Search and Pricing in Security Issues Markets[†]

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Abstract

We present a search model that incorporates two key features of securities issuance markets: search for investors and information gathering. In the model, a seller contacts investors sequentially and uses the revealed interest to update the price of the security and to decide whether to terminate the search. We characterize the seller's optimal strategy, which specifies how to structure the search, when to terminate the search, how to price the security, and how to allocate it to investors. We show how these choices are jointly determined and depend on the quality of investor information and search frictions. Our model provides unique predictions about offer outcomes, such as search length, security valuation, issue costs, underpricing, post-offer returns, and allocations. We find empirical support for these predictions in the setting of accelerated bookbuilt offers of seasoned equity, which involve simultaneous search and information gathering and which have become prevalent in recent years.

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I. Introduction

When offering new securities, issuers and their investment bankers often need to canvass many investors in search of buyers. In some settings, such as certain offerings of seasoned equity, private placements of debt and equity, and negotiated sales of corporate and municipal bonds, this process is dynamic and involves a series of bilateral interactions. By reaching out to investors, the seller tries to ascertain each investor's interest in the security, while each investor reveals their interest strategically. The offer concludes when the seller identifies enough investors to allocate the security at a price that incorporates both the information gathered during the search and the strategic considerations of the buyers.

We present a theoretical model to describe this dynamic process that combines search for new investors and information gathering. In our model, a seller contacts investors sequentially and uses the reported interest to learn about the distribution of investor information and update the value of the security. The seller may terminate the search at any time. We derive the seller's optimal strategy, which specifies how to structure and when to terminate the search and how to price and allocate the security to investors. We show how these choices depend on the quality of investor information and search frictions. We further derive equilibrium relations between the length of the search and offer outcomes, such as offering prices, issue costs, postoffer returns, and allocations. We then use the model to empirically examine accelerated bookbuilt offerings of seasoned equity. As we discuss later, such offerings have become prevalent in recent years and involve both search for new investors and information gathering. The empirical findings are consistent with the predictions of the model.

Our model considers a seller of a divisible security and a sufficient number of risk-neutral investors as potential buyers. The seller does not know the security's postoffer market price, P_1, which incorporates all relevant information, including information pertaining to the offer. Each investor has private information about P_1, where this information is imperfect and independent across investors and is either positive (with probability π) or negative (with probability $1-\pi$). At the beginning of the search, the seller knows neither which investors have positive information nor what the exact value of π is. The seller approaches investors one at a time and assesses each investor's interest in the security, a process we call "search." If an investor reports positive information, then the seller updates π and P_1 upwards; otherwise, the seller updates π and P_1 downwards. The seller wants to maximize offer proceeds net of search costs while each investor is ready to purchase a portion of the security for a price that does not exceed its fair value conditional on all gathered information. The seller reaches out to investors until the cost of the next round of search exceeds its marginal benefit. Once the search process ends, the seller sets the offer price and allocates the security among investors that have already been contacted.

We study equilibria in which each investor truthfully reports their information while the seller devises a pricing and allocation strategy that is incentive compatible. In such equilibria, reporting positive information comes with an opportunity cost, which is equal to the expected gain from lying—by reporting negative instead of positive information, the investor can bring the offer price down and obtain the security at a price below fair value.[1] To induce truthful reporting, the seller compensates investors for this opportunity cost and underprices the security by a commensurate amount. In equilibrium, the opportunity cost is endogenous and the seller can reduce it by engaging in longer searches, by first contacting investors with relatively lower opportunity costs of reporting positive information, by underpricing the security strategically, and by promising to allocate it to investors reporting positive information. Investors reporting negative information receive allocations only when an insufficient number of investors report positive information. In such cases, it is optimal to favor investors contacted early in the search process.

The duration of the search has two distinct components. The first component is chosen *ex ante* and is equal to the maximum number of searches the seller may conduct. This component balances the reduction in expected underpricing with the increase in expected search costs as the number of searches increases. The second component is path dependent and is realized *ex post*. With positive search costs, it is strictly optimal to stop the search once the whole issue can be placed with investors reporting positive information, regardless of whether the seller has contacted the planned maximum number of investors. As a result,

[1] In the model, investors with negative information do not gain from misrepresenting their information.

equilibrium prices and allocations are path dependent and vary with *ex post* search length.[2]

Using this setup, we study optimal search strategies, allocations, and valuation in a unified framework that includes both search and information gathering. The seller determines the *ex ante* maximum number of investors to contact, where this number decreases with search costs and increases with the value of investor information. In equilibrium, the seller keeps on contacting investors until either this maximum is reached or the offer can be allocated exclusively to investors reporting positive information, whichever comes first. Once the search completes, all investors reporting positive information receive full allocations in the offer. Investors reporting negative information receive allocations from the remaining portion of the offer, if any. In such cases, the seller would find it optimal to favor investors that have been contacted early in the search sequence. Because search termination is path dependent, our model makes predictions about *ex post* search length and its relations to the gathered information and to the value of the security. On the one hand, shorter searches will reflect more favorable investor reception than longer searches, all else equal. On the other hand, shorter searches will tend to be more underpriced and will gather less information. Our model also provides insights into the use of confidential search, which we discuss below and which is common in certain types of equity offerings.

As part of the optimal search strategy, the seller first contacts investors with a relatively low opportunity cost of reporting positive information. In the context of underwritten offers, one set of such investors are those who participate regularly in offers underwritten by the same investment bank. Regular investors benefit from being included repeatedly in underpriced offers (Benveniste and Spindt 1989 and Sherman 2000). The banker can reduce regular investors' overall opportunity cost of reporting positive information by committing to move them down the search sequence in future deals, or to exclude them altogether, if they withhold positive information in the current deal. In effect, the one-time benefit of withholding positive information for regular investors is reduced by a loss of expected future underpricing due to a reduced probability of receiving future allocations.

[2]Variability in outcomes (e.g., dispersion of prices) is common in search markets, even when goods are homogeneous (see, for example, Stigler 1961). As one would expect, when search costs approach zero, the planned maximum number of searches approaches infinity, the opportunity cost of revealing positive information approaches zero, and the offer price converges to the informationally efficient price.

Search models have been built to study non-centralized security markets by Duffie, Gârleanu and Pedersen (2005, 2007), Vayanos and Wang (2007), and Weill (2008).[3] In these models, investors differ in their valuation of the asset. Sellers and buyers meet at random times and bargain for a mutually beneficial price under symmetric information.[4] In our model, we assume rational expectations so that while investors are *ex ante* endowed with different information, *ex post* they agree and attach the same value to the asset. The seller contacts potential buyers at fixed intervals and tries to uncover their information. Because *ex ante* the seller does not know each investor's type, in our model too the time to meet an investor of a given type is random. Our model further differs from the search models cited above in that it considers uniform pricing, which is a unique and important feature in many financial markets. Therefore, the model can be used to study search markets in which some form of uniform pricing is present.

Information gathering in security issues markets has been studied in the context of initial public offerings (IPOs) by Benveniste and Spindt (1989), Benveniste and Wilhelm (1990), Spatt and Srivastava (1991), Sherman (2000), and Sherman and Titman (2002). These studies use a static framework in which the IPO underwriter simultaneously gathers indications of interest from a predetermined pool of asymmetrically informed investors.[5] Moreover, all participants know the exact probability with which an investor may have positive information. In contrast, in our model, the seller contacts investors sequentially and uses the revealed interest to learn about the distribution of information, where this distribution is *ex ante* uncertain. The seller may terminate the search at any time, which is a valuable option that leads to dynamic behavior and path dependent outcomes.

For an empirical validation of the model, we examine accelerated bookbuilt seasoned equity offerings (SEOs), which have increased in popularity in the U.S. and around the

[3]Feldhütter (2012) uses a search model to design and validate a measure of selling pressure in over-the-counter markets of corporate bonds. Duffie, Gârleanu and Pedersen (2002) use a search model to describe the market for security lending and short selling.
[4]Vayanos and Wang (2007) consider a case in which investors are privately informed about their probability of switching types.
[5]The models of Sherman (2000) and Sherman and Titman (2002) allow for investors to acquire additional private information once they have been selected to participate in an offering. Acquisition of additional private information by investors, however, is less relevant in offers that complete over a relatively short period of time, which are the focus of this study.

world in recent years.[6] Accelerated bookbuilt SEOs are completed within a couple of days, and often within a few hours, following their initial announcement. Investment bankers, working on behalf of issuers, focus their efforts on reaching out to investors and soliciting each investor's interest in the offer. This process is dynamic and usually takes place when markets are closed. Once the bankers identify enough investors, the offer is completed and an offer price is announced. Some accelerated SEOs are preceded by "confidential marketing," during which the banker contacts a few investors confidentially and gets their non-binding indications of interest prior to offer announcement. Confidential marketing provides the issuer with an opportunity to learn about demand early on and to privately withdraw the offer if demand is low. Section III describes both accelerated SEOs and confidential marketing in more detail.

We use our model and derive a collection of new and interrelated predictions with respect to several outcomes in accelerated bookbuilt SEOs, including the speed of offer completion, gross spreads, offer discounts, announcement returns, underpricing, allocations, and the choice of confidential marketing. The overall evidence is consistent with the predictions of the model. For example, as predicted by the model, offers that take less time to complete (faster offers) pay lower gross spreads, incur lower discounts, and experience more favorable announcement returns than offers that take more time to complete (slower offers). However, faster offers are more underpriced, particularly when uncertainty is high. The findings pertaining to confidential marketing are also consistent with the model. For example, the model explains why small risky firms conduct a confidential search prior to public announcement and why gross spreads, offer discounts, and underpricing are higher for confidentially marketed offers. Using institutional ownership data around the SEO, we find evidence consistent with the model's predictions that regular investors will be more likely to receive allocations in faster offers and in offers preceded by a confidential search.

The remainder of the paper is organized as follows. Section II presents the model. Section III describes accelerated SEOs. Section IV presents the main empirical findings.

[6] Section III further discusses the main venues firms use to issue seasoned equity and the popularity of these venues over time. A rising trend of accelerated bookbuilt offers following the late 1990s, both globally and in the U.S., has been reported as early as Bortolotti, Megginson and Smart (2008) and Gao and Ritter (2010). Huang and Ramírez (2010) report a rising preference for high-speed issues in debt markets as well.

Section V concludes the paper.

II. Model

This section presents our model and derives properties of the proposed equilibrium. The model features a security issuer as the seller and a sufficient number of investors as potential buyers. Each investor possesses private information about the postoffer value of the security. This information is imperfect and independent across investors. The valuation approach is similar to the one used in Benveniste and Spindt (1989), so that positive information increases the expected postoffer value of the security while negative information reduces it (see also Benveniste and Wilhelm 1990, Sherman 2000, and Sherman and Titman 2002). As in these traditional bookbuilding models, we assume that the seller cannot affect the postoffer price. Instead, through communications with investors, the seller gathers value-relevant information that facilitates price discovery.[7] However, in contrast to traditional models, in which the seller solicits interests from all investors in a predetermined pool, in our model, the seller contacts investors sequentially and may stop the search at any point. During this dynamic process, the seller uses the gathered information to continually update their beliefs about the distribution of investor information and the value of the security. Search termination is path dependent and occurs when the marginal benefit of the next search is lower than its marginal cost.

A. Setup

An issuer seeks to sell Q units of a security, where Q is predetermined and perfectly divisible. Each unit has a preoffer price of P_0 and a postoffer price of P_1, where:

$$P_1 = P_0 - (1 - 2\pi)\,\lambda. \tag{1}$$

The preoffer price P_0 is known. The postoffer price P_1 is *ex ante* unknown and reflects all value-relevant information at time 1. Value-relevant information is captured in π, where $\pi \in [0, 1]$ and its exact value is *ex ante* unknown. The parameter λ ($\lambda > 0$) captures

[7] Gao and Ritter (2010) present a model in which the seller engages in marketing efforts prior to the offer, with the goal of shifting the demand curve upwards and increasing the postoffer price of the security. See also Huang and Zhang (2011).

how information affects the value of the security. As we show later, the value of each investor's information depends not only on λ but also on each investor's position in the search sequence.

There is a sufficient number of risk-neutral investors to purchase the whole issue. Each investor is willing to purchase up to $\bar{q}$ units at an offer price P_f not exceeding the security's expected postoffer value, conditional on all information gathered during the search, including the investor's own information. The seller must sell the security at a uniform price so that P_f cannot vary across different investors.[8] We define N ($N \in \mathbb{N}_1$) as the smallest number of investors needed to complete the offer, where $N = \lceil Q / \bar{q} \rceil$. The parameters Q, $\bar{q}$, P_0, and λ are offer-specific and are known to all participants.

The seller sequentially solicits and receives non-binding indications of interest from up to $N + J$ investors, where $J \in \mathbb{N}_0$. The maximum number J of additional investors the seller may contact is chosen *ex ante* to maximize expected proceeds net of search cost. Each investor possesses either positive or negative information about the offer, where information is imperfect and independent across investors. The probability that a given investor possesses positive information is π, while the probability that the investor possesses negative information is $1 - \pi$. As mentioned above, the value of π is unknown *ex ante*. The seller uses all information gathered from investors during the search to learn about the distribution of π and thus about the value of the security.

