that is a potential source of selection bias. We have three potential selection effects to consider. First, our model predicts that firms with a low value of p do not enter the market. Second, our HTV proxy fails to account for the role of cross peer learning in the IPO decision. Third, firms with venture capital backing can use the reputation of the VC firm to go public.

It is unavoidable that some bias arises on HTV, stemming from the self-selection to conduct an IPO. ETV firms with a low p effectively stay out of the market. In this case, the observed quality of ETV firms in our sample is likely to be upward biased. This reduces quality heterogeneity among ETV firms relative to HTV firms. To alleviate concerns about this heterogeneity, we perform matching on several characteristics: investment opportunities, profitability, size, leverage, cash holdings, IPO heat, Top UW, UW premium and VC backing. These characteristics are likely to capture different dimensions of quality. M/B, profitability, leverage are all part of the Asness, et al. (2019) quality measure. Underwriters and VCs have strong selection mechanisms due to potential reputational and monetary losses in case they certify low quality firms (Booth and Smith, 1986; Megginson, et al., 2017). Also IPO heat can be linked to quality, as Khanna, et al. (2008) and Yung, et al. (2008) conclude that firm quality is greater during cold IPO markets. The matching of ETV and HTV firms enables us to capture firms of comparable observable quality. We match the top tercile of HTV firms with the two lower terciles of HTV using propensity scores, we use a caliper of 0.01 and no-replacement. Due to the large differences between HTV firms and the control group, we end up with 1,678 observations. Results in Table 7 Columns (1) and (2) provide continued support for a negative impact of both HTV proxies on IPO size. Columns (3) and (4) shows that the SEO likelihood remains positively affected by the HTV proxy.

<Table 7 about here>

A second selection concern comes from the possibility that uncertainty concerning the value of p (reflected in q in our model) is affected by external factors such as peer group valuation levels and their

information content. Prior literature establishes that firms can obtain a greater precision in their valuation by learning from peer firms that are already listed (Agahamolla and Thakor, 2020; Foucault and Fresard, 2014; Grennan, 2019; Kaustia and Rantala, 2015).¹⁶ To test for this case of learning, we create peer groups of listed firms based on Hoberg and Phillips (2010; 2016) peer group classification, which builds on product market similarity scores. A peer group is assigned to an IPO firm if they are included in the Hoberg and Phillips data within the two years following the IPO. We create two peer group measures at the time of the IPO. First, we observe the valuation of the peer group, measured by the average M/B, as defined by Foucault and Fresard (2014). Second, we create a measure of informativeness of the peers' valuations through aggregating the peer group's analyst following. We then sort firms on peer group valuation and peer group informativeness.

<Table 8 about here>

Our findings in Panel A of Table 8 points towards a strong selection effect. Firms that are easier to value [(HTV) is low] have low valuations and less informative peers. The outcome from the sortings suggests that cross-peer learning can play a moderating role on individual firm uncertainty. Low and uninformative prospective valuations effectively keep high uncertainty firms out of the market. This results in a selection bias, where high uncertainty firms can only go public when their peer valuations are high and informative.¹⁷ The moderating role played by the precision and level of the peer group valuations suggests that our estimates could be in the lower bound.

To further study the effect of peer group information on sequential equity financing and thus robustness of our main findings, we add the peer group variables as controls. Due to the high correlation between peer group information and our HTV proxy¹⁸ we cancel out the peer group effect present in the

¹⁶In related theoretical work, Benveniste, et al. (2002) argue for learning from recent peer firm IPOs. Benveniste, et al. (2003), find empirical evidence of firms from the same industry going public on similar terms (common valuation factor).

¹⁷ A possible channel keeping high uncertainty firms out of the IPO market is that the elevated peer group uncertainty maps into higher cost of capital causing low valuation expectations (see, e.g., Colak, et al., 2017).

¹⁸ HTV has a correlation coefficient of 0.24 with average peer group M/B and 0.38 with the number of peer group analysts.

HTV proxy by orthogonalizing that proxy with the peer group M/B and peer group analysts per firm. Orthogonalizing the variables allows us to study the individual valuation uncertainty on IPO size and SEO likelihood.¹⁹ This approach provides us with an indication of the direction of the bias. Using the Hoberg and Phillips (2010; 2016) peer groups significantly reduces our sample size from 3,625 to 2,615, since the data is only available from 1989 onwards. We therefore re-estimate the base case models for comparability.

Columns (1) and (2) in Panel B of Table 8 show the baseline estimates using the reduced sample. In line with prior estimates, HTV has a negative impact on IPO size and a positive impact on the SEO likelihood. When we add the peer group controls in Columns (3) and (4), the relation between HTV and IPO size strengthens, but the finding on SEO-likelihood (in Column 4) is no longer statistically significant. Orthogonalizing the measures in Columns (5) and (6) strengthens the relationship between HTV and both IPO size and SEO likelihood. In our setting, we cannot observe the counterfactual of firms not conducting an IPO. Therefore, we can only make predictions concerning the selection bias. In an attempt to bound the bias, we control for available peer information in a regression setting and report an absolute increase in the coefficient estimates.²⁰ After taking into account one source of potential selection bias, we can observe that our HTV estimates are not downward biased.

<Table 8 about here>

Finally, a third source of IPO-selection can potentially stem from venture capital backed IPOs. Venture capital firms often invest in young and R&D intensive firms operating in the tech sector. As shown in Table 1, 72% of the HTV firms are VC backed, compared to only 15.5% in the ETV sample. Venture capitalists usually sell most of their portfolio companies through trade sales and publicly list only the highest quality ones (Bayar and Chemmanur, 2011; 2012). To verify that our finding is not purely driven by venture capital backed firms, we exclude all venture capital backed IPO firms from our sample and re-estimate the models of Table 3. The estimations of Table 9 show that our findings are robust to excluding

¹⁹ Orthogonalization of the main independent variable is used in other studies to cancel out a selection effect (Bhattacharya, et al, 2015) or to extract private from public information (Aggarwal and Hauswald, 2020).

²⁰ Grosse-Rueschkamp et al. (2019) use a similar approach to bound the selection bias.

venture capital backed firms, HTV has a negative impact on IPO size and the time to the SEO and a positive impact on the SEO likelihood.

<Table 9 about here>

5.3 Post-IPO returns and alternative explanations

In our next set of empirical tests, we pursue alternative explanations behind our results. First, firms may time the market for their subsequent SEO issuance, and such timing could correlate with our measures of valuation uncertainty. While we use year fixed effects in our tests to account for market-wide patterns, market timing on firm-level information is a possibility. Our model predicts that positive post-IPO returns trigger firms to conduct an SEO, but seasoned equity offerings that follow high returns can also be driven by market timing (Baker and Wurgler, 2002; Taggart, 1977), 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 10, we report the pre- and post-SEO Alphas, along with the coefficients for the factors of the Fama-French five-factor model, for calendar-time portfolios that are formed based on terciles of valuation uncertainty. The first three columns study the return patterns from IPO to SEO, while the remaining three columns show the post-SEO return estimations. The sample includes firms that follow their IPOs with SEOs within two years. If the main motive for SEO issuance were market timing based on firm-specific information, the alphas should be negative in the period following the SEO. Our findings in columns (1) to (3) of Table 10 show that pre-SEO alphas are highest for high valuation uncertainty firms. While this is in line with our model, it could also indicate that managers just time the market. Therefore, we analyze the post-SEO returns in columns (4) to (6). Contrary to a market timing explanation, post-SEO alphas are strongly positive, which suggests that market timing is not a major consideration when firms make their decision to float a follow-on SEO.

<Table 10 about here>

As our model predicts that returns subsequent to the IPO trigger an SEO, we next study the impact of the first 12-months return on the SEO likelihood. Our findings in Table 11 show a decreasing sensitivity of SEO likelihood to returns over time with two exceptions. First, the SEO likelihood is the most sensitive to returns during month 6. A potential explanation is that lock-ups normally expire after 180 days and insiders may sell secondary shares through an SEO. Second, month 3 exhibits the third highest sensitivity after month 6 and month 1. The benefits from two-way learning should occur predominantly quickly after the IPO. Results in Table 11 provide support for this notion.

<Table 11 about here>

Another alternative explanation to our findings could be investors' risk aversion and resulting unwillingness to participate in IPOs of hard to value firms, which would force firms to conduct smaller IPOs and later return to the equity markets for an IPO. To explore this explanation, we interact hard to value with two measures of risk aversion. First, we use the Zhou (2018) variance risk premia²¹. Second, we use the Baker and Wurgler (2006) sentiment index²². We interact the highest (lowest) tercile of variance risk premium (market sentiment) with the top tercile of the HTV proxy. Since, both variance risk premium and market sentiment are time-series variables, we exclude year fixed effects from the estimations. To control for macro-economic heterogeneity we include U.S. GDP growth and the fed funds rate. Our findings in Table 12 suggest that hard to value firms are not disproportionately affected by investors' risk aversion.

