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Public Information and IPO Underpricing

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Abstract

We analyze the effect of public information on rational investors' incentives to reveal private information during the bookbuilding process and their demand for allocations in the IPO. Our model generates several new predictions. First, investors require more underpricing to truthfully reveal positive private information in bear markets than in bull markets (the incentive effect). Second, the fraction of positive private signals and of underpriced IPOs is increasing in market returns (the demand effect). Combined, these two effects can explain why IPO underpricing is positively related to pre-issue market returns, consistent with extant evidence. Using a sample of 5,000 U.S. IPOs from 1981-2008, we show that the empirical implications of the model are borne out in the data.

Keywords: public information, partial adjustment, underpricing, IPOs, bookbuilding

JEL Classifications: G10, G32

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1 Introduction

Extant evidence shows that first-day returns in initial public offerings (IPOs) of equity are affected by public information available before the final offer price is set. In particular, first-day stock returns tend to increase with market-wide equity returns observed prior to the offering, suggesting that underwriters fail to fully adjust offer prices for information that is widely known. As pointed out by, e.g., Loughran and Ritter (2002) and Lowry and Schwert (2004), partial adjustment to prior market returns is puzzling since it implies that underwriters compensate investors for easily available public information.[1]

Several papers have analyzed the partial adjustment of the IPO offer price to public information. Loughran and Ritter (2002) argue that irrational issuers care more for their newly discovered wealth than for leaving "money on the table", bargaining the price less aggressively when market-wide stock returns are high. Derrien (2005) proposes that investor sentiment correlated with market conditions drives demand, and hence boosts the initial returns in hot market IPOs. In Edelen and Kadlec (2005), a rational issuer sets the offer price by trading off the proceeds from a successful IPO against the likelihood that the issue fails. If the firm's value is correlated to the market value of its publicly traded peers, the first-day returns will increase with industry-wide stock returns. Finally, Sherman (2005) shows that partial adjustment will arise in a Benveniste and Spindt (1989) setup if investors' opportunity costs of getting informed are higher when equity markets are performing well.[2]

In the Benveniste and Spindt (1989) model, underwriters compensate investors for truthfully revealing *private* information during the bookbuilding period by giving them allocations of underpriced shares. We expand their setting to include a public signal, which is unconditionally correlated but conditionally uncorrelated to the private signal.[3] In our model, public information

[1]See also Logue (1973), Hanley (1993), Bradley and Jordan (2002), Benveniste, Ljungqvist, Wilhelm, and Yu (2003), and Kutsuna, Smith, and Smith (2009). Ince (2008) argues that the literature may understate the magnitude of partial adjustment due to the omission of withdrawn deals. Using French IPOs, Derrien and Womack (2003) show that the offer price adjusts more fully to market returns in auctions than in the bookbuilding process. Da, Engelberg, and Gao (2009) and Liu, Sherman, and Zhang (2009) find that IPO underpricing increases with pre-IPO media coverage.

[2]See also Leite (2007), who shows that positive public information reduces adverse selection and thus the winner's curse problem in a Rock (1986) setting. If issuers price the IPO more conservatively to increase the probability of success, the degree of underpricing will be positively correlated to market returns.

[3]This positive correlation is a straightforward implication of Bayes' rule from the assumption that the public signal and investors' private signals all are informative about the true underlying value of the firm. This is discussed further below.

affects the first-day returns in two ways: through investors' demand for allocations and through their incentives to truthfully reveal private information to the underwriter. Whenever the demand effect dominates the incentive effect—which happens for a wide range of parameter values—the issue price will adjust partially to public information.[4]

Our paper contributes to the IPO literature in three ways. First, it provides a rational explanation for the empirical observation that IPO prices fail to fully adjust for publicly available information. This follows from an increased investor demand for IPO allocations—and a higher likelihood that the issue is underpriced—when public information is favorable. Second, it offers a novel test of the incentive mechanism proposed by Benveniste and Spindt (1989). In particular, our model predicts that investors' incentives to truthfully reveal private information during the bookbuilding period are weaker in bear markets than in bull markets. Third, using a sample of 5,000 IPOs from 1981-2008, we show that both empirical implications are borne out in the data.

In our model, public information affects the distribution in investors' demand for allocations. The issuer optimally underprices the IPO only when the demand for issuer stock is sufficiently high, i.e., when a large number of investors get positive private signals. Since the private signals and the public signal are positively unconditionally correlated, it is a higher likelihood of sufficient investor demand to induce underpricing when the public information is positive. We refer to this mechanism as the demand effect.

The underwriter's optimal rule for the allocation of shares in the IPO favors investors who report a positive private signal.[5] An investor with positive private information can deflate the IPO price by falsely reporting a negative signal, but at the same time risk being left without any allocation at all. Since the probability of being awarded underpriced shares after falsely reporting a negative signal is higher when the public signal is negative, investors' incentives to lie are also stronger. Thus, in order to induce truthful revelation of favorable private information, the underwriter must compensate investors by underpricing the issue more when the public information is bad. We label this mechanism the incentive effect.

The relative strength of the two effects determines how public information ultimately is related

[4]In contrast to Sherman (2005), there is no role for information costs in our model. Instead, the partial adjustment is directly related to information revelation incentives.

[5]Cornelli and Goldreich (2001, 2003) find that investors submitting limit order (price specific) bids bet greater allocation, while Jenkinson and Jones (2004) report that final offer prices are closely related to the limit order bids in the order book.

to underpricing. While the incentive effect predicts a negative relation between public information and underpricing, the demand effect pulls in the opposite direction and predicts a positive relation. Whenever the demand effect dominates the incentive effect, underpricing is positively related to public information and the offer price partially adjusts for market-wide returns. This is the case when the number of investors in the issue is sufficiently large.

We test the empirical implications of the model for a sample of 5,093 U.S. IPOs in the period 1981-2008. As a proxy for private information, we use the residual from a regression of the offer price revision at the end of the registration period on the S&P500 index, effectively purging any effect of market-wide returns from the price revision. The predictions of the model are all borne out in the data. Importantly, for a given increase in private information, the first-day returns increase more in downmarkets than in upmarkets, consistent with the incentive effect. This effect is concentrated to issues where demand for the shares offered in the IPO is high. Moreover, the probability of positive first-day returns is higher when public markets are doing well, consistent with the demand effect.

Our paper offers a novel indirect test of the Benveniste and Spindt (1989) argument. A direct test of their argument requires that actual share allocations are related to investors' indications of interest. However, such tests require proprietary data, which is not easily available.[6] An alternative is to show that greater upward revisions in the offer price during the subscription period give higher underpricing, as first done by Hanley (1993).[7] We extend this approach by examining how public information affects investors' incentives to reveal private information, as implied by the incentive effect.

The rest of the paper is organized as follows. Section 2 describes the model. The relation between public information and underpricing is discussed in Section 3. In Section 4, we report the result from our empirical tests of the model. Section 5 summarizes. All proofs are found in Appendix A.

[6]Cornelli and Goldreich (2001, 2003) and Jenkinson and Jones (2004) examine proprietary bid and allocation data from two separate U.K. investment banks. Bubna and Prabhala (2010) use similar data from Indian IPOs. Three of these four studies find support for the Benveniste and Spindt (1989) model.

[7] Ljungqvist and Wilhelm (2002) estimate a structural model of IPO allocations and find greater institutional allocation to be associated with larger price revisions, consistent with information production.

2 The model

We start with a firm that is about to offer its shares to outside investors through an IPO. The firm's V value is good $G = 1$ with probability α and bad $B = 0$ with probability $1 - \alpha$. For simplicity, the number of shares to be floated is normalized to one, and investors are allocated fractions of this share. All agents are risk neutral, and the risk-free interest rate is zero.

There are $N \geq 2$ investors participating in the offering. Each investor $i = 1, \ldots, N$ observes at a zero cost a private signal $s_i = \{g_i, b_i\}$, where g_i represents positive information about the firm and b_i negative information. We may think of these investors as constituting the underwriter's pool of regular investors, and the information signal s_i as their unique knowledge about the firm, as well as information about their own demand and liquidity.[8] Let $n \in [0, N]$ denote the number of investors who observe positive private signals. The precision in the private signal s_i is the same across all investors and equals $\gamma = q(g_i|G) = q(b_i|B) > 1/2$, where $q(\cdot|\cdot)$ and $q(\cdot)$ denote conditional and unconditional probabilities throughout. The symmetry assumption that $q(g_I|G) = q(b_I|B)$ is made to simplify the exposition. The assumption that $\gamma > 1/2$ means that the signal is informative about the true value of the firm and hence that $q(G|g_I) > q(G) > q(G|b_I)$.

In addition, all investors observe a common public signal $s = \{g, b\}$, where $s = g$ represents positive information and $s = b$ negative information. The precision in the public signal is given by $\mu = q(g|G) = q(b|B)$, where $\mu > 1/2$. We can think of the public signal as market-wide information—such as changes in aggregate demand or the business cycle—that affects the value of the firm. Empirically, we use the market-wide stock returns observed prior to the IPO as a proxy for the public signal.

We assume that signals are informative in the sense that a signal is more likely to be positive if the true value of the firm is high, that is, $q(g_i|G) > 1/2$ and $q(g|G) > 1/2$. Similarly, if the value of the firm is low, a signal is more likely to be negative, so that $q(b_i|B) > 1/2$ and $q(b|B) > 1/2$. In addition, we assume that signals are unconditionally correlated in the sense that $q(s_i, s) \neq q(s_i)q(s)$, and conditionally uncorrelated so that $q(g_i, g|G) = q(g_i|G)q(g|G)$ and $q(g_i, g|B) = q(g_i|B)q(g|B)$.

[8] Alternatively, we may assume that investors' private signals are costly and that the underwriter is able to distinguish informed from uninformed investors, and will allow only informed investors to participate in the bookbuilding process. If now the underwriter is unable to commit to compensate investors for their informational costs, then the number N of investors in the offering will be determined endogenously from investors' incentive constraint and the pricing of the issue will be as under our zero-cost assumption.

These informational assumptions are standard.[9] By Bayes' rule, they imply the following:

Lemma 1 *The probability that an investor's private signal s_i is positive (negative) is higher if the public signal s is positive (negative) than if the public signal is negative (positive); in other words,* $q(g_i|g) > q(b_i|g)$ *and* $q(b_i|b) > q(b_i|g)$.

The positive unconditional correlation between the public signal and investors' private signals implied by Lemma 1 follows directly from the assumption that signals are informative about the same underlying value.[10] It is a key driver of both the incentive effect and the demand effect. Intuitively, this assumption implies that the distribution of investors' private signal will depend on the realization of the public signal.

Let $v(n, s)$ denote the (true) aftermarket value of the firm, i.e., the value of the firm after it is publicly listed. The aftermarket value of the firm is assumed to fully reflect all available information at the time of the offering. That is, the function $v(n, s)$ is the expected value of the firm conditional on the n positive private signals observed by investors and the public signal s. The specification of $v(n, s)$ as a conditional expectation implies that the marginal impact of each investor's private signal on the firm's aftermarket value is decreasing in the number of investors in the offering (N). This is in contrast to Benveniste and Spindt (1989), who specifically assume that the aftermarket value is additive in investors' private signals and hence that each private signal "has an equal (absolute) marginal impact on the stock's value" (p. 347).

Because the aftermarket value of the firm increases in the number of positive private signals n, n is also a measure of the demand for shares in the issue, and where a higher value of n corresponds to higher demand. Indeed, the case for which $n = N$, and hence all investors observe positive private signals, is referred to as the high-demand state. In contrast, the case for which $n = 0$ and all investors observe negative private signals, is called the low-demand state.