Let π_s and P_s denote the expected values of π and P_1 conditional on all information gathered during the search. The valuation that results from the search is *ex ante* uncertain and is equal to:

$$P_s = P_0 - (1 - 2\pi_s)\,\lambda. \tag{2}$$

We make a distinction between π and π_s, and thus between P_1 and P_s. While both π and π_s are *ex ante* uncertain, π does not depend on the search whereas π_s is search-dependent. The value of P_s that will result from any finite search will be imperfectly related to the postoffer

[8] Companies issuing equity to U.S. public investors are subject to fixed price rules. Prior to 2011, fixed pricing was regulated by NASD Rules 2730, 2740, and 2750, collectively known as the "Papilsky" Rules. Effective February 8, 2011, the Securities and Exchange Commission (SEC) approved FINRA Rule 5141, which aimed to simplify the "Papilsky" Rules. Benveniste and Wilhelm (1990) examine the value of price discrimination in equity offerings.

value of the security so that the search will lead to a noisy estimate of P_1. Specifically,

$$\begin{cases} \pi = \pi_s + \epsilon \\ P_1 = P_s + 2\lambda\epsilon \end{cases}, \tag{3}$$

where ϵ captures relevant information not uncovered during the search so that $E(\epsilon) = 0$ and ϵ is independent of π_s and P_s.

The proceeds per one unit of the security are reduced by potential underpricing U and by search costs K/Q, where U and K are *ex ante* unknown.[9] The proceeds per one unit of the security, net of underpricing and search costs, are uncertain *ex ante* and are equal to:

$$P^* = P_s - U - \frac{K}{Q} = P_0 - (1 - 2\pi_s)\lambda - U - \frac{K}{Q}. \tag{4}$$

The seller maximizes expected proceeds, net of underpricing and search costs. Conditional on the maximum number J of additional investors the seller plans to contact, *ex ante* expected net proceeds are equal to:

$$E_0(P^* | J) = P_0 - (1 - 2\bar{\pi}_0)\lambda - E_0(U | J) - \frac{E_0(K | J)}{Q}. \tag{5}$$

In the above equation, $\bar{\pi}_0$ equals the seller's *ex ante* expected probability of positive information (i.e., prior to the seller contacting any investors). Expected underpricing and search costs depend on the allocation and pricing strategy of the seller as well as on J.

The seller approaches investors sequentially and solicits each investor's interest in the offer, using the reported information to update the distribution of π. After receiving positive information, the seller updates the estimate of π upward. In contrast, after receiving negative information, the seller updates the estimate of π downward. The seller's *ex ante* search strategy specifies the maximum number J of additional investors that may be contacted, the conditions under which the search will stop, and the rules that will be used to price the security and allocate it to investors.

We initially solve the model under the assumption that J is given. The optimal choice of J, which we derive in Section II.E, balances a reduction in underpricing against

[9]Search costs K are the total costs incurred by the seller in relation to the offer. Such costs could include direct costs (e.g., time and effort), but they could also include opportunity costs of delaying offer completion.

an increase in search costs as J increases.

B. Optimal Search Termination

The objective of the seller is to maximize the net proceeds of the offer. We examine equilibria in which investors truthfully report their information. To ensure truthful reporting, the seller chooses when to stop the search and how to price and allocate the security so that investors have sufficient incentives to reveal positive information. Moreover, because investors' indications of interest are non-binding, we examine only equilibria in which investors do not participate in any deal in which they expect to lose money.

To find buyers, the seller needs to contact at least N investors, and may further contact up to J additional investors. As mentioned earlier, we initially assume that J is given. Each additional investor is uniquely identified by their position $j = 1, \ldots, J$ in this secondary search sequence.[10] We let $N + j^*$ equal the total number of investors contacted *ex post*, where $j^* = 0, \ldots, J$. Proposition 1 states when it is optimal for the seller to stop the search, which in turn determines j^*. All proofs are provided in Appendix A.

PROPOSITION 1: *If a total of N investors have reported positive information, then it is optimal for the seller to stop the search and allocate the security to these N investors.*

(see proof in Appendix A)

In order to engage in additional searches, the seller must expect a benefit. This benefit may come either from an increase in the expected value of the security or from a reduction in expected underpricing. However, if a total of N investors have already reported positive information, then neither of these two benefits are present. First, the expected value of the security is a linear function of the expected value of π. Because all participants are rational and π is stationary, if one conditions on all information gathered up to and including investor $N + j$, then the expected value of π_{N+j+1} is equal to the expected value of π_{N+j}, or $E_{N+j}(\pi_{N+j+1}) = E_{N+j}(\pi_{N+j})$. And second, the main reason the seller contacts additional investors is to reduce the underpricing needed to induce truthful reporting of

[10] As shown later, the order in which the first N investors are contacted does not affect equilibrium outcomes.

positive information. Once the security can be placed with investors reporting positive information, there is no need to contact more investors.

If investors truthfully report their information, then the optimal strategy of the seller is to contact investors until there is one of two outcomes: either (a) a total of N investors report positive information or (b) the seller contacts the maximum number J of additional investors, whichever comes first. In outcome (a), the security is exclusively allocated to investors reporting positive information. Investors reporting negative information receive allocations only when all $N + J$ investors have been contacted and fewer than N of the contacted investors have reported positive information.

As we elaborate later in the paper, an *ex ante* commitment to continue the search when fewer than N of the contacted investors have reported positive information may be optimal. Such a commitment gives investors an incentive to report their positive information so that they receive allocations in the security. This in turn reduces expected underpricing and, depending on search costs, may increase expected net offer proceeds.

C. Valuation

To price the security, the seller needs to determine its value as well as the minimum amount of underpricing needed to induce truthful reporting. In this section we examine how the seller determines the value of the security conditional on all gathered information. Underpricing is examined in the next section.

If the seller stops the search after contacting $N + j$ investors and if y investors have reported positive information, then the value of the security is equal to:

$$E\left(P_1 \,|\, N + j, y\right) = E\left(P_s + 2\lambda\epsilon \,|\, N + j, y\right) = P_0 - \left(1 - 2\bar{\pi}_{N+j,y}\right)\lambda, \tag{6}$$

where $\bar{\pi}_{N+j,y} = E\left(\pi \,|\, N + j, y\right)$. This value incorporates all information gathered during the search. The seller forms prior beliefs about the distribution of π based on *ex ante* available information. The seller's prior beliefs are common knowledge. The seller updates their prior beliefs conditional on the information gathered during the search. We assume that, if participants are provided with the same information set, they all arrive at the same distributional properties of π and the same value of the security.

From the seller's perspective, we assume that π follows a beta distribution with prior parameters α_0 and β_0, or $\pi_0 \sim \text{Beta}(\alpha_0, \beta_0)$. Because the beta distribution is a conjugate prior for the binomial distribution, if y out of $N+j$ investors report positive information, then the updated π also follows a beta distribution with parameters $\alpha_0 + y$ and $\beta_0 + N + j - y$, or $\pi_{N+j,y} \sim \text{Beta}(\alpha_0 + y, \beta_0 + N + j - y)$. As a result, the expected value of the security conditional on the gathered information equals:

$$E(P_1 | N+j, y) = P_0 - \left(1 - 2\frac{\alpha_0 + y}{\alpha_0 + \beta_0 + N + j}\right)\lambda. \tag{7}$$

As we show in the previous section, the search ends with one of two outcomes. If the offer is completed before all J additional investors have been contacted, so that $j^* < J$, it must be the case that exactly N investors have reported positive information and j investors have reported negative information. Alternatively, if the seller has contacted all J additional investors, so that $j^* = J$, then it must be the case that, before contacting the last investor, the seller has received positive information from fewer than N investors. The following proposition presents the expected value of the security conditional on each outcome:[11]

Proposition 2: *If the search stops after the seller has contacted $N + j^*$ investors, then the expected value of the security is equal to:*

$$E(P_1 | N + j^*) = \begin{cases} P_0 - \left(1 - 2\frac{\alpha_0 + N}{\alpha_0 + \beta_0 + N + j^*}\right)\lambda & \text{, if } j^* < J \\ P_0 - \left(1 - 2\frac{\sum_{y=0}^{N-1}(\alpha_0 + y)\omega(y)}{\alpha_0 + \beta_0 + N + J - 1}\right)\lambda & \text{, if } j^* = J \end{cases},$$

where

$$\omega(y) = \int_0^1 \frac{\binom{N+J-1}{y}\pi^y (1-\pi)^{N+J-y-1}}{\sum_{y=0}^{N-1}\binom{N+J-1}{y}\pi^y (1-\pi)^{N+J-y-1}} f_0(\pi)\, d\pi$$

and $f_0(\pi)$ is the density of the beta distribution with parameters α_0 and β_0.

(see proof in Appendix A)

As can be seen from the above proposition, the expected value of the security is a function of the prior parameters, α_0 and β_0, the size of the offer N, and the number

[11] To derive Proposition 2, we note that the stopping rule in our model is likelihood non-informative. For more details, see Bernardo and Smith (1994), specifically their Proposition 5.1.

of additional investors $j^* = 0, \ldots, J$ contacted during the search. The following corollary derives the expected value of the security under the assumption of a flat prior distribution for π so that $\pi_0 \sim \text{Beta}(1,1)$.

COROLLARY 2.1: *Let $\alpha_0 = 1$ and $\beta_0 = 1$. If the search stops after the seller has contacted $N + j^*$ investors, then the expected value of the security is equal to:*

$$E(P_1 | N + j^*) = \begin{cases} P_0 - \left(1 - 2\frac{N+1}{N+j^*+2}\right)\lambda & \text{, if } j^* < J \\ P_0 - \left(1 - \frac{N+1}{N+J+1}\right)\lambda & \text{, if } j^* = J \end{cases}.$$

(see proof in Appendix A)

Based on Proposition 2 and the corollary, the *ex post* value of the security is inversely related to j^*. Therefore, keeping N and λ fixed, longer searches will be associated with lower *ex post* valuation than shorter searches, on average. The difference in valuations between longer and shorter searches is due to the revealed new information—all else equal, offers that are received more favorably by investors will complete sooner than offers that are received less favorably.[12] These predictions, which relate search length to information and valuation, are distinct from traditional static models in which the seller contacts a fixed pool of investors. Our model, therefore, provides unique implications for offer returns and discounts in certain security issue markets, such as accelerated offers of seasoned equity. For example, the model predicts that offers that complete more quickly will experience relatively higher announcement returns and lower offer discounts. We discuss these and other implications in Section III.C.

D. Equilibrium Underpricing

An investor with positive information faces an opportunity cost. By reporting negative rather than positive information, the investor can reduce the value that the seller infers from the search, leading to a low offer price. If the investor then receives an allocation, they stand to profit from the difference between the fair value and the offer price of the security. To induce truthful reporting, the seller compensates investors for this opportunity

[12]The value of j^* is not informative if $J = 0$.

cost by setting the offer price P_f below the value P_s discovered during the search. We label this difference underpricing U, where $U = P_s - P_f$. In what follows, we examine underpricing that results from the seller's goal to extract positive information from investors.[13]

For investor $i = 1, \ldots, N+J$ to truthfully report positive information, underpricing should be at least equal to the profit the investor expects to make if they instead report negative information. Let $F^{N+j}_{y|i,G}$ denote the expected probability that the offer will complete at $N+j$ investors, out of which, exactly y investors report positive information. This probability is conditional on investor i's information set, which includes knowledge that investor i possesses positive information and that the offer is not completed by the time investor i is contacted.[14] The probability is also conditional on investor i reporting positive (i.e., "Good") information. To reduce notation, we group the first N investors together by defining i' as the larger of i and N so that $i' = \max(i, N)$. While each of the first N investors possesses their own private information about the offer, they do not learn about other investors' information from the fact that the offer is not yet completed. Taking into consideration the two possible outcomes from the search, $F^{N+j}_{y|i,G}$ equals:

$$F^{N+j}_{y|i,G} = \begin{cases} \int_0^1 \frac{1}{\varphi(i)} \binom{N+j-1-\mathbb{1}(i'<N+j)}{N-1-\mathbb{1}(i'<N+j)} \pi^{N-1}(1-\pi)^j f_i(\pi) d\pi & \text{if } (i'-N) \leq j < J \text{ and } y = N \\ \int_0^1 \frac{1}{\varphi(i)} \binom{N+J-1-\mathbb{1}(y=N)}{y-1-\mathbb{1}(y=N)} \pi^{y-1}(1-\pi)^{N+J-y} f_i(\pi) d\pi & \text{if } j = J \text{ and } 0 < y \leq N \\ 0 & \text{otherwise} \end{cases}, \quad (8)$$

where $f_i(\pi)$ is the probability density function of π conditional on investor i's information set and $\mathbb{1}(.)$ is an indicator function equal to 1 if the condition in the function is satisfied and 0 otherwise. The standardizing term $\varphi(i)$ equals the probability that the search reaches investor i, or $\varphi(i) = \sum_{y=0}^{N-1} \binom{i'-1}{y} \pi^y (1-\pi)^{i'-y-1}$. Equivalently, $\varphi(i)$ is the probability that the search ends at or after investor i.

Similarly, let $F^{N+j}_{y|i,B}$ denote this same probability if investor i conceals their positive

[13]The model can be extended to allow for additional underpricing that may be needed to induce investor participation in the offer.