<Table 12 about here>

Next, we pursue a motive for sequential equity financing suggested by the literature on underpricing and sequential offerings (See, e.g., Allen and Faulhaber 1989; Jegadeesh, et al., 1993; Welch, 1989). In an asymmetric information setting, firms may signal their quality through underpricing. High quality firms know that their valuation will increase at a later stage, and therefore conduct a smaller IPO and at a later stage issue equity at a higher valuation. As the HTV proxy is positively correlated with both underpricing and post-IPO asymmetric information measures, it is possible that our findings are driven by staged equity

²¹ The data is retrieved from Hao Zhou's webpage: <https://sites.google.com/site/haozhouspersonalhomepage>

²² The data is retrieved from Jeffrey Wurgler's webpage: <http://people.stern.nyu.edu/jwurgler/>

financing determined by asymmetric information. To control for the underpricing signaling channel of staged financing, we include underpricing in the IPO size regressions as in Boone et al. (2016). Column (1) in Table 13 shows that the relation between HTV and IPO size remains intact after the inclusion of first day return as a right hand side variable.

<Table 13 about here>

Finally, equity financing may occur to finance long-term cash flow deficits (Huang and Ritter, 2020). Denis and McKeon (2020) find that cash flow deficits play a role in staged equity financing. They further document that firms raising cash through frequent equity issues are R&D intensive firms within the tech and health care sectors. Hence, it is likely that our HTV measures correlate with negative cash flow firms. Next, we test if the correlation between the HTV metric and firms' cash needs is driving our results. To measure cash needs, we follow Denis and McKeon (2020) and include a net cash flow variable and an indicator for negative cash flows together with an interaction term. We measure net cash flows as cash flows from operations plus cash flows from investment activities. Column (2) of Table 13 indicates that firms with higher cash flows conduct larger IPOs. However, our findings in Column (3) fail to support a connection between negative cash flows and SEO likelihood. Our HTV proxy remains a significant determinant for IPO size and SEO likelihood after controlling for negative cash flows and first day returns.

5.4 The role of learning in the IPO process

Our HTV proxy uses information from the period prior to the IPO process. Theoretically, we can decompose valuation uncertainty into three components. First, the symmetric but imperfect information that is known to both insiders and outsiders of the firm. Second, the proprietary information of the management, creating information asymmetries for outsiders. Third, following Benveniste and Spindt (1989), the IPO process can be seen as a partial learning channel reflecting q in our model, as outsiders potentially possess information to aid management in learning the true valuation of their firm. During the IPO process, the S-1 filings and the following road shows are in place to reduce management's private information of the firm's prospects. The road shows also offer two-sided learning, where not only

information asymmetries are reduced but also management learns about firm valuation from outsiders. However, in our model we assume that the information asymmetry is zero at the time of the IPO. Even though, recent evidence suggest that the S-1 filings already provide substantial information of the IPO, even above and beyond the value of road shows (Blankespoor, et al., 2020). The informativeness of the S-1 filings also varies across IPOs (Boone, et al., 2016; Hoberg and Hanley, 2010).

In order to study the effect pre-IPO information and IPO process learning on IPO size and SEO likelihood, we include absolute price revision in the regression along with gross spread, first day return and Post-IPO analyst following, as these variables should capture information about the IPO process uncertainty (Ritter, 2000). By separating pre-IPO process and IPO process uncertainty, we are able to study the importance of sequential learning occurring in the IPO process.

<Table 14 about here>

The results in Table 14 align with our previous findings. HTV has a negative impact on IPO size and a positive impact on SEO likelihood. We report that gross spread is negatively related to IPO size and that post-IPO analyst following also correlates positively with the SEO likelihood. In line with Loughran and Ritter (2002), and Lowry and Schwert (2004), our findings suggest partial learning during the IPO process. However, the remaining explanatory power of variables from the S-1 filings and IPO size in determining the SEO likelihood suggests that such learning is incomplete. The incomplete information production in the IPO process further incentivizes managers who are uncertain about their pre-IPO valuations to stage their firms' equity issuance.

6. Conclusions

We examine the impact of valuation uncertainty on staged equity financing. We seek to shed light on why a number firms choose to return to the equity market shortly after their IPOs. We develop a simple model that indicates that under valuation uncertainty, firms may stage their equity issuance. We obtain 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 these predictions using a sample of 3,625 U.S.

IPOs between 1.1.1980–31.12.2018. 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 a simple rationale and empirical support for the idea that information asymmetry is not a necessary criterion for raising equity financing in stages.

As our contribution is mainly on the empirical side, our theoretical model leaves open many exiting questions. For example, we have been agnostic as to the owner's use of the funds raised from a public listing. A future work should consider the owner's choice of whether to go public so as to cash out or to raise funds for a real investment project affecting the firm value. The net present value of the project could depend on its size and there could be learning about the value after the IPO.

References

- Agarwal, S., and Hauswald, R., 2020, Information Disclosure and the Choice Between Arm's-Length and Inside Debt. *Journal of Monetary Economics*, forthcoming.
- Aghamolla, C., and Thakor, R. T., 2020, IPO Peer Effects, University of Minnesota working paper.
- Aghion, P., Van Reenen, J., and Zingales, L., 2013, Innovation and Institutional Ownership. *American Economic Review* 103, 277-304.
- Allen, F., and Faulhaber G., R, 1989, Signaling by Underpricing in the IPO Market, *Journal of Financial Economics* 23, 303-323.
- Alti, A., 2005, IPO Market Timing, *Review of Financial Studies* 18, 1105–1138.
- Alti, A., 2006, How Persistent Is the Impact of Market Timing on Capital Structure, *Journal of Finance* 61, 1681-1709.
- Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of financial markets* 5, 31-56.
- Angrist, J., and Pischke, J., 2008, Mostly Harmless Econometrics: An Empiricists Companion, Princeton, NJ: Princeton University Press.
- Asness, C. S., Frazzini, A., and Pedersen, L. H., 2019, Quality minus junk, *Review of Accounting Studies* 24, 34-112.
- Aussenegg, W., Pichler, P., and Stomper, A., 2006, IPO pricing with bookbuilding and a when-issued market, *Journal of Financial and Quantitative Analysis* 41, 829-862.
- Baker, S. R., Bloom, N., and Davis, S. J., 2016, Measuring Economic Policy Uncertainty, *Quarterly Journal of Economics* 131, 1593-1636.
- Baker, M., and Wurgler, J., 2002, Market Timing and Capital Structure, *Journal of Finance* 57, 1 -32.
- Baker, M., and Wurgler, J., 2006, Investor Sentiment and the Cross-Section of Stock Returns, *Journal of Finance* 61, 1645-1680.
- Bartov, E., and Mohanram, P., 2004, Private Information, Earnings Manipulations, and Executive Stock-Option Exercises, *Accounting Review* 79, 889-920.
- Bayar, O., and Chemmanur, T., 2011, IPOs versus Acquisitions and the Valuation Premium Puzzle: A Theory of Exit Choice by Entrepreneurs and Venture Capitalists, *Journal of Financial and Quantitative Analysis* 46, 1755-1793.
- Bayar, O., and Chemmanur, T., 2012, What Drives the Valuation Premium in IPOs versus Acquisitions? An Empirical Analysis, *Journal of Corporate Finance* 18, 451-475.
- Benveniste L., M., and Spindt P., A., 1989, How Investment Bankers Determine the Offer Price and Allocation, *Journal of Financial Economics* 24, 343–361.
- Benveniste, L., M., Busaba; W., Y., and Wilhelm Jr. W., J., 2002, Information Externalities and the Role of Underwriters in Primary Equity Markets, *Journal of Financial Intermediation* 11, 61–86.
- Benveniste, L. M., Ljungqvist, A., Wilhelm Jr, W. J., and Yu, X., 2003, Evidence of Information Spillovers in the Production of Investment Banking Services, *Journal of Finance* 58, 577-608.
- Bergstrasser, D., and Philippon, T., 2006, CEO Incentives and Earnings Management, *Journal of Financial Economics* 80, 511-529.
- Bhattacharya, U., Borisov, A., and Yu, X., 2015, Firm Mortality and Natal Financial Care, *Journal of Financial and Quantitative Analysis* 50, 61-88.