The bookbuilding process is conducted as follows. Investors observe their private signals along with the public signal. Bids are submitted to the underwriter effectively by reporting the private

[9]Using the normal distribution as a reference point, our informational assumptions are akin to having the true value of the firm V be normally distributed with some mean $\bar{V}$ and variance σ_V^2, and letting each investor i observing a signal $s_i = V + \epsilon_i$, where ϵ_i has a zero mean, $cov(\epsilon_i, \epsilon_j) = 0$ for $i \neq j$ (i.e., signals are conditionally uncorrelated), and $cov(s_i, s_j) = \sigma_V^2 > 0$ (i.e., signals are unconditionally correlated). Similarly, for a public signal $s = V + \epsilon_p$, it will be the case that $cov(\epsilon_i, \epsilon_p) = 0$, and $cov(s_i, s) = \sigma_V^2$.

[10]A corresponding result in the case of the normal distribution is that the expectation of s_i conditional on s is increasing in s.

signal. Each investor submits a "high" or a "low" bid, which is to say that she reports either a positive or negative signal. In equilibrium, an investor who observes a positive private signal reports this truthfully by bidding high. Similarly, an investor with a negative signal reports this truthfully by submitting a low bid.

The firm pays no fees for the services of the underwriter. Before investors submit their bids, the underwriter states his pricing and allocation policy. He then responds to investors' bids according to this pre-committed policy, which maximizes the proceeds to the issuer. In equilibrium, the underwriter receives all the relevant information from investors about the firm. Thus, when determining the offer price, he correctly anticipates the firm's aftermarket value $v(n, s)$.

Let $p(n, s)$ denote the IPO price if n investors report positive private signals ($s_i = g_i$) and given the public signal s.[11] Let $z(g_i, n)$ denote the fraction of the issue allocated to an investor who submits a high bid, and $z(b_i, n)$ denote the fraction awarded to an investor submitting a low bid. Since all private signals have the same precision, investors with identical bids receive equal allocations. In other words, the issue is allocated pro-rata among investors who submit identical bids. We assume, as do Benveniste and Spindt (1989), that the issuer is committed to price the firm at or below its aftermarket value, so that $p(n, s) \leq v(n, s)$. Unlike Benveniste and Spindt (1989), however, we place no restrictions on the number of shares that can be allocated to one investor.[12] This implies that the entire issue may be allocated to one investor. As discussed below, as long as at least one investor observes a positive private signal $s_i = g_i$, it is optimal to allocate the issue exclusively to investors with favorable information. One implication of this is that an investor who submits a low bid will receive an allocation only if the remaining $1 - N$ investors submit low bids as well.

Let us now consider investors' incentives to truthfully reveal their private signals. Trivially, an investor with negative information has little incentive to misrepresent her signal. If she lies and submits a high bid, she is awarded a fraction of the issue at a price exceeding the aftermarket value of the firm implied by her private signal. Thus, she is better off truthfully submitting a low bid, and possibly be allocated a share of the IPO at a price correctly reflecting her negative signal.

Instead, we need to worry about the incentives of investors with positive private signals. These

[11] Since in our model the number of shares is one, the offer price is equal to the proceeds in the IPO.
[12] In a more general version of the model in Appendix B, we incorporate allocation restrictions.

investors may benefit from misrepresenting their private information, pretending to posses a negative signal in order to lower the issue price. The potential drawback of such a strategy is, however, that other investors may submit high bids, leaving the untruthful investor without any allocation in the offering.

For an investor i with a positive private signal, the expected payoff from submitting a high bid that truthfully reveals her signal is

$$U = \sum_{n=1}^{N} q(n|s) z(g_I, n)[v(n, s) - p(n, s)], \tag{1}$$

where $q(n|s)$ is the probability that a total of n investors receive positive private signals conditional on investor i observing the private signal $s_i = g_i$ and the public signal s. Recall that $z(g_i, n)$ is the fraction of the issue allocated to investor i for a given n if she submits a high bid. The expected payoff to investor i is thus her fraction of the IPO initial returns, probability-weighted across different n.

The expected payoff to the same investor from misrepresenting her information by submitting a low bid equals

$$\hat{U} = \sum_{n=1}^{N} q(n|s) z(b_I, n)[v(n, s) - p(n-1, s)]. \tag{2}$$

For a given n and s, the offer price is now lower, $p(n-1, s) < p(n, s)$, and the probability of receiving an allocation in the IPO is now $z(b, n) < z(g, n)$. That is, by submitting a low bid, the investor would get a higher return for a given allocation, but at the same time risks getting a smaller (or no) fraction of the issue.

The payoff $\hat{U}$ is the minimum rent for an investor with a positive private signal and hence represents this investor's reservation value.[13] To induce this investor to truthfully reveal her signal, the expected payoff U from bidding high must equal or exceed the expected profits $\hat{U}$ from submitting a low bid. The issue must thus be priced and allocated to satisfy the truth-telling (incentive) constraint $U \geq \hat{U}$.

[13] As discussed above, investors with negative private information earn zero informational rents in equilibrium.

The expected proceeds $E\Pi$ from the IPO are given by

$$E\Pi = \sum_{n=0}^{N} q(n|s)p(n,s). \tag{3}$$

Formally, the objective of the underwriter (firm) is to maximize $E\Pi$ with respect to allocations $z(s_i, n)$ and prices $p(n, s)$ subject to the incentive constraint $U \geq \hat{U}$. Since issuance costs are exclusively determined by investors' informational rents $\hat{U}$, maximizing $E\Pi$ is equivalent to minimizing $\hat{U}$. The underwriter will further price and allocate the issue such that the investor's truth-telling constraint is satisfied as an equality, $U = \hat{U}$.

The absence of allocation restrictions allows the underwriter to allocate shares only to investors who submit high bids (i.e., report positive private information), regardless of the number of investors submitting high bids. In equilibrium, this allocation rule sets $z(b_i, n) = 0$ for all $n > 0$. That is, investors reporting a negative signal get a zero allocation as long as at least one investor reports a positive signal. This in turn minimizes the gains $\hat{U}$ from lying and thus maximizes the IPO proceeds $E\Pi$. In the event that all investors obtain negative signals ($n = 0$), and in equilibrium submit low bids, the issue is allocated pro-rata among the N investors. In other words, the issue is never withdrawn in the low-demand state.[14]

The given allocation rule implies that an investor who submits a low bid receives no shares unless the remaining $N-1$ investors also submit low bids, in which case each investor is allocated a fraction $1/N$ of the issue. The underwriter further reduces $\hat{U}$ (and hence increases $E\Pi$) by not underpricing the issue in the low-demand state; i.e., by setting $p(0, s) = v(0, s)$. The expected payoff to an investor with a positive private signal from submitting a low bid now is

$$\hat{U} = q(1|s)\frac{1}{N}[v(1,s) - v(0,s)], \tag{4}$$

which is strictly positive since $v(1, s) > v(0, s)$.

The expected payoff to an investor with a positive private signal from truthfully revealing his

[14]Busaba (2006) shows that it may be optimal to commit to withdraw the issue with a positive probability if demand is low. Busaba, Benveniste, and Guo (2001) find empirically that such a threat reduces underpricing. In our setting, however, it is never optimal to withdraw the issue.

signal by submitting a high bid is

$$U = \sum_{n=1}^{N} q(n|s) \frac{1}{n} [v(n, s) - p(n, s)]. \tag{5}$$

The set of prices $p(n, s);\ n = 1, \ldots, N$ that satisfies the investor's incentive constraint $U = \hat{U}$ is indeterminate, since there are N prices to be determined from only one constraint. For tractability (and without loss of generality), let the issue be fairly priced (no underpricing), so that $p(n, s) = v(n, s)$ for each $n = 1, \ldots, N - 1$. Now the offer price in the high-state, $p(N, s)$, is uniquely determined from $U = \hat{U}$. With $\hat{U} > 0$, it follows that $U > 0$, which requires that $p(N, s) < v(N, s)$. That is, the issue is underpriced in the high-demand state where all investors observe positive private signals.[15]

Since the issue price is set to the firm's aftermarket value $v(n, s)$ in all states where $n < N$, the payoff in these states are zero ($U = 0|n < N$). The expected payoff to an investor with a positive signal of submitting a high bid therefore collapses to the expected payoff in the high-demand state where $n = N$:

$$U = q(N|s) \frac{1}{N} [v(N, s) - p(N, s)]. \tag{6}$$

The offer price $p(N, s)$ in the high-demand state is determined from the investor's incentive constraint $U = \hat{U}$, which gives

$$p(N, s) = v(N, s) - \frac{q(1|s)}{q(N|s)} [v(1, s) - v(0, s)]. \tag{7}$$

Since $v(1, s) > v(0, s)$, the issue is at all times underpriced in the high-demand state, i.e., $p(N, s) < v(N, s)$. In other words, the issue is underpriced as the underwriter is only partially adjusting the offer price to the information learned by investors during the bookbuilding process.

The initial return associated with this upward revision in the offer price is given by

$$r(N, s) = \frac{v(N, s)}{p(N, s)} - 1. \tag{8}$$

[15] In Appendix B, we present a more general model with allocation restrictions in which the indeterminacy of prices for high realizations of n is resolved by having the IPO be underpriced *in expectation* across high-demand states. Numerical simulations show that the more general model with allocation restrictions yields identical insights and empirical implications as the simpler model analyzed in the text.

The probability of an upward revision is $q(N|s)$, and hence the expected initial return equals

$$Er(s) = q(N|s)r(N,s), \tag{9}$$

which measures the expected underpricing of the issue.

The analysis so far has established that IPOs are expected to be underpriced in order to induce truthful revelation of positive private information, similar to Benveniste and Spindt (1989). In the next section, we go beyond this standard argument and examine the relation between public information and underpricing.

3 Public information and underpricing

As shown in Equation (9) above, the expected IPO initial return, $Er(s)$, is the product of the initial return in the high-demand state, $r(N,s)$, and the probability that this state occurs, $q(N|s)$. A key contribution of this paper is the insight that the public signal affects the expected initial return through both $r(N,s)$ (the incentive effect) and $q(N|s)$ (the demand effect), as discussed next.

Proposition 1 (The incentive effect) *The initial return in the high-demand state is negatively related to the public signal s, so that* $r(N,g) < r(N,b)$*.*

The public signal affects the initial return in the high-demand state by affecting the incentives of investors to truthfully reveal their positive signals. Intuitively, the likelihood of being allocated shares in the IPO for an investor with positive private information who falsely submit a low bid is higher when the public signal is negative than when it is positive. The reason is that such an investor is successful in getting allocated underpriced shares only when all the other investors report negative signals as well. Since the probability of this event is negatively correlated with the public signal, $q(1|b) > q(1|g)$, the expected gains from lying are negatively related to the public signal.[16] Thus, investors' incentives to hide favorable private information are negatively correlated with the public signal. As a result, the amount of underpricing required by investors to truthfully reveal

[16]Formally, $r(N,g) < r(N,b)$ requires that $q(1|b)/q(0|b) < q(1|g)/q(0|g)$. This inequality holds if the private and public signals are informative, which further imply that $q(0|b) > q(0|g)$ and $q(1|b) \geq q(1|g)$, for any $N \geq 2$. This follows as a consequence of Lemma 1.

their positive signals is lower when the public outlook is good. This mechanism is the incentive effect.