[14]We focus on the case in which each investor's information about the exact state of demand by prior investors is incomplete. In our model, the seller does not expect to benefit if, prior to offer completion, they fully disclose to investor i all gathered information up to that investor.

information and instead reports negative (i.e., "Bad") information. Here, $F^{N+j}_{y|i,B}$ equals:

$$F^{N+j}_{y|i,B} = \begin{cases} \int_0^1 \frac{1}{\varphi(i)} \binom{N+j-1}{N} \pi^N (1-\pi)^{j-1} f_i(\pi) d\pi & \text{if } (i'-N) < j < J \text{ and } y = N \\ \int_0^1 \frac{1}{\varphi(i)} \binom{N+J-1-\mathbb{1}(y=N)}{y-\mathbb{1}(y=N)} \pi^y (1-\pi)^{N+J-y-1} f_i(\pi) d\pi & \text{if } j = J \text{ and } 0 \leq y \leq N \\ 0 & \text{otherwise} \end{cases}, \quad (9)$$

If investor i reveals their positive information, they expect to receive a profit of:

$$\sum_{j=0}^{J} \sum_{y=0}^{N} F^{N+j}_{y|i,G} U_{N+j,y} q^G_{i,N+j,y}. \quad (10)$$

In the above equation, $U_{N+j,y}$ equals the amount of underpricing per one unit of the security if y out of $N+j$ investors report positive information and $q^G_{i,N+j,y}$ equals the allocation investor i receives in this case. If investor i conceals their positive information, and instead reports negative information, they expect to receive a profit of:

$$\sum_{j=0}^{J} \sum_{y=0}^{N} F^{N+j}_{y|i,B} \left(\delta_{N+j}\lambda + U_{N+j,y}\right) q^B_{i,N+j,y}. \quad (11)$$

In this equation, $\delta_{N+j}\lambda$ equals the expected undervaluation per one unit due to the investor concealing positive information, where $\delta_{N+j}\lambda = E\left(P_1 | N+j, y\right) - E\left(P_1 | N+j, y-1\right)$. Now investor i receives allocation $q^B_{i,N+j,y}$.[15]

Combining Equations (10) and (11), the following condition needs to hold in order for investor i to reveal their positive information:

$$\sum_{j=0}^{J} \sum_{y=0}^{N} F^{N+j}_{y|i,G} U_{N+j,y} q^G_{i,N+j,y} \geq \sum_{j=0}^{J} \sum_{y=0}^{N} F^{N+j}_{y|i,B} \left(\delta_{N+j}\lambda + U_{N+j,y}\right) q^B_{i,N+j,y}. \quad (12)$$

To reduce underpricing while inducing truthful reporting of positive information, the seller needs to reduce the right-hand side of this inequality (i.e., the opportunity cost of reporting positive information). The seller can do that by setting $q^B_{i,N+j,y} = 0$, whenever possible, which in turn means setting $q^G_{i,N+j,y} = \bar{q}$. In other words, if an investor reports positive information they should receive the maximum allocation possible, while if an investor reports negative information they should receive no allocations. In cases when a portion of the security

[15] We assume the seller determines allocations conditional on how many investors report positive information but not on the exact order in which such information is reported. We believe this assumption is warranted. While investors may use the postoffer price to infer information about overall demand, verifying the exact order in which positive and negative information is revealed during the search is difficult.

needs to be allocated to investors reporting negative information, so that $q^B_{i,N+j,y} > 0$, the seller should set $U_{N+j,y} = 0$ and not underprice the security.[16]

If the seller has already contacted $N + J$ investors and fewer than N investors have reported positive information, then a portion of the offer needs to be allocated to investors reporting negative information. Let N_G equal the number of investors reporting positive information at the end of the search. Also, let $R_B = Q - \bar{q}N_G$ so that R_B is the part of the offer that cannot be allocated to investors reporting positive information and thus must be allocated to investors reporting negative information. The following proposition characterizes the set of optimal allocations to investors reporting negative information in outcomes when $R_B > 0$. For the proposition, we assume $N > 1$.[17]

Proposition 3: *If $N_G < N$ so that $R_B > 0$, then it is strictly suboptimal to allocate R_B such that an investor $i = 1, \ldots, N$ reporting negative information receives no allocations. Moreover, it is weakly optimal to allocate R_B such that all investors $i = N + 1, \ldots, N + J$ reporting negative information receive no allocations.*

(see proof in Appendix A)

One important contribution of our model is that it identifies allocation strategies that optimize information gathering while maximizing offer proceeds within a search framework. We find that there could be multiple optimal allocation strategies when fewer than N investors report positive information. However, as the proposition states, in any optimal allocation, any investor $i = 1, \ldots, N$ reporting negative information must receive some allocation from R_B.

As we derive in Appendix A, expected underpricing equals:

$$E_0(U|J) = \delta_{N+J}\lambda \int_0^1 \sum_{y=0}^{N-1} \left[\binom{N+J-1}{y} \pi^{y+1}(1-\pi)^{N+J-y-1} \frac{(N-y)}{N} \right] f_0(\pi) d\pi. \qquad (13)$$

This result does not depend on the exact equilibrium allocations. Again, let π follow a beta prior distribution with α and β equal to 1, or $\pi_0 \sim \text{Beta}(1,1)$. Noting that $\delta_{N+J} = 2/(N + J + 2)$,

[16] The participation constraint implies that underpricing cannot be negative.

[17] When $N = 1$, so the security can be sold to a single investor, allocations in cases when all investors report negative information do not affect expected underpricing (see the proof of Proposition 3). As a result, any *ex ante* allocation in such cases leads to an equilibrium with identical expected net offer proceeds.

ex ante expected underpricing per one unit of the security equals:

$$E_0(U|J) = \lambda \frac{(N+1)(N+2)}{3(N+J)(N+J+1)(N+J+2)}. \tag{14}$$

Figure 1, Panel A uses Equation (14) to plot *ex ante* expected underpricing as a function of the minimum number of investors needed to sell the security (N) and the maximum number of additional investors the seller plans to contact (J). For the figure, we need a value for λ. Solving Equation (1) for λ, we get $\lambda = -xP_0/(1-2\pi)$, where $x = (P_1 - P_0)/P_0$. We let $\pi = 0.4$, $x = -5\%$, and $P_0 = 40$ and obtain $\lambda = 10$.

[Insert Figure 1 around here]

As can be seen from the figure, expected underpricing declines with J. Specifically, if the seller contacts one additional investor, underpricing is expected to change by the following amount:

$$\begin{aligned} \Delta E_0(U|J) &= E_0(U|J+1) - E_0(U|J) \\ &= -\lambda \frac{(N+1)(N+2)}{(N+J)(N+J+1)(N+J+2)(N+J+3)}. \end{aligned} \tag{15}$$

In the next section, we examine how this reduction in underpricing compares with the increase in search costs as J increases, which allows us to find the optimal choice of J.

E. Search Costs and the Choice of Maximum Search Length

As we show in the previous section, the *ex ante* maximum number J $(J \in \mathbb{N}_0)$ of additional investors the seller plans to contact affects net proceeds by reducing expected underpricing. However, contacting additional investors is costly. We assume that, when contacting each additional investor, the seller incurs a cost of $\kappa > 0$. For simplicity, we assume that κ is the same across investors.[18] The seller chooses the optimal J to maximize expected proceeds net of underpricing and search costs.[19]

Taking into account the equilibrium derived in the previous section, *ex ante* expected

[18] The predictions remain similar if we assume investor-specific cost κ_i, as long as $\kappa_i > 0$ and $\kappa_i' \geq 0$ (i.e., κ_i does not decrease with i). Indeed, if the cost κ differs across investors, the seller will find it optimal to contact investors with relatively lower costs before contacting investors with relatively higher costs.

[19] We solve our model under the assumption that the seller retains any search cost savings due to early search termination. However, the predictions remain similar if we assume, for example, that the seller keeps a positive and fixed proportion of any such savings.

total search costs are equal to:

$$E_0\left(K\,|\,J\right) = \kappa \int_0^1 \left[N + \sum_{j=0}^{\infty}\left[\binom{N+j-1}{N-1}\pi^N\left(1-\pi\right)^j \min(j,J)\right]\right] f_0(\pi)d\pi. \tag{16}$$

If we let $\pi_0 \sim \text{Beta}\left(1,1\right)$, then *ex ante* expected total search costs are equal to:

$$E_0\left(K\,|\,J\right) = \kappa N\left(1 + H_{N+J} - H_N\right), \tag{17}$$

where H_n is the n^{th} harmonic number. Figure 1, Panel B, plots this expected cost per one unit of the security. An increase in the maximum number J of additional investors the seller plans to contact leads to an increase in expected search costs. Specifically, an increase in J by one investor leads to an increase in search costs per one unit of the security by:

$$\frac{\Delta E_0\left(K\,|\,J\right)}{Q} = \frac{E_0\left(K\,|\,J+1\right) - E_0\left(K\,|\,J\right)}{Q} = \frac{\kappa}{Q}\frac{N}{N+J+1}. \tag{18}$$

To maximize expected proceeds net of underpricing and search costs, the seller sets J such that $\Delta E_0\left(U\,|\,J\right)Q + \Delta E_0\left(K\,|\,J\right) = 0$. Noting that $Q = \bar{q}N$ (ignoring rounding) leads to the following equilibrium condition:

$$\frac{\kappa}{\lambda\bar{q}} = \frac{\left(N+1\right)\left(N+2\right)}{\left(N+J\right)\left(N+J+2\right)\left(N+J+3\right)}. \tag{19}$$

Based on this condition, we derive the following proposition that describes the optimal choice of J.

Proposition 4: *The optimal choice of J increases with the value of investor information (λ) and with the maximum allocation each investor may receive ($\bar{q}$) and decreases with search costs (κ).*

(see proof in Appendix A)

When the value of information is relatively high, investors with positive information will expect to receive higher underpricing in exchange for reporting their information than when the value of information is relatively low, all else equal. To counter this effect, as the value of information increases, the seller will find it optimal to increase search length in the case of weak demand. This is because investors' opportunity costs of reporting positive information decline as planned search length $N + J$ increases, which in turn reduces the underpricing needed to induce truthful reporting. Keeping N fixed, a decrease in κ and an increase in $\bar{q}$ will lead to lower search costs per unit, which makes it less costly to contact additional investors. The optimal choice of J may either increase or decrease with N.

F. Confidential Search

In this section, we model the possibility that the seller may conduct a confidential search prior to publicly announcing the offer. This analysis is motivated by a feature in equity issue markets where the seller, represented by an investment banker, conducts a confidential search (also known as "confidential marketing") prior to announcement. While confidential search, by its nature, is limited in scope and is unlikely to influence the demand for the security, it allows the seller to search for investors without announcing the offer and to privately withdraw it if investor interest is low. If public withdrawal is costlier than private withdrawal, then the seller may conduct a confidential search prior to official announcement.

In our model, we let the seller contact investors confidentially if the *ex ante* probability of withdrawal is sufficiently high. This can be described as a sufficiently high probability that the postoffer price P_1, which is conditional on offer announcement, falls below a certain reservation price P_{min}:

$$\Pr\left(\tilde{P}_1 < P_{min}\right) > \theta^*. \tag{20}$$

Assuming that $P_{min} < P_0$, we derive the following proposition:

Proposition 5: *The seller will be more likely to engage in confidential search if the value of investor information, λ, is higher rather than lower.*

(see proof in Appendix A)

If the value of investor information is positively related to *ex ante* uncertainty, then the above proposition also implies that offers with higher *ex ante* uncertainty will be more likely to involve a confidential search prior to announcement relative to offers with lower *ex ante* uncertainty.

Because additional effort is required to keep the offer confidential, we assume that the search costs of a confidential search are higher than the search costs of a public search. As a result, if the probability of withdrawal is relatively low (i.e., less than θ^*), the seller will prefer to publicly announce the offer rather than engage in a confidential search. During the confidential search, the seller contacts investors until one of two outcomes occurs. In the first outcome, a sufficient number of investors report positive information so that $\Pr\left(\tilde{P}_1 < P_{min}\right) > \theta^*$ and the seller officially announces the offer. In this outcome, the seller will continue contacting additional investors until either the security can be allocated to investors reporting positive information or the maximum number of $N + J$ investors has been contacted, whichever comes first. In the second outcome, confidentially contacted investors reveal negative information so that $\Pr\left(\tilde{P}_1 < P_{min}\right)$ increases. Once this probability reaches a sufficiently high value of θ^{**} ($\theta^{**} > \theta^*$), then the seller withdraws the offer.

G. The Role of Regular Investors

Security sellers usually employ the services of investment banks that are constantly present in security issue markets and thus may choose to establish long-term relations with some institutional investors. Such investors, which the literature terms "regular" investors, benefit from being included repeatedly in underpriced offers. By choosing when to contact a given regular investor in the search sequence of future deals, or even whether to contact the investor at all, banks can manipulate that investor's overall opportunity cost of reporting positive information. To reduce this cost, the bank can commit to move a given regular investor further down the search sequence in future deals, or to exclude them altogether, if they withhold positive information in the current deal. In effect, for regular investors, the one-time benefit of withholding positive information is reduced by an expected loss due to a lowered probability of receiving allocations in future underpriced deals. Because the minimum underpricing required for the truthful reporting of positive information is equal to investors' opportunity cost of reporting positive information, and because this cost is lower for regular relative to non-regular investors, we derive the following proposition:

Proposition 6: *All else equal, the investment bank, acting on behalf of the seller, will approach regular investors before approaching non-regular investors.*

While we do not provide a complete mathematical proof of the above proposition, we present the following arguments. The ability of the investment bank to reduce underpricing in a given offer while allocating the security to a given set of investors is directly related to the present value of underpricing these investors expect to receive in all future deals by the same bank. We let this present value be equal to L. All else equal, L is higher (lower) when the investor expects to participate in more (fewer) future offers underwritten by the bank. Because investors earlier in the search sequence have a higher probability of receiving allocations when compared to investors later in the search sequence, a tendency to contact regular investors relatively early in the search increases L and thus the ability of the bank to reduce underpricing and to increase offer proceeds.

III. An Application to Accelerated SEOs

A. Search in Accelerated SEOs

A typical accelerated bookbuilt equity offer is drawn from a pre-existing shelf registration and is completed within 48 hours.[20] The offer is launched with a press release shortly after market close, where the press release contains the contact information of the bookrunner(s) and may contain additional information, such as shares offered and use of proceeds. Syndicate members then reach out to potential investors, which usually include institutional investors, such as mutual funds, hedge funds, and investment advisors.[21] Bankers expedite the process by targeting regular investors rather than a comprehensive pool of institutional investors.