- Blankespoor, E. Hendricks, B. E. and Miller, G. S., 2020, The Pitch: Managers' Disclosure Choice during IPO Roadshows, SSRN working paper.
- Boehme, R., and Colak, G., 2012, Primary Market Characteristics and Secondary Market frictions of Stocks, *Journal of Financial Markets* 15, 286-327.
- Bond, P., Edmans, A., and Goldstein, I., 2012, The Real Effects of Financial Markets, *Annual Review of Financial Economics* 4, 339-360.
- Boone, A. L., Floros, I. V., and Johnson, S. A., 2016, Redacting Proprietary Information at the Initial Public Offering, *Journal of Financial Economics* 120, 102-123.
- Booth, J. R., and Smith II, R. L., 1986, Capital Raising, Underwriting and the Certification Hypothesis, *Journal of Financial Economics* 15, 261-281.
- Bradley, D. J., and Jordan, B. D., 2002, Partial Adjustment to Public Information and IPO Underpricing, *Journal of Quantitative and Financial Analysis* 37, 595-616.
- Brau J., C., Li, M., and Shi, J., 2007, Do Secondary Shares in the IPO Process have a Negative Effect on Aftermarket Performance?, *Journal of Banking and Finance* 31, 2612-2631.
- Brau J., C., and Fawcett, S., E., 2006, Initial Public Offerings: An Analysis of Theory and Practice, *Journal of Finance* 61, 399-436.
- Chang, C., Chang, Y., Qian Y., and Ritter J., R., 2017, Pre-market Trading and IPO Pricing, *Review of Financial Studies* 30, 835-865.
- Chahine, S., Colak, G., Hasan, I., and Mazboudi, M., 2020, Investor Relations and IPO Performance, *Review of Accounting Studies*, Forthcoming.
- Chemmanur, T., and Fulghieri P., 1999, A Theory of the Going-Public Decision, *Review of Financial Studies* 12, 249-279.
- Chen, H. C., and Ritter, J. R., 2000, The Seven Percent Solution, *Journal of Finance* 55, 1105-1131.
- Chen, Q., Goldstein, I., and Jiang, W., 2007, Price Informativeness and Investment Sensitivity to Stock Price, *Review of Financial Studies* 20, 619-650.
- Chen, Y., Goyal, A., Veeraraghavan, M., and Zolotoy, L., 2020, Media Coverage and IPO Pricing around the World, *Journal of Financial and Quantitative Analysis* 55, 1515-1553.
- Colak, G., Durnev, A., and Qian, Y., 2017, Political Uncertainty and IPO Activity: Evidence from U.S. Gubernatorial Elections, *Journal of Financial and Quantitative Analysis* 52, 2523-2564.
- Cole, R. A., Floros, I. V., and Ivanov, V. I., 2019, U.S. Exchange Upgrades: Reducing Uncertainty through a Two-Stage IPO, *Journal of Financial Intermediation*, 38, 45-57.
- Cornelli, F., and Yosha, O., 2003, Stage Financing and the Role of Convertible Securities, *Review of Economic Studies* 70, 1-32.
- Damaraju N., L., Barney, J., B., and Makhija A., K., Real Options in Divestment Alternatives, *Strategic Management Journal* 36, 728-744.
- Correia, S., 2015, Singletons, Cluster-Robust Standard Errors and Fixed Effects: A Bad Mix. Technical Note, Duke University.
- Dang, T. V., Gorton, G., Holmström, B., and Ordonez, G., 2017, Banks as Secret Keepers, *American Economic Review* 107, 1005-1029.
- Denis D. J., and McKeon S., B., 2020, Persistent Negative Cash Flows, Staged Financing, and the Stockpiling of Cash Balances, *Journal of Financial Economics*, forthcoming.

- Derrien, F., 2005, IPO pricing in “hot” market conditions: Who leaves money on the table?. *Journal of Finance* 60, 487-521.
- Derrien, F., and Kecskés, A., 2007. The Initial Public Offerings of Listed Firms, *Journal of Finance* 62, 447–479.
- Dow, J., Goldstein, I., and Guembel, A., 2017, Incentives for Information Production in Markets Where Prices Affect Real Investment, *Journal of the European Economic Association* 15, 877-909.
- Dow, J., and Gorton G., 1997, Stock Market Efficiency and Economic Efficiency: Is There a Connection?, *Journal of Finance* 52, 1087–1129.
- Dyck, A., and Zingales, L., 2004, Private Benefits of Control: An International Comparison. *Journal of Finance* 59, 537-600.
- Edmans, A., Goldstein, I., and Jiang, W., 2015, Feedback Effects, Asymmetric Trading, and the Limits to Arbitrage, *American Economic Review* 105, 3766-97.
- Edmans, A., Jayaraman, S., and Schneemeier, J., 2017, The Source of Information in Prices and Investment-price Sensitivity, *Journal of Financial Economics* 126, 74-96.
- Fama, E., and French, K., 2015, A Five-Factor Asset Pricing Model, *Journal of Financial Economics* 116, 1-22.
- Foucault, T., and Fresard, L., 2014, Learning From Peers' Stock Prices and Corporate Investment, *Journal of Financial Economics* 111, 554-577.
- Francis, B.B., and Hasan, I., 2001, The Underpricing of Venture and Nonventure Capital IPOs: An Empirical Investigation, *Journal of Financial Services Research* 19, 99-113.
- Francis, B.B., Hasan, I., Lothian, J.R., and Sun X., The Signaling Hypothesis Revisited: Evidence from Foreign IPOs, *Journal of Financial and Quantitative Analysis* 45, 81-106.
- Gompers, P. A., 1995, Optimal Investment, Monitoring, and the Staging of Venture Capital, *Journal of Finance* 50, 1461-1489.
- Grennan, J., 2019, Dividend Payments as a Response to Peer Influence. *Journal of Financial Economics* 131, 549-570.
- Grosse-Rueschkamp, B., Steffen, S., and Streit, D., 2019, A Capital Structure Channel of Monetary Policy, *Journal of Financial Economics* 133, 357-378.
- Habib, M. A., and Ljungqvist, A. P., 2001, Underpricing and Entrepreneurial Wealth Losses in IPOs: Theory and Evidence, *Review of Financial Studies* 14, 433-458.
- Hanley, K. W., and Hoberg, G., 2010, The Information Content of IPO Prospectuses, *Review of Financial Studies* 23, 2821-2864.
- Hertzel, M. G., Huson, M. R., and Parrino, R., 2012, Public Market Staging: The Timing of Capital Infusions in Newly Public Firms, *Journal of Financial Economics* 106, 72-90.
- Hoberg, G., 2007, The Underwriter Persistence Problem, *Journal of Finance* 62, 1169-1206.
- Hoberg, G., and Phillips, G., 2010, Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis, *Review of Financial Studies* 23, 3773-3811.
- Hoberg, G., and Phillips, G., 2016, Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy* 124, 1423-1465.

- Holmström, B., 1982, Managerial Incentive Problems – A Dynamic Perspective. In *Essays in Economics and Management in Honor of Lars Wahlbeck*, 209-230, Swedish School of Economics and Business Administration: Helsinki.
- Hsieh, J., Lyandres, E., and Zhdanov, A., 2011, A Theory of Merger Driven IPOs, *Journal of Financial and Quantitative Analysis* 46, 1367-1405.
- Huang R., and Ritter J. R., 2020, Corporate Cash Shortfalls and Financing Decisions, *Review of Financial Studies*, Forthcoming.
- Jegadeesh, N., Weinstein, M., and Welch, I., 1993, An Empirical Investigation of IPO Returns and Subsequent Equity Offerings, *Journal of Financial Economics* 34, 153-175.
- Jensen M. C., 1986, Agency Cost of Free Cash Flow, Corporate Finance and Takeovers, *American Economic Review* 76, 323-329.
- Jiang, G., Lee, C. M., and Zhang, Y., 2005, Information Uncertainty and Expected Returns, *Review of Accounting Studies* 10, 185-221.
- Jordan, B., D., and Riley, T., B., 2015, Volatility and Mutual Fund Manager Skill, *Journal of Financial Economics* 118, 289-298.
- Kaustia, M., and Rantala, V., 2015, Social Learning and Corporate Peer Effects, *Journal of Financial Economics* 117, 653-669.
- Khanna, N., Noe, T. H., and Sonti, R., 2008, Good IPOs draw in bad: Inelastic banking capacity and hot markets, *The Review of Financial Studies* 21, 1873-1906.
- Korkeamäki, T. P., and Moore, W. T., 2004, Convertible Bond Design and Capital Investment: The Role of Call Provisions, *Journal of Finance* 59, 391-405.
- Kumar, A., 2009, Hard-to-Value Stocks, Behavioral Biases, and Informed Trading, *Journal of Financial and Quantitative Analysis* 44, 175-1401.
- Leary, M. T., and Roberts, M. R., 2010, The Pecking Order, Debt Capacity, and Information Asymmetry, *Journal of Financial Economics* 95, 332-355.
- Ljungqvist, A., and Wilhelm Jr, W.J., 2003, IPO pricing in the dot-com bubble, *Journal of Finance* 58, 723-752.
- Loughran, T., & Ritter, J. R., 2002, Why don't Issuers Get Upset About Leaving Money on The Table in IPOs?, *Review of Financial Studies* 15, 413-444.
- Loughran T., and Ritter, J. R., 2004, Why has Underpricing Changed Over Time?, *Financial Management*, 3, 5-37.
- Lowry, M., Officer, M. S., and Schwert, G. W., 2010, The Variability of IPO Initial Returns, *Journal of Finance* 65, 425-465.
- Lowry, M., and Schwert, G. W., 2004, Is the IPO Pricing Process Efficient?, *Journal of Financial Economics* 71, 3-26.
- Mayers, D., 1998, Why Firms Issue Convertible Bonds: The Matching of Financial and Real Investment Options, *Journal of Financial Economics* 47, 83-102.
- McLean, R.D., 2011, Share issuance and cash savings, *Journal of Financial Economics* 99, 693-715.
- McLean, R.D., and Zhao, M., 2014, The Business Cycle, Investor Sentiment, and Costly External Finance, *Journal of Finance* 69, 1377-1409.

