Strategic Waiting in the IPO Markets∗

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Abstract

The paper analyzes the strategic waiting tendencies of IPO firms. Our model shows why some high-quality firms may strategically delay their initial public offering until a favorable signal about the economic conditions is generated by other issuing firms. Survival analysis suggests that IPOs in the highest quality decile have significantly higher median waiting days (since the start of a rising IPO cycle) than the IPOs in the lowest decile. During the early stages of an expanding IPO cycle the average firm quality is lower than in its later stages. We find supporting evidence also from the IPOs of future S&P 500 firms.

Keywords: IPO clustering, IPO cycles, social learning, strategic waiting, survival analysis

JEL Classification: C41, C72, D82, D83, G30, E32
1. Introduction

The recent activity in the initial public offerings (IPOs) markets has been anemic, and the overall U.S. economy was in recession (e.g., there were only two IPOs issued in the U.S. for the Q4 of 2008). This study analyzes the strategic considerations that affect the timing of the IPO decision in such conditions.\(^1\) It shows how some firms that are about to go public would benefit from strategically delaying their issuance to obtain more information about the current economic conditions. Extra information about economic conditions is valuable, because an IPO during an economic slowdown is more likely to be unsuccessful,\(^2\) causing the firm to lose money and managerial labor.

In the game theoretical model we develop, the economic activity and the IPO market have a potential to improve, but there is uncertainty about when they might do so. No single economic actor knows the aggregate state of the economy to the fullest extent. Even the most informed economic actors, like the National Bureau of Economic Research (NBER) or the FED, cannot confirm a recession or an expansion until after it starts (for example, the latest U.S. recession that started in the fourth quarter of 2007 was confirmed by NBER one year later, in late 2008.). Each individual economic agent, however, has a reliable private signal about the particular part(s) of the economy it specializes on. For example, car dealers receive *timely* information about the demand for cars, realtors about the demand for housing, investment bankers about the desire for new corporate deals, etc. In short, the information is dispersed in the hands of the public (i.e., investors).

When one of the private firms goes public successfully or unsuccessfully, the other actors in the economy obtain new information about the aggregate economic conditions. That is, a

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\(^2\) Lowry (2003), Pastor and Veronesi (2005), and Ivanov and Lewis (2008) document that IPO activity is closely related to the current state of the economy. Our Figure 1 also shows that the periods with the lowest number of IPOs coincide with economic slowdowns. This lack of IPO activity during economic slowdowns indicates a real or perceived risk of failure by the equity sellers. Thus, there is enough evidence to suggest that the private firms believe their IPO’s success to be dependent not only on their own quality, but also on the aggregate state of the economy. This makes the information on the economy valuable for them. Likewise, Choe, et al. (1993) and Korajczyk, et al. (1991) show that the seasoned equity issuances depend on the business cycle.
successful or a failed IPO is the event that helps aggregating this privately held information. If the first IPO fails, it will incur monetary and labor costs. If successful, however, it will draw in many more IPOs,\(^3\) as a result of social learning among firms.\(^4\) In such a game, the informational advantages of delayed issuance (i.e., information externalities) cause the private firms to engage in strategic waiting.\(^5\) This strategic behavior of private firms leads to several interesting outcomes.

Our model explicitly describes the process of endogenously selecting the order of issuance in an improving IPO market based on the quality of the competing firms’ projects. For the first time in the literature, it demonstrates that the higher quality firms do have an incentive to issue later than the lower quality firms. It essentially predicts that the first issuers, the ones that cause the social learning (or the information spillover) wave, do not have to be of the highest quality. Various empirical tests we perform confirm this prediction. This outcome separates our model from the rest of the literature (see Hoffmann-Burchardi (2001) and Alti (2005) for some examples of papers finding or assuming opposite sequencing outcomes).

This study also deals with the literature that explains the IPO clustering. Pastor and Veronesi (2005)’s model relates the IPO clustering to the business cycles. Hoffmann-Burchardi (2001) and Alti (2005), demonstrate theoretically how IPO clustering can occur through information spillovers: early IPOs produce information about the market’s favorable conditions, which in turn originates a wave of new issuances. Our paper, in return, provides a different perspective on the causes of variation in the IPO volume. All the firms in our model have incentives to delay their issuance until the favorable conditions are confirmed by another firm (strategic waiting). When the first successful IPO is observed, everyone will realize that enough IPO investors must have received a positive signal, which can happen only if the true economic

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\(^3\)According to Lowry and Schwert (2002) and Benveniste et al. (2003), the number of new IPOs entering the market is significantly affected by the success (and/or underpricing) of recent and contemporaneous offerings. Lowry and Schwert (2002), in particular, suggest that more positive information revealed during the registration period leads to higher initial returns and higher subsequent IPO activity.

\(^4\)Learning from others’ actions is called social learning in the economics literature. Chamley (2004) and Chamley and Gale (1994) are two well known examples of this literature. Throughout this paper we will use the terms “social learning” and “information spillovers” interchangeably, because we do not see any differences between them in regards to their application to the IPO market.

\(^5\)Hendricks and Kovenock (1989) is one of the first papers in the strategic waiting literature. Such actions are considered “strategic,” because firms wait for each other to act first and bear the costs of generating new information about the market conditions.
state is good. This revelation will lead to convergence of all the opinions toward the truth (information aggregation). As a result, the remaining firms will enter the market en mass, and cause IPO clustering and IPO waves.

The importance of first issuers in revealing information has also been emphasized by several other studies. Within the product market competition framework, Maksimovic and Pichler (2001) and Spiegel and Tookes (2008) emphasize that the first issuers face a dilemma: they do not want to reveal their new know-how to potential entrants into the industry by issuing early, but they need the capital. Benveniste, et al. (2002) propose a model explaining how first IPOs reveal information about the growth opportunities in their industry, and thus trigger a new wave of free-riding firms from the same industry that benefit from this information generation. In their model the firm qualities are ex-ante identical, and the order of moves are exogenously determined. In contrast, in our model, this order is endogenously determined due to strategic competition over who will bear the risks of failure. The quality of the firm determines its order of going public which, in turn, affects when in the cycle its IPO event will take place.

Another relevant strand of the IPO literature started with Ritter (1984), who suggested that the risk composition among IPO firms during “hot issue markets” may be changing. In a related analysis, Yung, et al. (2008) conclude that, due to the opportunistic issuance of some truly bad firms (with negative NPV), the variance of the firm quality composition during hot markets will increase. They make no predictions, however, about the mean of the quality composition, since little is known about the dynamics that affect the number of good and mediocre firms during such periods. Our study, in contrast, shows that the strategic waiting by better quality firms could affect the mean quality composition across the cycle.

The model we propose makes predictions that are in probabilistic terms. It suggests a certain pattern of issuance by attaching probabilities to events. For example, it implies that the probability of lower quality firms issuing first followed by higher quality firms is greater

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6For a more in-depth treatment of information aggregation, see Diamond and Verrecchia (1981), Pesendorfer and Swinkels (1997), and Günay (2008b), among others.

7In an empirical study on German IPOs, Petersen (2007) looks into the within-wave differences of firm characteristics associated with adverse selection costs. He claims that his findings imply the presence of sequential learning among IPOs within a wave. Our study demonstrates the presence of such learning, both theoretically and empirically.
than the probability of the reversed order of issuance. Hence, we are dealing with averages and
generalized patterns. The model does not imply, for example, that good firms will never issue
first. Furthermore, all the firms in our model have valuable projects, albeit of different quality.
The project’s success depends on two factors: the individual firm and the aggregate state of
the economy. Our model can incorporate two forms of uncertainty: asymmetric information
between firms and investors, and uncertainty due to aggregate state of the economy. To achieve
tractability, we first concentrate on the latter form of uncertainty.\textsuperscript{8} Then in the Appendix,
we show that incorporating the asymmetric information into the model does not change the
qualitative outcomes.

We perform several empirical tests to check the model’s predictions. Since we want to
compare various firms’ times of issuance relative to the starting point of the rising IPO cycle,
we use survival (or duration) analysis. In our case “death” or “failure” refers to the IPO event.
We estimate and compare the survival functions of various quality groups. We find that lower-
quality firms are likely to go public, on median, between 28 and 88 days earlier in the cycle
than the higher-quality ones (depending on the technique used to measure quality). We also
report that, on average, firm quality is lower in the early stages of a typical rising IPO cycle in
comparison to the mid-to-late stages of the cycle, suggesting that most high-quality firms wait
for confirmation of the favorable conditions before going public.

The issuance patterns of a special group of successful IPOs, the ones that are later on
included in the S&P 500 index, are also analyzed to determine any strategic waiting tendencies.
We find that the IPOs of future S&P 500 firms like to issue in the mid-stages of an expanding
cycle. These firms are not first to issue even in their own industry, which means that they
prefer to issue during periods of confirmed market heat. As far as we know, this is the first
study to report on issues related to the IPOs of the S&P 500 firms.

At the very minimum, these results imply that the pioneering IPOs in a rising cycle are not
always of the best quality. Another implication of our results is related to the market timing
hypothesis of Baker and Wurgler (2002) and the peaking cash flows hypothesis of Benninga,
et al. (2005). IPO firms’ apparent ability to time the market by issuing predominantly during

\textsuperscript{8}In such a set-up, since the uncertainty is primarily in the aggregate economic state, successful or failed IPOs
in one industry are informative to the firms in another industry.
periods of overvaluation in the equity markets or when their cash flows peak, may occur (par-
tially or fully) due to strategic waiting.\textsuperscript{9} Firms wait for a favorable signal about the aggregate
economic conditions. When there is an exogenous shock that improves the economy and the
first IPO successfully issues, many of them initiate the IPO process, which can last more than
few months.\textsuperscript{10} Thus, by the time they observe the first successful issuance(s) and finish their
own IPO, the stock market is on the rise and their cash flows are higher due to the same
underlying economic shock.

While these arguments suggest that strategic waiting\textsuperscript{11} is a competing hypothesis to the
market and the cash flow timing hypotheses, it can be complementary to them, as well. Waiting
can be a part of the market timing strategy of the private firms. These hypotheses differ in
the reasons for the waiting. Waiting for another firm to generate favorable signal about the
economy, or waiting for the stock market to rise, or waiting for the cash flows to peak? In
short, the hypothesis that the private firms time the stock market is indistinguishable from our
strategic waiting hypothesis.

\section{Strategic Waiting and Real Options}

Strategic waiting behavior of an IPO resembles an action of a firm that is facing a real option
to wait before undertaking an event that is hard to reverse, because of various fixed costs
associated with failure (loss of managerial labor, difficulties in returning to the market in the
future (see Dunbar (1998)), financial fees and expenditures, etc.). Thus, by waiting, the IPO
does improve its chances of success.

The economics literature is abundant with studies that analyze a firm’s option to wait before
undertaking an irreversible investment during the periods of uncertainty. Most relevant to us are

\textsuperscript{9}Schultz (2003) calls this phenomena “pseudo market timing.” He shows that the apparent market timing
ability of IPOs have alternative explanations. Our strategic waiting hypothesis is one of those alternative
explanations.

\textsuperscript{10}For the IPOs in our sample, the separation between the filing date and the issuing date is, on average, 77
days. If we include the period of searching for a lead underwriter (which is not easily measurable) and the
period between “all-hands” meeting and filing with SEC (which typically lasts between 6 to 8 weeks), we can
safely assume that the IPO process lasts longer than one quarter.

\textsuperscript{11}The word “strategic” implies that the firms time their issuance according to other issuers, rather than
according to the stock market level (strategic timing vs. stock market timing).
the theoretical models by Cukierman (1980) and Bernanke (1983), who show how the option to wait can lead to business cycles: if projects are irreversible, uncertainty about economic conditions can lead to depressed current investments,\textsuperscript{12} because waiting for new information is valuable. Similar arguments can be applied to the IPO markets, except that our paper’s emphasis is on the “strategic” or the competitive feature of the waiting: firms compete on who could delay their IPO until the necessary information is generated. This waiting suppresses the current IPO activity, and prolonged stretches with very few IPO events in them are observed. Such periods coincide with the economic slowdowns, because that is when the uncertainty about the IPO market’s conditions are very high, and the private firms’ need to wait for each other is the highest. This strategic waiting will subsequently lead to IPO waves when the information about the first successful IPO is received and the uncertainty is lifted.

Like us, Pastor and Veronesi (2005) also emphasize the IPO firm’s option to delay until the confirmation of the favorable market conditions, but without the “strategic” or competitive aspect to it. They do not focus on the issuance sequence of various IPO quality groups, either. Draho (2000) also analyzes the option to wait in the IPO markets. In his model, IPO firms try to time their issuance according to the difference between the public and the private valuations of the firm. Finally, in a dynamic agency model Philippon and Sannikov (2007) study the option to wait before large investment. The value of this option is driven by the presence of incentive contracts within the firm, and so one of the implications of their model is that moral hazard and agency conflicts can affect the timing of the IPO.