In addition to affecting investors' incentives, the public signal also impacts the probability $q(N|s)$ that there is sufficient demand n for the issue to be underpriced in the first place. This is the demand effect:

Proposition 2 (The demand effect) *The probability of the high-demand state, and hence the probability that the IPO is underpriced, is positively related to the public signal, i.e., $q(N|g) > q(N|b)$.*

Specifically, positive public information increases the probability that investors obtain favorable private signals and hence submit high bids. Obviously, a higher probability of investors having favorable private information increases the likelihood that the issue is underpriced in the first place. Thus, through the demand effect, the probability that an issue is underpriced is positively related to the public signal.

The incentive effect and the demand effect have opposite implications for the relationship between public information and underpricing. Our model therefore allows expected initial returns to be positively or negatively related to the public signal, depending on which of the two effects that dominates. The next proposition shows that as long as the number of investors in the issue is sufficiently large the demand effect will dominate to create a positive relation consistent with the evidence of partial adjustment to public information.

Proposition 3 *Whenever the number of investors in the issue, N, is sufficiently large, the demand effect strictly dominates the incentive effect. In this case, initial returns are positively related to public information.*

As the number of investors in the issue increases, the marginal impact of each investor's signal on the aftermarket value of the firm declines. This reduces the potential payoff, $v(1, s) - v(0, s)$, to the investor of hiding her positive private signal, lowering the amount of underpricing required to induce truthful revelation. In other words, an increase in the number of investors decreases the relative importance of the incentive effect. Once the demand effect strictly dominates, the public signal will be positively related to underpricing. Indeed, Proposition 3 predicts a positive relation between public information and initial returns—consistent with partial adjustment to public information—whenever the number of investors in the issue is sufficiently large.

The result that the incentive effect weakens with the number of investors N stems from our assumption that the aftermarket value of the firm represents the expected value of the firm conditional on investors' private signals and the public signal. This in turn ensures that the marginal impact on firm value of each investor's signal declines in N. The result is consistent with standard micro structure models where investors' private information is reflected in the stock's price through the trading process.[17] It does not arise in the Benveniste and Spindt (1989) setup where each investor's signal is assumed to have an equal marginal impact on the aftermarket value irrespective of the number of informed investors in the IPO. Formal proofs of our propositions can be found in Appendix A.

Overall, our model provides a rational explanation for the empirical fact that offer prices adjust only partially to pre-issue market returns. We propose that this partial adjustment is a result of favorable private information and a resulting high demand for shares in the issue. We further identify a counteracting incentive effect, which produces a negative relationship between public information and underpricing. As long as investor demand in the IPO is sufficiently high, the demand effect will dominate, resulting in a positive correlation between initial returns and market returns.

Table 1 summarizes how the incentive and demand effects play out for different information sets. When private information is negative (low-demand state), there is little need for the underwriter to underprice the issue. In contrast, when investors have positive private information, their expected gains from lying are positive, and higher in bad times than in good times. As a result, conditional on a high-demand state, the level of underpricing will be higher when public information is negative rather than positive. Table 1 further shows that, conditional on negative public information, the probability is higher of investors receiving a negative (versus positive) private signal, and vice versa for positive public information. Since the model predicts underpricing only when private information is favorable, this implies that the probability of an issue being underpriced is higher when the public signal is positive. Comparing the likelihood and magnitude of underpricing across

[17] See, e.g., Kyle (1985). In Chen and Wilhelm (2008) a similar effect in the IPO aftermarket leads early stage investors to bid aggressively as they expect their information to become less important as new informed investors enters the market.

the different information sets will allow us to empirically test the model.

The incentive and demand effects have several empirical implications that are relatively straightforward to test. For example, the demand effect implies that the fraction of underpriced IPOs will be higher when issued in upmarkets than when issued in downmarkets.[18] Moreover, the incentive effect implies less underpricing in good markets than in bad markets. Thus, initial returns should be more sensitive to private information in IPOs preceded by negative rather than positive market returns. We now turn to an empirical examination of the implications of the model.

4 Empirical tests of the model

4.1 Sample selection and description

We identify 8,498 U.S. IPOs in the period 1970-2008 from the Global New Issues databases in Thompson Financial's SDC. Since the model analyzes the bookbuilding process, we restrict the sample to 6,301 cases with a positive pricing range, i.e., with a positive spread between the high and low filing price. Because SDC does not report a filing range prior to 1981, this restriction effectively eliminates all IPOs in the 1970s.

We require firms to have a filing midpoint of at least $5 per share, to be listed in CRSP, and to be traded by the 40th trading day after the public listing on NYSE, AMEX or NASDAQ. All unit offerings, real estate investment trusts (REITs), American Depository Receipts (ADRs), and closed-end funds are eliminated. We further require the IPO firm to have a founding year in the Field-Ritter founding dataset and a lead underwriter rank in the Ritter underwriter ranking dataset.[19] Our final dataset consists of 5,093 IPOs in 1981-2008, all of which have a complete set of control variables.

Table 2 reports the number of cases, and the average first-day return and market return by year. Two-thirds of the sample firms go public in the 1990s, one quarter in the 2000s and one tenth in the 1980s. Column 3 shows the first-day return $IR1 = p_1/p_0 - 1$, where p_1 is the firm's closing price on the first day of trading and p_0 is the final offer price. To curb extreme outliers, we winsorize $IR1$ at 200%. All stock price data is from CRSP. If there is no trade on a given day, we use the

[18] A substantial fraction of IPOs are overpriced. See, e.g., Ruud (1993) and more recently Lowry, Officer, and Schwert (2010).

[19] We thank Jay Ritter for making this data available on his webpage at the University of Florida.

midpoint of the bid-ask spread. The average one-day return is 19% and varies substantially over time. The largest underpricing takes place in years 1999 and 2000, with a mean first-day return of 63% and 54%, respectively. In contrast, the average $IR1$ never exceeds 6% in any one year during the 1984-1989 period. In the empirical analysis below, we use the first-day return ($IR1$) as a proxy for the underpricing of the offering.

The next three columns of Table 2 show the return on the S&P500 index over the 45 trading days preceding the IPO issue date ($SP500$), and the proportion of IPOs that take place in positive ($SP500 > 0$) and negative ($SP500 \leq 0$) market conditions, respectively. The average pre-issue market return is 2.7% and three-quarters of the sample IPOs take place in bull markets. Interestingly, also in the bubble period (1998-2000), a fair proportion of the IPOs (21%-42% per year) take place in a downmarket. In the following, we use the S&P500 45-day return as a proxy for the public information that reaches investors during the bookbuilding period. We choose a 45-day window to match the number of trading days in the registration period for a typical IPO in our data. The last column of Table 2 presents the proportion of IPOs with a negative first-day return. We report this for completeness as our model assumes that the offer price is set at or below the firm's "true" value. This, of course, cannot hold ex-post for each case in the realized distribution.

4.2 Univariate analysis

In the model, the expected underpricing depends on the relative size of the two counteracting effects of public information on investors' incentives and their demand for allocations. On the one hand, when public information is negative, underwriters must underprice the issue more in order to induce investors to reveal their positive private information (the incentive effect). On the other hand, since public and private signals are unconditionally correlated, the demand for shares in the IPO—and thus the likelihood that the issue is underpriced—is lower when publicly available information is negative (the demand effect). These two effects have several empirical implications. First, for a given set of private information we should observe more underpricing in downmarkets than in upmarkets. Second, when public information is positive, investors are more likely to also have favorable private information and the proportion underpriced offerings should be higher. In the following, we perform different tests of these predictions. We start by examining the univariate differences in underpricing across various information sets.

Testing the model requires a measure for private information. Since private information in itself is unobservable, we follow Hanley (1993) and turn to the outcome of the bookbuilding process. As discussed above, the objective of this process is to uncover investors' private information. Any revision in the final offer price from the indicated price in the initial filing range will—at least partly—reflect new information revealed by investors to the underwriter during the road show. We define the price revision as $PU = p_0/p_{mid} - 1$, where p_{mid} is the filing range midpoint. Using PU as a proxy for private information assumes that all information captured by the price revision is private, also if it overlaps with concurrent public information.

Table 3 reports the average initial return (IR1) split by positive ($SP500 > 0$) and negative ($SP500 \leq 0$) public information, respectively. Variable definitions and data sources are shown in Table 4. In Panel A of Table 3, the sample is further split by the sign of the price revision (positive, zero, and negative). Interestingly, the univariate results for different information sets are consistent with the empirical patterns predicted by the model. When private information is dismal ($PU < 0$), the average level of underpricing is relatively small, with initial returns of 5% in upmarkets and 4% in downmarkets. Consistent with Benveniste and Spindt (1989), the level of underpricing is much higher when private information is good ($PU > 0$). Unique to our model predictions, however, the average underpricing conditional on positive private information is particularly high when the issue takes place in a downmarket ($IR1 = 42\%$) compared to an upmarket ($IR1 = 35\%$). Also, when public information is positive ($SP500 > 0$), a higher fraction of the issues involve positive rather than negative private information (48% vs. 40%), while the opposite holds when public markets are down (33% IPOs with positive vs. 55% IPOs with negative private information).

As pointed out above, the final revision of the offer price (PU) accounts for broadly available information that reaches the market during the registration period. To isolate information that is truly private, we compute a measure for investors' private information, *Private*, that purges the content of market-wide information from the offer price revision. Specifically, *Private* is the residual from the regression $PU = \beta * SP500 + \epsilon$. In other words, *Private* is any information in the price revision above and beyond what can easily be inferred from the public markets. It is the result of the extreme view that only information in the price revision that cannot be attributed to the public signal is considered private.[20]

[20] Although the price revision has been shown to vary with other offer characteristics (e.g. stock exchange, total

Price updates, however, are discrete and done in tick size increments.[21] Thus, also when PU is correctly adjusted for the $SP500$ and there is no private information in the update, it is unlikely that ϵ exactly equals zero. Thus, for 286 cases where $|\epsilon| < 1\%$ of the mid-range price, we set $Private$ to zero.[22] Panel B of table 3 shows the average first-day return split by the sign of $Private$. Interestingly, this split generates initial return averages that closely map the ones reported for PU in Panel A.

As in Benveniste and Spindt (1989), our model predicts underpricing only when investor demand is high. As a coarse measure for investor demand, we define three dummy variables that indicate whether or not the final offer price is set outside the initial filing range. The high-demand state (HDS) represents IPOs where the offer price is on or above the upper bound of the filing range. Similarly, the low-demand state (LDS) indicates bookbuilding processes that yield an offer price on or below the lower bound of the filing range. Finally, the medium-demand state (MDS) indicates that the final offer price is within the initial filing range.

Panel C of Table 3 shows the average first-day returns across the three demand states. A similar pattern as for PU and $Private$ emerges. Again, the average first-day return is marginal (4%-5%) in the low-demand state, and higher in the high-demand state when the S&P500 return is negative (48%) vs. positive (38%). Also, most offerings (48%) are in LDS when markets are down, while most offerings (42%) are in HDS when markets are up. Overall, the predictions of the model appear to hold in the univariate across our different proxies for private information and high investor demand. We next test if the incentive and demand effects also hold in the cross-section.

4.3 Tests of the incentive effect

When the private signal is negative, investors have little incentive to hide their information. In contrast, in order to persuade investors to reveal positive private information, underwriters have to underprice the offering. A novel and central prediction of our model is that investors require more underpricing to reveal their private signal in downmarkets than in upmarkets. We test this prediction by regressing the initial return ($IR1$) on our proxy for private information ($Private$),

proceeds raised, underwriter rank, etc.), these characteristics are known already at the beginning of the bookbuilding process and therefore do not represent new information in our setting.