- Meggison, W.L., and Weiss, K.A., 1991, Venture Capitalist Certification in Initial Public Offerings, *Journal of Finance* 46, 879-903.
- Meggison, W.L., Meles, A., Sampagnaro, G., and Verdoliva, V., 2019, Financial Distress Risk in Initial Public Offerings: How Much Do Venture Capitalists Matter?, *Journal of Corporate Finance* 59, 10-30.
- Myers, S., L., and Majluf N., S., 1984, Corporate Financing and Investment Decisions when Firms Have Information that the Investors Do not Have, *Journal of Financial Economics* 13, 187-221.
- Oster, E., 2019, Unobservable Selection and Coefficient Stability: Theory and Evidence, *Journal of Business & Economic Statistics* 37, 187-204.
- Purnanandam, A.K., and Swaminathan, B., 2004, Are IPOs Really Underpriced?, *Review of Financial Studies* 17, 811-848.
- Sahlman, W., 1990, The Structure and Governance of Venture-Capital Organizations, *Journal of Financial Economics* 27, 473-524.
- Schultz, P., 1993, Unit Public Offerings: A Form of Staged Financing, *Journal of Financial Economics* 34, 199-229.
- Stiglitz, J., and Weiss, A., 1981, Credit Rationing in Markets with Imperfect Competition, *American Economic Review* 71, 393-410.
- Strebulaev, I., A., Zhu, H., and Zryumov, P., 2016, Optimal Issuance under Asymmetric Information and Accumulation of Cash Flows, Stanford University working paper.
- Taggart R., 1977, A Model of Corporate Financing Decisions, *Journal of Finance* 32, 1467-1484.
- Welch, I., 1989, Seasoned Equity Offerings, Imitation Costs, and the Underpricing of Initial Public Offerings, *Journal of Finance* 44, 421-449.
- Yung, C., Colak, G., and Wang W., 2008, Cycles in the IPO Market, *Journal of Financial Economics* 89, 192-208.
- Zhang, X, F., 2006, Information Uncertainty and Stock Returns, *Journal of Finance* 61, 105-136.
- Zhou, H., 2018, Variance Risk Premia, Asset Predictability Puzzles, and Macroeconomic uncertainty. *Annual Review of Financial Economics* 10, 481-497.
- Zingales, L., 1995, Insider Ownership and the Decision to Go Public. *Review of Economic Studies* 62, 425-448.

Table 1: Descriptive statistics

The table below reports descriptive statistics for our sample firms. Our sample consists of 3,525 U.S. IPOs between 1.1.1980–31.12.2018. We sort the firms on difficulty to value (HTV). We measure the difficulty to value with the first principal component from R&D scaled by sales, firm age and a high tech indicator. For variable definitions see appendix 1. ***, **, * denote 1%, 5%, 10% significance, respectively.

	Full Sample				Easy to Value		Mid		Hard to Value		t/z-stat ETV - HTV
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
IPO Size	0.325	0.188	0.083	1.000	0.375	0.200	0.322	0.183	0.277	0.166	0.10***
SEO 1/0	0.361	0.480	0.000	1.000	0.315	0.465	0.333	0.472	0.436	0.496	-0.12***
Participation Ratio	0.154	0.224	0.000	1.000	0.207	0.260	0.131	0.202	0.124	0.196	0.08***
Secondary/Total	0.054	0.100	0.000	1.000	0.079	0.126	0.045	0.088	0.038	0.074	0.04***
R&D	4.816	10.327	0.000	65.104	0.365	1.257	1.739	2.972	12.436	14.985	-12.07***
Missing R&D	0.367	0.482	0.000	1.000	0.593	0.491	0.448	0.497	0.059	0.235	0.53***
Ln(Age)	2.484	0.890	0.693	4.635	3.336	0.658	1.871	0.569	2.249	0.678	1.09***
Abs(Revision)	0.134	0.112	0.000	0.500	0.115	0.096	0.147	0.121	0.144	0.118	-0.03***
Earnings <0	0.373	0.484	0.000	1.000	0.164	0.370	0.389	0.488	0.567	0.496	-0.40***
Hi Tech	0.261	0.439	0.000	1.000	0.000	0.000	0.000	0.000	0.788	0.409	-0.79***
ROA	0.048	0.324	-1.187	0.609	0.189	0.141	0.048	0.315	-0.093	0.396	0.28***
M/B	2.879	2.182	0.773	13.669	2.022	1.237	3.153	2.556	3.466	2.250	-1.44***
Ln(Sales)	4.282	1.670	-0.737	8.359	5.224	1.359	3.992	1.475	3.627	1.718	1.60***
Leverage	0.339	0.301	0.000	1.450	0.438	0.287	0.333	0.291	0.246	0.293	0.19***
Cash Holdings	0.202	0.245	0.000	0.993	0.071	0.103	0.190	0.225	0.346	0.286	-0.27***
IPO Heat	1.514	0.780	0.102	3.710	1.635	0.815	1.583	0.748	1.323	0.740	0.31***
Top Underwriter	0.585	0.493	0.000	1.000	0.543	0.498	0.590	0.492	0.624	0.485	-0.08***
UW Premium	0.214	0.162	-0.028	0.870	0.174	0.127	0.226	0.181	0.243	0.167	-0.07***
VC Backing	0.464	0.499	0.000	1.000	0.155	0.362	0.506	0.500	0.734	0.442	-0.58***
Ln(Analyst)	1.029	0.513	0.000	2.833	0.946	0.530	1.003	0.489	1.138	0.499	-0.19***
First Day Return	0.184	0.344	-0.170	2.021	0.088	0.169	0.239	0.408	0.225	0.383	-0.14***
1-Month Return	0.031	0.198	-0.404	0.841	0.010	0.140	0.031	0.213	0.053	0.228	-0.04***
1-Month Std Dev	0.039	0.024	0.008	0.134	0.029	0.016	0.043	0.028	0.044	0.024	-0.01***
N	3,516				1,172		1,182		1,162		

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

The table shows sorting on the difficulty to value (HTV). We measure the difficulty to value with the first principal component from R&D scaled by sales, firm age and a high tech indicator. 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 sorting on valuation uncertainty, we further sort on the firms' one month return after the IPO. ***, **, * denote 1%, 5%, 10% significance, respectively.

Panel A: Valuation Uncertainty Sortings

	1-Month		3-Month	
	IVOL	VOL	IVOL	VOL
ETV	0.025	0.030	0.029	0.031
Mid	0.034	0.043	0.039	0.043
HTV	0.036	0.044	0.041	0.045
T-stat	-16.59***	-17.04***	-18.90***	-18.70***

Panel B: SEO Likelihood Sorted on Returns and Valuation Uncertainty

	Low Return	mid	High Return	Z-stat
ETV	0.232	0.192	0.337	-3.24***
Mid	0.301	0.357	0.419	-3.44***
HTV	0.414	0.452	0.557	-3.98***
Z-stat	-5.45***	-7.80***	-6.16***	-9.27***

Table 3: Base case regression models

Columns (1) and (2) of this table report regressions on IPO size measured as number of shares issued in the IPO scaled by the number of post-IPO shares. Columns (3) and (4) report regressions on an indicator variable taking value one if the firm conducts an SEO within 24 months following the IPO (SEO 1/0). Columns (5) and (6) report results from Cox hazard models with time from IPO to first SEO as the dependent variable. A positive coefficient estimate indicates a shorter time to failure (time to first SEO). We track the firms for two years following the IPO, i.e. our distributions are truncated at 730 days. We use the hard to value principal component (HTV) as our main explanatory variable. A three component PCA (HTV) including R&D scaled by sales, firm age and a high tech indicator. All variables are defined as in appendix 1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