In the next section of the paper we describe our game theory model and its predictions. Section 4 describes our data sources and our sample selection. Section 5 elaborates on the various empirical procedures we employ to test the implications of our model. Section 6 presents the results from the tests, and Section 7 concludes the paper. The Appendix includes the proofs and some extensions of our model that allow for presence of asymmetric information about firm quality or the presence of a social planner).

\textsuperscript{12}Some examples of empirical papers that show the negative relationship between investment and uncertainty are Caballero and Pindyck (1996), Leahy and Whited (1996), and Bulan (2005).
3. The Model

Two private firms, denoted by $j = g, b$, have an investment project that requires an external financing of $K$. The project’s return is a random variable that may be equal to 0 or $X$. The success/return probability of the project $\pi_{ij}$ depends on the aggregate state of the economy $i = G, B$ and the individual quality of the firm, $j = g, b$. When the economy is in a good state, the probability that the return will be $X$ is higher than when it is in a bad state. That is, we have $\pi_{Bj} = 0 < \pi_{Gj}$ for $j = g, b$.\(^{13}\) Also, the individual firm’s quality determines the success probability; a good quality firm will always have a higher success probability than the bad quality firm in a good state; to be more exact, we have $\pi_{Gh} < \pi_{Gg}$. The ex-ante probability that the aggregate state is good or bad is equal to $\frac{1}{2}$.

There is a continuum of atomistic investors with a positive mass of $R$. When the state is good, each investor independently receives a good signal with probability $p > 0.5$ and a bad signal with probability $(1 - p)$. When the state is bad, each one receives a bad signal with probability $p$, and a good signal with probability $(1 - p)$. Note that the signals are correlated with the aggregate state (i.e., the signals are informative since $p > 0.5$), but imperfect since we assume that $p < 1$.\(^{14}\) The following table summarizes the signal structure.

<table>
<thead>
<tr>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good Signal</td>
<td>p</td>
</tr>
<tr>
<td>Bad State</td>
<td>1-p</td>
</tr>
</tbody>
</table>

In this section, we assume that investors and firms are uninformed about the aggregate state, but the individual firm quality is common knowledge.\(^{15}\) Such an assumption helps isolating the effects of aggregate uncertainty on the outcomes, without the convoluting effects of asymmetric

\(^{13}\)As long as, $\pi_{Bj}$ is low enough, our qualitative results will hold. Assuming $\pi_{Bj} = 0$ simplifies our calculations.

\(^{14}\)There are numerous signals generated every day about the conditions in the various parts of the overall economy. These signals include the available information in the markets plus the idiosyncratic or individual experiences about the economic conditions. However, they are imperfect for everybody, including the most informed economic agents, such as the FED or NBER. That is, these signals are unable to definitively reveal the economic state to everybody. Thus, there is a need for an event – which is highly correlated with the economic state – that will help aggregate the dispersed information. Like in our case, Caplin and Leahy (1994) also use similar signal structure that leads to information aggregation.

\(^{15}\)Comparable assumptions are made by others in the literature. Pastor and Veronesi (2005) assume that both the investors and the firms have identical information (see p.1717 of their paper). On the other hand, Alti (2005) assumes that some investors have more information than the firms (see p.1111 of his paper).
information. However, given that asymmetric information is an important part of the IPO markets, in the Appendix, we analyze the case in which firm quality is unknown to the investors i.e., there is asymmetric information between the firms and the investors about each firm’s quality. The model becomes quite cumbersome. With the help of simulations, we show that our predictions with regard to issuance patterns shown in this section are still valid.

We also make the following assumptions, and then discuss how the IPO events aggregate privately held information of the investors; that is, the investors will learn the aggregate state from the success or failure of the IPOs.

**Assumptions:** 1) \((1 - p)R < K\); 2) \(pR > 2K\).

The first assumption guarantees that not enough investors receive a good signal in a bad state. Each investor will receive a good signal with probability \((1 - p)\) in a bad aggregate state. The investors who have the wrong belief/information about the state have a mass of \((1 - p)R\) by the law of large numbers. These optimistic investors’ demand for equity will not be sufficient to buy all \(K\) that the firm is issuing in a bad state. At this stage, the firm will withdraw its IPO. In short, IPO will be unsuccessful. Every investor (or firm) watching the outcome of this event will learn that the state is bad (i.e. agents’ beliefs will converge toward the truth).

The second assumption shows that, in a good state, a mass of \(pR\) investors will receive a good signal, and their demand will be enough for both IPOs. Hence, IPOs will be successful, and everyone will deduct that the aggregate state is good.

We assume that the game continues for 2 periods. A firm \(j = g, b\) will go public by offering a certain percentage of its equity \(\alpha\) in return for \(K\). If a firm goes public and cannot raise (all of) \(K\), then its IPO will be unsuccessful. The firm’s payoff will be \(-\gamma < 0\) from an unsuccessful IPO.

We are looking for a Bayesian Nash equilibrium. In this equilibrium, the (optimistic) investors who receive a good signal will demand the IPO shares in the first period. The ones who

### Footnotes

16. These two assumptions put additional constraint on \(p\), and imply that \(p > \frac{2}{3}\).
17. A continuum of investors are receiving a good signal with probability \((1 - p)\) in a bad state. Hence, an aggregate of \((1 - p)R\) will receive a good signal in a bad state.
18. \(\gamma\) includes financial costs and opportunity costs (such as, loss of managerial labor). Note that this cost is the same for both firms; hence, the outcome of our model do not come from assuming heterogeneous waiting costs for the firms. On the contrary, our results will be robust to even assuming a lower waiting cost for the bad firm. We believe this is easy to see by the experienced reader, so we do not report this robustness result here.
received a bad signal (pessimistic investors) will not buy it unless the state is revealed as good. We will denote the firms’ action of going public in the first period as IPO1, and waiting in the first period with W1. Both firms going public in the first period (IPO1,IPO1) cannot be an equilibrium, since each firm has an incentive to deviate and wait (assuming that unsuccessful IPO’s cost $\gamma$ is not too small). By waiting, the deviating firm will learn the aggregate state from the success/failure of the other firm’s IPO, and it will save a cost of $\gamma$, if the aggregate state turns out to be bad. Thus, deviation is profitable, so this cannot be an equilibrium. On the other hand, both firms waiting (W1,W1) cannot be an equilibrium, either. In that case, firms will not learn the aggregate state. Since waiting is somewhat costly (because of the discount factor, $\delta$; $\delta < 1$) and cost $\gamma$ is not too big, it is better for one of the firms to deviate to IPO1.$^{19,20}$

An alternative equilibrium is the mixed strategy equilibrium, in which firms randomize between IPO1 and W1. Let $m_j$ be firm $j$’s probability of going public in the first period. The following proposition shows the outcome of this mixed Bayesian Nash equilibrium. The details of the firms’ actions and payoffs are explained in the proof, which is in the Appendix.

**Proposition 1** Assume that $(1 - \delta)\pi_{Gg}X - \frac{K}{p} + \delta K < \gamma < \pi_{Gb}X - \frac{K}{p}$. The mixed Bayesian Nash equilibrium for firm $j = g, b$ is

$$m_b = \frac{(\pi_{Gg}X - \frac{K}{p} - \gamma)(1 - \delta)}{\delta (\frac{K}{p} + \gamma - K)}$$ (1)

$$m_g = \frac{(\pi_{Gb}X - \frac{K}{p} - \gamma)(1 - \delta)}{\delta (\frac{K}{p} + \gamma - K)}$$ (2)

$^{19}$We also assume that $\frac{1}{2}(\pi_{Gj}X - \frac{K}{p}) < \frac{1}{2}(\pi_{Gj}X - \frac{K}{p}) + \frac{1}{2}(-\gamma)$; that is, the firm does not find it profitable to lower the IPO’s price (by raising $\alpha$ too much) to sell to the pessimistic investors who received a bad signal.

$^{20}$A relevant argument we need to discuss in our model’s context is this. “Why in a bad state (i.e., when the investor demand is low) the firms do not lower substantially their price to make sure that their IPO is not a failure? Then, they would not need a signal about the economic state, and they can issue at any economic state.” To answer this question let’s consider two important points: 1) Lowering the offer price is costly (i.e., the percentage of shares they need to sell, $\alpha$, is high enough) that firms will still find it valuable to wait for information. So the strategic competition will still take place, with the same outcomes, because of this value of the signal. 2) However, this does not mean that pricing ability of the firms is ignored in our model. In the Appendix D (see also footnote 44), we emphasize that $\alpha$ is endogenously determined in our model, which implies that lowering $\alpha$ is part of the “tools” available for the firms in the strategic competition environment we are considering.
We are interested in the relation between the quality of firm $\pi_{Gj}$ and the probability of going public in the first period $m_j$.

**Corollary 2** The good quality firm is more likely to go public in the second period.

**Proof:** From Equations 3 and 4, we see that $m_g < m_b$ iff $\pi_{Gg} > \pi_{Gb}$. The latter is true by assumption. ■

In proposition ???, we have an assumption which makes the reputation cost big enough for both firms. Otherwise, the game will have trivial pure equilibria. In one of these equilibria, when $(1 - \delta)\pi_{Gj}X - \frac{K}{p} + \delta K > \gamma$ both firms will simultaneously go public in the first period, because the costs of failure are extremely small. In another equilibria, when $(1 - \delta)\pi_{Gg}X - \frac{K}{p} + \delta K > \gamma > (1 - \delta)\pi_{Gb}X - \frac{K}{p} + \delta K$ (i.e., if the reputation cost relative to the payoff from going public in the first period is big enough for the bad firm but small enough for the good firm), the good firm will always go public in the first period and the bad firm will always go public in the second period. However, Dunbar (1998) shows that costs of failure in the IPO markets are substantial for all firms, thus such cases are of little practical importance.

So, the reputation costs are substantial for both types of firms, which leads to mixed strategy equilibrium. Since firms use mixed strategy, the outcomes will be probabilistic. We summarize the outcomes (and their probabilities) in the following corollary.

**Corollary 3** Assuming that the revealed state is good:

a) The probability that only firm $b$ goes public in the first period and that firm $g$ goes public in the second period is $m_b(1 - m_g)$.

b) The probability that only firm $g$ goes public in the first period and that firm $b$ goes public in the second period is $m_g(1 - m_b)$.

c) The probability of both, firm $g$ and firm $b$, going public in the first period is $m_gm_b$.

d) The probability that neither firm goes public in the first period is $(1 - m_g)(1 - m_b)$.

The proof is straightforward by using the equilibrium behavior described in Proposition 1. Note that, since $m_g < m_b$, it is clear that the outcome (or issuance sequence) described in a) is more likely than the one described in b).
We have already shown that the bad firm is more likely to go public in the first period (see Corollary 2). Good firm will follow in the second period. Part a) of Corollary 3 gives the probability of this issuance sequence. The emphasis of the corollary is that the other outcomes are also possible. Namely, the good firm may go public in the first period followed by the bad firm in the second period (part b), both type of firms may go public in the first period (part c), or neither of the firms will go public in the first period (part d).

Part d) of the corollary has a testable implication. It shows that there is a nonzero probability of neither firm issuing in the first period. As a result of their mixed strategy, both firms may end up waiting for each other for a long time before going public. This means that there will be periods (mostly during economic slowdowns) when we could observe many days and weeks without having an IPO event. While there may be other explanations for this phenomenon (for example, during slowdowns demand for new equity may be low due to increased risk averseness or due to investor sentiment (Derrien, 2005) of the investors), our model describes it from the perspective of the rational equity suppliers. We essentially show that the prolonged stretches of low IPO activity can be explained with strategic waiting, as well.

Note that we have kept the above model as parsimonious as possible to keep the focus on our core arguments. One can extend the mode to include 1) three quality types (good, medium, and bad); 2) two quality types, but with many firms in each type ($N$ good firms and $M$ bad firms); 3) the case when one of the firms has negative NPV; 4) the case when there is asymmetric information between the investors and the firms; or 5) the case when there is an all powerful underwriter (or a social planner). Extensions 1) and 2) are available from the authors, and extensions 3), 4), and 5) are presented in the Appendix.

3.1. Numerical Example

Below, we give a numerical example to demonstrate the main points of our model. Note how the price of the IPO firm is endogenously determined in the model, implying that lowering its price is part of the firm’s strategy (see also footnote 20 and footnote 42).

Let’s assume that the firms want to raise 6 ($K = 6$) for a project that can return 100 ($X = 100$) in a good state. The success probabilities of good and bad firms in a good state are
\[ \pi_{G_g} = \frac{3}{4} \text{ and } \pi_{G_b} = \frac{1}{4}, \] respectively. The signal strength is \( p = \frac{4}{5} \).