[21] Stocks are traded on NYSE, AMEX and NASDAQ in price increments of \$1/8 or \$1/16, referred to as tick sizes.

[22] With an average mid-range price of \$14 in our sample, 1% corresponds roughly to one tick size. Virtually none of the price updates (PU) are smaller than 1%.

split by different public information sets. The first regression specification is:

$$IR1 = \alpha + \beta_1 \; Private * SP500_{POS} + \beta_2 Private * SP500_{NEG} + \beta_3 SP500_{POS} + e. \tag{10}$$

$SP500_{POS}$ and $SP500_{NEG}$ are two mutually exclusive dummy variables. The variable $SP500_{POS}$ takes the value of one if the 45-day pre-issue market return is positive ($SP500 > 0$) and $SP500_{NEG} = 1$ if $SP500 \leq 0$. The interaction variables $Private * SP500_{POS}$ and $Private * SP500_{NEG}$ hence capture the effect of private information on underpricing when public information is positive and negative, respectively. Our model predicts that $\beta_1 < \beta_2$. We further include the dummy $SP500_{POS}$ separately to allow for the two interaction variables to have different intercepts.

The second regression specification is:

$$IR1 = \gamma + \delta_1 Private + \delta_2 Private * SP500_{POS} + \delta_3 SP500_{POS} + u. \tag{11}$$

This equation provides a direct test of whether the two coefficients β_1 and β_2 are different from each other. Specifically, the coefficient δ_2 for $Private * SP500_{POS}$ is such that $\delta_2 = \beta_1 - \beta_2$, and we predict $\delta_2 < 0$.[23]

The coefficient estimates from ordinary least squares (OLS) estimations are shown in Table 5. The t-statistics reported in parenthesis use standard errors clustered on listing month and Fama-French 49 industry. The first regression simply verifies that extant findings of partial adjustment to private and public information also hold in our sample. As shown in column (1), the coefficient on $Private$ is positive and highly significant (p-value <0.001). That is, the final offer price is only partially adjusted for private information revealed during the bookbuilding process, consistent with the Benveniste and Spindt (1989) model. Moreover, by including both $SP500$ and $SP500_{POS}$, we allow the partial adjustment to be asymmetric with respect to positive and negative public information. The coefficient for $SP500$ is positive and significant, consistent with the standard result of partial adjustment to public information. The coefficient for $SP500_{POS}$ is marginal and

[23]To see why, note that equation (11) can be rewritten as

$$IR1 = \gamma + \delta_1 Private * (SP500_{POS} + SP500_{NEG}) + \delta_2 Private * SP500_{POS} + \delta_3 SP500_{POS} + u, \text{ or}$$

$$IR1 = \gamma + (\delta_1 + \delta_2) Private * SP500_{POS} + \delta_1 Private * SP500_{NEG} + \delta_3 SP500_{POS} + u.$$

Compare this with equation (10) and it is obvious that $\delta_1 + \delta_2 = \beta_1$ and $\delta_1 = \beta_2$, such that $\delta_2 = \beta_1 - \beta_2$.

of a much smaller magnitude, indicating that the effect of public information on initial returns is largely symmetric.

The next two regressions use the specifications presented in equations (10) and (11), respectively. As shown in columns (2) and (3), the coefficients for $Private * SP500_{POS}$ and $Private * SP500_{NEG}$ are $\beta_1 = 0.89$ and $\beta_2 = 1.08$, respectively, both highly significant from zero. Moreover, the difference between the two coefficients, δ_2, is negative with a p-value < 0.05.[24] This suggests that investors require more underpricing in downmarkets than in upmarkets to reveal a given set of private information, as predicted by the model.

The last three columns of table 5 add other characteristics of the offering that have previously been shown to affect IPO initial returns. These control variables include the logarithm of the number of years since the firm was founded (*Age*), the percentage of the shares sold that are newly issued ($Primary$), the logarithm of the total $ proceeds raised in the IPO ($Proceeds$), the logarithm of the total number of shares sold in the issue ($Shares$), and the average rank of the lead underwriter (*Rank*). Underwriters are ranked on a scale from 0 to 9, where a higher number imply higher underwriter quality. We further add dummy variables indicating that the firm is in a high-tech industry ($HighTech$), is listed on the New York Stock Exchange ($NYSE$) or NASDAQ ($NASDAQ$), and that the IPO takes place in the period 9/1998-8/2000 (*Bubble*), respectively. Finally, since high-technology firms were in particularly high demand during the bubble period, we also add an interaction variable $Bubble * HighTech$.

Many of the control variables produce significant coefficients. The initial returns are decreasing in firm age and the $ proceeds raised in the IPO, and increasing in the percent newly issued shares, the number of shares offered and the average rank of the lead underwriter. Moreover, first-day returns tend to be higher for high-tech firms and offerings during the bubble period, and in particular for high-tech firms listed in the 1999-2000 period. Importantly, the empirical predictions of our model also hold when the regressions include the control variables. As reported in columns (5) and (6), the coefficients $\beta_1 = 0.78$ and $\beta_2 = 0.92$ are both positive and highly significant. Also, $\beta_1 < \beta_2$, with the difference being significantly different from zero at the 5%-level. In sum, our regressions support the existence of the incentive effect.

[24]The table shows a two-sided t-test of the difference, while the model in fact only requires a one-sided t-test of the difference, effectively doubling the significance of the test.

For robustness, we run the same OLS regressions instead using the price update PU as a proxy for private information. The regression results are reported in Table 6. The standard errors are clustered on listing month and Fama-French 49 industry, and shown in parenthesis. Importantly, the results are similar to the ones reported above for $Private$. The coefficients for $PU * SP500_{POS}$ and $PU * SP500_{NEG}$ are $\beta_1 = 0.90$ and $\beta_2 = 1.07$, respectively, and significantly different at the 5%-level (columns 2 and 3). The inferences for PU hold when adding all our control variables (columns 4-6), which produce coefficients similar to those reported above. However, because PU is positively correlated to $SP500$, the latter variable receives an insignificant coefficient in Table 6.

One implication of the model is that underpricing is required only in the high-demand state—and not in the low-demand state—in order to induce investors to truthfully reveal their private information. As a further test of the incentive effect, we examine the impact of the interaction variables $Private * SP500_{POS}$ and $Private * SP00_{NEG}$ on $IR1$ separately for the different demand states: high, medium and low. The results from OLS regressions with the first-day underpricing as dependent variable are presented in Table 7. As before, the t-statistics (in parenthesis) use standard errors clustered on Fama-French 49 industry and listing month. All regressions include the full set of controls discussed above. While not shown in the table for expositional purposes, all the control variables receive coefficients of similar magnitude and significance as in Table 5.

The first column of Table 7 shows how the first-day return varies across different demand states and with private information. The initial return tends to be lowest in the low-demand state, with a coefficient for LDS of -0.06 and highest in the high-demand state, with a coefficient for HDS of 0.04, both significant at the 0.1%-level. Moreover, the change in the first-day return for a given change in private information is highest in the high-demand state (the coefficient for $Private * HDS$ is 1.03 and highly significant); intermediate in the medium-demand state (the coefficient for $Private * MDS$ is 0.53 with a p-value< 0.001); and insignificant from zero in the low-demand state. Moreover, as shown in model (2), the three coefficients are significantly different from each other ($p < 0.001$). This suggests that the compensation investors require for truthfully disclosing their private information is highest in the high-demand state and close to zero in the low-demand state, as predicted by the model.

The remaining two columns of Table 7 examine the coefficient for $Private$ conditional on positive and negative public information, respectively, and across the low- and high-demand states. From models (3) and (4), the coefficient for $Private * HDS$ is significantly smaller in upmarkets than in downmarkets. That is, the coefficients for $Private * HDS * SP500_{POS}$ and $Private * HDS * SP500_{NEG}$ of 0.96 and 1.30, respectively, are significantly different (p-value<0.01). In contrast, the coefficient for $Private * LDS$ is close to zero and insignificantly different across the two public information sets.[25] To sum up, these regressions indicate that the underpricing compensating investors for the revelation of private information is largely related to the high-demand state and not relevant for the low-demand state.

Overall, the regression results support the existence of the incentive effect as predicted by the model. Investors' incentives to reveal their private information—and therefore the required level of underpricing—depends on nature of the public information. Specifically, investors require less compensation to disclose favorable private signals when market-wide prospects are good than when the general outlook is gloomy. Having empirically established the existence of the incentive effect in the data, we now turn to tests of the effects of private and public information on investors' demand for shares.

4.4 Tests of the demand effect

In general, investor demand for IPO allocations depends on their private information: the better the private signal, the higher demand for shares in the IPO. In our model, the demand effect arises from the positive unconditional correlation between public and private information, based on the assumption that all of these signals are informative. Given positive public information, investors are more likely to have positive private signals. As a result, investor demand and thus the proportion underpriced IPOs is higher in bear markets. This is the implication of the demand effect that we test empirically.

We first test the effect of public information on the likelihood that the first-day return is positive. Table 8 reports the coefficient estimates from probit regressions of the determinants of a positive (versus nonpositive) first-day return, $IR1_{POS}$. As predicted by the model, the coefficients for $SP500$ and $SP500_{POS}$ are positive and significant at the 0.1%-level. The higher the pre-issue market return, the more likely is the first-day stock return to be positive. When including $SP500$

[25] Cornelli, Goldreich, and Ljungqvist (2006) find that grey-market trading by individual investors on a forward (when-issued) basis is informative for the aftermarket price only when demand is high (versus low).

and $SP500_{POS}$ at the same time, reported in column 3, the dummy variable becomes largely insignificant, suggesting that the effect is symmetric across positive and negative market returns. That is, the likelihood of a positive first-day return increases with the registration period market returns, both in upmarkets and downmarkets.

While public information helps predict the occurrence of underpricing, the variable *Private* also produces a positive and significant coefficient ($p<0.001$). That is, the more favorable the private information, the more likely is the offer to have a positive first-day return. This result is robust across all six regression specifications, also when including the standard controls (columns 4-6). As shown in the table, the probability that the first-day return is positive decreases with the size of the offering (*Proceeds*) and is higher the more shares that are issued (*Shares*), and for firms listed on NASDAQ and NYSE (versus AMEX).

We run the same set of regressions using *PU* as a proxy for information. The results are shown in Table 9. Again, the proability of underpricing is higher the better the private information. Controlling for *PU*, the coefficients for $SP500$ and $SP500_{POS}$ are highly significant, as predicted by our model. When entering the two stock-market return variables at the same time, however, they both become insignificant. It appears that the multicolinearity with *PU* eliminates the significance of $SP500$ in the presence of the upmarket dummy. The control variables produce similar coefficients as before, with the exception of *NASDAQ*, which now enters the regressions with a positive coefficient.

As a third test of the demand effect, we regress indicators for the high-demand state and low-demand state, respectively, on the S&P500 return. Table 10 reports the coefficients from probit regressions estimating the probability that the IPO is in a high-demand state (columns 1-4) and a low-demand state (columns 5-8), respectively. Recall that, in the model, all investors must have positive private signals in order for the high-demand state to occur. Thus, the high-demand state can be viewed as coarse—and therefore robust—proxy for issues with positive private information.