	(1) IPO Size	(2) IPO Size	(3) SEO 1/0	(4) SEO 1/0	(5) time to SEO	(6) Time to SEO
HTV	-0.015*** (-4.38)	-0.008** (-2.52)	0.021** (2.59)	0.024** (2.45)	0.055** (2.48)	0.067*** (3.26)
Leverage	0.045*** (3.23)	0.038*** (3.71)	0.146*** (3.87)	0.133*** (4.20)	0.576*** (4.63)	0.536*** (5.38)
ln(Sales)	-0.006 (-1.51)	-0.008** (-2.28)	-0.000 (-0.01)	-0.003 (-0.41)	-0.006 (-0.25)	-0.021 (-0.67)
M/B	-0.034*** (-6.72)	-0.033*** (-6.27)	-0.031** (-2.99)	-0.030** (-2.90)	-0.133*** (-3.24)	-0.130*** (-3.06)
Cash/Assets	-0.055*** (-3.29)	-0.051** (-2.58)	0.141 (1.33)	0.095 (0.87)	0.318 (1.26)	0.155 (0.59)
VCB	-0.008 (-0.93)	-0.009 (-1.31)	0.005 (0.31)	0.015 (0.95)	0.036 (0.91)	0.065 (1.32)
ROA	-0.003 (-0.37)	-0.002 (-0.20)	-0.103** (-2.76)	-0.074* (-1.95)	-0.292*** (-3.45)	-0.202** (-2.44)
IPO Heat	-0.000 (-0.01)	-0.001 (-0.06)	-0.016 (-0.57)	-0.018 (-0.65)	-0.204** (-2.18)	-0.208** (-2.16)
Top Underwriter	0.006 (0.63)	0.004 (0.47)	0.027** (2.81)	0.032** (3.00)	0.131*** (4.19)	0.166*** (3.94)
UW Premium	0.025 (0.75)	0.027 (0.78)	-0.028 (-0.57)	-0.011 (-0.21)	-0.134 (-0.62)	-0.066 (-0.28)
IPO Size			-0.182** (-2.83)	-0.188** (-2.97)	-0.839*** (-3.57)	-0.883*** (-3.53)
First Day Return			0.079*** (3.66)	0.090*** (4.09)	0.347*** (4.61)	0.397*** (4.97)
Ln(Analyst)			0.230*** (5.37)	0.235*** (6.01)	1.184*** (6.83)	1.212*** (7.46)
1-Month Return			0.408*** (6.62)	0.408*** (6.38)	1.682*** (9.36)	1.675*** (9.07)
1-Month Std Dev			-0.553 (-1.37)	-0.322 (-0.74)	-2.770* (-1.86)	-2.190 (-1.47)
Constant	0.439*** (10.47)	0.450*** (11.20)	0.335*** (4.15)	0.328*** (4.04)		
Observations	3,516	3,516	3,516	3,516	3,516	3,516
R-squared	0.231	0.245	0.141	0.151	-	-
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y

Table 4: Interaction models

The table below shows the interactions between IPO Size, post-IPO alpha and valuation uncertainty. We include indicators if the IPO firm belongs to the bottom tercile of IPO Size, top tercile of 1-month post-IPO return and the top tercile of the hard to value PCA (HTV). All variables are defined as in appendix 1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (SIC-3) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

	(1) SEO 1/0	(2) SEO 1/0	(3) Time to SEO	(4) Time to SEO
High HTV	0.048 (1.69)	0.059* (1.88)	0.193* (1.81)	0.257** (2.20)
Small IPO	0.057 (1.27)	0.068 (1.51)	0.253 (1.58)	0.297* (1.78)
High HTV x Small IPO	-0.048 (-0.79)	-0.053 (-0.88)	-0.197 (-0.80)	-0.209 (-0.86)
High Return	0.154*** (5.99)	0.154*** (6.22)	0.647*** (7.56)	0.660*** (7.78)
High HTV x High Return	-0.028 (-1.00)	-0.031 (-1.06)	-0.191 (-1.45)	-0.220* (-1.70)
Small IPO x High Return	-0.038 (-0.75)	-0.038 (-0.72)	-0.125 (-0.58)	-0.119 (-0.55)
High HTV x Small IPO x High Return	0.112** (3.01)	0.108** (2.68)	0.407** (2.11)	0.373* (1.92)
Constant	0.210** (3.10)	0.199** (2.94)		
Observations	3,516	3,516	3,516	3,516
R-squared	0.130	0.140	-	-
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	N	Y	N	Y

Table 5: Secondary shares

The table below reports regressions using secondary share sales in the IPO (models 1 and 2) and post IPO-returns (3-6) as dependent variables. All variables are defined as in appendix A1. The models include year fixed effects. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

	(1) Participation Ratio	(2) Secondary/Total shares	(3) 1-Month Return	(4)	(5) 6-Months Return	(6)
HTV	-0.009* (-2.20)	-0.006** (-2.94)	0.012** (2.79)	0.012** (2.70)	0.011 (0.84)	0.010 (0.78)
Participation ratio			0.037** (2.95)		0.050 (1.74)	
Secondary/Total shares				0.011 (0.39)		-0.043 (-0.46)
Leverage	-0.119*** (-5.19)	-0.039*** (-3.38)	-0.019 (-1.47)	-0.023 (-1.80)	-0.029 (-0.70)	-0.037 (-0.88)
ln(Sales)	0.027*** (3.93)	0.008*** (3.33)	-0.001 (-0.39)	-0.000 (-0.02)	-0.012 (-1.32)	-0.010 (-1.16)
M/B	0.012* (2.07)	-0.001 (-0.63)	-0.014*** (-4.56)	-0.013*** (-4.50)	-0.042*** (-4.21)	-0.041*** (-3.92)
Cash/Assets	0.004 (0.13)	-0.003 (-0.27)	-0.024 (-1.79)	-0.024 (-1.81)	0.027 (0.48)	0.027 (0.47)
VCB	-0.004 (-0.53)	-0.002 (-0.44)	0.012 (1.29)	0.011 (1.28)	-0.020 (-1.43)	-0.020 (-1.45)
ROA	0.120*** (4.10)	0.031** (3.16)	0.030 (1.66)	0.034* (1.82)	0.049 (0.92)	0.057 (1.05)
IPO Heat	-0.015 (-0.73)	-0.002 (-0.32)	-0.006 (-0.38)	-0.007 (-0.42)	-0.077 (-1.55)	-0.078 (-1.56)
Top Underwriter	0.029** (2.36)	0.010 (1.67)	-0.007 (-0.73)	-0.006 (-0.64)	0.003 (0.08)	0.005 (0.13)
UW Premium	-0.024 (-0.81)	-0.008 (-0.71)	-0.035** (-2.48)	-0.035** (-2.59)	0.084 (1.71)	0.083 (1.69)
Ln(Analyst)			0.037*** (6.84)	0.038*** (7.05)	0.122*** (4.61)	0.122*** (4.59)
First Day Return			0.007 (0.21)	0.005 (0.15)	0.011 (0.26)	0.008 (0.18)
1-Month Std Dev			2.050** (2.83)	2.039** (2.81)	2.206** (2.73)	2.186** (2.71)
Constant	0.050 (0.98)	0.033** (2.47)	-0.025 (-0.49)	-0.023 (-0.47)	0.121 (1.44)	0.125 (1.47)
Observations	3,514	3,514	3,514	3,514	3,514	3,514
R-squared	0.218	0.127	0.093	0.092	0.124	0.124
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	N	N

Table 6: Inclusion of alternative uncertainty measures

The table below reports regressions using IPO size as dependent variable in columns (1) and (2) and an indicator SEO 1/0 if the firm conducts an SEO within two years following the IPO in columns (3) and (4). The main independent variable is HTV proxy and the alternative uncertainty measures (Amihud, Std Dev and IVOL), all alternative measures are captured up to one month following the IPO. The variables are defined in appendix A1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

	(1) IPO Size	(2) IPO Size	(3) SEO 1/0	(4) SEO 1/0
HTV	-0.015*** (-4.03)	-0.008* (-2.22)	0.020* (2.03)	0.024** (2.28)
1-Month Std Dev	0.257 (0.72)	0.266 (0.74)	-0.142 (-0.27)	0.016 (0.03)
1-month IVOL	-0.261 (-0.68)	-0.267 (-0.70)	-0.303 (-0.29)	-0.171 (-0.15)
Amihud	-301.162** (-3.05)	-294.707*** (-4.28)	-612.054 (-1.57)	-625.737 (-1.55)
Leverage	0.045*** (3.33)	0.038*** (3.27)	0.142** (3.13)	0.130*** (3.33)
ln(Sales)	-0.007 (-1.58)	-0.009** (-2.32)	-0.003 (-0.38)	-0.006 (-0.68)
M/B	-0.034*** (-6.31)	-0.034*** (-5.44)	-0.031** (-2.85)	-0.030** (-2.78)
Cash/Assets	-0.058** (-3.08)	-0.054* (-1.93)	0.132 (1.12)	0.089 (0.75)
VCB	-0.008 (-0.91)	-0.010 (-1.04)	0.001 (0.04)	0.012 (0.66)
ROA	-0.003 (-0.23)	-0.001 (-0.10)	-0.099** (-2.37)	-0.070 (-1.73)
IPO Heat	0.002 (0.15)	0.001 (0.07)	-0.029 (-0.91)	-0.029 (-0.96)
Top Underwriter	0.003 (0.34)	0.002 (0.17)	0.026* (1.97)	0.030* (2.22)
UW Premium	0.026 (0.73)	0.027 (0.69)	-0.025 (-0.48)	-0.008 (-0.15)
IPO Size			-0.192** (-3.05)	-0.197** (-3.10)
First Day Return			0.225*** (4.57)	0.231*** (5.20)
Ln(Analyst)			0.065** (2.58)	0.076** (2.95)
1-Month Return			0.394*** (5.65)	0.394*** (5.52)
Constant	0.445*** (10.72)	0.456*** (11.26)	0.384*** (4.51)	0.371*** (4.21)
Observations	3,404	3,404	3,404	3,404
R-squared	0.230	0.244	0.141	0.151
Year FE	Y	Y	Y	Y
Industry FE	N	Y	N	Y