Concentrate on the good quality firm. If this firm wants to raise 6, then it should sell \( \alpha \) per cent of the company to the investors. The investors who received a good signal will ask for an \( \alpha \) share of the company such that \( \alpha \frac{\pi_{G_g}}{3} \frac{100}{4} = 6 \) (that is \( \alpha p \pi_{G_g} X = K \)) should hold (see the proof in the Appendix for more details on the exact formula). This gives \( \alpha = 0.1 \). If the parameters change, so would \( \alpha \). For instance, if the signal’s strength is lower (i.e., there is high number of pessimistic investors), \( \alpha \) will increase, accordingly.

In our example, if we assume that \( \delta = 0.9 \), we can find the reputation cost \( \gamma \) that will satisfy the assumption of the proposition which is \((1 - \delta)\pi_{G_g} X - \frac{K}{p} + \delta K < \gamma < \pi_{G_b} X - \frac{K}{p} \).

\[
0.1 \frac{3}{4} \frac{100}{4} - \frac{6}{0.8} + (0.9)(6) < \gamma < \frac{1}{4} \frac{100}{4} - \frac{6}{0.8}
\]

\[ 5.4 < \gamma < 17.5 \]

Any gamma in the defined range will satisfy our assumption. Let’s pick \( \gamma = 7 \) and calculate the firm’s expected payoff. The mixed strategy payoff must be equal to the payoff from going public in the first (or the second period) with certainty (check the appendix, for more details on the mixed strategy equilibrium). We can use this to calculate the equilibrium payoff which is:

\[
\frac{1}{2} \{ (0.9)(100) \frac{3}{4} - 7 \} = 31.75
\]

In footnote 19, we explain that the firm can not lower the price indiscriminately (as long as the parameters are within reasonable range) in order to sell to all the investors, with good and bad signal. Such an action will require lowering its offer price (i.e., increasing \( \alpha \)) so much (in order to avoid the costs of failure) that its payoff actually becomes less than $31.75. To show this, let’s calculate the payoff from using such a price-lowering strategy. Pessimistic investors will buy only if \( \alpha \frac{13}{5} \frac{100}{4} = 6 \) holds. This gives \( \alpha = .4 \). That is, the firm now should sell 40 percent of the company. Then, the payoff for the firm is:
\( (1 - \alpha)X \pi_{Gg} \frac{1}{2} = 0.6(100) \frac{3}{4} = 30 \)

Hence, a rational firm will not find it profitable to lower \( \alpha \) substantially to sell to the investors who received the bad signal. Instead, in such situations, it has an incentive to wait for confirmation of the market conditions. That is, the mixed strategy described in the equilibrium in the previous subsection becomes dominant strategy over price-lowering, and thus, the firms will wait with positive probability as shown in the proposition above.

Note that, for the above parameters, the bad quality firm will go public in the first period with an approximate probability of 0.8 and the good quality firm will go public with an approximate probability of 0.15.

### 3.2. Testable Predictions

Our model has three testable predictions:

**Prediction 1**: It is more likely that, as a new rising IPO cycle starts, lower quality firms will issue ahead of the higher quality firms. Thus, these lower quality firms are more likely to go public in the earlier periods of the new expanding cycle (Corollary 2).

Prediction 1 is a novel one, and our study analyzes it for the first time in the literature. Thus, the testing of this prediction will be the emphasis of our empirical analysis.

Note that this prediction does not suggest that truly bad firms (i.e., firms with negative expected NPV) will issue first. Its emphasis is on the issuance order of the firms with smaller, but positive, expected NPVs relative to the “best” IPOs. As we show in the Appendix, the truly low quality firms can only issue during periods when the state is confirmed to be good in the second period, because their expected payoff from issuing during uncertain periods is so low that it does not overcome the risks of the IPO.

**Prediction 2**: During economic slowdowns (i.e. periods of elevated aggregate uncertainty), there will be fewer IPO events (Corollary 3d).

This last prediction has been tested before (see Lowry, 2003; and Pastor and Veronesi, 2005, for instance). It is based on our model’s insight that even if projects arrive randomly, the private firms will not issue immediately, but they will wait for more favorable signals about the
economic conditions. When the economy is in recession, their projects are worth less ($\pi_{Bj}$ is smaller than $\pi_{Gj}$), and the chances that their IPO will be unsuccessful are higher (not enough investors receive a “buy” signal). The private firms will delay their issuance during such periods, because they have been “learning” about these conditions from the recently failed IPOs.

It is possible to generalize our model to cases where there are more than two firms (proofs available from the authors). In this case, our model has an implication related to IPO clustering, as well.

**Prediction 3.** IPO issuances will tend to cluster in certain periods.

The first successful IPO will reveal to all the remaining firms that the aggregate state is good. As a result, all the firms with valuable projects will enter the IPO market en masse, because waiting is no longer optimal for any firm (it has a cost). Furthermore, in the periods that follow, any private firm that discovers a new profitable project will issue immediately (without waiting), because the aggregate state is known to be good. This process will continue until the rising IPO cycle ends.

Prediction 3 has been the focus of several theoretical studies (see Hoffmann-Burchardi, 2001; Benveniste, et al., 2002; and Alti, 2005). From an empirical stand point, our Figure 1 makes it obvious that there are periods of intense IPO clustering. So we will not focus our attention on analyzing this prediction any further. However, it is important to note that our model provides a previously unexplored explanation to the IPO clustering phenomenon. Namely, learning through information aggregation can lead to such clustering.

**A forecast:** In our model the “game” starts when the IPO market is very slow or completely shut down. Therefore, our paper has a specific, and very timely, prognosis of the type of firms that will issue when the current trough of the IPO cycle is replaced by the expanding stage. As the new IPO cycle starts to form from the current, extremely low levels of activity, it is probabilistically more likely that mediocre firms (low quality, but with positive NPV) will dominate the pioneering cohort of issuers. The really high-quality firms (say future S&P 500 firms) will likely issue in the later, confirmed, stages of the rising cycle. The lowest quality ones (with negative NPV) will issue even later, when it is close to the top of the cycle (see the Appendix for more details).
4. Data

Next, we provide some details about our data sources and our sample selection process.\textsuperscript{21}

4.1. The IPO Sample

To construct our sample of initial public offerings (IPOs) we apply the following sample selection criteria. We extract all the IPOs between 1973 and 2007 included in the Securities Data Company (SDC)’s database (Pre-1973 coverage of IPO events by SDC is not that reliable. See Gompers and Lerner (2003).). After eliminating REITs, closed-end funds, ADRs, unit offers, and MLPs, there are 9,676 common stock IPOs left in the sample. We do not exclude IPOs with offer price less than $5, because such screening will eliminate disproportionately more low quality firms, which can bias our results. Since our analysis relies on market trading data, we drop out any IPO that does not have data in CRSP weekly or monthly files. We are left with 8,593 distinct IPO events in the SDC sample.

For the period between 1975 to 1984, we also use Jay Ritter’s hand collected data – obtained from his webpage – to append our SDC sample. Again, we are interested only in CRSP listed, common stock, and firm-commitment IPOs. There are 361 such firms that are not covered by the SDC data. Another data source we rely on is Registered Offering Statistics (ROS)\textsuperscript{22} dataset to find common stock, firm-commitment, and CRSP listed IPO firms not reported in any of

\textsuperscript{21}Ideally, to test our hypothesis, we would use the universe of all the private firms that could go public at each point in time, but such a sample is unavailable to us. However, using the sample of observable IPO events – which is very commonly used in the IPO literature for testing various IPO hypotheses – is not a bad alternative for three reasons. First, since nobody knows the quality distribution of private firms that can go public at any point in time, it can be assumed that it is normally distributed (by Central Limit Theorem). Hence, one should expect to see an evenly split sample of higher quality and lower quality private firms going public at a given point in time; assuming there are no other effects changing this composition. Our tests clearly show that, on average, relatively more high quality firms go public in the mid-to-late stages of the rising cycles than in its starting stage. Therefore, there must be an external factor that changes this composition, and we claim that it is the strategic waiting by the higher quality firms. Second, it is not unrealistic to assume that sooner or later (almost) all the firms that could have gone public (i.e., had a good project with positive NPV) do ultimately go public, because waiting too long is costly. Thus, (almost) all such private firms do eventually show up in our IPO sample. Third, the effect of those private firms that do not show up in our IPO sample will be minimal, and it will be averaged out, since we are averaging across the cycles and within firm quality groups. So, just like in any statistical inference, we rely on the law of large numbers.

\textsuperscript{22}This dataset is created by compiling the records of the Securities and Exchange Commission (SEC) from January 1970 through December 1988 in regards to the effective registrations of domestic business and foreign government securities under the Securities Act of 1933.
our previous sources. We find 59 such IPOs. Thus, our combined initial sample is 9,013 IPOs.

In some instances CRSP does not have trading data for the months immediately following the issuance of the new public firm. Also, for various reasons CRSP may stop coverage of some firms. In those cases, the missing return observations are replaced with CRSP value-weighted index’s return. As recommended by Barber, Lyon, and Tsai (1999), such missing return observations are replaced with CRSP value-weighted index’s return.

In a robustness test, instead of replacing the missing returns, we assume that all the firms that match with CRSP, but have too many missing observations, are of lowest quality (decile 1). In most instances these firms are the ones that get delisted from CRSP due to inability to meet the exchange standards. Then, we perform the same tests as below. Our results are qualitatively unchanged, suggesting that such a sample selection problem has a minimal impact on them.

The IPO data items we retrieve from SDC, Ritter, and ROS data files are the CUSIP of the firm, the date of the issue, its total assets at the time of issuance, its industry classification (at 2- and 3-digit SIC level), its offer price, its underpricing, total proceeds it raised, and its founding year used to calculate its age at the time of issuance. The monthly trading data of our sampled IPO firms are obtained from CRSP. The accounting data is from COMPUSTAT.

4.2. The S&P 500 Sample

For some of our tests we need to determine which of our sampled IPOs end up being listed in the prestigious S&P 500 index. These are the most successful IPO firms and thus, the ones that are most likely to engage in strategic waiting. For that purpose we identify all the firms that were part of the S&P 500 index for each year between 1973 and 2007. We use the dataset

\footnote{If it is missing, we use assets from COMPUSTAT for the first quarter after the issuance.}

\footnote{We calculate this variable in two different ways: 1) using the first-day return data available from SDC and 2) using CRSP daily data. For the calculations in 2), we essentially retrieve the closing price for the first trading date of the firm. When the first trading date in CRSP does not match the issuance date in SDC, we use the earliest date with nonmissing price data that is at most three days separated from the issuance date; otherwise, we leave the observation empty. In the instances when both the underpricing from SDC and the underpricing from CRSP are available, we use the later one, because we consider the CRSP data to be more reliable.}

\footnote{For further information on this variable, we also rely on Field-Ritter dataset of company founding dates, as used in Field and Karpoff (2002) and Loughran and Ritter (2004). When we see inconsistencies between this data and our main data sources, we rely on the former.}
available through Wharton Research Data Services (WRDS) that lists the historic S&P 500 Index constituents. We hand check this data to assure that the name of the firm matches with its correct CUSIP in COMPUSTAT and correct PERMNO in CRSP. According to this dataset, in December of every year between 1973 and 2007 there are exactly 500 firms listed in the S&P 500 index. During 1973-2007 period, total of 771 firms (with distinct CUSIPs) were added to this index. When we match these firms with the above IPO sample, we identify 219 IPO firms that ultimately became part of the S&P 500 index.

5. Testing Procedures

In this section, we set up our testing procedure. These empirical set-ups are designed to test the main prediction of our model, which is that in a rising IPO cycle the best firms can afford to wait until the market’s heat is confirmed. Multiple empirical set-ups are created to triangulate the results, and to avoid any criticism that any particular test may be biased.

5.1. Rising IPO Cycle

The model describes the behavior of private firms around the time when the IPO market starts to heat up i.e., model’s predictions are primarily related to the periods when the IPO cycle is rising. Thus, as a first step, we need to identify the periods of rising IPO activity.

We use the number of IPOs in each quarter as our most relevant measure of market heat.\textsuperscript{26} The aggregate issuance data is from Jay Ritter’s website. It includes the number of IPOs and the equally-weighted underpricing of these offerings in each month going back to 1960. Converting this data into quarterly observations is straightforward.

We first take the moving average MA(4)\textsuperscript{27} of the quarterly IPO issuance observations. Then, we identify a rising IPO cycle as the period when this MA(4) has risen for at least three back-to-back quarters of positive growth in such nonresidential investment activity, and we find that on average the low-quality firms lead the high-quality ones by one to three months (the difference is significant at 5% level). These results are available upon request.

\textsuperscript{26}One can also use alternative measures of market heat, such as the growth rate in real private nonresidential investment (see Lowry (2003), Pastor and Veronesi (2005), and Yung, et al. (2008)). We have done our survival analysis tests using this measure of investment activity, where a rising cycle is defined as at least three back-to-back quarters of positive growth in such nonresidential investment activity, and we find that on average the low-quality firms lead the high-quality ones by one to three months (the difference is significant at 5% level). These results are available upon request.