As shown in the table, the probability of pricing an issue above the filing range (*HDS*) is higher in upmarkets and increases in the magnitude of the market return. As expected, the opposite results are obtained when a dummy for the low-demand state (*LDS*) is the dependent variable. Here, the probability for an issue to be priced *below* its filing range is lower in upmarkets and decreases with the return on the market index during the registration period.

Overall, the data supports the existence of both the incentive effect and the demand effect, tested for separately. Our model is interesting because it provides a rational explanation for partial adjustment of the offer price to public information. The novel mechanism is the incentive effect, which ties the sign of public information to investors' incentives to reveal their positive private signals. As predicted by the model, and played out in the data, investors receive more compensation for positive private information in downmarkets than in upmarkets. Moreover, the counteracting demand effect, implying a higher probability of positive private information and hence underpricing in bull markets than in bear markets, also receives strong support by the data. Combined, these two effects and the way public information affects investors' incentives to disclose private information can explain the partial adjustment to public information that has been observed by many.

5 Summary

This paper presents a model that explains the relationship between *public* information and IPO initial returns. Building on the framework of Benveniste and Spindt (1989), where investors are compensated with underpriced shares for disclosing private information, we show that publicly available information is related to IPO underpricing through two different mechanisms.

First, and unique to our model, market-wide information affects the underpricing required for investors to reveal their positive private signal. When the public outlook is negative, the expected profits from hiding favorable private information is higher. Accordingly, investors require a higher compensation—in the form of more underpricing—to disclose good news when public information is bad. This is the incentive effect.

Second, because public and private signals are informative, they are also unconditionally correlated. That is, the probability of receiving a good private signal given a positive market outlook is higher than when the market outlook is poor. Consequently, investors are more likely to have positive signals—which is necessary for the issue to be underpriced in the first place—in upmarkets than in downmarkets. As a result, the probability that an issue is underpriced is higher when public information is positive. This is the demand effect.

Whether underpricing ultimately is positively or negatively related to public information depends on which of the two effects dominates. If the number of investors in the offering is sufficiently large, the demand effect will dominate and initial IPO returns will be increasing in pre-issue market returns. While not explicitly incorporated in the model, if the price investors require to disclose their private information increases, the incentive effect will dominate and IPO returns will decrease in market returns. Our model thus allows for the possibility of either under- or over adjustment to public information in the offer price.

We test the predictions of the model for a sample of 5,093 U.S. IPOs in 1981-2008. As a proxy for private information, we use the residual from an OLS regression of the final offer price revision on the pre-issue market returns. This purges any effect of market-wide information from the price revision, attributing the remaining change to investors' private signals.

In cross-sectional tests, we show that initial returns change more for a given change in private information in downmarkets than in upmarkets. In other words, investors' private information is more completely incorporated into the IPO price when pre-IPO market-wide returns are positive rather than negative. This effect is particularly pronounced for issues that are priced above the filing range and largely absent in issues that are priced below the filing range. This is consistent with the incentive effect in our model, and provides indirect support for the incentive mechanism proposed by Benveniste and Spindt (1989).

We further find a positive correlation between the stock market index and the likelihood that an issue has positive first-day returns. Market-wide equity returns also increase the probability of the high-demand state, i.e., when the issue ultimately is priced above its initial filing range. This is all consistent with the demand affect.

Our model provides a rational explanation for partial adjustment in the offer price to public information, as observed by many others. One potential extension is to explore the mechanisms that determine the relative strengths of the demand and the incentive effect. Another extension is to develop the model's predictions with respect to the volatility of initial returns, and understand how return volatility is affected by market conditions. Both extensions could help us better understand the larger mechanisms behind IPO pricing and allocations.

A Appendix

Proof of Lemma 1.

It follows by Bayes' rule that

$$q(g_i|g) = \frac{q(g_i, g)}{q(g)} \tag{12}$$

where

$$\begin{aligned} q(g_i, g) &= q(g_i, g|G)q(G) + q(g_i, g|B)q(B) \\ &= q(g_i|G)q(g|G)q(G) + q(g_i|B)q(g|B)q(B) \\ &= \gamma\mu\alpha + (1-\gamma)(1-\mu)(1-\alpha) \end{aligned} \tag{13}$$

Similarly,

$$q(g) = q(g|G)q(G) + q(g|B)q(B) = \mu\alpha + (1-\mu)(1-\alpha) \tag{14}$$

and hence

$$q(g_I|g) = \frac{\gamma\mu\alpha + (1-\gamma)(1-\mu)(1-\alpha)}{\mu\alpha + (1-\mu)(1-\alpha)} \tag{15}$$

It is then immediate that

$$q(g_I|b) = \frac{\gamma(1-\mu)\alpha + (1-\gamma)\mu(1-\alpha)}{(1-\mu)\alpha + \mu(1-\alpha)} \tag{16}$$

and furthermore that

$$q(g_i|g) - q(g_i|b) = \frac{\alpha(1-\alpha)(2\mu-1)(2\gamma-1))}{[\mu\alpha + (1-\mu)(1-\alpha][(1-\mu)\alpha + \mu(1-\alpha)]} > 0 \tag{17}$$

since $\mu > 1/2$ and $\gamma > 1/2$. It can similarly be shown that $q(b_I|b) > q(g_I|b)$ if $\mu > 1/2$ and $\gamma > 1/2$.

■

To setup the proofs to Propositions 1 - 3 we use the following probabilistic assumptions and Bayes' rule.

$$
\begin{aligned}
V &= \{G = 1, B = 0\} \\
s_i &= \{g_i, b_i\} \\
s &= \{g, b\} \\
q(g_i \mid G) = q(b_i \mid B) = \gamma &> q(b_i \mid G) = q(g_i \mid B) = (1-\gamma) \qquad (18) \\
q(g \mid G) = q(b \mid B) = \mu &> q(b \mid G) = q(g \mid B) = (1-\mu) \qquad (19) \\
q(G) = \alpha & \quad\ q(B) = (1-\alpha) \\
q(s) &= q(s|G)q(G) + q(s|B)q(B) \\
q(G \mid g) = \pi &= \frac{\mu\alpha}{\mu\alpha + (1-\mu)(1-\alpha)} \\
q(B \mid g) = \bar{\pi} &= (1-\pi) \\
q(B \mid b) = \beta &= \frac{\mu(1-\alpha)}{\mu(1-\alpha) + (1-\mu)\alpha} \\
q(G \mid b) = \bar{\beta} &= (1-\beta)
\end{aligned}
$$

Assumptions (18) and (19) imply that the signals (s_I, s) are informative, and hence

$$
\begin{aligned}
q(G|g) &> q(G) \\
\frac{\mu\alpha}{\mu\alpha + (1-\mu)(1-\alpha)} &> \alpha \\
\mu &> \mu\alpha + (1-\mu)(1-\alpha) \\
(2\mu - 1) &> (2\mu - 1)\alpha \\
q(g|G) = \mu &> 1/2
\end{aligned}
$$

which holds for all $\alpha \in (0, 1)$.

Further, the probability for n positive private signals (g_I) given a good firm (G), and the probability of n positive private signals given the public signal (s) is given by

$$\begin{aligned} q(n \mid G) &\sim Binomial[N, \gamma] \\ q(n \mid B) &\sim Binomial[N, (1-\gamma)] \\ q(n \mid s) &= q(n \mid G)q(G \mid s) + q(n \mid B)q(B \mid s) \end{aligned}$$

Finally the expected aftermarket value, $v(n, s)$, of the firm given the number of private signals, n, and the public signal s,

$$v(n, s) = G \times q(G \mid n, s) = 1 \times \frac{q(n \mid G)}{q(n \mid s)} q(G \mid s)$$

Proof of Proposition 1.

(i) The initial return associated with the high-demand state equals

$$r(N, s) = \frac{v(N, s)}{p(N, s)} - 1; s \in \{b, g\}, \tag{20}$$

where

$$p(N, s) = v(N, s) - \frac{q(1 \mid s)}{q(N \mid s)} \left[v(1, s) - v(0, s) \right]. \tag{21}$$

We want to show that $r(N, g) < r(N, b)$, or that

$$\frac{v(N, g)}{p(N, g)} < \frac{v(N, b)}{p(N, b)}, \tag{22}$$

which is equivalent to

$$\frac{q(N \mid g)v(N, g)}{q(N \mid b)v(N, b)} > \frac{q(1 \mid g)}{q(1 \mid b)} \frac{[v(1, g) - v(0, g)]}{[v(1, b) - v(0, b)]} \tag{23}$$

This inequality may be written as

$$\frac{q(G \mid g)}{q(G \mid b)} > \frac{q(1 \mid g)}{q(1 \mid b)} \frac{\left[\frac{q(1|G)}{q(1|g)} - \frac{q(0|G)}{q(0|g)} \right] q(G \mid g)}{\left[\frac{q(1|G)}{q(1|b)} - \frac{q(0|G)}{q(0|b)} \right] q(G \mid b)} \tag{24}$$

which again can be expressed as

$$1 > \frac{q(0 \mid b)}{q(0 \mid g)} \frac{q(1 \mid G)q(0 \mid g) - q(0 \mid G)q(1 \mid g)}{q(1 \mid G)q(0 \mid b) - q(0 \mid G)q(1 \mid b)} \tag{25}$$

Substituing $Z_s = \frac{1}{N}\frac{q(1|s)}{q(0|s)}$ inequality (25) simplifies to

$$1 > \frac{q(1 \mid G) - q(0 \mid G)NZ_g}{q(1 \mid G) - q(0 \mid G)NZ_b} = \frac{\gamma - (1-\gamma)Z_g}{\gamma - (1-\gamma)Z_b} \tag{26}$$

Inequality (26) holds if $Z_g > Z_b$, and we therefore must have that

$$\begin{aligned}
Z_g = \frac{1}{N}\frac{q(1 \mid g)}{q(0 \mid g)} &> \frac{1}{N}\frac{q(1 \mid b)}{q(0 \mid b)} = Z_b \\
\frac{q(1 \mid G)q(G \mid g) + q(1 \mid B)q(B \mid g)}{q(0 \mid G)q(G \mid g) + q(0 \mid B)q(B \mid g)} &> \frac{q(1 \mid G)q(G \mid b) + q(1 \mid B)q(B \mid b)}{q(0 \mid G)q(G \mid b) + q(0 \mid B)q(B \mid b)} \\
\frac{\gamma(1-\gamma)^{N-1}\pi + \gamma^{N-1}(1-\gamma)\bar{\pi}}{(1-\gamma)^N\pi + \gamma^N\bar{\pi}} &> \frac{\gamma(1-\gamma)^{N-1}\bar{\beta} + \gamma^{N-1}(1-\gamma)\beta}{(1-\gamma)^N\bar{\beta} + \gamma^N\beta}
\end{aligned} \tag{27}$$