Table 7: Matched sample

The table below reports regressions using a matched sample based on propensity scores. IPO size is the dependent variable in columns (1) and (2) and an indicator SEO 1/0 if the firm conducts an SEO within two years following the IPO in columns (3) and (4). All variables are defined in appendix A1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

	(1) IPO Size	(2) IPO Size	(3) SEO 1/0	(4) SEO 1/0
HTV	-0.019*** (-6.21)	-0.011** (-2.33)	0.024*** (3.41)	0.042*** (3.67)
Leverage	0.041 (1.77)	0.030* (2.16)	0.105** (2.35)	0.121** (2.84)
ln(Sales)	-0.019*** (-4.72)	-0.022*** (-6.55)	0.024*** (4.27)	0.016** (2.40)
M/B	-0.054*** (-8.57)	-0.054*** (-9.20)	-0.006 (-0.39)	-0.006 (-0.38)
Cash/Assets	0.020 (0.53)	0.007 (0.20)	0.213 (1.57)	0.245 (1.60)
VCB	-0.005 (-0.58)	-0.007 (-0.85)	0.051 (1.81)	0.059* (2.01)
ROA	0.053 (1.68)	0.064* (2.08)	-0.233*** (-3.45)	-0.233** (-3.03)
IPO Heat	-0.013 (-1.12)	-0.014 (-1.31)	0.006 (0.17)	0.005 (0.16)
Top Underwriter	0.030** (2.67)	0.028** (2.66)	-0.006 (-0.24)	0.003 (0.10)
UW Premium	-0.003 (-0.07)	0.002 (0.05)	0.001 (0.01)	0.025 (0.31)
IPO Size			-0.107 (-1.40)	-0.102 (-1.28)
First Day Return			0.305** (2.81)	0.291** (2.84)
Ln(Analyst)			0.106*** (4.01)	0.114*** (4.23)
1-Month Return			0.524*** (10.07)	0.528*** (9.13)
1-Month Std Dev			-0.815 (-1.56)	-0.661 (-1.26)
Constant	0.539*** (11.54)	0.565*** (13.91)	0.119 (1.28)	0.137 (1.46)
Observations	1,678	1,678	1,678	1,678
R-squared	0.193	0.224	0.179	0.190
Year FE	Y	Y	Y	Y
Industry FE	N	Y	N	Y

Table 8: HTV, peer group Q and peer group analysts

Panel A of the table shows sortings of IPO firms into terciles based on peer group M/B and the number of peer group analysts according to the Hoberg and Phillips (2010, 2016) classification. The table shows the value of the HTV proxy in the different terciles. Panel B reports regressions using IPO size as the dependent variable in odd columns and SEO likelihood in even columns. The main independent variable is the HTV proxy. Peer M/B is the average Q of the peer group firms according to the Hoberg and Phillips (2010; 2016) classification. Peer Analyst is the peer group's number of analysts according to the same classification. Columns (3) and (4) use orthogonalized values of HTV, peer analyst and peer M/B. Models in odd columns include the controls of column (1) of Table 3 and even columns the controls of column (3) of Table 3. All variables are defined as in appendix A1. All models include year fixed effects. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

Panel A:	Low M/B	Mid	High M/B	Diff
Low Analyst	-0.751	-0.570	-0.129	0.621***
Mid	-0.388	0.272	0.713	1.101***
High Analyst	0.203	0.864	0.873	0.670***
Diff	0.954***	1.434***	1.002***	1.624***

Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
	IPO Size	SEO 1/0	IPO Size	SEO 1/0	IPO Size	SEO 1/0
HTV	-0.007*	0.018*	-0.013***	0.016		
	(-1.83)	(1.86)	(-3.30)	(1.58)		
Peer Analyst			0.008**	-0.004		
			(2.94)	(-0.36)		
Peer M/B			0.002	0.014		
			(0.47)	(1.01)		
HTV Orthogonalized					-0.017**	0.028*
					(-2.60)	(2.13)
Peer Analyst Orthogonalized					-0.000	0.019
					(-0.00)	(1.55)
Peer M/B Orthogonalized					0.002	0.019
					(0.29)	(0.85)
Constant	0.435***	0.463***	0.383***	0.459***	0.421***	0.495***
	(6.27)	(4.67)	(5.19)	(3.55)	(6.04)	(4.84)
Observations	2,265	2,265	2,265	2,265	2,265	2,265
R-squared	0.253	0.141	0.244	0.133	0.242	0.134
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	N	N

Table 9: Excluding VC backed IPOs

Columns (1) and (2) of this table report regressions on IPO size measured as number of shares issued in the IPO scaled by the number of post-IPO shares. Columns (3) and (4) report regressions on an indicator variable taking value one if the firm conducts an SEO within 24 months following the IPO (SEO 1/0). Columns (5) and (6) report results from Cox hazard models with time from IPO to first SEO as the dependent variable. A positive coefficient estimate indicates a shorter time to failure (time to first SEO). We track the firms for two years following the IPO, i.e. our distributions are truncated at 730 days. We use the hard to value principal component (HTV) as our main explanatory variable. A three component PCA (HTV) including R&D scaled by sales, firm age and a high tech indicator. All variables are defined as in appendix 1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	IPO Size	IPO Size	SEO 1/0	SEO 1/0	Time to SEO	Time to SEO
HTV	-0.020*** (-6.70)	-0.013*** (-5.51)	0.023** (2.27)	0.037** (3.01)	0.067* (1.83)	0.120*** (3.04)
Leverage	0.054*** (3.67)	0.047*** (3.33)	0.092* (1.82)	0.099* (2.04)	0.441*** (3.05)	0.465*** (3.48)
ln(Sales)	-0.017*** (-4.22)	-0.019*** (-5.55)	0.022** (2.24)	0.016 (1.35)	0.091** (2.22)	0.054 (1.08)
M/B	-0.048*** (-8.26)	-0.048*** (-7.51)	-0.004 (-0.37)	-0.006 (-0.48)	-0.002 (-0.04)	-0.012 (-0.20)
Cash/Assets	0.017 (0.35)	0.017 (0.38)	0.149 (1.17)	0.153 (1.21)	0.458 (1.25)	0.462 (1.40)
ROA	0.002 (0.11)	0.010 (0.54)	-0.135* (-2.03)	-0.117 (-1.63)	-0.396* (-1.77)	-0.269 (-1.09)
IPO Heat	-0.003 (-0.28)	-0.005 (-0.45)	-0.015 (-0.43)	-0.013 (-0.38)	-0.156 (-1.62)	-0.126 (-1.29)
Top Underwriter	0.022** (2.24)	0.020** (2.34)	0.004 (0.28)	0.008 (0.45)	0.049 (0.80)	0.094 (1.30)
UWAgencytotal	0.041 (1.15)	0.042 (1.14)	-0.051 (-0.70)	-0.038 (-0.52)	-0.164 (-0.53)	-0.088 (-0.30)
IPO Size			-0.092 (-1.49)	-0.101 (-1.59)	-0.387 (-1.25)	-0.475 (-1.42)
First Day Return			0.085** (2.66)	0.093** (2.91)	0.398*** (2.76)	0.450*** (2.96)
Ln(Analyst)			0.225** (2.72)	0.221** (2.70)	1.106*** (2.95)	1.158*** (2.88)
1-Month Return			0.559*** (6.92)	0.565*** (7.23)	2.427*** (9.24)	2.516*** (8.08)
1-Month Std Dev			-0.383 (-0.75)	-0.271 (-0.46)	-2.592 (-0.75)	-2.109 (-0.62)
Constant	0.504*** (12.54)	0.522*** (12.92)	0.167* (1.94)	0.187* (2.13)		
Observations	1,883	1,883	1,883	1,883	1,883	1,883
R-squared	0.189	0.205	0.155	0.163		
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y