\textsuperscript{27}There are about 40% fewer IPOs issued in the 1st quarter of the calendar year than in its 4th quarter. MA(4) controls for this seasonality effect.
back quarters. Figure 1 shows the plot of the quarterly IPO activity and its 4-quarter moving average. According to the above definition, there are twelve rising (or expanding) cycles between 1970 and 2007. A typical rising cycle lasts between 5 to 7 quarters (7 of the 11 rising cycles are such), but we have three expanding cycles that lasted only 3 or 4 quarters, and one that lasted 14 quarters (between 78/2 and 81/3).

Also, we perform the following robustness test on an alternatively defined “rising cycle.” We eliminate any cycle that does not have its trough (i.e., its starting point) below the historical average of the quarterly IPO events (again, we use the above described time series on IPO volume that goes back to 1960s.). Rising cycles that have their lower turning point (i.e., their troughs) very high up may not represent the true spirit of a “slow” IPO market, which is when our model predicts that strategic waiting would be most valuable. There are three cycles that fit this description: 85/3 – 87/1, 93/3 – 94/2, and 95/3 – 96/4. See Figure 1 and Table 1 for reference. After eliminating the IPOs that were issued in these three rising cycles, we perform our main tests (see below) on the IPOs issued in the remaining eight rising cycles. Our qualitative conclusions still hold. Results available from the authors.

5.2. Location on the Rising Cycle

Our model’s main prediction is related to the issuance order of IPOs with different qualities. One way to test this prediction is by determining whether the firms going public in the early parts of a rising cycle are of different quality from the ones issuing in the later parts of it.

After identifying each rising cycle, we rank the quarters (or in some instances the months) within each cycle as the $1^{st}$, $2^{nd}$, ..., $n^{th}$ quarter/month since the beginning of the rise. As noted earlier, there is only one incidence when the quarter count reaches 8 or above. So, to avoid any results that are driven only by a single cycle, we do not consider the quarters (months) that are located beyond the $7^{th}$ quarter ($21^{st}$ month).\footnote{It is interesting to note that, the most intense quarter of the rising cycles (in terms of the number of issues) is the $4^{th}$ quarter.}
5.3. Firm Quality

How do we determine an IPO firm’s quality? There are various measures used by the literature, but the one that is most relevant to us is the long-run return performance of the firm after issuance. Long-run returns should reflect most of the quality components (investment opportunities, operating efficiency, profitability, etc.) of a firm. So, we use the 3-year and 5-year post issuance performance of IPO firms, as an *ex post* measure of their quality.29 As a robustness check, we employ two other indicators of quality: 1) average cash flows the firm generates within 3 (or 5) years after issuance, and 2) Standard&Poor’s Index Committee’s judgment on which firm is good enough to be a part of the S&P 500 index.

To calculate a firm’s long-run return, we use the market adjusted model. Namely, let $R_{jt}$ represent firm $j$’s stock return (with dividends) for month $t$. The abnormal return is $AR_{jt} = R_{jt} - R_{mt}$, where $R_{mt}$ returns are represented by the contemporaneous return on the CRSP equally-weighted market index (with dividends).

Firm $j$’s cumulative abnormal return (CAR) and buy-and-hold abnormal return (BHAR) across $T$ periods are defined as

$$CAR_{jt} = \sum_{t=1}^{T} AR_{jt}$$

$$BHAR_{jT} = \prod_{t=1}^{T} (1 + R_{jt}) - \prod_{t=1}^{T} (1 + R_{mt}).$$

Using their long-run returns, we sort all the firms issued during rising cycles into quality deciles. Firms with the best post-issuance performance are in decile 10 and the worst ones are in decile 1. Sorting into deciles within each rising cycle separately, makes little difference in our results.

5.4. Survival Analysis

Some of our empirical tests rely on survival or duration analysis, which is commonly used to model time to event data. In our case the event is, of course, the initial public offering. Survival

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29 According to Helwege and Liang (2004), the *ex-ante* measures of quality are not very reliable, so we refrain from using them.
time refers to the timespan between the beginning of an up cycle and the date the firm goes public (measured in days). The beginning of an up cycle is considered to be the first day of the first quarter of a rising cycle.\footnote{This date may seem a little arbitrarily chosen – empirically it is very difficult to pinpoint a particular day when an expanding IPO cycle starts. For our purposes the most important thing is to pick a starting point. We compare all the following issuance dates \textit{relative} to it.}

Many studies in financial economics have used survival functions (or the corresponding hazard rates) in their analysis (see Whited, 2006, for a recent example). While there are many ways to estimate survival functions and the corresponding hazard rates, the most appropriate technique in our case is the Kaplan-Meier (KM)’s nonparametric method. KM produces an estimate of survival function without having to specify the distribution of lifetimes.

KM defines an estimate of survival function as follows. Let there be a total of \(k\) IPO events in the sample. The event times are denoted with \(t_1 \leq t_2 \leq \ldots \leq t_k\). Let \(m_i\) represent the number of firms that go public at time \(t_i\), where \(i = 1, 2, \ldots, k\). Let \(n_i\) be the number of firms that are yet to go public (i.e. all the firms in the analyzed sample that will go public after \(t_i\)). The KM estimate of the survival function at \(t_i\) is the cumulative product

\[
\hat{S}(t_i) = \prod_{j=1}^{i} \left(1 - \frac{m_j}{n_j}\right)
\]

\(\hat{S}(t_i)\) is a right-continuous step function with jumps in the event times (i.e., the events at \(t_i\) are included in the estimate of \(S(t_i)\)). In our case we have no censored data. All the firms in our sample ultimately end up going public. So, the number of events is equal to the number of firms.

6. Results

This section presents the results from the above described testing setups.

6.1. Descriptive Statistics of the Cycles

Before we proceed with our empirical tests, we first describe the cycles in terms of various IPO features. Table 1 shows the start and the end of each cycle, its duration, the total number of
IPOs that went public in it, and what percentage of these IPOs had positive 5-year returns (BHAR or CAR). Other IPO characteristics of the firms issued in these cycles are also displayed for reference: the mean returns (BHAR and CAR), mean and median underpricing, mean and median proceeds (in year 2000 dollars\textsuperscript{31}), mean and median age, and mean and median size (measured by total assets just before or just after the issuance converted to year 2000 dollars).

An immediate observation from the table is the huge difference in the total number of IPOs issued in each cycle. For example, even though the expanding cycle of 95/3 – 96/4 lasted only for six quarters, it had 1,044 firms go public in it. Other cycles with comparable length had far fewer IPO issuances. The up cycle of 03/3 – 05/1, for instance, lasted seven quarters, but had one-third of the number of IPOs in it. Similar, but less striking, results can be found across the contracting IPO cycles. These findings suggest that the length of the cycle does not necessarily imply more IPO activity (the Spearman correlation between the length of the cycle in quarters and the number of firms in it is 0.13 for the rising IPO cycles and 0.19 for the declining IPO cycles, and both are insignificant at 10% level.)

As expected, there are more IPO activity taking place in the rising cycles than in the declining cycles. On average, 499 IPOs go public in a rising cycle vs. 321 in a falling cycle. Note that, we had equal number of rising and falling cycles during 1973-2007 period, which is 11.

Across the rising cycles (and to a lesser extent across the falling cycles) we see major variation in both the long-run (5-yr BHARs and CARs) and the first-day returns (underpricing). Similar observations can be made about other IPO characteristics in the table. The main conclusion from this table is that the expanding cycles – which are the focus of this paper – can be very different from each other in terms of the IPO features. For example, the two most notable expanding cycles with strikingly different IPO characteristics are the 75/3 – 76/4 and the 99/2 – 00/1 cycles. While the former cycle features IPOs that are older, less-underpriced, and of better quality (as captured by larger percentage of IPOs with positive long-run returns or by the higher mean long-run returns), the latter one has the opposite features.

The sub-sections that follow present our empirical results, which are averaged across the

\textsuperscript{31}For this purpose we use monthly CPI data obtained from Bureau of Labor Statistics website.
rising cycles. Performing the tests separately for each cycle would be tedious and too over-
whelming for this paper. While analyzing each of the eleven cycles separately could lead to
interesting insights, our focus is on our model’s implications.\textsuperscript{32} The prediction(s) of our model
are general and in probabilistic terms, and thus we have to deal with cross-cyclical averages
and general patterns. The fact that our hypothesis of IPOs engaging in strategic waiting holds
across cycles of such diverse nature should be considered as a testament to its strength.\textsuperscript{33}

6.2. Survival Analysis of the IPO Quality Groups

As the first test of our hypothesis, we estimate (using the KM method described above) the
survival functions of each IPO quality group. Then, we compare them to find out which quality
group “survives” longer (i.e. issues later in the rising cycle). This survival analysis is the most
direct test of our hypothesis.

As our “high-quality” (“low-quality”) group we take the IPOs that are in the top (bottom)
performance decile measured either with BHAR or CAR (3- or 5-year time horizon).\textsuperscript{34} Figure
2A plots the estimated survival functions of high- and low-quality IPO sub-samples when 3-
year BHARs are used to rank the firms.\textsuperscript{35} The survival function for high-quality IPOs is
consistently above the survival function of low-quality IPOs, which implies that high-quality
firms wait longer after the start of the rising cycle before enacting an IPO event. Figures 2B-2D
show the same plot for 5-year BHAR, 3-year CAR, and 5-year CAR, correspondingly.

Table 2 presents the mean and the median survival days of each quality sub-sample. The
Log Rank and the Wilcoxon nonparametric tests for the null hypothesis of identical survival
curves across these quality sub-samples are also presented. As we can see from the table, all
of the tests reject (at 5\% significance level) this null hypothesis, in favor of lower quality IPOs

\textsuperscript{32} We would gladly present the results for each cycle separately to any interested reader
\textsuperscript{33} In unreported results, we performed our analyses by removing each cycle one at a time, and run our tests.
The main conclusions still hold.
\textsuperscript{34} Alternatively, we define as high quality the IPOs with positive long-run returns. The rest of the IPOs are
low quality. The qualitative conclusions are unchanged.
\textsuperscript{35} We truncated the number of days at 640 (or 7-quarters), because as noted earlier, we have only one incidence
of an up cycle lasting beyond 7 quarters. Inclusion of the days beyond 640 would make the analysis dependent
on a particular cycle, which is not our goal. We should not that the results when such a truncation is not
performed still hold, but they create a discontinuity in the survival functions, which could be confusing for the
reader. These results are available upon request.
issuing one-to-three months earlier (on median). The mean/median waiting days of the firms from all quality deciles, not only the highest and the lowest ones, are available from the authors.

6.3. Average IPO Quality Across The Rising Cycle

After sequencing the months of an up cycle the way described earlier, we check the average quality of the firms in each month. Our proxies for quality are 3-year and 5-year return measures (CARs or BHARs). For this test we use months instead of quarters, because for monthly quality averages provide a more refined information on the quality composition along the rising cycle. We will use these refined data points to run a simple OLS regression of quality vs. time trend. Table 3 shows the mean IPO quality for each month of the rising cycle (averaged across the rising cycles). Again, we stop the count at the 21st month (7th quarter), because, as explained earlier, only one rising cycle lasts longer than that.

Figures 3A and 3B plot the MA(6) of the mean quality of issuing firms in each month. Taking the moving average (MA(6)) helps with graphically observing the secular trend across the cycle. It is noticeable that, the average IPO quality is generally higher in the later stages of the cycle than in its early parts. Of course, we are dealing with averages and generalized patterns, here. We are not claiming that each consecutive month should have higher mean quality. For us, the only important thing is to show that good firms tend to avoid issuing in the early stages of the cycle, which seems to be reflected by the graph. This is more easily seen using the coefficient estimates from a simple OLS regression of the corresponding quality measure on the time trend (see the bottom part of Table 3). All four of them are positive, and with the exception of one, all are significant at 5% level. The coefficient for 5-year BHARs is significant at 10% level. In short, as the cycle is rising, and the certainty on the favorable issuance environment increases, the mean IPO quality improves, as well.

In unreported results, we find that the 4th – 6th quarters of the rising cycle are the ones that have the highest percentage of IPOs with positive post-issuance returns (3-to-5 year CARs and BHARs).

As we explained in Section 2.1, and proved in the Appendix, it is possible that during the mid-to-late stages of a rising cycle there are some extremely bad quality firms with negative
expected NPV going public. The results above show that the quantity of these IPOs is apparently not enough to substantially lower the mean quality of all IPOs going public during these periods. However, such truly bad quality firms can, and do, influence the variance in the quality composition during hot IPO markets (see Yung, et al. (2008) and Lowry, et al. (2010)).

6.4. Evidence from S&P 500 Firms

Next, we investigate when in the rising IPO cycle, the future S&P 500 firms prefer to go public. The IPOs that are later on included in the S&P 500 index are special group of very successful IPOs. Not only that they provide an alternative testing group for our hypothesis, but also they are an interesting sub-sample of IPOs that no study we know of has focused on before. If our theory is correct, these are the firms that can afford to engage in strategic waiting the most.