Dividing by γ^N and substituting $\Gamma = \frac{1-\gamma}{\gamma}$ we get

$$\begin{aligned}
\frac{\Gamma^{N-1}\pi + \Gamma\bar{\pi}}{\Gamma^N\pi + \bar{\pi}} &> \frac{\Gamma^{N-1}\bar{\beta} + \Gamma\beta}{\Gamma^N\bar{\beta} + \beta} \\
\frac{\Gamma^N\pi + \Gamma^2\bar{\pi}}{\Gamma^N\pi + \bar{\pi}} &> \frac{\Gamma^N\bar{\beta} + \Gamma^2\beta}{\Gamma^N\bar{\beta} + \beta} \\
\frac{\Gamma^N\pi + \Gamma^2\bar{\pi} + \bar{\pi} - \bar{\pi}}{\Gamma^N\pi + \bar{\pi}} &> \frac{\Gamma^N\bar{\beta} + \Gamma^2\beta + \beta - \beta}{\Gamma^N\bar{\beta} + \beta} \\
1 - \frac{(1-\Gamma^2)\bar{\pi}}{\Gamma^N\pi + \bar{\pi}} &> 1 - \frac{(1-\Gamma^2)\beta}{\Gamma^N\bar{\beta} + \beta} \\
\frac{(1-\Gamma^2)\beta}{\Gamma^N\bar{\beta} + \beta} &> \frac{(1-\Gamma^2)\bar{\pi}}{\Gamma^N\pi + \bar{\pi}}
\end{aligned}$$

assuming $\Gamma < 1$, which implies $\gamma > 1/2$, we have

$$\begin{aligned}
\beta[\Gamma^N\pi + \bar{\pi}] &> \bar{\pi}[\Gamma^N\bar{\beta} + \beta] \\
\Gamma^N[\pi\beta - \bar{\pi}\bar{\beta}] &> 0
\end{aligned} \tag{28}$$

As long as $\Gamma^N > 0$, we have that

$$
\begin{aligned}
\pi\beta &> \bar{\pi}\bar{\beta} = (1-\pi)(1-\beta) \\
\pi\beta &> 1 - \pi - \beta + \pi\beta \\
\pi + \beta &> 1 \qquad (29) \\
\pi + \beta = \frac{q(g|G)q(G)}{q(g)} + \frac{q(b|B)q(B)}{q(b)} &> 1 \\
q(g|G)q(G)q(b) + q(b|B)q(B)q(g) &> q(g)q(b) \\
q(g|G)q(G)q(b) + q(b|B)q(B)q(g) &> [q(g|G)q(G) + q(g|B)q(B)]q(b) \\
q(b|B)q(B)q(g) &> q(g|B)q(B)q(b) \\
q(b|B)q(g) &> q(g|B)q(b) \\
\mu[\mu\alpha + (1-\mu)(1-\alpha)] &> (1-\mu)[\mu(1-\alpha) + (1-\mu)\alpha] \\
\mu^2\alpha &> (1-\mu)^2\alpha \\
\mu &> 1/2 \qquad (30)
\end{aligned}
$$

Thus, for any $\gamma, \mu > 1/2$, $\alpha \in (0, 1)$ and $\Gamma^N > 0$ we have that $r(N, g) < r(N, b)$. ■

Proof of Proposition 2.

By Bayes' rule it follows that

$$
\begin{aligned}
q(N \mid g) &= q(N \mid G)q(G \mid g) + q(N \mid B)q(B \mid g) \qquad (31) \\
&= \gamma^N \pi + (1-\gamma)^N \bar{\pi} \\
q(N \mid b) &= q(N \mid G)q(G \mid b) + q(N \mid B)q(B \mid b) \qquad (32) \\
&= \gamma^N \bar{\beta} + (1-\gamma)^N \beta
\end{aligned}
$$

Take the difference to prove the proposition.

$$\begin{aligned}
q(N \mid g) &> q(N \mid b) \\
\gamma^N \pi + (1-\gamma)^N \bar{\pi} &> \gamma^N \bar{\beta} + (1-\gamma)^N \beta \\
\pi + \left(\frac{1-\gamma}{\gamma}\right)^N \bar{\pi} &> \bar{\beta} + \left(\frac{1-\gamma}{\gamma}\right)^N \beta \\
(\pi - \bar{\beta}) + \Gamma^N (\bar{\pi} - \beta) &> 0 \\
(\pi + \beta - 1)(1 - \Gamma^N) &> 0 \qquad (33)
\end{aligned}$$

Hence we see using the same reasoning as from (29) to (30) that $q(N \mid g) > q(N \mid b)$ holds for any $\mu > 1/2$, $\alpha \in (0, 1)$ and $\Gamma^N < 1$ (which holds if $\gamma > 1/2$). ■

Proof of Proposition 3.

The proposition is proved by showing that

$$\lim_{N\to\infty} \frac{Er(g)}{Er(b)} = \lim_{N\to\infty} \frac{r(N,g)}{r(N,b)} \frac{q(N \mid g)}{q(N \mid b)} > 1 \qquad (34)$$

Assuming the signals are informative ($\gamma, \beta > 1/2$) we have the following.

Taking the limit of (28) and (33) implies

$$\begin{aligned}
\lim_{N\to\infty} \frac{r(N,g)}{r(N,b)} &= 1 \qquad (35) \\
\lim_{N\to\infty} \frac{q(N \mid g)}{q(N \mid b)} &> 1 \qquad (36)
\end{aligned}$$

which completes the proof. ■

B Appendix

Consider now a more general version of the model. In particular, assume that the underwriter is constrained to allocate no more that a fraction $\bar{m} < 1$ of the issue to one investor. A central implication of Benveniste and Spindt is that it is optimal to allocate as few shares as possible to investors who report negative information, and hence as many shares as possible to investors who report positive information. In the present setting, this optimal allocation rule implies that if $n\bar{m} \geq 1$, then only investors who report positive information will be allocated shares, each receiving a fraction $1/n$ of the issue. If $n\bar{m} < 1$, then a fraction $n\bar{m}$ of the issue will be allocated to investors who report positive information, each receiving a fraction $1/\bar{n}$. The remaining shares, $1 - n\bar{m}$, are allocated to investors who report negative information, each receiving a fraction $\left(\frac{1}{N-n}\right)\left(1 - \frac{n}{\bar{n}}\right)$ of the issue. This allocation policy implies a cut-off value for n, denoted $\bar{n}$, such that an investor who reports negative information will be allocated shares only if $n < \bar{n} = 1/\bar{m}$.

The underwriter prices the issue after collecting investors' bids, committing to price the issue so that it is never overpriced *in expectation*. In particular, for the case $n \geq \bar{n}$, the issuer sets a price $p_H(s)$ in order to induce investors with positive private information to report this truthfully. For the case $n < \bar{n}$, the underwriter sets a price $p_n(s) = v(n, s)$, which ensures that investors who report negative information earn zero excess returns, in equilibrium.[26] The pricing $p_H(s)$ for the case $n \geq \hat{n}$ may be interpreted as an upward revision in the offer price relative to the midpoint of the initial range, and similarly the pricing for the case $n < \hat{n}$ as a downward revision.

To find $p_H(s)$, consider first the expected payoff to an investor with positive private information who reports this as negative:

$$\hat{U}(s) = \sum_{n=0}^{\bar{n}-1} \left(\frac{1}{N-n}\right)\left(1 - \frac{n}{\bar{n}}\right) q(n|s, g_I)(v(n+1, s) - v(n, s)) \tag{37}$$

[26] An alternative pricing strategy is to offer a fixed price $p_L(s)$ that, in equilibrium, gives a zero expected return to investors with low bids. It can be shown, however, that this alternative pricing strategy will yield strictly higher incentives to submit low bids for investors with positive information, and hence it will yield higher underpricing. In other words, this alternative pricing strategy is not optimal. Importantly, the main results are unaffected by which of the two pricing strategies are employed.

where

$$q(n|g_I,g)=\binom{N-1}{n}\left(\frac{\gamma^{n+1}(1-\gamma)^{N-1-n}\mu\alpha+(1-\gamma)^{n+1}\gamma^{N-1-n}(1-\mu)(1-\alpha)}{\mu\gamma\alpha+(1-\mu)(1-\gamma)(1-\alpha)}\right) \tag{38}$$

$$q(n|g_I,b)=\binom{N-1}{n}\left(\frac{\gamma^{n+1}(1-\gamma)^{N-1-n}(1-\mu)\alpha+(1-\gamma)^{n+1}\gamma^{N-1-n}\mu(1-\alpha)}{(1-\mu)\gamma\alpha+\mu(1-\gamma)(1-\alpha)}\right) \tag{39}$$

$$v(n,g)=\frac{\gamma^n(1-\gamma)^{N-n}\mu\alpha}{\gamma^n(1-\gamma)^{N-n}\mu\alpha+(1-\gamma)^n\gamma^{N-n}(1-\mu)(1-\alpha)} \tag{40}$$

and

$$v(n+1,g)=\frac{\gamma^n(1-\gamma)^{N-n}\mu\alpha}{\gamma^n(1-\gamma)^{N-n}\mu\alpha+(1-\gamma)^n\gamma^{N-n}(1-\mu)(1-\alpha)}. \tag{41}$$

The expression for $\hat{U}(s)$ reflects the assumption that the underwriter sets a price that fully impounds the information contained in investors' bids whenever $n<\hat{n}$.

Next, we establish the offer price $p_H(s)$ that is needed to induce investors with positive private information to submit 'high' bids. The incentive constraint for such an investor is

$$\sum_{n=\bar{n}-1}^{N-1}\frac{1}{1+n}q(n|g_I,s)(v(n+1,s)-p_H(s))\geq\hat{U}(s). \tag{42}$$

Solving this constraint as an equality with respect to $p_H(s)$ gives

$$p_H(s)=\left(\sum_{n=\bar{n}-1}^{N-1}\frac{1}{1+n}q(n|g_I,s)\right)^{-1}\left(\sum_{n=\bar{n}-1}^{N-1}\frac{1}{1+n}q(n|g_I,s)v(n+1,s)-\hat{U}\right). \tag{43}$$

The expected aftermarket value of the firm conditional on an upward revision in the offer price (i.e., $n\geq\bar{n}$) is given by

$$v_H(s)=\Big(\sum_{n=\bar{n}}^{N}q(n|s)\Big)^{-1}\sum_{n=\bar{n}}^{N}q(n|s)v(n,s). \tag{44}$$

The issue is underpriced if $v_H(s)>p_H(s)$, which obtains whenever $\hat{U}>0$.[27] The initial return

[27] This is seen by noting that $p_H(s)$ may be written as $p_H(s)=v_H(s)-\frac{\hat{U}(s)}{\sum_{n=\bar{n}-1}^{N-1}\frac{1}{1+n}q(n|s)}$ and hence $p_H(s)<v_H(s)$ if (and only if) $\hat{U}(s)>0$.

associated with an upward revision in the offer price is then

$$r(s) = \frac{v_H(s)}{p_H(s)} - 1 \tag{45}$$

and the expected initial return is

$$Er(s) = \sum_{n=\bar{n}}^{N} q(n|s) r(s). \tag{46}$$

In other words, as in the simpler model in the text, the expected initial return $Er(s)$ consists of the probability $\sum_{n=\bar{n}}^{N} q(n|s)$ of an upward revision in the offer price, and the initial return $r(s)$ conditional on this upward revision.

As before, partial adjustment to public information requires that

$$Er(g) > Er(b). \tag{47}$$

The incentive effect and the demand effect imply, respectively, that

$$\frac{r(g)}{r(b)} < 1 \tag{48}$$

and

$$\frac{\sum_{n=\bar{n}}^{N} q(n|g)}{\sum_{n=\bar{n}}^{N} q(n|b)} > 1. \tag{49}$$

It can be shown numerically that this more general version of the model behaves similarly to the simpler model solved analytically in the text. In particular, the incentive effect and the demand effect both hold (unequivocally), and the demand effect dominates the incentive effect to ensure partial adjustment to public information whenever the number of investors is sufficiently large. Finally, the intuition as well as the empirical implications of the effects remain unaltered.