When contacting investors, bankers communicate an expected price range, usually framed in terms of discounts, and an expected pricing date, which serves as a tentative deadline.[22] Investors, in turn, communicate their non-binding interest in the offering. All indications of interest and other feedback are forwarded to the managing bank(s), who build the book and control allocations. During this short bookbuilding process, bankers provide investors with verbal updates, which may include, for example, the percent of the offer for

[20] The following discussion has benefited greatly from conversations with our contacts at two large U.S. investment banks.

[21] In some cases, bankers may reach out to high net worth individuals. Such investors, however, usually do not influence the offer price directly. The participation of index investors is less common.

[22] If an issuer has an immature institutional shareholder base, a longer search may be planned. In addition, some issuers of accelerated bookbuilt offers may decide to extend the offer for a day or two, which provides such issuers with time to communicate further information pertinent to the offering.

which demand has been expressed and the intent to close the books that night. Bankers also provide updates to the issuer's management team (i.e., the firm's CEO), who may also engage in discussions with investors to better assess investor demand and, in the process, may decide to make changes to the size of the offer. Once the issuer, the managing bank(s), and contacted investors all agree to the terms and pricing of the transaction, the offer is completed.

Some accelerated bookbuilt offerings are preceded by confidential marketing. These offerings are known as confidentially marketed public offerings (CMPOs). The confidential marketing occurs prior to offer announcement and involves a select group of investors. In their initial approach, the investment bankers do not reveal the issuer's identity, but they do share key information regarding the size and the timing of the offer, the intended use of proceeds, and the issuer's industry. The bankers gauge each investor's interest and inquire whether the investor is willing to be "brought over the wall." The "wall crossing" entails the investor receiving hitherto confidential information, most notably the issuer's identity and other details of the offer. The investor commits not to trade the issuer's shares, until the CMPO transaction is concluded or withdrawn. If the information gathered during the confidential stage is relatively favorable to the firm, the transaction transforms into a public offering, which follows the process described in the previous two paragraphs.[23]

Accelerated offerings differ from traditional fully marketed offerings, in which investment banks market the offer through a road show and other bookbuilding efforts over an extended period (typically two weeks). In the public marketing period, and particularly during the road show, investment banks and the issuer's management team communicate with investors, financial analysts, and other market participants to expand investor demand for the offer through their marketing efforts (Gao and Ritter 2010, Huang and Zhang 2011).[24]

Our model captures several of the features of accelerated offers that distinguish them from fully marketed offers. First, in accelerated offers, the seller focuses on searching for

[23] See also Autore et al. (2021) and "Market Trends 2019/20: Confidentially Marketed Public Offerings" by Eric Johnson, Michael Blankenship, Ben Smolij, and John Niedzwiecki (https://www.winston.com/images/content/2/0/v2/202804/Market-Trends-201920-Confidentially-Marketed-Public-Offerings-mu.pdf).

[24] Earlier literature has proposed that firms opt for fully marketed offerings, despite the fact that they are costlier than Rule 415 offers, because of the need for certification (Bhagat, Marr and Thompson, 1985 and Denis, 1991).

investors to buy the security and on gathering information rather than on marketing the shares and increasing investor demand. This feature is clearly evident in CMPOs, where the confidential nature of the search restricts the seller's ability to market the security. Second, to expand investor demand in fully marketed offers, the bank should focus on attracting new investors. In contrast, in accelerated offers, the bank may canvass both new and existing investors, with a focus on investors associated with relatively lower search costs and lower opportunity costs of reporting positive information. Third, the marketing effort in fully marketed offers is pre-planned and may take a few weeks. In contrast, the search in accelerated offers is sequential and dynamic and may conclude in a few hours.

B. The Rise of Accelerated SEOs

In public issues of seasoned equity, fully marketed offers were the dominant offer type until the late 1990s (see also Gao and Ritter 2010 and Gustafson and Iliev 2017). Around the turn of the century, firms conducting seasoned equity offerings (SEOs) increasingly turned to accelerated issuance mechanisms (see also Bortolotti, Megginson and Smart 2008). As shown in Figure 2, Panel A, almost all (or 99.4 percent) of the 326 SEOs in 1996 were fully marketed. In 2001, there were a total of 218 SEOs. Of these, 74.3 percent were fully marketed, while the remaining 25.7 percent were accelerated, which included bought deals (19.3 percent) and accelerated bookbuilt SEOs (6.4 percent).[25] In 2008, accelerated offerings constituted 60.6 percent of all SEOs, with bought deals representing 40.4 percent and accelerated bookbuilt SEOs representing 20.2 percent.

[Insert Figure 2 around here]

In December 2007, the Securities and Exchange Commission (SEC) relaxed restrictions against exchange-listed issuers with a public float below $75 million to issue securities using the shelf-registration process, provided that such firms are up to date with their SEC obligatory reports, to issue securities using the shelf-registration process. Studying the choice between public offering and private placement, Gustafson and Iliev (2017) document that post-deregulation many smaller issuers, instead of relying on private placements,

[25] In a bought deal, the investment banker makes an outright purchase of the entire offer. Following the purchase, the bank solicits interest from institutional investors and typically sells the shares within 24 hours.

moved to the public equity market. Public equity offerings by smaller issuers have further contributed to the growth of accelerated deals (Gustafson 2018).

In 2018, the final year of our sample, among the 433 SEOs, only 6.2 percent were fully marketed. Bought deals and accelerated bookbuilt offers constituted the remaining 93.8 percent of SEOs. The share of bought deals has remained largely stable for much of the post-2008 period and represents around 19.9 percent of all SEOs in 2018. By 2018, around three quarters (or 73.7 percent) of all SEOs were conducted as accelerated bookbuilt offerings. Partly in response to the 2007 SEC liberalization of the shelf registration rules and the rise of small issuers in the public equity market, CMPOs have become an important form of accelerated offering, and accounted for 21.5 percent of all public offerings in 2018.

C. Empirical Implications

We use our model to derive several novel empirical implications related to the market for accelerated offerings of seasoned equity. We then test these implications using a sample of accelerated offers between 2009 and 2018. The first implication relates the speed of pricing to the gross spread of the offer. We use the speed of pricing as a measure of search length and the gross spread as a measure of search costs. We expect offers that price more quickly to pay lower gross spreads than offers that price more slowly. This prediction follows directly from our model, in which search costs increase monotonically with the length of the search.

Based on Proposition 2, we derive our second empirical implication, which relates the speed of pricing to the expected value of the shares after the offer. To measure the expected value of the shares after the offer, we use the postoffer price of the shares. Specifically, we expect accelerated SEOs that price more quickly to experience less negative stock returns from pre offer to post offer than accelerated SEOs that price more slowly. As an alternative measure of investor reception of the offer, we use the offer discount, which in our model equals to the pre-offer price minus the offer price $(P_0 - P_f)$. The discount can be calculated as the difference between the realized underpricing, which equals to the post-offer price minus the offer price $(P_1 - P_f)$, and the announcement return, which equals to the post-offer price minus the pre-offer price $(P_1 - P_0)$. While underpricing could be higher for offers that price more quickly, such offers also experience more favorable investor reception. We expect the net effect to lead to more favorable offer prices and thus to lower discounts for offers that price more quickly than for offers that price relatively more slowly.

Our third empirical implication is based on Proposition 3 and relates the underpricing of accelerated SEOs to their speed of pricing. We expect that, after controlling for *ex ante* uncertainty, expected underpricing to be higher in offers that price more quickly than in offers that price more slowly. Empirically, this effect should be more pronounced for offers with greater uncertainty, in which the value of positive investor information is likely to be higher.

To derive our fourth implication, we use Proposition 4, which describes the optimal choice of the maximum number of additional searches J. We do not directly observe the *ex ante* maximum number of searches planned for each offer. However, using an *ex post* measure of when the offer is priced, we expect generally riskier firms to price their offers more slowly whereas less risky firms to price their offers more quickly.

We use Proposition 6 to derive a fifth empirical implication that relates the speed of pricing to the allocation of SEO shares to regular investors. Given that sellers in our model prefer to contact regular investors prior to non-regular investors, non-regular investors may receive allocations only after regular investors have already been contacted and have reported negative information. We, therefore, expect accelerated SEOs that price more quickly to exhibit greater allocations to regular investors than accelerated SEOs that price more slowly.

Finally, we use our model to derive empirical implications related to offers that involve confidential marketing. Because confidentially marketed offers involve an extra (confidential) stage, they result in longer overall searches and thus should pay higher spreads, all else equal. Regarding announcement returns, our model produces mixed expectations. On the one hand, CMPOs are employed by riskier firms, implying that CMPOs might experience relatively lower announcement returns than non-CMPOs. On the other hand, only those CMPOs that gather sufficiently favorable information reach the public offering stage. The positive selection implies that these surviving CMPOs should experience relatively higher announcement returns than non-CMPOs, all else equal. The positive selection further implies that CMPOs will reward their investors with greater underpricing than non-CMPOs.

IV. Empirical Results

A. Sample

We gather a sample of accelerated SEOs using the Securities Data Corporation (SDC) database. The starting sample contains 1,893 accelerated SEOs of primary shares that are conducted by firms with common stock in the Center for Research in Security Prices (CRSP share codes 10 or 11) and are priced between January 1, 2009 and December 31, 2018. We exclude 113 bought deals.[26] To avoid potential pricing biases, we also exclude 70 deals that contain warrants. For the remaining sample of 1,710 accelerated bookbuilt SEOs, we use the equity issues and company news features provided by the Bloomberg Terminal to hand-collect information on announcement and pricing dates. Bloomberg further provides information on whether an offer was priced before market open, after market close, or during market hours on a given day.[27]

We focus our empirical analysis on accelerated SEOs that are announced after market close between Monday and Thursday and are priced either after market close on the same day or before market open on the next day.[28] Offers that price after market close on the same day are classified as "priced before midnight" and offers that price before market open on the next day are classified as "priced after midnight." Based on the Global Industry Classification Standard (GICS), we exclude SEOs by financial firms (two-digit GICS code 40), utility firms (two-digit GICS code 55), and real estate firms (two-digit GICS code 60). The sample further excludes offers with preoffer stock prices below \$3 per share.[29] Following

[26] While bought deals may also involve a search for new investors, the issuance process is materially different from the one employed in accelerated bookbuilt offerings. In bought deals, the investment bank buys all shares directly from the issuer and then sells the shares to outside investor. Due to the direct purchase of shares, there is no gross spread in bought deals; instead, only an offer discount is disclosed. Also, the investment bank does not disclose the time(s) and price(s) at which shares are sold to outside investors.

[27] Whenever this information is not directly reported, we search the Bloomberg Company News feature to identity the time when an offer price was officially announced.

[28] The pricing and allocations of accelerated offerings that price one or two trading days after announcement are further influenced by the market's reaction to the offer announcement. Because we cannot verify whether such offers are delayed *ex ante* or are delayed *ex post* due to low demand, in our main analysis we use accelerated offerings that are announced and priced before the market opens. Nevertheless, in additional analysis, we also include in our sample accelerated offerings that price one or two trading days after announcement. Our results, available upon request, are similar if we use this extended sample.

[29] We verify that our findings remain similar if we include financial firms, utility companies, real estate firms, or firms with stock prices below \$3 per share.

these selection criteria, our main sample contains 753 accelerated SEOs.

To identify whether an issue is confidentially marketed prior to announcement, we gather data from the *PrivateRaise* database. Our initial dataset of confidentially marketed public offerings (CMPOs) includes 1,078 completed CMPOs in the U.S. for the time period of 2009 to 2018, of which 725 CMPOs are conducted by firms that are not in the financial, utility, or real estate industries. Within our main sample of 753 offers, 478 offers are preceded by a confidential marketing stage.

B. Summary Statistics

In this section, we provide summary statistics for SEO spreads, announcement returns, discounts, underpricing, and several variables related to firm and offer characteristics. All variables are described in Appendix B.

In Table 1, Panel A, we present summary statistics of gross spreads, announcement returns, discounts, and underpricing for the complete sample. The average (median) gross spread in our sample is 5.3 (6.0) percent, with the first quartile at 5.0 percent and the third quartile at 6.0 percent. Gross spreads in our sample are similar in magnitude to the gross spreads reported in Corwin (2003), who examines all firm commitment public offerings between 1980 and 1998 and finds average gross spreads of 5.4 percent. With respect to announcement returns, stock prices decline by 5.5 percent at announcement, on average. The median decline in prices is similar, at 5.8 percent. The decline in stock prices for accelerated SEOs is higher than the 2.2 percent average decline for fully marketed SEOs reported in Eckbo, Masulis and Norli (2007).[30] In addition to including issues that complete over a longer time window, prior studies analyze returns on public equity offerings in the 1980s and 1990s, which could explain the differences in findings relative to prior studies. The average (median) discount is 9.2 (8.2) percent. Offer discounts show substantial variation, with the first quartile at 4.7 percent and the third quartile at 12.4 percent.

[Insert Table 1 around here]

The average (median) offer in our sample is underpriced by around 4.0 (2.5) percent

[30] Eckbo, Masulis and Norli (2007) review the related academic literature on market reactions in firm commitment seasoned equity offerings, with the event windows analyzed being either the two-day event window of [-1,0] or the three-day event window [-1,+1], with day 0 being the announcement day.

with the first quartile at 0.0 percent and the third quartile at 7.1 percent. The underpricing of accelerated offerings in our sample is higher than the average underpricing of 2.2 percent reported in all firm commitment public equity offerings in Corwin (2003) but is similar to the average underpricing of 3.5 percent reported in Chemmanur, He, and Hu (2009). In addition to being positive on average, underpricing is positively skewed, a finding consistent with prior literature (see, for example, Altinkiliç and Hansen 2003, Fig. 1).