As mentioned earlier, there are 219 IPOs issued between 1973 and 2007 that were subsequently listed in the S&P 500 index. Of these IPOs, 130 (or 59%) are issued during a rising IPO cycle. Using this sample of 130 S&P 500 firms, we perform two tests. In the first test we check how many of these firms are issued in each location (or quarter) of a rising cycle. 11 IPOs are issued in quarters (8 through 14), so we exclude them from the sample for this test. They represent the exception: they belong to the only cycle that lasted more than 7 quarters. Thus, we focus our analysis on 119 IPOs that were issued in a quarter located from the 1st in line to the last (7th) in line of a rising cycle.

Table 4 presents some of the results from the tests associated with this IPO subsample. In comparison to the first quarter, the mean number of firms per cycle per location is much higher for quarters 2 through 5. The mean issuance jumps from 2.57 in the first quarter to 3.67 in the fifth quarter: a 43% jump. Similarly, we have a total of 26 IPOs issued in the fourth quarter, which is 44% higher than the corresponding number in the first quarter, 18. This is despite the fact that, by definition, not all of our rising cycles has to last until the fourth quarter. All of them, of course, have at least three quarters. In short, it is not the first quarter that is the most active one with regards to the IPOs of the future S&P 500 firms, but the quarters following it (especially, quarters 4 and 5). So, most S&P 500 IPOs (112 out of 130, or 86%) were not issued in the first quarter, which is what one would expect, if the best firms were engaging in
strategic waiting.

In the second test we ask “Were the S&P 500 firms first to issue within their industry?” For each rising cycle (remember that there are 11 of them), within each 2-digit (or alternatively 3-digit) industry, we order all the issuing firms from 1st to n-th to go public. The beginning of the cycle is the first day of the first quarter of the corresponding cycle. Then, we find the issuance order of each S&P 500 firm within their industry. Table 5 shows that for 2-digit SIC sorting, mean issuance order is changing from 3.89 to 32.60 from cycle to cycle. Thus, the evidence indicate that S&P 500 firms are not first to issue in their industry when the IPO market starts to heat up. Usually, there are at least 3 or 4 firms in their industry issuing before them.

As we narrow the sorts to be within 3-digit SIC industries, the chances that the S&P 500 firms will issue first are increasing, of course, but still for majority of the cycles (7 out of 9 cycles with an S&P 500 firm issuance in it) there are at least two other firms in the industry that issued earlier (based on median issuance orders in each industry in each cycle). In unreported results, we look at each S&P 500 firm individually, and find that 77% of them were not the first to issue in their 3-digit SIC industry. For example, Genentech Inc. was 5-th, Apple Inc. and Microsoft Corp. were both 18-th, and Starbucks Corp. was 15-th to issue within their corresponding 3-digit industry.

Note that, these last tests are biased against our model’s prediction. Our model does not relate to the industry of the IPOs; the information about the aggregate state of the economy is released regardless of the industry of the first issuing firm. All of our prior tests have shown that, normally, the good quality firms are not first to issue as the cycle starts to expand. In this test, however, we find a stronger support for our model: the best firms (i.e. S&P 500 firms) are not the first issuers even in their own industry.

For reference, we also report the issuance order of S&P 500 firms within all the firms in the corresponding cycle, not just within their industry. As shown in column (3) of the table, for the majority of the cycles, literally hundreds of firms issued ahead of these S&P 500 firms.

In a robustness test, we perform the same analysis on S&P 500 IPOs as above, but we eliminate any firm that has merged with another firm before it became part of the index. Such cases are not that informative about the quality of the original IPO firm. We obtain
Mergers&Acquisitions data from SDC, we match it with our sample of 130 IPOs, and we check whether and when they engaged in any form of M&A activity. If it is before the inclusion in the index, we drop it from the sample. These restrictions leave us with 72 IPOs that were included in the index on their own right (without merger). Tables 4 and 5 show the results for this subsample, as well (under the columns named “Subsample”). Our main conclusion, that the first quarter is not the most active quarter for these high-quality firms, still holds. Second through the fifth quarters seem to be the most active ones for these firms (see Table 4). Similarly, our main conclusion from Table 5, of S&P 500 IPOs not being first-to-issue in their industry, is qualitatively unchanged by the use of the above subsample of non-merged IPOs.

In unreported analysis, we also eliminated the firms that did not became part of the index within certain period of time (say 5 years). These two restrictions (no merger and inclusion within 5 years) eliminated most of our sampled IPO firms: there were only 35 of them left. For these remaining firms, the most active quarters were 2nd and 4th quarters, and the 1st quarter was among the least active ones, thus confirming our main findings above. Detailed results available upon request.

Therefore, based on the results from this subsection, we conclude that S&P 500 firms 1) are usually not the first movers in their industry as the new expanding cycle starts; and 2) they prefer to go public during periods of confirmed market heat (after the initial, more uncertain, quarter is over).

6.5. An Alternative Definition of Quality

To check whether our results are robust to an alternative definition of quality, we use the average post-issuance cash flows of the firm as an indicator of its quality at the time of issuance. Specifically, using COMPUSTAT data, we calculate the average annual cash flows\(^{36}\) of each firm during the first 3 years (or alternatively, 5 years) of its public trading. There are total of 3,370 (or 3,390) IPOs issued in a rising cycle, for which there are enough data points to calculate the 3-year (or 5-year) average annual cash flows.

\(^{36}\)We define cash flows as \([\text{Income Before Extraordinary Items} + \text{Depreciation}\&\text{Amortization} - \text{Dividends (Preferred} + \text{Common)}] / \text{Assets}\). In an alternative definition, we use \(\text{Sales}\) as a scaling variable in the previous equation; our qualitative results do not change.
We sort these firms into deciles based on their average post-issuance cash flows, such that the firms with the highest (lowest) cash flows are in decile 10 (decile 1). We, then, perform the same tests as above, but with this new definition of quality. For brevity, we report only the results from the most direct test of our hypothesis, namely survival analysis. As we can see from Figures 2E and 2F, and Table 2, Panel C, our results from this robustness test confirm that high quality firms (decile 10) wait, on median, 35 to 43 days longer than the low quality ones (decile 1) before issuing.

6.6. Determinants of Strategic Waiting

Next, we estimate what affects the waiting time of the firms. Specifically, we determine whether after controlling for other factors, our quality measures still have explanatory power over the waiting days. The dependent variable is the number of days passed between the start of the rising cycle and the IPO date of the firm (WaitingDays). The explanatory variable capturing the firm’s quality is approximated by seven different measures: a dummy indicating the inclusion in the S&P 500 index; the rank of the firm’s 3-year CAR within the same returns of all the other IPOs in our sample (in deciles); same rank when 5-year CARs, 3-year BHARs, and 5-year BHARs are used; the decile rank of the firm when its 3-year and 5-year average post-issuance cash flows are used.

The remaining explanatory variables are as follows. Age, defined as the logarithm of one plus the firm’s age at the time of issuance relative to the founding date. HiTech is a dummy variable that is 1 if the IPO firm is in a hi-tech industry and 0 if otherwise.37 Leverage is calculated as the total debt of the firm divided by its total assets. Both total debt and total assets are for the first fiscal year of public trading. NI/Sales denotes the net income of the firm divided by its sales (both net income and sales are for the first fiscal year of public trading). Reputation shows the updated Carter and Manaster (1990) underwriter prestige rankings obtained from Jay Ritter’s website. This data is not available for the 1970s, so we extrapolate an underwriter’s reputation from 1980-1984 period to be its reputation for the earlier periods. ROA is the return-on-assets

37Hi-tech industries are those that have a three-digit SIC code in 283, 357, 366, 367, 381, 382, 383, 384, 737, 873, and 874. These SICs belong to sectors such as biotech, computing, computer equipment, electronics, medical equipment, pharmaceuticals, software, etc.
during the first fiscal year of the new public firm retrieved directly from COMPUSTAT. Size is measured by the logarithm of the total sales of the firm at the end of the first fiscal year, converted to year 2000 dollars. VC is a dummy variable that indicates whether the IPO was backed by one or more venture firms (=1) or not (=0). The information on venture capital presence is obtained from the SDC datafiles and the Ritter’s website. Finally, the variables Offer Price and Underpricing are already defined in section 3.1.

Table 6 displays the results from the OLS estimation of the determinants of the strategic waiting days for all the IPOs issued in a rising cycle. There are total of 5,484 such firms. Because of the missing data problem associated with various variables retrieved from COMPUSTAT, the number of firms used in each regression is much lower than the above number (see the bottom of the table for more information). This trade off between having enough observations with non-missing data and having many more control variables from COMPUSTAT on the right-hand-side of the estimation equations was the determining factor on how many explanatory variables we can afford to put in our regressions.

The main conclusion from the table is that our quality measures are significantly positively related to WaitingDays, even after we control for many other factors. Note that, the control variables we use are likely capturing other quality dimensions of the firm. For example, it is likely that IPOs with high NI/Sales for the first year are of good quality, as well. So, inclusion of many such explanatory variables to the right-hand-side convolutes the conclusions that we can derive from such regression. However, we are satisfied that our quality measures have positive OLS coefficient estimates in relation to WaitingDays, which is what one would expect if high-quality firms are strategically waiting for favorable signals about the issuance conditions.

7. Concluding Remarks

To the best of our knowledge, this is the first study to explain how a good IPO firm may benefit from strategically delaying its issuance to obtain more information about the market conditions. As we demonstrate above, our model has novel predictions about the issuance order of IPOs with different qualities and the composition of the firms in each stage of an expanding cycle. Our empirical results show that the pioneering IPOs are not usually the best ones within an
expanding IPO cycle. For example, we find that IPOs of S&P 500 caliber quality mostly prefer to issue during the mid-stages of a typical expanding IPO cycle. They are not the pioneering issuers even in their own industry.

Our papers’ demonstration of how the best firms are usually not the first to issue in a rising cycle is an important one. We show, both theoretically and empirically, that any assumption (or postulation) that the first issuers are always the best firms and all the followers are of lower quality is a shaky one. Indeed, the reverse order is more likely to happen in a typical rising IPO cycle.

Another implication of our model is related to the timing of the IPO issuance. We show that IPOs engage in timing due to strategic motives, and not necessarily due to reasons related to market overvaluation (Baker and Wurgler, 2002; and Pagano, et al., 1998) or peaking cash flows (Benninga, et al., 2005). Many IPOs delay their issuance for the purposes of discovering the market conditions. By the time the information about the aggregate state of the economy is spread among waiting private firms and they act on it, the stock market is already rising, and the private firms’ cash flows are at high levels due to the same underlying economic reasons that also caused an increase in the IPO activity. Thus, most IPO issuances appear to coincide with the market’s overvaluation.

Finally, our model yields a new explanation of the IPO clustering. Upon issuance of the first successful IPO(s), the investors’ aggregate their private information, uncertainty about the economic and the market conditions is lifted, and all the remaining waiting firms, which were strategically delaying their issuance, are entering the market en mass. Therefore, strategic timing (waiting) can, partially or fully, explain this phenomenon.

Analyzing the strategic waiting competition among firms that are issuing seasoned equity, or among the IPOs within the same industry may also yield fruitful insights. Further empirical work can be done to find whether there is any meaningful issuance order in a declining IPO cycle. Similar analysis can also be performed for each individual cycle separately, and then compare the cycles. More detailed empirical analysis is needed also to decompose the true character of issuing IPO cohorts at various stages of the cycle.
Appendix.

In this appendix, we first give the proof of Proposition 1. Then, we show two generalizations of our model. The case when there are two positive NPV firms (good and mediocre), and one negative NPV (truly bad) firm. The second generalization shows the outcomes when there is a social planner (or an underwriter with a very large market share) in the model. We also present an alternative version of our model when there are two forms of uncertainty: asymmetric information about firm quality between investors and firms, and uncertainty due to aggregate economic state.

Appendix A. The Proofs

Proof: (Proposition ??) In order to calculate the firm’s payoff from a successful IPO, we should first determine the percentage of its equity it will sell to the (optimistic) investors. All investors initially believe that the probability of a good aggregate state is $\frac{1}{2}$. Due to Bayesian learning, the investors who receive the good signal will update this probability as $p$, while the investors who receive the bad signal will update it to $1 - p$. They also know that firm $j$’s project in a good state will be successful with probability $\pi_{Gj}$; hence, firm $j$ has to sell $\alpha$ percentage of equity such that
$$\alpha p \pi_{Gj} X = K$$
holds. In this case, only the optimistic investors demand the IPO.\footnote{The pessimistic investors will require a higher percentage of equity to buy IPO; specifically, they will require the equation $\alpha(1 - p) \pi_{Gj} X = K$ to hold. Since $p > 0.5$ implies $\alpha(1 - p) \pi_{Gj} X < \alpha p \pi_{Gj} X = K$, the pessimistic investors will not buy IPO.} Then, the payoff for firm $j$, assuming that a good state occurred, is
$$\left(1 - \alpha \right) X \pi_{Gj} = \left( \pi_{Gj} X - \frac{K}{p} \right).$$
Note that, as the investors become more optimistic about the state (i.e., as $p$ increases), the firm’s payoff increases, as well.