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Table 1: **Mechanism, conditional probability and underpricing across different information sets**

The table shows the intuition for the mechanism generating underpricing (or no underpricing), the conditional probability for the private signal and the required underpricing across different information sets with respect to positive/negative public information and positive/negative private information, respectively.

Public information	**Private information**	**Demand state**	**Mechanism**	**Intuition of the mechanism**	**Under-pricing**
Positive	Positive	High	Incentive effect	Investors are less likely to be allocated shares in the IPO if positive private information is concealed $\Longrightarrow$ less compensation required for truthful revelation of the private signal	Yes (less)
			Demand effect	Probability of positive private signal is greater than if public information is negative	
	Negative	Low	Incentive effect	No incentive to hide negative private information	No
			Demand effect	Probability of negative private signal is smaller than if public information is negative	
Negative	Positive	High	Incentive effect	Investors are more likely to be allocated shares in the IPO if positive private information is concealed $\Longrightarrow$ more compensation required for truthful revelation of the private signal	Yes (more)
			Demand effect	Probability of positive private signal is smaller than if public information is positive	
	Negative	Low	Incentive effect	No incentive to hide negative private information	No
			Demand effect	Probability of negative private signal is greater than if public information is positive	

Table 2: **Sample return characteristics**

The table shows the annual distribution of the sample of 5,093 U.S. IPOs in 1981-2008, and the average first-day return and stock market return by year. The first-day return is $IR1 = p_1/p_0 - 1$, where p_1 is the closing price on the first trading day and p_0 is the offer price, winsorized at 200%. The return on the S&P500 index ($SP500$) is measured over the 45 trading days preceding the issue. Market conditions report the proportion of IPOs that take place in a positive market ($SP500 > 0$) and negative market ($SP500 \leq 0$), respectively. The final column reports the proportion negative first-day returns by year and in total.

Listing year	Sample size (N)	First-day return (IR1)	S&P500 return (SP500)	Market conditions: proportion positive	Market conditions: proportion negative	Proportion $IR1 < 0$
1981	4	3.9%	-1.5%	50.0%	50.0%	25.0%
1982	1	4.7%	1.6%	100.0%		0.0%
1983	14	11.1%	2.5%	71.4%	400.0%	0.0%
1984	10	2.0%	1.9%	40.0%	42.9%	10.0%
1985	46	5.4%	4.0%	78.3%	100.0%	21.7%
1986	207	4.1%	2.6%	70.0%	134.8%	28.0%
1987	194	5.6%	6.3%	88.7%	10.6%	18.0%
1988	72	4.8%	2.0%	63.9%	13.4%	16.7%
1989	58	5.7%	4.4%	72.4%	22.2%	5.2%
1990	69	9.2%	0.3%	60.9%	46.6%	8.7%
1991	226	10.9%	1.4%	58.4%	136.2%	11.1%
1992	305	9.0%	2.1%	66.6%	45.1%	12.8%
1993	417	11.6%	1.4%	82.5%	23.9%	10.3%
1994	324	8.7%	-0.6%	45.1%	42.7%	6.8%
1995	359	20.5%	5.1%	99.7%	0.3%	7.0%
1996	571	15.9%	4.1%	82.1%	28.4%	8.8%
1997	381	14.2%	5.3%	83.7%	10.9%	6.8%
1998	256	20.8%	5.4%	78.9%	14.2%	9.8%
1999	421	63.4%	2.5%	73.2%	44.1%	11.9%
2000	323	53.8%	0.2%	57.9%	32.3%	10.5%
2001	68	14.6%	0.2%	48.5%	10.8%	10.3%
2002	49	8.0%	-3.8%	26.5%	52.9%	18.4%
2003	53	12.7%	4.1%	92.5%	8.2%	15.1%
2004	162	12.2%	1.7%	64.2%	109.4%	19.1%
2005	162	11.7%	1.2%	65.4%	34.6%	22.2%
2006	168	11.4%	2.5%	81.0%	19.8%	20.8%
2007	157	13.3%	2.0%	66.2%	31.5%	24.8%
2008	16	2.4%	-3.3%	50.0%	5.1%	56.3%
Total	5,093	19.2%	2.7%	73.1%	26.9%	12.5%

Table 3: **First-day returns split by positive and negative information**

The table shows the average first-day return, split by positive and negative public information ($SP500$), respectively. The first-day return is $IR1 = p_1/p_0 - 1$, where p_1 is the closing price on the first trading day and p_0 is the offer price, winsorized at 200%. The table shows a further split by the sign of the final revision of the offer price (PU, Panel A), the price revision residual ($Private$, Panel B), and the demand state ($HDS/MDS/LDS$, Panel C). All variables are defined in Table 4. The sample is 5,093 U.S. IPOs, 1981-2008.

Panel A: Price update (PU)

Public information:	Positive ($SP500 > 0$)			Negative ($SP500 \leq 0$)		
Price update:	Positive	Zero	Negative	Positive	Zero	Negative
First-day return (IR1)	34.7%	11.0%	4.6%	42.4%	12.1%	3.5%
Number of cases, N	1788	448	1485	455	168	749
Percent of cases	48%	12%	40%	33%	12%	55%

Panel B: Price update residual ($Private$)

Public information:	Positive ($SP500 > 0$)			Negative ($SP500 \leq 0$)		
Private information:	Positive	Zero	Negative	Positive	Zero	Negative
First-day return (IR1)	36.1%	11.0%	6.0%	37.8%	9.6%	3.5%
Number of cases, N	1681	188	1852	542	98	732
Percent of cases	45%	5%	50%	40%	7%	53%

Panel C: Demand state ($HDS/MDS/LDS$)

Public information:	Positive ($SP500 > 0$)			Negative ($SP500 \leq 0$)		
Demand state:	High	Medium	Low	High	Medium	Low
First-day return (IR1)	37.9%	9.4%	4.5%	47.5%	9.0%	3.5%
Number of cases, N	1577	880	1264	396	320	656
Percent of cases	42%	24%	34%	29%	23%	48%

Table 4: **Variable definitions**

The table shows names and definitions of, and sources for, the variables used in the analysis. Ken French and Jay Ritter refer to their respective data webpages. p_0 is the final offer price, and p_L and p_H are the lower and upper bound, respectively, of the filing range.

Name	Definition	Sources
A: Variables critical for testing the model		
$IR1$	One-day initial return, defined as $IR1 = p_1/p_0 - 1$, where p_1 is the firm's closing price on the first trading day, winsorized at 200%. Proxy for underpricing.	SDC, CRSP
$SP500$	Return on the S&P500 index over the 45 trading days preceding the offer (the book building period). Proxy for public information.	CRSP
PU	Revision in the final offer price from the initial filing range midpoint (price update), defined as $PU = p_0/p_{mid} - 1$, where p_{mid} is the midpoint of the filing range.	SDC
$Private$	The residual (ϵ) from the regression of the price update on the S&P500 return: $PU = \beta * SP500 + \epsilon$, and set to zero when $\lvert\epsilon\rvert < 1\%$. Proxy for private information.	SDC, CRSP
$_{POS}$, $_{NEG}$	The subscript $_{POS}$ and $_{NEG}$ indicate a dummy taking the value of one if the variable is positive and non-positive, respectively.	
HDS	Dummy indicating that the final offer price is above the initial filing range, defined as $p_0 \geq p_H$. Proxy for high demand state.	SDC
MDS	Dummy indicating that the final offer price is within the initial filing range, defined as $p_L < p_0 < p_H$. Proxy for medium demand state.	SDC
LDS	Dummy indicating that the final offer price is below the initial filing range, defined as $p_0 \leq p_L$. Proxy for low demand state.	SDC
B: Control variables		
Age	Log of firm age since the founding year.	Jay Ritter
Primary	Percentage of shares sold in the IPO that are newly issued (primary shares).	SDC
Proceeds	Log of total $ proceeds raised in the IPO.	SDC
Shares	Log of total number of shares sold in the IPO.	SDC
Rank	Average rank of the lead underwriter.	Jay Ritter
HighTech	Dummy indicating that the IPO firm is a high-technology firm.	SDC
Bubble	Dummy indicating that the IPO took place in the period 9/1998-8/2000.	SDC
$NASDAQ$	Dummy indicating that the IPO firm is listed on Nasdaq.	CRSP
$NYSE$	Dummy indicating that the IPO firm is listed on the New York Stock Exchange (NYSE).	CRSP
C: Clustering Variables		
$FF49id$	Fama-French 49 industries.	Ken French

Table 5: **Tests of the incentive effect (I): first-day returns**

Tests of the incentive effect using OLS regressions. The dependent variable is the first-day return ($IR1$). All variables are defined in Table 4. The t-statistics (in parenthesis) use standard errors clustered on Fama-French 49 industry and listing month. +, *, **, and *** denotes significance at the 10%, 5%, 1%, and 0.01% level, respectively. The sample is 5,093 U.S. IPOs in 1981-2008.

	(1)	(2)	(3)	(4)	(5)	(6)
$Private$	0.942***		1.080***	0.812***		0.922***
	(20.96)		(13.47)	(21.78)		(15.28)
$Private * SP500_{POS}$		0.894***	-0.186*		0.778***	-0.144*
		(18.25)	(-2.12)		(18.98)	(-2.17)
$Private * SP500_{NEG}$		1.080***			0.922***	
		(13.47)			(15.28)	
$SP500$	0.410**	0.420**	0.420**	0.531***	0.540***	0.540***
	(2.74)	(2.82)	(2.82)	(4.52)	(4.59)	(4.59)
$SP500_{POS}$	-0.025^{+}	-0.027^{+}	-0.029^{+}	-0.027*	-0.030*	-0.0300*
	(-1.78)	(-1.95)	(-1.95)	(-2.33)	(-2.49)	(-2.49)
Age				-0.010***	-0.010***	-0.010***
				(-3.77)	(-3.76)	(-3.76)
$Primary$				0.035***	0.033**	0.033**
				(3.39)	(3.26)	(3.26)
$Proceeds$				-0.048**	-0.050**	-0.050**
				(-2.92)	(-3.15)	(-3.15)
$Shares$				0.048*	0.051**	0.051**
				(2.54)	(2.78)	(2.78)
$Rank$				0.002^{+}	0.002*	0.002*
				(1.91)	(1.97)	(1.97)
$HighTech$				0.024***	0.025***	0.025***
				(3.92)	(4.07)	(4.07)
$Bubble$				0.142***	0.139***	0.139***
				(4.06)	(3.99)	(3.99)
$Bubble * HighTech$				0.233***	0.233***	0.233***
				(4.81)	(4.82)	(4.82)
$NASDAQ$				0.029*	0.029*	0.029*
				(2.09)	(2.02)	(2.02)
$NYSE$				-0.000	-0.000	-0.000
				(-0.03)	(-0.04)	(-0.04)
$Constant$	0.206***	0.209***	0.209***	0.215**	0.218**	0.218**
	(17.60)	(17.29)	(17.29)	(3.25)	(3.28)	(3.28)
Adjusted R^2	0.366	0.369	0.369	0.497	0.498	0.498

Table 6: **Tests of the incentive effect (II): first-day returns**

Tests of the incentive effect using OLS regressions. The dependent variable is the first-day return ($IR1$). All variables are defined in Table 4. The t-statistics (in parenthesis) use standard errors clustered on Fama-French 49 industry and listing month. +, *, **, and *** denotes significance at the 10%, 5%, 1%, and 0.01% level, respectively. The sample is 5,093 U.S. IPOs in 1981-2008.