Table 10: Market timing

This table shows regressions on the pre-SEO excess returns in columns (1) to (3) and the 12-month post-SEO excess returns in column (4) to (6). We create calendar time portfolios based on the valuation uncertainty measures. HTV tercile 1 (3) indicates the firms with the lowest (highest) valuation uncertainty. All calendar time models are estimated on monthly data using Fama-French 5-benchmark factors. ***, **, * denotes 1%, 5%, 10% significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-SEO			Post-SEO		
	R-Rf	R-Rf	R-Rf	R-Rf	R-Rf	R-Rf
HTV Tercile	1	2	3	1	2	3
Market	1.167*** (30.81)	1.156*** (24.39)	1.232*** (25.40)	1.005*** (10.00)	1.162*** (7.92)	1.149*** (7.73)
SMB	0.991*** (16.05)	0.921*** (10.93)	1.032*** (14.03)	0.826*** (4.71)	0.889*** (3.59)	1.580*** (7.69)
HML	0.228*** (3.14)	-0.071 (-0.73)	-0.747*** (-8.28)	-0.543*** (-2.90)	-0.737** (-2.51)	-1.197*** (-4.33)
RMW	0.470*** (5.69)	-0.337** (-2.55)	-0.577*** (-4.61)	0.342 (1.64)	-0.417 (-1.41)	-0.281 (-0.96)
CMA	-0.161 (-1.45)	-0.225 (-1.29)	-0.055 (-0.37)	0.354 (1.31)	0.226 (0.56)	-0.351 (-0.87)
Alpha	-0.357*** (-2.62)	-0.090 (-0.49)	0.526*** (3.23)	2.583*** (6.40)	4.164*** (7.23)	3.583*** (7.01)
Observations	468	474	478	452	430	460
R-squared	0.472	0.288	0.154	0.48	0.259	0.373

Table 11: Monthly Returns

This table shows regressions on SEO likelihood (SEO 1/0). The main independent variable is the HTV proxy and the monthly returns following the IPO. All models include the controls of column (3) in Table. All variables are defined as in appendix A1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denotes 1%, 5%, 10% significance, respectively.

	(1) SEO 1/0	(2) SEO 1/0
HTV	0.018** (2.89)	0.028*** (3.30)
1st Month's Return	0.391*** (7.85)	0.391*** (7.59)
2nd Month's Return	0.315*** (6.86)	0.314*** (6.97)
3rd Month's Return	0.362*** (9.32)	0.363*** (9.73)
4th Month's Return	0.327*** (5.36)	0.331*** (5.60)
5th Month's Return	0.296*** (7.63)	0.298*** (7.82)
6th Month's Return	0.394*** (5.86)	0.391*** (5.73)
7th Month's Return	0.262*** (9.24)	0.267*** (8.52)
8th Month's Return	0.296*** (4.20)	0.294*** (4.43)
9th Month's Return	0.218*** (4.35)	0.220*** (4.35)
10th Month's Return	0.209*** (3.79)	0.208*** (3.64)
11th Month's Return	0.285*** (3.52)	0.287*** (3.58)
12th Month's Return	0.165** (2.99)	0.170** (3.08)
Constant	0.245*** (4.18)	0.236*** (3.78)
Observations	3,490	3,490
R-squared	0.258	0.267
Controls	Y	Y
Year FE	Y	Y
Industry FE	N	Y

Table 12: Investors' risk aversion

This table shows regressions on IPO size in columns (1) and (2) and SEO likelihood (SEO 1/0) in columns (3) and (4). The main independent variables are indicators taking the value of 1 if the firm/month belong to the top tercile of the HTV proxy, bottom tercile of Baker and Wurgler's (2006) sentiment index, top tercile of Zhou (2018) variance risk premia, and their interactions. Models (1) and (2) include the controls of column (1) of Table 3 and model (3) and (4) the controls of column (3) of Table 3. All variables are defined as in appendix A1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denotes 1%, 5%, 10% significance, respectively.

	(1) IPO Size	(2) IPO Size	(3) SEO 1/0	(4) SEO 1/1
Top tercile HTV	-0.022*** (-5.37)	-0.007 (-1.17)	0.034* (2.07)	0.051* (1.85)
Bottom Tercile Sentiment	-0.014 (-1.30)		-0.018 (-0.41)	
Top Tercile HTV x Bottom Tercile Sentiment	0.015 (1.39)		0.063 (1.52)	
Top Tercile Variance Risk Premia		0.007 (0.94)		-0.037 (-1.14)
Top Tercile HTV x Top Tercile Variance Risk Premia		-0.018 (-1.38)		-0.014 (-0.31)
Constant	0.497*** (16.29)	0.450*** (12.36)	0.481*** (6.73)	0.542*** (5.88)
Observations	3,517	2,742	3,517	2,742
R-squared	0.223	0.233	0.122	0.115
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Table 13: Alternative explanations

This table shows regressions on IPO size in columns (1) and (2) and SEO likelihood (SEO 1/0) in column (3). The main independent variable is the HTV proxy, first day return, net cash flows, a negative net cash flow indicator and the interaction between net cash flows and the net cash flow indicator. Models (1) and (2) include the controls of column (1) of Table 3 and model (3) the controls of column (3) of Table 3. All variables are defined as in appendix A1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denotes 1%, 5%, 10% significance, respectively.

	(1) IPO Size	(2) IPO Size	(3) SEO 1/0
HTV	-0.014*** (-4.37)	-0.014** (-3.02)	0.020* (1.91)
Negative Cash flow		0.013 (0.77)	0.003 (0.15)
Net Cash Flows		0.128*** (3.32)	0.066 (0.42)
Negative Cash Flows x Net Cash Flows		-0.086* (-2.12)	-0.133 (-0.81)
First Day Return	0.119*** (6.87)		0.241*** (4.95)
Constant	0.451*** (12.71)	0.395*** (5.94)	0.383*** (4.17)
Observations	3,517	2,802	2,802
R-squared	0.251	0.240	0.124
Controls	Y	Y	Y
Year FE	Y	Y	Y
Industry FE	N	N	N

Table 14: IPO process information revelation

The table below reports OLS models where IPO size is the dependent variable in odd columns and SEO likelihood in even columns. The main independent variable is the HTV proxy. Models in odd columns include the controls of column (1) of Table 3 and even columns the controls of column (3) of Table 3. All variables are defined as in appendix A1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denotes 1%, 5%, 10% significance, respectively.

	(1) IPO Size	(2) SEO 1/0	(3) IPO Size	(4) SEO 1/0
HTV	-0.022*** (-6.50)	0.036** (3.08)	-0.019*** (-3.65)	0.055*** (3.61)
Abs(Revision)	-0.057 (-1.68)	0.037 (0.36)	-0.057 (-1.77)	0.045 (0.46)
IPO cost	-0.027*** (-4.07)	-0.018 (-1.12)	-0.025*** (-5.19)	-0.027 (-1.56)
Ln(Analyst)	-0.001 (-0.12)	0.075** (2.54)	0.005 (0.54)	0.085** (3.09)
First Day Return	0.088*** (3.90)	0.292** (2.90)	0.086*** (3.74)	0.291** (3.11)
Constant	0.739*** (11.19)	0.502* (2.21)	0.734*** (16.82)	0.582** (2.34)
Observations	1,927	1,927	1,926	1,926
R-squared	0.242	0.115	0.256	0.130
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Appendix 1: Variable definitions

Variable	Formula	Description	Source
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
abs(Revision)	Abs(Offerprice/Midrange filing price-1)		SDC
Alpha		The alpha from a Fama-French 5 factor model	CRSP/ Kenneth French
Amihud		The Amihud (2002) Illiquidity measure	CRSP
Average Underpricing		Average quarterly underpricing of all IPO issues	Jay Ritter
Earnings <0		Indicator variable taking value 1 if the firm has negative pre-IPO earnings	COMPUSTAT
Economic Uncertainty		The three component economic uncertainty index by Baker et al. (2016)	https://www.policyuncertainty.com/
Fed Funds Rate			FRED
Firm Age	$\ln(1 + \text{IPO Year} - \text{Founding year})$		SDC/Jay Ritter
First Day Return	First day Close/Offer price-1		SDC
GPD Growth			FRED
Gross spread		The gross spread in percentage	SDC
High Tech Indicator		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
HTV		PCA constructed from R&D/Sales, high tech indicator and $\ln(+1 \text{ firm age})$	CRSP/ COMPUSTAT/SDC
HTV2		The variables from the 3 variable PCA plus absolute offer price revision and a negative earnings indicator	CRSP/ COMPUSTAT
IPO heat		Measured as in Yung et al. (2008) using Jay Ritter's IPO data	Ritter
IPO Size	Shares Offered in IPO/Post-IPO Shares Outstanding		SDC/CRSP
IVOL		The idiosyncratic volatility from a 5-factor Fama and French model	CRSP/ Kenneth French
Leverage	$(\text{Long term} + \text{Short Term debt}) / \text{Total Assets}$	Pre-IPO long term and short term debt scaled by pre-IPO total assets	COMPUSTAT
Ln(Analyst)	$\ln(1 + \text{nr. of analysts})$	Number of analysts measured at 60 days following the IPO as in Rajan and Servaes (1995)	IBES
ln(Sales)	$\ln(\text{Sales})$	the natural logarithm of pre-IPO sales	COMPUSTAT
M/B	$(\text{MV}(\text{equity}) + \text{total assets} - \text{BV}(\text{equity})) / \text{total assets}$	Market value of equity at the IPO day, post-IPO total assets, post-IPO Book equity. Following Altı (2005), all values above 10 is given the value 10	CRSP/COMPUSTAT
Net Cash Flows	Cash flow from operations + cash flows from investments		COMPUSTAT
Negative Cash Flows		An indicator taking the value of one if the firm has negative pre-IPO cash flows	COMPUSTAT
Participation Ratio	Secondary Shares in the IPO/Total shares in the IPO	Proportion of secondary shares in the IPO	SDC
Peer M/B	$\text{M/B} = (\text{MV}(\text{equity}) + \text{total assets} - \text{BV}(\text{equity})) / \text{total assets}$	The average Q of the listed peer group according to Hoberg and Phillips (2010; 2016) classification	COMPUSTAT/Gerard Hoberg