In Table 1, Panel B, we examine spreads, announcement returns, discounts, and underpricing separately for deals that price before midnight and deals that price after midnight. Gross spreads and discounts are significantly lower for offers that price before midnight. For example, for offers that price before midnight, average spreads and discounts are 4.3 percent and 6.9 percent, respectively. In contrast, for offers that price after midnight, average spreads and discounts are 5.5 percent and 9.7 percent, respectively. The differences of −1.3 percent and −2.8 percent are significant at the 0.01 level, based on a χ^2-statistic from a non-parametric Kruskal-Wallis test. We reach similar conclusions if we examine median spreads and discounts. Examining announcement returns, we find that the average announcement return for offers that price before midnight is 2.8 percentage points higher than the average announcement return for offers that price after midnight. This difference is significant at the 0.01 level. Based on the univariate analysis, we find that underpricing is similar between accelerated SEOs that price before midnight and those that price after midnight.

In Table 2, Panel A, we provide summary statistics for variables related to firm characteristics, offer characteristics, and institutional investor buying activity. Firm-related variables encompass firm size, risk, performance, growth opportunities, leverage, liquidity, ownership, and analyst coverage. Offer-related variables include relative offer size and the Carter-Manaster reputation rank (e.g., Carter and Manaster 1990) of the most reputable underwriter from the group of lead, co-lead, and book managers. To adjust for inflation, all dollar amounts are expressed in 2018 US dollars, using the GDP implicit price deflator from the Federal Reserve Bank of St. Louis.[31]

The average firm in our sample of accelerated SEOs has a market capitalization of $1.2

[31] https://fred.stlouisfed.org/series/GDPDEF.

billion in 2018 USD. The median market capitalization is lower, at $0.4 billion, indicating positive skewness. Furthermore, the average firm is covered by close to 7.0 analysts. Average daily volatility prior to the offer is 4.3 percent, average daily share turnover is 1.5 percent, average bid-ask spread is 2.3 percent, and average institutional ownership prior to the offer is around 50.0 percent.

[Insert Table 2 around here]

The market value of firm assets is around 3.5 times their book value, on average, indicating that firms in our sample have valuable investment opportunities. Consistent with the presence of such opportunities, the average R&D spending is around 27.3 percent of assets, with a median of 19.3 percent of assets. Examining the financial side of firms, we find that firms involved in accelerated SEOs carry a total debt ratio of around 49.9 percent. The firms also show high corporate liquidity, with an average and median cash-to-assets ratios close to 50.0 percent. However, issuing firms show poor profitability, with an average ROA of −37.2 percent.

Offer proceeds are around $112.2 million on average, with a median value of $52.9 million. The average offer sells around 15.7 percent of the firm's pre-SEO shares outstanding. Offers in our sample are underwritten by underwriters with an average Carter-Manaster reputation rank of 7.2, with a median rank of 8.0. Underwriter reputations within our sample are lower than reputations reported in Gao and Ritter (2010) for a comprehensive sample of SEOs between 1996 and 2007, where average bookrunner rank is reported at 8.3. One possible explanation for this difference is the post-2007 increase in public equity offerings, especially accelerated offerings, by smaller and riskier firms (Gustafson and Iliev 2017). Such firms also tend to employ underwriters with relatively lower reputations. Echoing prior literature that examines fully marketed SEOs, we find that accelerated SEOs follow periods of good market performance (e.g., Schultz 2003). For example, the stock prices of issuers in our sample exhibit a considerable 90-day run-up prior to an offer, amounting to around 24.0 percent, on average.

In our sample, most institutional buyers (around 74.0 percent, on average) during the quarter of the SEO are classified as regular institutional buyers, having bought shares in past accelerated SEOs by the same lead, co-lead, or book managers. We view the presence of prior relations with institutional investors to be a key factor for investment bankers' ability to complete the SEO quickly.

One of the implications from our search framework is that accelerated SEOs with higher valuation uncertainty will tend to experience longer searches than accelerated SEOs with lower valuation uncertainty. To examine the validity of this implication, we compare offers that price before midnight to offers that price after midnight along multiple issuer dimensions, including firm size, growth opportunities, profitability, return volatility, leverage, liquidity, and ownership. These comparisons are presented in Table 2, Panel B, where we report the mean of each variable separately for offers that price before midnight and those that price after midnight. The table also reports the differences in means between subsamples and χ^2-statistics from Kruskal-Wallis tests of the significance of these differences.

Examining Panel B of Table 2, we find that accelerated SEOs that price before midnight are generally conducted by firms whose market capitalization, stock market liquidity, profitability, institutional ownership, and analyst coverage are higher relative to those of firms that price their SEOs after midnight. In terms of firm size, for example, issuers of offers that price before midnight have a pre-SEO market capitalization of around \$2.4 billion in 2018 dollars. In contrast, issuers of offers that price after midnight have a pre-SEO market capitalization of around \$0.9 billion in 2018 dollars. The difference of \$1.5 billion is significant at the 0.01 level. Issuers of offers that price before midnight also have lower growth opportunities relative to issuers of offers that price after midnight, as evident by lower market-to-book ratios (by 1.0 on average) and lower R&D-to-assets ratios (by 14.7 percentage points on average).

While preliminary, the evidence presented in this section is consistent with the implications of our model. For example, we find that offers that price more quickly pay lower gross spreads than offers that price more slowly. Further, offers that price more quickly experience less negative announcement returns and lower offer discounts than offers that price more slowly. Based on the univariate analysis, we do not find significant differences in underpricing between offers that price before midnight and offers that price after midnight. However, in subsequent analysis we examine SEO underpricing while controlling firm risk, which affects both the speed of pricing and underpricing.

The evidence related to firm characteristics is also consistent with our model, which predicts that the speed of pricing is negatively related to *ex ante* uncertainty about the value of the firm. Larger firms tend to be more visible and generally less risky than smaller firms so that *ex ante* uncertainty is typically lower for larger firms. Moreover, the value of growth opportunities is generally more uncertain than the value of tangible assets; this in turn leads to higher valuation uncertainty for higher growth firms relative to lower growth firms. Similar arguments could be made for firm profitability, institutional ownership, analyst coverage, and stock market liquidity, where higher values of these variables imply a less uncertain information environment.

C. Regression Analysis

In this section, we use regression analysis to examine how early offer pricing is related to gross spreads, announcement returns, offer discounts, and underpricing. We also examine how these outcomes vary with the use of confidential marketing prior to announcement.

We start our analysis by estimating baseline regressions in Table 3, Panel A, where SEO oucomes are modeled as a function of early pricing and pre-announcement confidential marketing. Examining the estimates from model (1), we find that offers that price before midnight pay gross spreads that are around 0.7 percentage points lower than the spreads paid by offers that price after midnight. This estimate is significant at the 0.01 level.[32] To assess the economic significance of this estimate, we consider the average SEO in our sample, which pays a gross spread of around 5.3 percent. For the average SEO, the estimated coefficient implies a 14.1 percent higher spread for offers that price after midnight relative to offers that price before midnight. Evaluated at the average offer with proceeds of $112.2 million, the difference in gross spreads amounts to around $0.8 million. These findings are consistent with our model, which predicts that accelerated SEOs that take more (less) time to price should involve higher (lower) search costs and thus pay higher (lower) gross spreads.

[Insert Table 3 around here]

In model (2) of Table 3, Panel A, we examine announcement returns, which allows

[32] All inferences are based on standard errors clustered at the issuer level (Petersen 2009).

us to directly test the implications from Proposition 2 and Corollary 2.1. We find that announcement returns are less negative for accelerated SEOs priced before midnight than for accelerated SEOs priced after midnight. The estimated coefficient, significant at the 0.01 level, shows that SEOs priced before midnight experience announcement returns that are by around 2.9 percentage points higher than the returns of SEOs that price after midnight. These findings are consistent with our model, which predicts that a more favorable reception by investors will lead to a faster offer completion.[33]

In model (3) of Table 3, Panel A, we examine the relation between early pricing and SEO discounts. We find that offers that price before midnight experience a discount that is 2.3 percentage points lower than the discount experienced by offers that price after midnight. The estimate is again highly significant, both statistically (at the 0.01 level) and economically. For an economic interpretation, we again consider the average SEO in our sample, with proceeds of \$112.2 million, in which case pricing after midnight implies an additional discount by about \$2.6 million.

The last model in Table 3, Panel A, examines how the speed of pricing in accelerated SEOs is related to SEO underpricing. We find that underpricing is around 0.6 percentage points higher for offers that price before midnight than for offers that price after midnight. This finding is consistent with Proposition 3, which predicts a positive relation between underpricing and the speed of pricing. However, the coefficient estimate is not significantly different from zero at conventional levels. In Table 4 below, we examine underpricing in more detail and find that a significant positive relation indeed exists between underpricing and the speed of pricing, but only for the sample of accelerated SEOs with relatively higher *ex ante* uncertainty.

To test the implications we derive regarding CMPOs, in all regressions of Table 3 we also include an indicator variable of whether the offer was confidentially marketed prior to announcement (CMPO dummy). Examining the estimates for this variable, we find

[33] In additional analysis, we examine short selling activity around accelerated SEOs. If there is informed short selling prior to the offer, information about the offer may be incorporated into the price prior to announcement. This in turn may affect our findings pertaining to offer discounts and announcement returns. We do not find evidence that our findings are affected by short selling activity around accelerated bookbuilt SEOs. Instead, our findings are consistent with Gustafson (2018), who shows that overnight SEOs (i.e., SEOs that announce and price before market open) constrain the ability of short sellers to take advantage of the negative returns that usually accompany equity offerings. These findings are available upon request.

that CMPOs, when compared to non-CMPOs, incur spreads that are higher by around 1.5 percentage points (significant at the 0.01 level). This finding consistent with our search framework, in which the investment banker incurs greater search costs in CMPOs and thus charges higher spreads. Also consistent with our model, which predicts that investors in CMPOs are rewarded with additional underpricing for reporting positive information during the confidential marketing stage, we find that CMPOs are underpriced by around 1.9 percentage points more than non-CMPOs.

We find that CMPOs are discounted by around 1.5 percentage points more than non-CMPOs, yet announcement returns are similar between CMPOs and non-CMPOs. As discussed in Section III.C, the predictions from our model with respect to announcement returns are mixed. While confidential marketing should be undertaken for *ex ante* riskier issuers (predicting lower announcement returns), *ex post*, only issues for which the confidentially marketed stage has produced sufficient favorable information transition to a public offering (predicting higher returns). Based on the estimates, neither of the two effect dominates announcement returns.

To ensure the robustness of our findings, in Panel B of Table 3 we estimate regression models that control for firm and offer characteristics. We also control for fixed effects for underwriter rank, year, and industry. Industries are defined based on two-digit Global Industry Classification Standard (GICS) codes. We again find that offers that price before midnight incur lower spreads (by 0.45 percentage points), lower discounts (by 2.0 percentage points), and less negative announcement returns (by 2.5 percentage points) than offers that price after midnight. These estimates are somewhat lower in magnitude when compared to the estimates in Panel A, but are again economically and statistically significant.

After controlling for firm and offer characteristics, we find that CMPOs experience higher spreads (by around 0.7 percentage points) and higher underpricing (by around 1.2 percentage points) when compared to non-CMPOs. The similarity in discounts and announcement returns between CMPOs and non-CMPOs, after controlling for risk-related variables, indicates that the market views CMPOs similarly to non-CMPOs. These findings are consistent with our model, in which the objective of the confidential search is to ensure, prior to public announcement, that investors' reception of the deal is not too negative.

For our final analysis in this section, we examine whether the relation between early pricing and underpricing depends on *ex ante* uncertainty. As discussed above, while the general relation is positive, it is statistically insignificant. All else equal, investors' positive information is more valuable in offers with higher *ex ante* uncertainty than in offers with lower *ex ante* uncertainty. We thus expect the positive relation between underpricing and the speed of pricing to be more pronounced for SEOs with relative high uncertainty.

Using the sample median of pre-SEO daily return volatility, we construct a variable of whether an offer is conducted by an issuer with high or with low uncertainty. Offers of issuers with above-median daily return volatility are classified as having high uncertainty, while all remaining offers are classified as having low uncertainty. We then create interaction variables between our measure of pricing speed and the two uncertainty dummies. This approach allows us to estimate two distinct relations between the speed of pricing and underpricing: one for high uncertainty offers and one for low uncertainty offers.

Table 4 reports estimates from a regression model based on the above approach. The regression further controls for all firm and offer characteristics used in the preceding analysis. For offers with high uncertainty, deals that price before midnight experience higher underpricing (by 2.0 percentage points) than deals that price after midnight. The estimated coefficient is significant at the 0.10 level and is consistent with the expectation that earlier offer completion rewards investors with greater underpricing than later offer completion. This finding is especially noteworthy given that offers that price more quickly tend to be less risky so that, all else equal, should experience lower, not higher, underpricing. Indeed, for low uncertainty offers we find that offers that price before midnight experience lower underpricing (by 0.7 percent) when compared to offers that price after midnight. However, this estimate is not statistically significant.[34]

[Insert Table 4 around here]

The overall findings presented in this section are consistent with the predictions of our model. For example, we find that early pricing is negatively related with the the gross spread

[34]The results are similar if we estimate the regression equation separately for high and for low uncertainty offers.

and positively related with the market's response to the offering. Moreover, for relatively high uncertainty offers, early pricing is positively related with underpricing. Our findings related to confidentially marketed offers are also consistent with the implications of the model. Specifically, confidentially marketed offers, which tend to involve longer searches than non-confidentially marketed offers, pay higher gross spreads. While confidentially marketed offers benefit from the opportunity to announce the offer only after sufficient favorable information has been uncovered during the confidential search stage, this favorable information comes at the cost of additional underpricing.