	(1)	(2)	(3)	(4)	(5)	(6)
PU	0.941***		1.072***	0.812***		0.917***
	(20.96)		(13.34)	(21.78)		(15.16)
$PU * SP500_{POS}$		0.896***	-0.176*		0.780***	-0.137*
		(18.33)	(-2.01)		(19.02)	(-2.06)
$PU * SP500_{NEG}$		1.072***			0.917***	
		(13.34)			(15.16)	
$SP500_{POS}$	-0.024^{+}	-0.029^{+}	-0.029^{+}	-0.027*	-0.030*	-0.030*
	(-1.73)	(-1.93)	(-1.93)	(-2.28)	(-2.46)	(-2.46)
$SP500$	-0.095	-0.078	-0.078	0.095	0.108	0.108
	(-0.62)	(-0.52)	(-0.52)	(0.80)	(0.90)	(0.90)
Age				-0.010***	-0.010***	-0.010***
				(-3.77)	(-3.75)	(-3.75)
$Primary$				0.035***	0.034**	0.034**
				(3.40)	(3.28)	(3.28)
$Proceeds$				-0.048**	-0.051**	-0.051**
				(-2.93)	(-3.16)	(-3.16)
$Shares$				0.048*	0.051**	0.051**
				(2.55)	(2.79)	(2.79)
$Rank$				0.002^{+}	0.002*	0.002*
				(1.91)	(1.97)	(1.97)
$HighTech$				0.024***	0.025***	0.025***
				(3.92)	(4.07)	(4.07)
$Bubble$				0.142***	0.140***	0.140***
				(4.05)	(4.00)	(4.00)
$Bubble * HighTech$				0.233***	0.233***	0.233***
				(4.81)	(4.81)	(4.81)
$NASDAQ$				0.029*	0.028*	0.028*
				(2.10)	(2.01)	(2.01)
$NYSE$				-0.000	-0.000	-0.000
				(-0.02)	(-0.05)	(-0.05)
$Constant$	0.205***	0.210***	0.210***	0.215**	0.219**	0.219**
	(17.58)	(16.51)	(16.51)	(3.25)	(3.28)	(3.28)
Adjusted R^2	0.366	0.369	0.369	0.497	0.498	0.498

Table 7: **Tests of the incentive effect (III): first-day returns**

Tests of the incentive effect using OLS regressions. The dependent variable is the first-day return ($IR1$). All variables are defined in Table 4. The control variables (not shown here) are the same as in table 5. The t-statistics (in parenthesis) use standard errors clustered on Fama-French 49 industry and listing month. +, *, **, and *** denotes significance at the 10%, 5%, 1%, and 0.01% level, respectively. The sample is 5,093 U.S. IPOs in 1981-2008.

	(1)	(2)	(3)	(4)
$Private$		0.528^{***}		
		(4.58)		
$Private * HDS$	1.034^{***}	0.505^{***}		1.304^{***}
	(15.11)	(3.86)		(12.37)
$Private * MDS$	0.528^{***}		0.660^{***}	0.660^{***}
	(4.58)		(5.85)	(5.85)
$Private * LDS$	0.0531	-0.475^{***}		0.013
	(1.38)	(-4.14)		(0.26)
$Private * HDS * SP500_{POS}$			0.964^{***}	-0.340^{**}
			(13.27)	(-2.99)
$Private * HDS * SP500_{NEG}$			1.304^{***}	
			(12.37)	
$Private * LDS * SP500_{POS}$			0.093^{*}	0.080
			(2.19)	(1.45)
$Private * LDS * SP500_{NEG}$			0.013	
			(0.26)	
HDS	0.041^{***}	0.041^{***}	0.035^{**}	0.035^{**}
	(3.36)	(3.36)	(2.96)	(2.96)
LDS	-0.057^{***}	-0.057^{***}	-0.054^{***}	-0.054^{***}
	(-6.69)	(-6.69)	(-6.34)	(-6.34)
$SP500_{POS}$	-0.028^{*}	-0.028^{*}	0.001	0.001
	(-2.49)	(-2.49)	(0.09)	(0.09)
$SP500$	0.422^{***}	0.422^{***}	0.459^{***}	0.459^{***}
	(3.46)	(3.46)	(3.78)	(3.78)
Control variables:	Yes	Yes	Yes	Yes
Adjusted R^2	0.532	0.532	0.536	0.536

Table 8: **Tests of the demand effect (I): positive first-day returns**

Probit regressions testing for the demand effect. The dependent variable is a dummy for positive first-day returns ($IR1_{POS}$). All variables are defined in Table 4. t-statistics (in parenthesis) are clustered on Fama-French 49 industry and listing month. +, *, **, and *** denotes significance at the 10%, 5%, 1%, and 0.01% level, respectively. The sample is 5,093 U.S. IPOs in 1981-2008.

	(1)	(2)	(3)	(4)	(5)	(6)
$Private$	2.674***	2.661***	2.669***	2.911***	2.863***	2.905***
	(21.64)	(21.79)	(21.63)	(17.85)	(17.83)	(17.82)
$SP500$	3.373***		2.510***	3.700***		2.935***
	(7.59)		(4.08)	(8.27)		(4.72)
$SP500_{POS}$		0.305***	0.123+		0.319***	0.108+
		(6.61)	(1.89)		(6.85)	(1.65)
Age				0.000	-0.001	0.000
				(0.01)	(-0.06)	(0.00)
$Primary$				-0.057	-0.051	-0.057
				(-0.62)	(-0.57)	(-0.62)
$Proceeds$				-0.266**	-0.232**	-0.265**
				(-3.13)	(-2.75)	(-3.12)
$Shares$				0.319**	0.270**	0.317**
				(3.26)	(2.78)	(3.23)
$Rank$				0.011	0.011	0.011
				(1.36)	(1.40)	(1.39)
$HighTech$				0.062	0.071	0.064
				(1.32)	(1.51)	(1.37)
$Bubble$				-0.123	-0.075	-0.116
				(-1.08)	(-0.66)	(-1.02)
$Bubble * HighTech$				0.250+	0.189	0.240+
				(1.74)	(1.31)	(1.66)
$NASDAQ$				0.408***	0.382***	0.403***
				(3.79)	(3.55)	(3.74)
$NYSE$				0.311*	0.300*	0.311*
				(2.45)	(2.36)	(2.44)
$Constant$	0.705***	0.570***	0.639***	0.123	0.140	0.093
	(29.79)	(14.63)	(14.81)	(0.27)	(0.31)	(0.21)
Pseudo R^2	0.119	0.117	0.120	0.127	0.124	0.128

Table 9: **Tests of the demand effect (II): positive first-day returns**

Probit regressions testing for the demand effect. The dependent variable is a dummy for positive first-day returns ($IR1_{POS}$). All variables are defined in Table 4. t-statistics (in parenthesis) are clustered on Fama-French 49 industry and listing month. +, *, **, and *** denotes significance at the 10%, 5%, 1%, and 0.01% level, respectively. The sample is 5,093 U.S. IPOs in 1981-2008.

	(1)	(2)	(3)	(4)	(5)	(6)
PU	2.675^{***}	2.686^{***}	2.670^{***}	2.912^{***}	2.929^{***}	2.907^{***}
	(21.65)	(21.76)	(21.63)	(17.86)	(17.95)	(17.83)
$SP500$	1.954^{***}		1.078^{+}	2.155^{***}		1.376^{*}
	(4.40)		(1.76)	(4.87)		(2.24)
$SP500_{POS}$		0.203^{***}	0.125^{+}		0.209^{***}	0.111^{+}
		(4.36)	(1.93)		(4.48)	(1.69)
Age				0.000216	-0.000247	0.0000519
				(0.01)	(-0.01)	(0.00)
$Primary$				-0.0564	-0.0537	-0.0565
				(-0.62)	(-0.59)	(-0.62)
$Proceeds$				-0.267^{**}	-0.264^{**}	-0.266^{**}
				(-3.14)	(-3.11)	(-3.13)
$Shares$				0.320^{**}	0.311^{**}	0.318^{**}
				(3.27)	(3.17)	(3.24)
$Rank$				0.0105	0.0110	0.0108
				(1.36)	(1.41)	(1.39)
$HighTech$				0.0618	0.0663	0.0641
				(1.32)	(1.41)	(1.37)
$Bubble$				-0.123	-0.0972	-0.116
				(-1.09)	(-0.86)	(-1.02)
$Bubble * HighTech$				0.251^{+}	0.214	0.240^{+}
				(1.74)	(1.49)	(1.67)
$NASDAQ$				0.408^{***}	0.392^{***}	0.403^{***}
				(3.80)	(3.65)	(3.74)
$NYSE$				0.311^{*}	0.306^{*}	0.311^{*}
				(2.45)	(2.40)	(2.44)
$Constant$	0.705^{***}	0.610^{***}	0.638^{***}	0.123	0.127	0.0924
	(29.79)	(15.46)	(14.79)	(0.27)	(0.28)	(0.21)
Pseudo R^2	0.119	0.119	0.120	0.127	0.127	0.128

Table 10: **Tests of the demand effect (III): high- and low-demand state**

Probit regressions testing for the demand effect. The dependent variable is a dummy for the high-demand state (HDS) in columns 1-4, and for the low-demand state (LDS) in columns 5-8. All variables are defined in Table 4. t-statistics (in parenthesis) are clustered on Fama-French 49 industry and listing month. +, *, **, and *** denotes significance at the 10%, 5%, 1%, and 0.01% level, respectively. The sample is 5,093 U.S. IPOs in 1981-2008.

	HDS				LDS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SP500$	3.630***		3.941***		-3.974***		-3.724***	
	(7.01)		(7.86)		(-8.49)		(-7.66)	
$SP500_{POS}$		0.365***		0.380***		-0.358***		-0.324***
		(7.28)		(7.61)		(-8.16)		(-7.04)
Age			-0.0950***	-0.0963***			0.0644**	0.0664**
			(-4.64)	(-4.72)			(3.07)	(3.17)
Primary			-0.0260	-0.0171			0.00303	-0.00116
			(-0.29)	(-0.19)			(0.03)	(-0.01)
Proceeds			2.521***	2.528***			-2.367***	-2.372***
			(23.08)	(23.31)			(-24.62)	(-24.78)
Shares			-2.606***	-2.627***			2.617***	2.633***
			(-21.35)	(-21.66)			(24.18)	(24.45)
Rank			-0.0199*	-0.0186*			0.0310***	0.0300***
			(-2.25)	(-2.11)			(3.60)	(3.50)
HighTech			0.397***	0.406***			-0.190***	-0.196***
			(7.81)	(7.97)			(-3.98)	(-4.09)
Bubble			-0.173	-0.121			0.0412	-0.00982
			(-1.22)	(-0.88)			(0.30)	(-0.07)
*Bubble*HighTech*			0.864***	0.795***			-0.490**	-0.424**
			(5.37)	(5.12)			(-3.11)	(-2.78)
NASDAQ			0.586***	0.559***			-0.316*	-0.283*
			(3.53)	(3.44)			(-2.57)	(-2.33)
NYSE			0.153	0.148			-0.0878	-0.0708
			(0.86)	(0.84)			(-0.63)	(-0.51)
Constant	-0.388***	-0.557***	-5.832***	-5.825***	-0.212***	-0.0548	1.821***	1.768***
	(-13.16)	(-12.17)	(-11.10)	(-11.22)	(-8.50)	(-1.43)	(3.78)	(3.70)
Pseudo R^2	0.013	0.012	0.265	0.263	0.016	0.012	0.220	0.217

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