Given the firm’s belief that this is a good aggregate state with probability $\frac{1}{2}$, and its knowledge that the IPO will be unsuccessful in a bad state resulting in a loss of $\gamma$, the expected return to the firm from playing a pure strategy IPO$1$ will be
$$\frac{1}{2} \left( \pi_{Gj} X - \frac{K}{p} \right) + \frac{1}{2} (-\gamma) \quad (6)$$

By our assumption of $\gamma < \pi_{Gj} X - \frac{K}{p}$, this payoff is positive.\footnote{If not, it means $\gamma$ is too high; therefore, no firm will go public in this game.}

If the first IPO is successful, and hence, the revealed state is good, the other firm will go public in the second period. In the second period, investor’s beliefs, $p$, about the aggregate state will not be relevant any more. Since the discount factor is $\delta \in (0, 1)$, the ex-ante probability of having good state is $\frac{1}{2}$ in the first period when the decision is made, and the first period payoff from inaction is 0, firm $j$’s total payoff from waiting will be:
$$0 + \delta \frac{1}{2} (\pi_{Gj} X - K) \quad (7)$$

When the bad quality firm plays its mixed strategy, $(m_b, 1 - m_b)$, the good quality firm must be indifferent between playing the pure strategy of going public in the first period (IPO$1$), and
the pure strategy of waiting in the first period and then deciding in the second period (W1). Therefore, the bad quality firm will choose the probability of going public in the first period (i.e., its mixed strategy) by solving the following equation, in which the left hand side is the payoff from IPO1 and the right hand side is the payoff from W1 for the good quality firm when the bad quality firm plays its mixed strategy:

\[
\frac{1}{2}(\pi_G X - K_p - \gamma) = \delta m_b \frac{1}{2}(X\pi_G - K) + \frac{1}{2}\delta(1 - m_b)(\pi_G X - K_p - \gamma)
\]  

(8)

If the good quality firm goes public in the first period, then, regardless of how the bad quality firm plays, its payoff will be \(\frac{1}{2}(\pi_G X - K_p) + \frac{1}{2}(-\gamma)\).

If the good quality firm waits in the first period, then its payoff will depend on whether the bad quality firm went public in the first period or not. The bad quality firm goes public with probability \(m_b\) in the first period. The good quality firm will go public in the second period, only if it is revealed that it is a good state (that can happen with probability \(\frac{1}{2}\) according to the firm), which will result in a discounted payoff of \(\delta m_b \frac{1}{2}(X\pi_G - K)\). Note that there is no \(p\) in the payoff since the aggregate state will be revealed. If the revealed aggregate state is bad, the firm will not go public and get zero payoff. If the bad quality firm does not go public in the first period (which happens with probability \(1 - m_b\)), then the discounted payoff of good firm will be \(\frac{1}{2}(\pi_G X - K_p) + \frac{1}{2}(-\gamma)\) since the aggregate uncertainty will not be resolved even after the second period begins. Note that, the game ends at this second period, so it is better for the firm to go public even without knowing the aggregate state since \(\gamma < \pi_G X - K_p < \pi_G X - K_p\) by assumption and by the fact that \(\pi_G < \pi_G\).

By solving Equation 8, we have the result:

\[
m_b = \frac{(\pi_G X - K_p - \gamma)(1 - \delta)}{\delta(K_p + \gamma - K)}
\]

By using the symmetry of the problem, we can easily find the mixed strategy of the good quality firm:

\[
m_g = \frac{(\pi_G b X - K_p - \gamma)(1 - \delta)}{\delta(K_p + \gamma - K)}
\]

Our assumptions \(\gamma < (\pi_G b X - K_p)\) and \((1 - \delta)\pi_G X - K_p + \delta K < \gamma\) make sure that \(0 < m_j < 1\).

Appendix B. The Case With A Negative Expected NPV Firm

Our model can also incorporate a situation where among the private firms there are certain type of extremely bad quality firms with negative expected NPV. Next, we will derive the outcomes in such a situation.

**Proposition 4** Assume that there is one extremely bad quality firm with success probability \(\pi_{Ge}\) such that \(\frac{\pi_{Ge} + K}{px} > \pi_{Ge} > \frac{K}{X}\). This firm cannot go public before the aggregate state is revealed as good. Specifically, it cannot go public in the first period. (i.e., \(m_e = 0\).)
Proof: A firm will not go public in the first period if $\gamma > \pi_{Ge}X - \frac{K}{p}$, since the cost of going public, $\gamma$, is greater than the expected benefit of going public (right hand side of the inequality). However, if the state is revealed to be good, then the firm’s payoff changes, and it will go public only if $\pi_{Ge}X - K > 0$. The assumption $\frac{\gamma + K}{pX} > \pi_{Ge} > \frac{K}{X}$ in the proposition implies these two inequalities. Hence, the extremely bad quality firm cannot go public before the state is revealed as good.

From the above explanations, one can see that the extremely bad quality firm can never go public before the state is revealed as good, because its expected NPV is negative when the state is unknown. Then, assuming that there are good and bad quality firms, the game becomes a strategic waiting game between them, as in Proposition 1. As we showed in that proposition, $m_b > m_g$. So, the bad quality firm is more likely to go public in the first period, and the good quality firm will likely follow in the second period. If the extremely bad quality firm does go public, it can do so only in the second period and if the state is revealed as good.

**Appendix C. Social Planner**

In this section, we will show how the game changes in the presence of a social planner, who maximizes the society’s welfare. It is well-known in the literature that market inefficiencies can be corrected by a social planner. Since each firm wants the other firm to go public first to free-ride on the information generated, the social planner should “tax” the firm going public second, and subsidize the first firm. In other words, social planner transfers resources from the second firm to the first one.

In our model, the social welfare is determined as the expected payoff of the firms. The investors’ expected payoff is zero so we do not have to take them into account. It is easy to see that the social planner’s choice is whether to let the good firm or the bad firm go public first. In the parameter space we described in the main text, both firms going public first or both waiting for the second period cannot be optimal.

**Lemma 5** A social planner would make the good quality firm go public first and the bad quality firm go public second.

Proof: If the good quality firm goes public first, then the social welfare is

$$SW_g = \frac{1}{2}[(\pi_{Gg}X - \frac{K}{p}) + \delta(\pi_{Gb}X - K)] + \frac{1}{2}(-\gamma)$$

The first term is the good quality firm’s payoff in a good state. The second term is the bad quality firm’s payoff when it goes public in the second period after learning the good state. Since the state is revealed, we subtract only $K$ from the bad quality firm’s payoff. The third term is the payoff of good firm if it turns out to be a bad state.

Correspondingly, the social welfare if the bad-quality firm goes public first is:

$$SW_b = \frac{1}{2}[(\pi_{Gb}X - \frac{K}{p}) + \delta(\pi_{Gg}X - K)] + \frac{1}{2}(-\gamma)$$
A quick calculation shows that $SW_g > SW_b$ iff $\pi_{Gg} > \pi_{Gb}$. The latter is true by assumption.

We showed how the social planner will determine the order of issuance. This order will increase the expected social welfare. However, as is well known, there is no single all-controlling social planner in the IPO markets. However, alternative forms of organizations may arise to respond to such market externalities. According to Benveniste et. al. (2002), such an example of a market institution would be underwriters. If we have an underwriter in our model, he should “tax” the bad-quality firm, and reimburse the good-quality firm to achieve the social planner’s outcome in a market environment. We will, next, calculate the highest possible tax (payment), the bad-quality firm will accept to pay. We have to calculate the payoff of the bad quality firm in a market equilibrium (i.e., mixed strategy equilibrium) and the payoff when there is a social planner/underwriter. The difference is the maximum payment the bad quality firm will agree to pay.

The payoff of the bad quality firm in a mixed strategy equilibrium is equivalent to the payoff if it goes public in the first period with probability 1:

$$\frac{1}{2}(\pi_{Gb}X - K - \gamma)$$

This is true since the bad quality firm’s payoff must be the same for any action it takes with positive probability in the mixed strategy equilibrium (and hence, any probability distribution on these actions (in the support) gives the same payoff as the payoff from mixed strategy equilibrium). 40

In the social planner’s equilibrium, the bad quality firm’s payoff is

$$\delta \frac{1}{2}(\pi_{Gb}X - K)$$

since the firm will go public in the second period only if it is a good state. The difference is:

$$D = \delta \frac{1}{2}(\pi_{Gb}X - K) - \frac{1}{2}(\pi_{Gb}X - \frac{K}{p} - \gamma)$$

Next, we give our result:

**Proposition 6** Assume that the cost of using the underwriter is greater than $D$. Then, the firms will determine their order of issuance as in our mixed strategy equilibrium.

While the underwriter may solve the market inefficiency in some cases, there are problems associated with it. We calculated the maximum payment that the bad quality firm will accept to pay; however, there are infinitely many other payment options. Then, determining the transfer payment becomes a bargaining problem. This bargaining itself imposes cost to both firms and the underwriter. If this cost is higher than $D$, as we indicated in the proposition, at least one firm will not accept to go in the period the underwriter asks it to go. In addition,

40This is a well-known result. Alexander-Cook et. al. (1998) and Gunay (2008a) are two examples of papers that use this feature of mixed strategy equilibrium in different contexts.
as Benveniste et al. (2002) correctly points out, the underwriter must have a market power to correct this market inefficiency. Given that our empirical results suggest that bad quality firm goes public first more often than the good quality firm, we can indirectly conclude that either no single underwriter has high-enough market power or the bargaining cost is higher than the benefit of $D$.

Appendix D. The Case With Asymmetric Information

In this appendix, we will extend our model to allow for asymmetric information between investors and firms on the issuing firm’s quality. Specifically, the investors are uninformed about the firms’ quality. They only know that there is one good and one bad firm going public. Thus, their prior is such that each firm is equally likely to be a good firm.

We look for a mixed strategy equilibrium when investors do not know the firm quality. First, let us calculate the payoff from IPO1 for a good firm who goes public with probability $m_g$ in the first period, while the bad firm is going public with probability $m_b$. There are two cases we have to consider. In the first one, only good firm chooses IPO1 which happens with probability $(1 - m_b)$, and in the second one, bad firm also chooses IPO1 which happens with probability $m_b$. In the first case, good firm has to sell $\alpha$ percentage of equity such that $\alpha p(\pi_{Gg} + m_b \pi_{Gb})X = K$ should hold for investors to buy the shares. Note the Bayesian learning of consumers; if consumers see only one firm, they believe that it is a good firm with probability $(1 - m_b)m_g + (1 - m_g)m_b$ and it is a bad firm with probability $(1 - m_b)m_g + (1 - m_g)m_b$. In the second case, consumers see two firms in the first period. Hence, their posterior is the same as their prior which is $\frac{1}{2}$. Then the payoff from IPO1 for good firm is $(1 - \alpha)X \pi_{Gg}$ which has to be written for these two cases. In short, the payoff for good firm from IPO1 is:

$$\frac{1}{2} [(1 - m_b)(1 - \frac{K}{pX(\pi_{Gg} + \pi_{Gb})})X \pi_{Gg} + m_b(1 - \frac{K}{pX(\pi_{Gg} + \pi_{Gb})})X \pi_{Gb} - \frac{1}{2} \gamma] \quad (9)$$

The explanation of payoff from W1 is as follows. The first expression shows the case of bad firm going public in the first period and the second expression shows the case of bad firm going public in the second period. With probability $m_b$, the bad firm goes public in the first period and it turns out to be a good state with probability $\frac{1}{2}$. Good firm goes public in the second period. Due to Bayesian learning of consumers, if they see only one firm going public in the second

$$\frac{1}{2} m_b \delta (1 - \frac{K}{X(\pi_{Gg} + \pi_{Gb})})X \pi_{Gg} + \frac{1}{2} \delta (1 - m_b)[(1 - \frac{K}{pX(\pi_{Gg} + \pi_{Gb})})X \pi_{Gb} - \gamma] \quad (10)$$

The explanation of payoff from W1 is as follows. The first expression shows the case of bad firm going public in the first period and the second expression shows the case of bad firm going public in the second period. With probability $m_b$, the bad firm goes public in the first period and it turns out to be a good state with probability $\frac{1}{2}$. Good firm goes public in the second period. Due to Bayesian learning of consumers, if they see only one firm going public in the second
period, they believe that this firm is a good one with probability \( \frac{(1-m_b)m_g}{(1-m_b)m_g+(1-m_g)m_b} \). It is a bad firm with probability \( \frac{(1-m_g)m_b}{(1-m_b)m_g+(1-m_g)m_b} \). Hence, \( \alpha = \frac{K}{X(\frac{(1-m_g)m_b}{(1-m_b)m_g+(1-m_g)m_b} + \frac{(1-m_g)m_b}{(1-m_b)m_g+(1-m_g)m_b})} \).