D. Buying by Regular Institutional Investors

In this section, we examine the types of institutional investors that buy shares in firms conducting accelerated SEOs. We divide institutional buyers into two groups: those with prior relations with the managing underwriters (regular investors) and those without prior relations with the managing underwriters (non-regular investors). For each SEO, we measure the number of regular institutional buyers as a fraction of the number of all institutional buyers of the SEO (see also Appendix B). We then estimate a fractional logistic regression to examine how the resulting fraction depends on early pricing and on other firm and offer characteristics.[35]

The estimates from the model are reported in Table 5. We find that offers that price before midnight are more likely to involve regular institutional buyers than offers that price after midnight. The estimated coefficient of 0.3 is significant at the 0.05 level. Examining the average marginal effect, we find that the probability of an institutional buyer to be also a regular buyer is 4.7 percent higher for SEOs that price before midnight than for SEOs that price after midnight (all else equal). This result is consistent with our model, which predicts that, given the choice, investment bankers are more likely to engage regular investors early rather than late in the search process.

[Insert Table 5 around here]

We further find that CMPOs are more likely to engage regular institutional buyers than non-CMPOs. The coefficient for the CMPO dummy is equal to 0.2 and is significant

[35] Estimates from a linear regression lead to similar conclusions.

at the 0.10 level. The average marginal effect implies that the probability to engage regular institutional buyers is around 3.2 percent higher for CMPOs than for non-CMPOs. This finding is also consistent with our model. Because investment banks have a greater ability to extract positive information from regular investors rather than from non-regular investors, banks will be more likely to contact regular investors in the confidential and thus early part of the search.

V. Concluding Remarks

Motivated in part by the recent rise of accelerated security offerings, we develop a theoretical model of the search process that sellers follow in such offerings. Our model combines ideas of search in financial markets and information gathering in security offerings. In the model, a seller sequentially contacts privately informed investors and solicits their interest in the offer. Investors strategically decide whether to truthfully report their information or to misrepresent their information and reduce the offer price. To induce truthful reporting of positive information, the seller needs to underprice the security, in expectation. If reported demand is strong, then the seller completes the offer relatively quickly. If reported demand is weak, it may be optimal for the seller to contact additional investors. By planning to contact additional investors if demand is revealed to be weak, the seller can reduce expected underpricing. However, contacting additional investors increases the costs of the offer. The seller chooses the optimal number of investors to contact by balancing underpricing and search costs.

Our model produces new insights into the costs, pricing, allocations, and completion speed for certain security offerings. For example, the model predicts that security offers that complete more quickly, when compared to offers the complete more slowly, will pay lower issue costs, will reflect more favorable investor reception, and will be more likely to allocate the security to regular investors. However, offers that complete more quickly will tend to be more underpriced and will gather less information. The model further provides insights into the use of confidential search prior to offer announcement.

To validate the model, we empirically examine accelerated offerings of seasoned equity. Specifically, we examine how the speed of pricing in accelerated SEOs is related to gross spreads, stock market reactions, offer discounts, underpricing, and buying by regular institutional investors. Our findings are consistent with the predictions of the model. For example, we find that accelerated SEOs that price more slowly generally pay higher spreads and experience lower market returns than accelerated SEOs that price more quickly. We also find that underpricing and buying by regular institutional investors tend to be higher in offers that price more quickly than in offers that price more slowly. Our results related to confidential marketing are also consistent with the model. For example, highly risky firms appear to benefit from confidential marketing, which allows them to announce the offer only after sufficient positive information has been reported by investors; however, gathering such positive information comes at the cost of additional underpricing.

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Appendix A: Proofs

Proof of Proposition 1: We consider equilibria where investors truthfully report their information and where all participants rationally incorporate all available information when determining the value of the security. We assume that the seller has already contacted $N+j$ investors, where a total of N investors have reported positive information and j investors have reported negative information. It is sufficient to show that further searches (a) do not increase the expected value of the security and (b) do not reduce expected underpricing.

To prove (a) we focus on the expected value of π, which is the relevant component of the value from Equation (1) of the paper. We need to show that $E_{N+j}(\pi_{N+j+1}) = E_{N+j}(\pi_{N+j})$; i.e., conditional on all information gathered up to and including investor $N+j$, the expected value of π_{N+j+1} is equal to the expected value π_{N+j}. Given that market participants in our model are rational and incorporate all available information, and given that π does not change over time, this condition is indeed satisfied. Formally,

$$E_{N+j}(\pi_{N+j+1}) = \int_0^1 \pi f_{\pi_{N+j}}(\pi)\, d\pi = E_{N+j}(\pi_{N+j}). \tag{A1}$$

To prove (b), let $\boldsymbol{A} > 0$ be the minimum amount that all N investors reporting positive information need to receive jointly in order to disclose their information. For these investors to receive at least $\boldsymbol{A}$, underpricing needs to satisfy the following condition:

$$\boldsymbol{A} \leq U \sum_{n=1}^{N} q_n, \tag{A2}$$

where U equals the amount of underpricing per one unit of the security and q_n equals the number of units allocated to investors $n = 1, \ldots, N$. To minimize underpricing while satisfying the constraint in Equation (A2), the seller needs to maximize $\sum_{n=1}^{N} q_n$, in effect allocating all Q units of the security to the N investors reporting positive information, and thus ending the search. ■

Proof of Proposition 2: To prove the proposition, we focus on the expected value of π. Let y equal the number of investors with positive information out of a total of $N+j$ investors. The value of y follows a binomial distribution; i.e., $y \sim \text{Binomial}(N+j, \pi)$. We assume that, from the seller's perspective, π follows a beta prior so that $\pi \sim \text{Beta}(\alpha_0, \beta_0)$. Using Bayes' Theorem,

$$\begin{aligned} p(\pi|y) = \frac{p(y|\pi)p(\pi)}{p(y)} &\propto p(y|\pi)p(\pi) \\ &\propto \binom{N+j}{y}\pi^y(1-\pi)^{N+j-y}\frac{\Gamma(\alpha_0+\beta_0)}{\Gamma(\alpha_0)\Gamma(\beta_0)}\pi^{\alpha_0-1}(1-\pi)^{\beta_0-1} \\ &\propto \pi^{\alpha_0+y-1}(1-\pi)^{\beta_0+N+j-y-1}. \end{aligned} \tag{A3}$$

Therefore, the posterior distribution of π is a beta distribution with parameters $\alpha_0 + y$ and $\beta_0 + N + j - y$; i.e., $\pi\,|N+j, y \sim \text{Beta}(\alpha_0 + y, \beta_0 + N + j - y)$.

When the search ends with investor $N + j^*$, such that $j^* < J$, the expected value of π is equal to:

$$\bar{\pi}_{N+j^*,y} = \frac{(\alpha_0 + y)}{(\alpha_0 + \beta_0 + N + j^*)}. \tag{A4}$$

When $j^* < J$, $y = N$, which leads to the desired result.

When $j^* = J$, the expected value of π is equal to:

$$\bar{\pi}_{N+J-1,y<N} = \sum_{y=0}^{N-1} \iint_0^1 \theta \frac{\binom{N+J-1}{y}\pi^y(1-\pi)^{N+J-y-1}}{\sum_{y=0}^{N-1}\binom{N+J-1}{y}\pi^y(1-\pi)^{N+J-y-1}} f(\theta\,|N+J-1, y)\, f_0(\pi)\, d\theta d\pi. \tag{A5}$$

In the above equation, $f(.\,|N+J-1, y)$ is the *ex post* probability density function for π conditional on y out of $N + J - 1$ investors reporting positive information. Using Fubini's Theorem and the assumption that each investor's private information is independent from all other information, including the seller's prior distribution for π, the expected value of π can be re-written as:

$$\bar{\pi}_{N+J-1,y<N} = \sum_{y=0}^{N-1}\left[\omega(y)\int_0^1 \theta f(\theta\,|N+J-1, y)\, d\theta\right], \tag{A6}$$

where $\omega(y)$ is equal to:

$$\omega(y) = \int_0^1 \frac{\binom{N+J-1}{y}\pi^y(1-\pi)^{N+J-y-1}}{\sum_{y=0}^{N-1}\binom{N+J-1}{y}\pi^y(1-\pi)^{N+J-y-1}} f_0(\pi)\, d\pi \tag{A7}$$

Thus defined, $\omega(y)$ equals the *ex ante* probability that the search ends with y investors reporting positive information, conditional on the seller contacting all $N + J$ investors (i.e., conditional on fewer than J out of $N+J-1$ investors reporting positive information). Noting that $\int_0^1 \theta f(\theta|N+J-1,y)\,d\theta$ is the expected value from a beta distribution with parameters α_0+y and $\beta_0+N+J-y-1$ leads to the desired result. ■

Proof of Corollary 2.1: The corollary follows directly from solving the equations in Proposition 2 while assuming $\alpha_0=1$ and $\beta_0=1$.

Proof of Proposition 3: To prove the proposition, we simplify Equation (12) in the paper. We take into account two results: that underpricing occurs only when the offer is fully allocated to investors reporting positive information and that investors reporting negative information receive allocations only when fewer than N investors report positive information. The necessary and sufficient condition for investor i to reveal positive information then reduces to:

$$\begin{aligned}
&\int_0^1 \binom{i'-1}{N-1}\pi^{N-1}(1-\pi)^{i'-N}U_{i',N}\frac{f_i(\pi)}{\varphi(i)}d\pi \\
&+\int_0^1 \sum_{j=i'-N+1}^{J}\left[\binom{N+j-2}{N-2}\pi^{N-1}(1-\pi)^{j}U_{N+j,N}\right]\frac{f_i(\pi)}{\varphi(i)}d\pi \\
&\geq \frac{\delta_{N+J}\lambda}{\bar{q}}\int_0^1 \sum_{y=0}^{N-1}\left[\binom{N+J-1}{y}\pi^{y}(1-\pi)^{N+J-y-1}q^{B}_{i,N+J,y}\right]\frac{f_i(\pi)}{\varphi(i)}d\pi.
\end{aligned} \tag{A8}$$

Next, we note that $f_i(\pi)=p(\pi|G,y_i<N)$, which is the probability density of π conditional on investor i's positive ("Good") information and knowledge that the offer is not yet complete; i.e., the number y_i of investors reporting positive information prior to investor i is less than N. We use Bayes' Theorem to rewrite $f_i(\pi)$ as follows:

$$f_i(\pi)=p(\pi|G,y_i<N)=\frac{p(G,y_i<N|\pi)p(\pi)}{p(G,y_i<N)}. \tag{A9}$$

We further note that $p(G,y_i<N|\pi)=\varphi(i)\pi$ and that $p(\pi)=f_0(\pi)$. Moreover, because $p(G,y_i<N)$ does not depend on π and is greater than 0, it factors out of the integral and can be canceled from both sides of Equation (A8). The incentive compatibility constraint

thus reduces to:

$$\begin{aligned}
&\int_0^1 \binom{i'-1}{N-1}\pi^N(1-\pi)^{i'-N}U_{i',N}f_0(\pi)d\pi \\
&+\int_0^1 \sum_{j=i'-N+1}^{J}\left[\binom{N+j-2}{N-2}\pi^N(1-\pi)^j U_{N+j,N}\right]f_0(\pi)d\pi \qquad \text{(A10)}\\
\geq \frac{\delta_{N+J}\lambda}{\bar{q}} &\int_0^1 \sum_{y=0}^{N-1}\left[\binom{N+J-1}{y}\pi^{y+1}(1-\pi)^{N+J-y-1}q^B_{i,N+J,y}\right]f_0(\pi)d\pi.
\end{aligned}$$

To minimize underpricing, the seller should (a) give the remaining allocations to investors with the lowest opportunity cost of reporting positive information and (b) ensure that investors who do not receive allocations when they report negative information should not expect any underpricing (i.e., the constraint in the above equation is binding).

Regarding (a), we examine the right-hand side of the above inequality and find that the opportunity cost of reporting positive information does not depend on investor i's position in the search sequence.

Regarding (b), we compare the right-hand side and the left-hand side of Equation (A10) and ensure that they are equal. To prove the first part of the proposition, we point out that the left-hand side of Equation (A10) is strictly positive for investor $i=1,\ldots,N$ with positive information, which implies that the right-hand side must also be positive. Specifically, consider investor $i=1,\ldots,N$ reporting positive information. For this investor, expected underpricing is strictly positive because $U_{N+j,N}>0$ at least for one $j=0,\ldots,J$). In other words, the investor, by virtue of being first in the search sequence, is certain to receive allocations in any fully subscribed offer. To minimize underpricing, the seller should allocate at least part of the remaining security to the investor if they were to report negative information so that Equation (A10) holds as an equality.

To prove the second part of the proposition, we point out that the left-hand side of Equation (A10) could equal zero for investor $i=N+1,\ldots,N+J$ with positive information, which implies that the right-hand side could also be zero. Specifically, consider investor $i=N+1,\ldots,N+J$ reporting positive information. For such an investor, expected underpricing need not be strictly positive. This is because, by virtue of being later in the search sequence, the investor does not participate in all fully subscribed offers; i.e., the investor does not participate in offers that are completed prior to the seller contacting them. As a result, as long as the seller sets the left-hand side of Equation (A10) to zero, they will also set the right-hand side to zero so that the investor does not receive any allocations if they report negative information.