Peer Analyst		Natural logarithm of the number of analysts following the peer group according to the Hoberg and Phillips (2010; 2016) classification	IBES/Gerard Hoberg
R&D	R&D/Sales	Pre-IPO R&D expenses scaled by Pre-IPO sales, winsorized at 1%	COMPUSTAT
ROA	EBITDA/Total Assets	Pre-IPO EBITDA scaled by Pre-IPO Total Assets, winsorized at 1%	COMPUSTAT
Secondary	Secondary shares/total shares	Percentage of secondary shares offered in the IPO scaled by total shares offered in the IPO	SDC
Secondary/Total	Secondary Shares in the IPO/Post-IPO Shares outstanding	Proportion of secondary shares offered in the IPO scaled by total shares	SDC/CRSP
SEO 1/0		Indicator variable taking the value of 1 if the firm conducts an SEO within 24 months following the IPO	SDC
Top Underwriter		Indicator variable taking the value of 1 if the firm has at least one lead underwriter with score of 8 or 9 according to the Carter and Manaster Ranking	SDC/Jay Ritter
UW Premium		Average underwriter specific premium as in (Hoberg, 2007)	SDC
VC Backing		Indicator variable taking the value of one if the firm is VC backed	SDC

Table IA1: Debt issue regressions

This table shows regressions on two debt issue indicators. Debt Issue 1 (Debt Issue 2) takes the value of one if the firm has increased its debt by more than 5% one (two) year(s) following the IPO. The main independent variables are the HTV proxies. All variables are defined as in appendix A1. All models include year fixed effects. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

	(1) Debt Issue 1	(2) Debt Issue 2	(3) Debt Issue 1	(4) Debt Issue 2
HTV	-0.004 (-0.47)	0.013 (1.45)	-0.024** (-2.60)	-0.007 (-0.50)
Leverage	0.008 (0.16)	-0.028 (-0.79)	-0.002 (-0.03)	-0.034 (-0.74)
ln(Sales)	-0.024* (-2.02)	-0.019 (-1.70)	-0.031** (-2.88)	-0.022** (-3.02)
M/B	-0.031*** (-3.34)	-0.026** (-2.79)	-0.027*** (-3.69)	-0.020*** (-3.25)
Cash/Assets	-0.077 (-1.39)	-0.086* (-1.87)	-0.168** (-2.36)	-0.165*** (-3.46)
VCB	-0.046 (-1.42)	-0.027 (-0.83)	-0.078** (-2.71)	-0.053 (-1.61)
ROA	-0.103*** (-4.20)	-0.094** (-3.05)	-0.161*** (-4.94)	-0.147*** (-5.02)
IPO Heat	-0.001 (-0.07)	-0.005 (-0.29)	-0.036** (-2.33)	-0.038** (-2.56)
First Day Return	0.114** (2.90)	0.115** (2.95)	0.026 (1.34)	0.029 (1.27)
IPO Size	-0.000 (-0.00)	-0.021 (-0.40)	0.014 (0.29)	-0.006 (-0.12)
Top Underwriter	0.050** (3.14)	0.033* (1.99)	0.040 (1.75)	0.017 (0.63)
UW Premium	-0.040 (-0.68)	-0.034 (-0.59)	0.049 (0.86)	0.048 (0.81)
Ln(Analyst)	-0.013 (-0.68)	0.000 (0.01)	-0.013 (-0.66)	-0.003 (-0.12)
1-Month Return	-0.023 (-0.72)	-0.025 (-0.80)	-0.019 (-0.55)	-0.017 (-0.45)
1-Month Std Dev	-0.550 (-1.32)	-0.022 (-0.05)	-0.516 (-1.12)	0.229 (0.57)
Constant	0.456*** (4.82)	0.410*** (6.02)	0.745*** (5.85)	0.670*** (8.34)
Observations	3,516	3,516	3,516	3,516
R-squared	0.059	0.086	0.075	0.109
Year FE	Y	Y	Y	Y
Industry FE	N	N	Y	Y

Table IA2: Base case regression models (5- variable PCA)

Columns (1) and (2) of this table report regressions on IPO size measured as number of shares issued in the IPO scaled by the number of post-IPO shares. Columns (3) and (4) report regressions on an indicator variable taking value one if the firm conducts an SEO within 24 months following the IPO (SEO 1/0). Columns (5) and (6) report results from Cox hazard models with time from IPO to first SEO as the dependent variable. A positive coefficient estimate indicates a shorter time to failure (time to first SEO). We track the firms for two years following the IPO, i.e. our distributions are truncated at 730 days. We use the hard to value principal component (HTV) as our main explanatory variable, a three component PCA (HTV) including R&D scaled by sales, firm age, a high tech indicator, absolute price revision and a negative earnings indicator. All variables are defined as in appendix 1. Reported t-stats in parentheses are heteroscedasticity robust and double clustered on industry (FF-12) and year. ***, **, * denote 1%, 5%, 10% significance, respectively.

	(1) IPO Size	(2) IPO Size	(3) SEO 1/0	(4) SEO 1/0	(5) time to SEO	(6) Time to SEO
HTV	-0.017*** (-5.12)	-0.015*** (-3.56)	0.039*** (3.23)	0.052*** (3.78)	0.164*** (4.29)	0.233*** (5.60)
Leverage	0.047** (3.03)	0.039*** (3.44)	0.086 (1.74)	0.081 (1.76)	0.516*** (2.78)	0.535*** (3.42)
ln(Sales)	-0.013*** (-4.08)	-0.014*** (-5.59)	0.003 (0.26)	-0.007 (-0.53)	-0.010 (-0.23)	-0.058 (-1.00)
M/B	-0.040*** (-5.69)	-0.040*** (-5.32)	-0.043* (-2.19)	-0.041* (-2.25)	-0.274*** (-3.05)	-0.265*** (-3.04)
Cash/Assets	-0.089*** (-4.08)	-0.084*** (-3.37)	0.127 (1.01)	0.097 (0.79)	0.562 (1.05)	0.494 (1.05)
VCB	-0.001 (-0.17)	-0.003 (-0.41)	0.016 (0.54)	0.030 (1.01)	0.027 (0.23)	0.078 (0.61)
ROA	-0.008 (-0.58)	-0.001 (-0.05)	-0.045 (-0.95)	0.014 (0.24)	-0.097 (-0.56)	0.270 (1.08)
IPO Heat	-0.010 (-0.85)	-0.010 (-0.84)	-0.029 (-0.81)	-0.026 (-0.70)	-0.188 (-1.52)	-0.155 (-1.15)
Top Underwriter	0.009 (0.79)	0.010 (0.93)	0.035** (3.10)	0.041** (3.06)	0.202*** (4.23)	0.251*** (4.76)
UW Premium	0.001 (0.02)	0.001 (0.02)	-0.042 (-0.45)	-0.031 (-0.33)	-0.036 (-0.10)	0.033 (0.09)
IPO Size			-0.143 (-1.35)	-0.147 (-1.31)	-0.903* (-1.84)	-0.964* (-1.84)
First Day Return			0.086** (2.99)	0.102*** (3.34)	0.499*** (8.06)	0.569*** (7.12)
Ln(Analyst)			0.282** (2.77)	0.276** (2.91)	1.557*** (4.22)	1.567*** (4.62)
1-Month Return			0.388*** (3.96)	0.402*** (3.83)	1.627*** (7.22)	1.753*** (5.77)
1-Month Std Dev			-0.694 (-1.36)	-0.493 (-0.94)	-4.377* (-1.89)	-3.042 (-1.16)
Constant	0.502*** (19.65)	0.509*** (20.58)	0.349** (2.40)	0.349* (2.10)		
Observations	1,929	1,928	1,929	1,928	1,931	1,931
R-squared	0.225	0.241	0.116	0.131		
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y