Note that there is no \( \pi \) since the aggregate uncertainty is resolved, and good firm will go public when this is known to be a good state. In the second expression, with probability \( (1-m_b) \), bad firm does not go public and both firms go public in the second period when the uncertainty is not resolved. The second part shows this case.

The payoffs for the bad firm can be calculated in a similar fashion. The payoff from IPO1 for bad firm is:

\[
\frac{1}{2}[(1-m_b)(1-\frac{K}{pX(\frac{(1-m_b)m_g\pi_Gg}{(1-m_b)m_g+(1-m_g)m_b} + \frac{(1-m_g)m_b\pi_Gb}{(1-m_b)m_g+(1-m_g)m_b})})X\pi_Gb + \gamma] - \frac{1}{2}\gamma
\]

(11)

The payoff from W1 for the bad firm is:

\[
\frac{1}{2}m_b\delta[(1-\frac{K}{X(\frac{(1-m_b)m_g\pi_Gg}{(1-m_b)m_g+(1-m_g)m_b} + \frac{(1-m_g)m_b\pi_Gb}{(1-m_b)m_g+(1-m_g)m_b})})X\pi_Gb + \gamma] - \frac{1}{2}\delta(1-m_b)[(1-\frac{K}{pX(\frac{\pi_Gg+\pi_Gb}{2})})X\pi_Gb - \gamma]
\]

(12)

To find the solution, we have to equate the payoffs from W1 and IPO1 for good and bad firms. Then, we will have two non-linear equations with two unknowns, \( m_g \) and \( m_b \). While there is an analytical solution, it is too cumbersome to present here (it is available through the authors’ websites). Also, it is a solution that is not easy to draw conclusions on. So, instead, we utilize simulations.

Simulations

Next, we will demonstrate that for all the simulated cases, \( m_b > m_g \). The solutions for \( m_b \) and \( m_g \) are obtained by simultaneously solving the equations obtained through equating the payoffs from IPO1 and W1 for the good firm (Equation ?? = Equation ??) and for the bad firm (Equation ?? = Equation ??).

We have seven variables, \( X \), \( K \), \( p \), \( \delta \), \( \gamma \), \( \pi_Gg \), and \( \pi_Gb \). We tried different values for the fixed variables. For obvious space limitations, we report here only the outcomes from the following values: \( X = 3, K = 1, p = 0.8, \delta = 0.8, \gamma = 0.5, \pi_Gg = 0.85, \pi_Gb = 0.79 \) (or = 0.7 in one instance to make sure it is less than \( \pi_Gg \)).\(^{41}\) In the figures below we keep six of these parameters constant, and report the relationship between \( m_b \) and the varying seventh variable. Figure 4 shows these relationships. The variable on the x-axis takes 200 different values. As we see, in all the graphs, for all the parameter values, \( m_b \geq m_g \). Thus, we concluded that adding asymmetric information between investors and firms does not affect our main prediction.

\(^{41}\) The MATLAB code used to run the simulations is available through authors’ websites.
Further comments on the graphs are in order. 1) Figure 4A shows that as the potential return of the project, \( X \), increases, both \( m_g \) and \( m_b \) increase, because reward-to-risk ratio of going public in the first period increases. 2) According to Figure 4B, the probability of issuing in period 1 is declining as the capital needed to be raised for the project, \( K \), increases, because reward-to-investment (\( \frac{X}{K} \)) ratio is decreasing. 3) If the signal’s quality – measured by \( p \) – is increasing, the likelihood of IPO1 action by both firms is also increasing. In such cases the value of waiting for uncertainty resolution is less. See Figure 4C. 4) As \( \delta \) declines, waiting becomes costlier due to large discounting costs, which causes both \( m_b \) and \( m_g \) to decrease (Figure 4D). 5) As shown by Figure 4E, when the costs of IPO failure (\( \gamma \)) are high, probability of waiting by both firms is higher. 6) Figure 4F displays an interesting dynamic between \( m_b \) and \( m_g \). As bad firm’s quality (\( \pi_{Gb} \)) is approaching the good firm’s quality (\( \pi_{Gg} \), which stays constant in this simulation), then both firms issuing at time 1 increases. For both firms, the percentage of the proceeds they need to pay the investors to compensate for asymmetric information, \( \alpha \), is declining. Since, both firms are high quality, investors demand lower compensation for risk (i.e, they demand lower underpricing).\(^{42}\) Thus, bigger chunk of the proceeds are left to the firms. Due to the discounting effects, this makes it costlier for both of them to wait. 7) Figure 4G depicts a complex relationship between \( m_g \) and \( m_b \) as the discrepancy between the firms’ qualities is increasing. Early on, the quality discrepancy is small, which leads to the same type of relationship between \( m_g \) and \( m_b \) we described above. That is, both firms’ probability of IPO1 is rising. However, \( m_b \) is rising much faster than \( m_g \). After certain point, the discrepancy in quality becomes big enough for the good firm to wait and try to benefit from the new information i.e., the good firm’s benefits from new information becomes bigger than any discounting costs.

References


\(^{42}\)Note that, \( \alpha \) is endogenous in our model.


Derrien, F. “IPO Pricing in “Hot” Market Conditions: Who Leaves Money on the Table?”


This figure plots the quarterly number of IPOs (the line with the dots), and its four-quarter moving average, MA(4), (the solid black line). Timespan is between 1972 and 2007. For reference, the quarters when the U.S. economy was in a recession, as defined by NBER, are also shown with circles on the horizontal axis.
Figures 2A-2F plot the survival functions of the high- vs. low-quality IPO groups. An IPO is classified as high (low) quality one, if its post-issuance returns or cash flows are in the top (bottom) decile among all the firms issued during the rising cycles. Classification is done using 3-year (and 5-year) BHARs, CARs, and average annual cash flows. The survival function is estimated using Kaplan-Meier nonparametric method.
E: Ranking with Average Cash Flows (3 Years)

F: Ranking with Average Cash Flows (5 Years)
Figures 3A and 3B plot the smoothed mean quality measures of the IPOs issued in each month of the rising cycle. The quality of an IPO is measured by its BHAR or CAR, and the return horizons considered are 3 years and 5 years. A rising cycle is the one for which 4-period moving average (MA(4)) of the quarterly number of IPOs has been rising for at least 3 quarters. After the beginning and the end of the rising cycle is determined, the months in each rising cycle are ordered as 1st, 2nd, ..., 21st since the beginning of the cycle. To smooth out the monthly fluctuations in the quality means (i.e., to observe clearly the genuine trend along the rising cycle), their MA(6) is taken.
Figures 4A-4G show the results from our simulations that are explained in the Appendix. The plots display the relationship between a particular variable from our model and the first-period issuance probabilities of the good and the bad firms ($m_g$ and $m_b$). All the other variables are set to the parameters shown at the bottom of each graph. The seven variables from our model are $X$, $K$, $p$, $\delta$, $\gamma$, $\pi_{Gg}$, and $\pi_{Gb}$. The x-axis variable takes 200 different values in the range specified in the graph.
Table I: Descriptive Statistics of the Cycles

The table presents some descriptive statistics of the IPOs in each cycle. The rising and falling cycles are shown with their timespan, duration, IPO sample size, and various other descriptive statistics. A rising cycle is defined as at least three back-to-back quarters of increasing IPO activity. The rest of the quarters are considered as falling. For the IPOs issued in each cycle the following variables are presented under each enumerated column: (1) the duration of the cycle (in quarters), (2) the total number of IPOs, (3) percentage of IPOs with positive 5 year returns (BHAR and CAR), (4) mean returns (BHAR and CAR) in %, (5) mean and median underpricing (in %), (6) mean and median proceeds raised (in year 2000 $; in million $s), (7) mean and median age of the firms at the time of issuance (in years), and (8) mean size of the firms measured by their assets around the time of issuance (in year 2000 $; in million $s).

<table>
<thead>
<tr>
<th>Rising Cycles:</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Duration (qtrs)</td>
<td>(2) # of IPOs</td>
<td>(3) % with +ve 5yr BHAR(CAR)</td>
<td>(4) Mean 5yr BHAR (CAR)</td>
<td>(5) Mean(Med.) Underp.</td>
<td>(6) Mean(Med.) Proceeds</td>
<td>(7) Mean(Med.) Age</td>
<td>(8) Mean (Med.) Size</td>
</tr>
<tr>
<td>75/3 – 76/4</td>
<td>6</td>
<td>41</td>
<td>31.70(41.46)</td>
<td>-17.28(1.04)</td>
<td>+ 0.38(-0.75)</td>
<td>$27.56($17.52)</td>
<td>25.57(11)</td>
</tr>
<tr>
<td>78/2 – 81/3</td>
<td>14</td>
<td>453</td>
<td>19.43(37.53)</td>
<td>-74.08(-44.73)</td>
<td>+ 13.80(+4.08)</td>
<td>$18.33($10.94)</td>
<td>10.71(7)</td>
</tr>
<tr>
<td>83/1 – 84/1</td>
<td>5</td>
<td>751</td>
<td>32.76(48.60)</td>
<td>- 7.01(-11.02)</td>
<td>+ 9.17(+1.56)</td>
<td>$31.49($15.37)</td>
<td>16.16(8)</td>
</tr>
<tr>
<td>85/3 – 87/1</td>
<td>7</td>
<td>832</td>
<td>30.17(46.75)</td>
<td>-12.36(-15.96)</td>
<td>+ 14.23(+2.24)</td>
<td>$39.59($14.72)</td>
<td>19.61(7)</td>
</tr>
<tr>
<td>89/4 – 90/2</td>
<td>3</td>
<td>142</td>
<td>22.54(40.85)</td>
<td>-23.69(-24.18)</td>
<td>+ 14.31(+5.88)</td>
<td>$34.98($20.74)</td>
<td>15.24(8)</td>
</tr>
<tr>
<td>91/2 – 92/2</td>
<td>5</td>
<td>552</td>
<td>26.45(48.19)</td>
<td>-38.85(-15.52)</td>
<td>+ 10.96(+5.67)</td>
<td>$54.86($30.24)</td>
<td>18.62(9)</td>
</tr>
<tr>
<td>93/3 – 94/2</td>
<td>4</td>
<td>658</td>
<td>30.40(47.72)</td>
<td>+16.14(-7.74)</td>
<td>+ 9.68(+4.06)</td>
<td>$55.27($26.25)</td>
<td>13.05(8)</td>
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<tr>
<td>95/3 – 96/4</td>
<td>6</td>
<td>1,044</td>
<td>23.37(49.90)</td>
<td>-31.35(+3.25)</td>
<td>+ 19.89(+11.63)</td>
<td>$51.41($31.18)</td>
<td>11.86(8)</td>
</tr>
<tr>
<td>99/2 – 00/1</td>
<td>4</td>
<td>498</td>
<td>08.43(37.75)</td>
<td>-109.51(-55.38)</td>
<td>+ 78.26(+44.01)</td>
<td>$101.04($59.85)</td>
<td>9.81(5)</td>
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<tr>
<td>03/3 – 05/1</td>
<td>7</td>
<td>297</td>
<td>33.33(46.46)</td>
<td>-12.91(-18.84)</td>
<td>+ 10.91(+6.00)</td>
<td>$145.19($85.74)</td>
<td>18.55(9)</td>
</tr>
<tr>
<td>06/4 – 07/4</td>
<td>5</td>
<td>216</td>
<td>26.57(46.15)</td>
<td>-28.20(-16.19)</td>
<td>+ 19.54(+5.98)</td>
<td>$54.88($25.04)</td>
<td>14.86(8)</td>
</tr>
<tr>
<td>Total Rising Cycles</td>
<td>66</td>
<td>5,484</td>
<td>26.57(46.15)</td>
<td>-28.20(-16.19)</td>
<td>+ 19.54(+5.98)</td>
<td>$54.88($25.04)</td>
<td>14.86(8)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Falling Cycles:</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Duration (qtrs)</td>
<td>(2) # of IPOs</td>
<td>(3) % with +ve 5yr BHAR(CAR)</td>
<td>(4) Mean 5yr BHAR (CAR)</td>
<td>(5) Mean(Med.) Underp.</td>
<td>(6) Mean(Med.) Proceeds</td>
<td>(7) Mean(Med.) Age</td>
<td>(8) Mean (Med.) Size</td>
</tr>
<tr>
<td>73/1 – 75/2</td>
<td>10</td>
<td>53</td>
<td>24.53(47.17)</td>
<td>-39.30(+7.88)</td>
<td>- 2.44(+0.31)</td>
<td>$24.56($10.26)</td>
<td>23.46(6)</td>
</tr>
<tr>
<td>77/1 – 78/1</td>
<td>5</td>
<td>29</td>
<td>44.83(58.62)</td>
<td>+12.25(+3.68)</td>
<td>+ 5.56(-0.43)</td>
<td>$15.24($11.48)</td>
<td>9.68(8.5)</td>
</tr>
<tr>
<td>81/4 – 82/4</td>
<td>5</td>
<td>174</td>
<td>24.71(40.80)</td>
<td>-40.01(-35.68)</td>
<td>+ 6.99(+1.19)</td>
<td>$19.13($9.92)</td>
<td>11.36(7)</td>
</tr>
<tr>
<td>84/2 – 85/2</td>
<td>5</td>
<td>305</td>
<td>30.16(47.87)</td>
<td>-15.60(-16.64)</td>
<td>- 0.21(0)</td>
<td>$17.86($8.82)</td>
<td>17.33(10)</td>
</tr>
<tr>
<td>87/2 – 89/3</td>
<td>10</td>
<td>594</td>
<td>28.11(52.69)</td>
<td>-3.44(+5.06)</td>
<td>+29.47(+2.66)</td>
<td>$34.11($12.32)</td>
<td>19.39(7)</td>
</tr>
<tr>
<td>90/3 – 91/1</td>
<td>3</td>
<td>83</td>
<td>19.28(44.58)</td>
<td>-97.87(-21.30)</td>
<td>+10.66(+7.29)</td>
<td>$42.11($19.83)</td>
<td>14.71(8)</td>
</tr>
<tr>
<td>92/3 – 93/2</td>
<td>4</td>
<td>443</td>
<td>27.54(45.37)</td>
<td>-27.13(-20.01)</td>
<td>+10.89(+6.25)</td>
<td>$59.35($27.33)</td>
<td>17.07(9.5)</td>
</tr>
<tr>
<td>94/3 – 95/2</td>
<td>4</td>
<td>368</td>
<td>23.10(47.55)</td>
<td>-21.61(-9.03)</td>
<td>+16.58(+8.33)</td>
<td>$41.66($26.05)</td>
<td>12.82(8)</td>
</tr>
<tr>
<td>97/1 – 99/1</td>
<td>9</td>
<td>861</td>
<td>21.84(49.71)</td>
<td>-40.85(+4.68)</td>
<td>+20.54(+9.09)</td>
<td>$68.68($35.71)</td>
<td>14.69(8)</td>
</tr>
<tr>
<td>00/2 – 03/2</td>
<td>13</td>
<td>397</td>
<td>18.89(43.58)</td>
<td>-68.84(-22.88)</td>
<td>+52.07(+11.07)</td>
<td>$155.73($69.05)</td>
<td>14.76(8)</td>
</tr>
<tr>
<td>05/2 – 06/3</td>
<td>6</td>
<td>222</td>
<td>41.44(52.70)</td>
<td>+9.00(+1.80)</td>
<td>+ 8.49(+3.99)</td>
<td>$127.80($82.01)</td>
<td>22.51(10)</td>
</tr>
<tr>
<td>Total Falling Cycles</td>
<td>75</td>
<td>3,229</td>
<td>25.67(48.26)</td>
<td>-29.53(-6.43)</td>
<td>+20.70(+5.19)</td>
<td>$61.16($25.29)</td>
<td>16.13(8)</td>
</tr>
</tbody>
</table>
Table II: Days Since the Start of the Rising Cycle