If $N = 1$, then Equation (A10) reduces to:

$$U_{i,1} \int_0^1 \pi (1-\pi)^{i-1} f_0(\pi) d\pi \geq \frac{\delta_{N+J} \lambda q^B_{i,1+J,0}}{\bar{q}} \int_0^1 \pi (1-\pi)^J f_0(\pi) d\pi. \tag{A11}$$

Here, $\int_0^1 \pi(1-\pi)^{i-1} f_0(\pi) d\pi$ is the *ex ante* probability that the search ends with investor i and investor i reports positive information while $\int_0^1 \pi(1-\pi)^J f_0(\pi) d\pi$ is the *ex ante* probability that out of $J+1$ investors, only one investor possesses positive information. By choosing when to underprice the security, the seller can ensure that the incentive compatibility constraint in Equation (A11) is binding for all investors, regardless of how the seller plans to allocate the security when all investors report negative information. As a result, *ex ante* expected underpricing in equilibrium does not depend on how the seller plans to allocate the security when all investors report negative information. ■

Deriving expected underpricing: To derive the minimum expected underpricing in equilibrium, we let Equation (A10) hold as an equality for all investors. Summing both sides of Equation (A10) over all investors $i = 1, \ldots, N+J$, we obtain the following equality:

$$\begin{aligned} &N \int_0^1 \sum_{j=0}^{J} \left[\binom{N+j-1}{N-1} \pi^N (1-\pi)^j U_{N+j,N} \right] f_0(\pi) d\pi \\ &= \frac{\delta_{N+J} \lambda}{\bar{q}} \int_0^1 \sum_{y=0}^{N-1} \left[\binom{N+J-1}{y} \pi^{y+1} (1-\pi)^{N+J-y-1} (N-y) \bar{q} \right] f_0(\pi) d\pi. \end{aligned} \tag{A12}$$

To derive the above equality, we note that $\sum_{i=1}^{N+J} q^B_{i,N+J,y} = (N-y)\bar{q}$, so that investors reporting negative information receive the portion of the security not allocated to investors reporting positive information. Next, we note that the term $\int_0^1 \sum_{j=0}^{J} \left[\binom{N+j-1}{N-1} \pi^N (1-\pi)^j U_{N+j,N} \right] f_0(\pi) d\pi$ on the left-hand side of the equation is equal to the *ex ante* expected underpricing. As a result, *ex ante* expected underpricing is equal to:

$$E_0(U|J) = \delta_{N+J} \lambda \int_0^1 \sum_{y=0}^{N-1} \left[\binom{N+J-1}{y} \pi^{y+1} (1-\pi)^{N+J-y-1} \frac{(N-y)}{N} \right] f_0(\pi) d\pi. \tag{A13}$$

This completes the derivation of expected underpricing. ■

Proof of Proposition 4: To prove the proposition, we examine Equation (19) in the paper. The left-hand side of the equation increases with κ and decreases with $\bar{q}$ and λ. The right-hand side of the equation decreases with J. Because Equation (19) needs to hold in equilibrium, the desired results obtain. ■

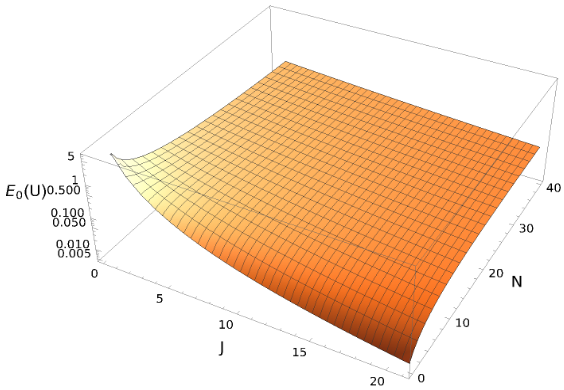
Proof of Proposition 5: We use Equation (1) in the paper to note that:

$$\Pr\left(\tilde{P}_1 < P_{min}\right) = \Pr\left(P_0 - (1 - 2\tilde{\pi})\,\lambda < P_{min}\right) = \Pr\left(\tilde{\pi} < \frac{1}{2} - \frac{P_0 - P_{min}}{2\lambda}\right). \tag{A14}$$

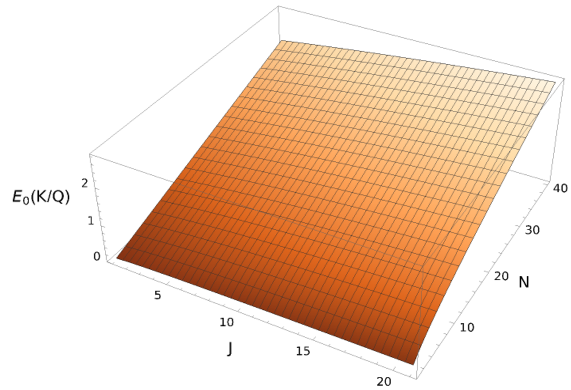
As long as $P_{min} < P_0$, the above probability increases with λ. ■

Appendix B: Definition of Variables

Variable	Description [data items in brackets, when available] {data source in braces}
Announcement return	Stock return from close before announcement to close after announcement. The return is adjusted for the CRSP equally-weighted market factor. {CRSP}
Bid-ask spread	Average daily bid-ask spread over the 90 days prior to offering, where daily spreads are calculated using the algorithm in Corwin and Schultz (2012). {CRSP}
Carter-Manaster rank	The rank of the most reputable lead, co-lead, or book underwriter in the SEO syndicate. Ranks are obtained from Prof. Jay Ritter's website. {https://site.warrington.ufl.edu/ritter/ipo-data/}
Cash-to-assets	Cash holdings [CHE] ÷ total assets [AT]; prior fiscal year. {Compustat}
CMPO dummy	Equals 1 if the SEO is a confidentially marketed public offering (CMPO); equals 0 otherwise. {PrivateRaise}
Daily share turnover	Average daily share turnover over the 90 days prior to offering, where daily share turnover equals daily traded shares ÷ shares outstanding [SHROUT]. {CRSP}
Discount	1 − (offer price ÷ closing price before announcement). {Bloomberg, Prospectus, CRSP}
Gross spread	Underwriter gross spread as a proportion of offer price. {Bloomberg, Prospectus}
Industry	One of eight industrial sectors based on the Global Industry Classification Standard (GICS). {Compustat}
Institutional ownership	The number of shares held by institutional investors ÷ shares outstanding; as of the quarter ending prior to SEO {Thomson Reuters 13F filings, CRSP}
Leverage	Total liabilities [LT] ÷ total assets [AT]; prior fiscal year. {Compustat}
Market cap	Stock price [PRC] × shares outstanding [SHROUT] at close before announcement. {CRSP}
Market-to-book	(Market cap + total liabilities [LT]) ÷ total assets [AT]; prior fiscal year. {CRSP, Compustat}
Number of analysts	Number of analysts providing one-year earnings forecasts prior to offer. {IBES}
Number of institutional buyers	Number of institutional investors increasing their ownership over the quarter of the SEO. {Thomson Reuters 13F filings, CRSP}
Number of regular institutional buyers	Number of institutional buyers that are regular investors for the SEO lead, co-lead, or book managers. To determine whether an institutional buyer in the current SEO is a regular investors for a given underwriter, we examine all accelerated SEOs over the past one year where that underwriter was a lead, co-lead, or book manager. If an institution is classified as a buyer in these past SEOs, we classify it as being regular for that underwriter. {Thomson Reuters 13F filings, CRSP}
Offered fraction	Shares offered ÷ shares outstanding [SHROUT] at close before announcement. {Bloomberg, Prospectus, CRSP}
Priced before midnight	Equals 1 if the issue is priced before midnight; equals 0 otherwise. {Bloomberg}
Proceeds	Offer price × shares offered pre-overallotment. {Bloomberg, Prospectus}
ROA	Net income [NI] ÷ total assets [AT]; prior fiscal year. {Compustat}
R&D-to-assets	R&D expenditures [XRD] ÷ Total assets [AT]; prior fiscal year. {Compustat}
Std. dev. of daily returns	Standard deviation of daily returns [RET] over the 90 days before offer. {CRSP}
Underpricing	(Closing price after announcement ÷ offer price) − 1. {Bloomberg, Prospectus}
90-day cumulative excess return	Cumulative stock return over the 90 days prior to offering, in excess of the corresponding cumulative return on the CRSP equally-weighted portfolio. {CRSP}

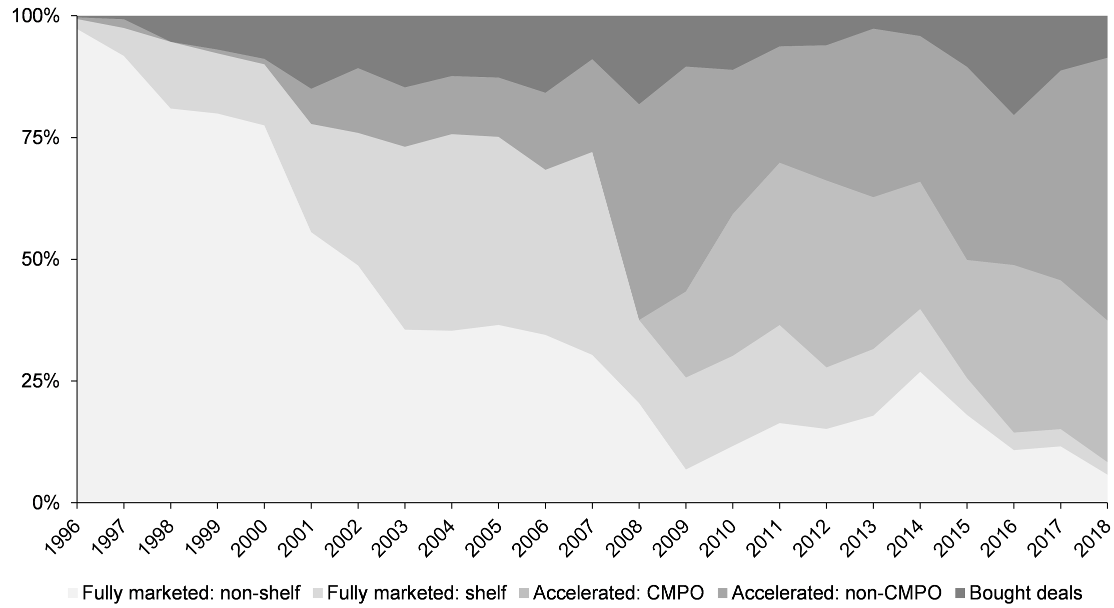


Panel A: Expected underpricing

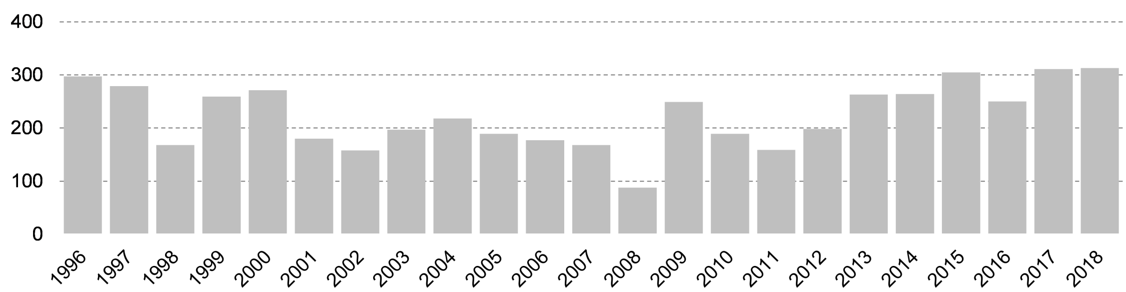


Panel B: Expected search cost

Figure 1. Expected underpricing and costs. The figure plots *ex ante* expected underpricing ($E_0\,(U)$, Panel A) and cost ($E_0\,(K/Q)$, Panel B), both as a percent of preoffer price, as a function of the minimum number of investors needed to sell the security (N) and the maximum number of additional investors the seller plans to contact (J). For the figure, we assume that $P_0 = 40$, $\lambda = 10$, and $\kappa/Q = 0.02$. Underpricing is plotted on a logarithmic scale.



Panel A: Proportion of SEOs by offer type



Panel B: Number of SEOs

Figure 2. Types of SEOs over time. The figure plots, by year, the percent of seasoned equity offerings (SEOs) by issue type (Panel A) and the total number of SEOs (Panel B). The sample is classified into five types (from bottom to top): fully marketed non-shelf offerings, fully marketed shelf offerings, accelerated confidentially marketed public offerings (CMPOs), accelerated non-confidentially marketed public offerings (non-CMPOs), and bought deals. The sample contains 5,150 SEOs of primary shares between 1996 and 2018. The sample is obtained from SDC and includes SEOs of primary shares by firms with common stock in the Center for Research in Security Prices (CRSP share codes 10 or 11) while excluding SEOs by financial firms (two-digit GICS code 40), utility firms (two-digit GICS code 55), and real estate firms (two-digit GICS code 60).

Table 1
Summary Statistics of Spreads, Returns, Discounts, and Underpricing
The table reports summary statistics of SEO gross spreads, announcement returns, discounts, and underpricing. All variables are described in Appendix B. Panel A reports summary statistics for the full sample. Panel B reports summary statistics for two subsamples, based on whether shares are priced before or after midnight. Panel B further reports the differences in means and medians between the two subsamples. The sample contains 753 SEOs of primary shares between 2009 and 2018, where all offers are announced after market close on day 0 and priced before market open on day 1. The sample includes offers by firms with common stock in CRSP (share codes 10 or 11) and excludes SEOs by financial firms (two-digit GICS code 40), utility firms (two-digit GICS code 55), and real estate firms (two-digit GICS code 60). The sample further excludes offers with preoffer stock prices below $3 per share. The χ^2-statistics for the differences in means are based on the non-parametric Kruskal-Wallis test. The χ^2-statistics for the differences in medians are based on the non-parametric Pearson's χ^2 test. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels.

Panel A: All 753 offers

Variable	Mean	Std.dev.	Quartile 1	Median	Quartile 3
Gross spread (%)	5.30	1.42	5.00	6.00	6.00
Announcement return (%)	−5.53	9.34	−11.27	−5.78	−0.36
Discount (%)	9.17	6.38	4.67	8.20	12.38
Underpricing (%)	3.97	6.44	0.00	2.53	7.14

Panel B: By speed of pricing

	Priced before midnight [131 SEOs]	Priced after midnight [622 SEOs]	Difference	χ^2-statistic
Means				
Gross spread (%)	4.25	5.51	−1.26	62.66***
Announcement return (%)	−3.23	−6.02	2.79	14.01***
Discount (%)	6.85	9.66	−2.81	24.34***
Underpricing (%)	3.90	3.99	−0.09	0.07
Medians				
Gross spread (%)	4.76	6.00	−1.24	10.89***
Announcement return (%)	−2.83	−6.61	3.78	16.44***
Discount (%)	5.90	8.87	−2.97	26.77***
Underpricing (%)	2.57	2.49	0.08	0.01

Table 2
Summary Statistics of Firm and Offer Characteristics
The table reports summary statistics of firm and offer characteristics. All variables are described in Appendix B. Panel A reports summary statistics for the full sample. Panel B reports summary statistics for two subsamples, based on whether shares are priced before or after midnight. Panel B further reports the differences in means and medians between the two subsamples. The sample contains 753 SEOs of primary shares between 2009 and 2018, where all offers are announced after market close on day 0 and priced before market open on day 1. The sample includes offers by firms with common stock in CRSP (share codes 10 or 11) and excludes SEOs by financial firms (two-digit GICS code 40), utility firms (two-digit GICS code 55), and real estate firms (two-digit GICS code 60). The sample further excludes offers with preoffer stock prices below $3 per share. The measure of regular institutional buyers requires data on changes in institutional investor ownership for SEOs over the past one year and is available for 639 accelerated SEOs between 2010 and 2018. The χ^2-statistics for the differences in means are based on the non-parametric Kruskal-Wallis test. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels.

Panel A: All 753 offers

Variable	Mean	Std.dev.	Quartile 1	Median	Quartile 3
CMPO dummy	0.63	0.48	0.00	1.00	1.00
Market cap (mill. 2018 USD)	1,160.61	2,643.88	166.58	347.71	888.72
Proceeds (mill. 2018 USD)	112.18	189.08	27.70	52.94	104.08
Offered fraction (%)	15.70	8.73	9.40	13.95	19.87
Std. dev. of daily returns (%)	4.30	2.19	2.96	3.84	4.94
Daily share turnover (%)	1.48	1.61	0.50	0.94	1.79
Bid-ask spread (%)	2.34	0.79	1.77	2.28	2.79
Market-to-book	3.53	3.44	1.45	2.52	4.16
R&D-to-assets (%)	27.31	32.48	0.15	19.33	39.26
Leverage (%)	49.89	37.53	21.63	42.52	67.05
Cash-to-assets (%)	49.95	36.10	11.95	52.12	87.25
ROA (%)	−37.21	36.78	−58.99	−32.14	−5.23
90-day cumulative excess return (%)	24.01	50.76	−5.72	12.95	41.22
Institutional ownership (%)	49.95	32.33	21.62	51.92	78.38
Number of analysts	6.62	6.10	3.00	5.00	8.00
Carter-Manaster rank	7.22	1.91	7.00	8.00	8.50
Regular / total institutional buyers (%)	74.04	26.23	63.49	83.33	93.22

Table 2 – continued

Panel B: By speed of pricing

	Priced before midnight [131 SEOs]	Priced after midnight [622 SEOs]	Difference	χ^2-statistic
CMPO dummy	0.34	0.70	−0.36	57.96***
Market cap (mill. 2018 USD)	2,355.10	909.03	1,446.07	67.70***
Proceeds (mill. 2018 USD)	233.91	86.54	147.37	64.89***
Offered fraction (%)	13.89	16.08	−2.19	6.17**
Std. dev. of daily returns (%)	4.01	4.36	−0.35	2.09
Daily share turnover (%)	1.86	1.40	0.46	20.01***
Bid-ask spread (%)	2.27	2.35	−0.08	1.13
Market-to-book	2.68	3.71	−1.03	14.62***
R&D-to-assets (%)	14.44	30.02	−15.58	40.66***
Leverage (%)	52.48	49.34	3.14	5.89**
Cash-to-assets (%)	35.58	52.98	−17.40	29.39***
ROA (%)	−25.06	−39.76	14.70	14.40***
90-day cumulative excess return (%)	16.14	25.67	−9.53	4.38**
Institutional ownership (%)	68.28	46.09	22.19	52.30***
Number of analysts	11.59	5.57	6.02	53.22***
Carter-Manaster rank	7.87	7.08	0.79	50.09***
Regular / total institutional buyers (%)	84.04	71.86	12.18	28.35***

Table 3

Pricing Speed and SEO Spreads, Returns, Discounts, and Underpricing

The table reports estimates from least squares regressions where the dependent variables are the SEO gross spread (model 1), announcement return (model 2), discount (model 3), and underpricing (model 4). In Panel A, as explanatory variables we include a variable of whether the SEO is priced before midnight and a variable of whether the offer was confidentially marketed prior to announcement (CMPO dummy). In Panel B, as explanatory variables we further include firm and SEO characteristics as well as fixed effects for Carter-Manaster rank, year, and industry. All variables are described in Appendix B. The sample contains 753 SEOs of primary shares between 2009 and 2018, where all offers are announced after market close on day 0 and priced before market open on day 1. The sample includes offers by firms with common stock in CRSP (share codes 10 or 11) and excludes SEOs by financial firms (two-digit GICS code 40), utility firms (two-digit GICS code 55), and real estate firms (two-digit GICS code 60). The sample further excludes offers with preoffer stock prices below $3 per share. For each coefficient estimate, the table further reports its t-statistic (in parenthesis) based on standard errors clustered at the firm level. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels. The last row of each panel reports the adjusted R-squared of the respective model.

Panel A: Baseline models

Dependent variable:	Gross spread (%)	Announcement return (%)	Discount (%)	Underpricing (%)
	(1)	(2)	(3)	(4)
Intercept	4.499***	−6.202***	8.646***	2.644***
	(39.116)	(−11.271)	(19.550)	(7.303)
Priced before midnight dummy	−0.747***	2.881***	−2.294***	0.592
	(−4.705)	(3.375)	(−3.987)	(0.904)
CMPO dummy	1.459***	0.263	1.461***	1.933***
	(12.489)	(0.373)	(2.836)	(4.134)
Observations	753	753	753	753
Carter-Manaster rank, year, and industry fixed effects	No	No	No	No
Adjusted R-squared (%)	33.58	1.04	3.66	1.67

Table 3 – continued

Panel B: Models with additional controls

Dependent variable:	Gross spread (%)	Announcement return (%)	Discount (%)	Underpricing (%)
	(1)	(2)	(3)	(4)
Priced before midnight dummy	−0.347***	2.470**	−1.955***	0.629
	(−2.720)	(2.542)	(−3.221)	(0.839)
CMPO dummy	0.669***	1.000	0.139	1.218*
	(6.861)	(1.220)	(0.275)	(1.941)
Market cap (2018 USD, log)	−0.593***	1.693***	−1.564***	−0.083
	(−10.121)	(3.018)	(−4.189)	(−0.205)
Offered fraction	−1.637***	10.755**	−6.799**	3.345
	(−3.450)	(2.156)	(−2.066)	(0.955)
Std. dev. of daily returns	2.515	4.863	2.499	10.574
	(1.176)	(0.160)	(0.137)	(0.563)
Daily share turnover (log)	−0.067	0.375	−0.019	0.240
	(−1.174)	(0.735)	(−0.056)	(0.711)
Bid-ask spread	8.306	−47.886	96.687**	68.461
	(1.354)	(−0.699)	(2.167)	(1.414)
Market-to-book (log)	0.096	0.508	−0.391	0.337
	(1.369)	(0.669)	(−0.864)	(0.626)
R&D-to-assets	−0.228*	0.160	−1.024	−1.433
	(−1.651)	(0.092)	(−0.932)	(−1.198)
Leverage	−0.141	−1.202	1.134	−0.025
	(−1.404)	(−0.964)	(1.570)	(−0.029)
Cash-to-assets	−0.084	−0.521	0.504	−0.778
	(−0.504)	(−0.295)	(0.421)	(−0.661)
ROA	−0.085	1.649	−0.891	0.445
	(−0.581)	(1.023)	(−0.858)	(0.455)
90-day cumulative excess return	0.170**	1.117	−0.766	0.194
	(2.560)	(1.230)	(−1.309)	(0.332)
Institutional ownership	−0.036	5.006***	−3.642***	1.502
	(−0.256)	(3.342)	(−3.643)	(1.305)
Number of analysts (log)	−0.145**	0.412	−0.249	0.188
	(−2.140)	(0.514)	(−0.503)	(0.366)
Observations	753	753	753	753
Carter-Manaster rank, year, and industry fixed effects	Yes	Yes	Yes	Yes
Adjusted R-squared (%)	60.69	10.28	21.81	4.80

Table 4
Pricing Speed and SEO Underpricing Conditional on Ex ante Uncertainty
The table reports estimates from a least squares regression where the dependent variable is SEO underpricing. To examine how the speed of pricing is related to SEO underpricing conditional on uncertainty, we construct a variable of whether a stock's volatility is above the sample median (high uncertainty dummy) and a variable of whether a stock's volatility is below the sample median (low uncertainty dummy). As explanatory variables, we then include interactions of the speed of pricing variable with the high uncertainty dummy and the low uncertainty dummy. The model also includes a variable of whether the offer was confidentially marketed prior to announcement and firm and SEO characteristics as well as fixed effects for Carter-Manaster rank, year, and industry. All variables are described in Appendix B. The sample contains 753 SEOs of primary shares between 2009 and 2018, where all offers are announced after market close on day 0 and priced before market open on day 1. The sample includes offers by firms with common stock in CRSP (share codes 10 or 11) and excludes SEOs by financial firms (two-digit GICS code 40), utility firms (two-digit GICS code 55), and real estate firms (two-digit GICS code 60). The sample further excludes offers with preoffer stock prices below $3 per share. For each coefficient estimate, the table reports its t-statistic (in parenthesis) based on standard errors clustered at the firm level. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels. The last row reports the adjusted R-squared of the model.

Dependent variable: SEO underpricing (%)	Coefficient	t-statistic
High uncertainty dummy	−0.726	(−0.930)
Priced before midnight dummy × High uncertainty dummy	2.033*	(1.840)
Priced before midnight dummy × Low uncertainty dummy	−0.726	(−0.930)
CMPO dummy	1.224*	(1.947)
Market cap (2018 USD, log)	−0.049	(−0.122)
Offered fraction	3.569	(1.022)
Std. dev. of daily returns	7.295	(0.368)
Daily share turnover (log)	0.244	(0.727)
Bid-ask spread	49.232	(0.982)
Market-to-book (log)	0.339	(0.632)
R&D-to-assets	−1.433	(−1.206)
Leverage	−0.037	(−0.042)
Cash-to-assets	−0.776	(−0.668)
ROA	0.400	(0.415)
90-day cumulative excess return	0.235	(0.401)
Institutional ownership	1.536	(1.363)
Number of analysts (log)	0.144	(0.283)
Observations	753	
Carter-Manaster rank, year, and industry fixed effects	Yes	
Adjusted R-squared (%)	5.29	

Table 5
Pricing Speed and Buying by Regular Institutional Investors
The table reports estimates from a fractional logistic regression where the dependent variable is the number of regular institutional buyers as a fraction of the number of all institutional buyers of the SEO. Using 13F filings from Thomson Reuters, we define an institutional buyer as an institution that increases its ownership during the quarter of the offer. To determine whether an institutional buyer is a regular investor for the SEO underwriters, we examine all accelerated SEOs by all lead, co-lead, or book underwriters of the current SEO during the prior one year. Institutional buyers in these prior offers are classified as regular investors for the underwriters of the current SEO. This classification is based on all lead, co-lead, or book underwriters in all offers. As explanatory variables, we include a variable of whether the SEO is priced before midnight and a variable of whether the offer was confidentially marketed prior to announcement. We also control for firm characteristics, offer characteristics, and fixed effects for Carter-Manaster rank, year, and industry. All variables are described in Appendix B. The base sample contains 753 SEOs of primary shares between 2009 and 2018, where all offers are announced after market close on day 0 and priced before market open on day 1. Requiring data on changes in institutional investor ownership for SEOs over the past one year leads to a sample of 639 accelerated SEOs between 2010 and 2018. The sample includes offers by firms with common stock in CRSP (share codes 10 or 11) and excludes SEOs by financial firms (two-digit GICS code 40), utility firms (two-digit GICS code 55), and real estate firms (two-digit GICS code 60). The sample further excludes offers with preoffer stock prices below $3 per share. For each coefficient estimate, the table reports its t-statistic (in parenthesis) based on standard errors clustered at the firm level and its average marginal effect [in square brackets]. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels. The last row of the table reports the pseudo R-squared of the model.

Dependent variable: The number of regular institutional buyers as a fraction of the number of all institutional buyers	Coefficient	t-statistic	Avg. marginal effect
Priced before midnight dummy	0.305**	(1.980)	[0.047]
CMPO dummy	0.212*	(1.844)	[0.032]
Market cap (2018 USD, log)	0.099	(1.015)	[0.015]
Offered fraction	0.813	(0.916)	[0.124]
Std. dev. of daily returns	−2.576	(−0.593)	[−0.394]
Daily share turnover (log)	−0.087	(−1.217)	[−0.013]
Bid-ask spread	10.256	(1.110)	[1.569]
Market-to-book (log)	0.029	(0.297)	[0.004]
R&D-to-assets	−0.530*	(−1.732)	[−0.081]
Leverage	−0.223	(−1.511)	[−0.034]
Cash-to-assets	0.608**	(2.241)	[0.093]
ROA	−0.183	(−0.761)	[−0.028]
90-day cumulative excess return	0.020	(0.125)	[0.003]
Institutional ownership	−0.338	(−1.491)	[−0.052]
Number of analysts (log)	−0.093	(−0.860)	[−0.014]
Observations		639	
Carter-Manaster rank, year, and industry fixed effects		Yes	
Pseudo R-squared (%)		17.47	