The table shows the mean and the median number of days passed since the start of the cycle for “high-” and “low-” quality IPOs. High-quality (Low-quality) IPOs are the firms that are ranked in the top (bottom) decile of the long-run returns or the average annual cash flows. Panels A, B, and C indicate that the quality classification is done using BHAR, CAR, and Cash Flows, correspondingly. The results for two time-horizons – 3-year returns and 5-year returns – are presented under the corresponding columns. The columns under “# of IPOs” present the number of IPOs in each decile. The p-values from two non-parametric tests (Log-Rank and Wilcoxon) for testing the homogeneity of survival functions across quality groups are also presented. The null is that the survival functions are identical across the two groups.

<table>
<thead>
<tr>
<th>Panel A: BHAR Returns</th>
<th>3 years</th>
<th>5 years</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (Days)</td>
<td>Median (Days)</td>
</tr>
<tr>
<td>High</td>
<td>274.68</td>
<td>281.00</td>
</tr>
<tr>
<td>Low</td>
<td>214.28</td>
<td>193.00</td>
</tr>
<tr>
<td>Tests</td>
<td>Log-Rank</td>
<td>0.0001</td>
</tr>
<tr>
<td></td>
<td>Wilcoxon</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: CAR Returns</th>
<th>3 years</th>
<th>5 years</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (Days)</td>
<td>Median (Days)</td>
</tr>
<tr>
<td>High</td>
<td>276.10</td>
<td>281.00</td>
</tr>
<tr>
<td>Low</td>
<td>241.45</td>
<td>226.00</td>
</tr>
<tr>
<td>Tests</td>
<td>Log-Rank</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>Wilcoxon</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Cash Flows</th>
<th>3 years</th>
<th>5 years</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (Days)</td>
<td>Median (Days)</td>
</tr>
<tr>
<td>High</td>
<td>273.58</td>
<td>279.00</td>
</tr>
<tr>
<td>Low</td>
<td>251.66</td>
<td>236.00</td>
</tr>
<tr>
<td>Tests</td>
<td>Log-Rank</td>
<td>0.0489</td>
</tr>
<tr>
<td></td>
<td>Wilcoxon</td>
<td>0.0337</td>
</tr>
</tbody>
</table>
The table presents the average quality of the IPOs issued in each month of a rising cycle. We measure the quality of an IPO by its 3-year (or alternatively, 5-year) BHAR and CAR. A rising cycle is the one for which 4-period moving average (MA(4)) of the quarterly number of IPOs has been rising for at least 3 quarters. After the beginning and the end of the rising cycle is determined, the months in each rising cycle are ordered as 1\textsuperscript{st}, 2\textsuperscript{nd}, ..., 21\textsuperscript{st} since the beginning of the cycle. The columns under “BHARs” and “CARs” present the results when the quality classification is done using BHAR or CAR, correspondingly. The columns under “Num. of Obs.” present the total number of IPOs (summed across rising cycles) issued in each month. At the bottom of the table, we present also some information about the coefficient estimates, significances, and $R^2$s from a simple OLS regression of the corresponding quality measure on the time trend. The estimated coefficients capture the time trend in the monthly quality averages.

<table>
<thead>
<tr>
<th>Period Count</th>
<th>BHARs</th>
<th>CARs</th>
<th>Num. of Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3-year</td>
<td>5-year</td>
<td>3-year</td>
</tr>
<tr>
<td>1\textsuperscript{st}</td>
<td>-29.75%</td>
<td>-48.26%</td>
<td>-21.06%</td>
</tr>
<tr>
<td>2\textsuperscript{nd}</td>
<td>-20.57%</td>
<td>-42.02%</td>
<td>-20.47%</td>
</tr>
<tr>
<td>3\textsuperscript{rd}</td>
<td>-30.38%</td>
<td>-43.75%</td>
<td>-19.59%</td>
</tr>
<tr>
<td>4\textsuperscript{th}</td>
<td>-38.04%</td>
<td>-35.00%</td>
<td>-27.10%</td>
</tr>
<tr>
<td>5\textsuperscript{th}</td>
<td>-18.23%</td>
<td>-5.03%</td>
<td>-21.29%</td>
</tr>
<tr>
<td>6\textsuperscript{th}</td>
<td>-36.43%</td>
<td>-43.13%</td>
<td>-29.68%</td>
</tr>
<tr>
<td>7\textsuperscript{th}</td>
<td>-23.80%</td>
<td>+33.53%</td>
<td>-27.76%</td>
</tr>
<tr>
<td>8\textsuperscript{th}</td>
<td>-38.02%</td>
<td>-63.15%</td>
<td>-30.10%</td>
</tr>
<tr>
<td>9\textsuperscript{th}</td>
<td>-19.11%</td>
<td>-37.40%</td>
<td>-23.71%</td>
</tr>
<tr>
<td>10\textsuperscript{th}</td>
<td>+1.97%</td>
<td>-19.87%</td>
<td>-11.01%</td>
</tr>
<tr>
<td>11\textsuperscript{th}</td>
<td>-15.27%</td>
<td>-28.49%</td>
<td>-20.26%</td>
</tr>
<tr>
<td>12\textsuperscript{th}</td>
<td>-10.42%</td>
<td>-22.45%</td>
<td>-13.24%</td>
</tr>
<tr>
<td>13\textsuperscript{th}</td>
<td>+0.23%</td>
<td>-14.75%</td>
<td>-7.07%</td>
</tr>
<tr>
<td>14\textsuperscript{th}</td>
<td>-1.73%</td>
<td>+0.86%</td>
<td>+2.23%</td>
</tr>
<tr>
<td>15\textsuperscript{th}</td>
<td>+31.66%</td>
<td>+26.29%</td>
<td>+7.40%</td>
</tr>
<tr>
<td>16\textsuperscript{th}</td>
<td>-12.71%</td>
<td>-23.95%</td>
<td>-1.43%</td>
</tr>
<tr>
<td>17\textsuperscript{th}</td>
<td>-14.17%</td>
<td>-24.92%</td>
<td>+0.65%</td>
</tr>
<tr>
<td>18\textsuperscript{th}</td>
<td>-11.56%</td>
<td>-28.57%</td>
<td>-8.29%</td>
</tr>
<tr>
<td>19\textsuperscript{th}</td>
<td>-11.16%</td>
<td>-28.97%</td>
<td>+2.37%</td>
</tr>
<tr>
<td>20\textsuperscript{th}</td>
<td>-41.02%</td>
<td>-37.57%</td>
<td>-38.01%</td>
</tr>
<tr>
<td>21\textsuperscript{st}</td>
<td>+5.84%</td>
<td>-8.98%</td>
<td>-2.49%</td>
</tr>
</tbody>
</table>

| OLS Coeff. | +1.3127 | +1.0110 | +1.1387 | +0.7124 |
| p-value | 0.0336 | 0.0988 | 0.0101 | 0.0307 |
| Adj. $R^2$ | 0.1751 | 0.0913 | 0.2635 | 0.1819 |
Table IV: Evidence from S&P 500 Firms

The table displays some information about issuance patterns of IPOs that are ultimately included in the S&P 500 index. After identifying a rising cycle the way described in the text, we rank the quarters within each rising cycle according to where in the cycle they are located: 1\textsuperscript{st} quarter, 2\textsuperscript{nd} quarter, ..., 7\textsuperscript{th} quarter since the beginning of the rise. The columns show (1) the mean number of future S&P 500 firms that are issued in each quarter, averaged across different rising cycles; (2) the total number of IPOs in each quarter (summed across the rising cycles); and (3) the number of waves that lasted that many quarters. Under each column we show the results for our main IPO sample of all the future S&P 500 firms, and for a subsample of these IPOs that were not involved in any Mergers and Acquisitions before their inclusion in the index.

<table>
<thead>
<tr>
<th>Quarter Count</th>
<th>(1) Mean Number of IPOs Per Cycle Per Quarter</th>
<th>(2) Total Number of IPOs</th>
<th>(3) Number of Up Cycles That Have IPOs Issued in The Quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Main Sample</td>
<td>Subsample</td>
<td>Main Sample</td>
</tr>
<tr>
<td>1\textsuperscript{st}</td>
<td>2.57</td>
<td>1.29</td>
<td>18</td>
</tr>
<tr>
<td>2\textsuperscript{nd}</td>
<td>3.29</td>
<td>2.57</td>
<td>23</td>
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<tr>
<td>3\textsuperscript{rd}</td>
<td>3.00</td>
<td>1.50</td>
<td>21</td>
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<tr>
<td>4\textsuperscript{th}</td>
<td>3.71</td>
<td>1.86</td>
<td>26</td>
</tr>
<tr>
<td>5\textsuperscript{th}</td>
<td>3.67</td>
<td>2.20</td>
<td>22</td>
</tr>
<tr>
<td>6\textsuperscript{th}</td>
<td>4.00</td>
<td>1.50</td>
<td>8</td>
</tr>
<tr>
<td>7\textsuperscript{th}</td>
<td>1.00</td>
<td>1.00</td>
<td>1</td>
</tr>
<tr>
<td>(8\textsuperscript{th} – 14\textsuperscript{th})</td>
<td>1.83</td>
<td>1.00</td>
<td>11</td>
</tr>
</tbody>
</table>
Table V: S&P500 Firms’ Order of Issuance Within Their Industries

The table presents issuance order of IPOs that are ultimately included in the S&P 500 index. After identifying a rising cycle the way described in the text, we rank each IPOs in the order of their issuance within their 2-digit (or 3-digit) industry since the beginning of the rise of the corresponding cycle (1st firm to issue in their industry, 2nd, ..., nth). The beginning of a rising cycle is considered to be the first day of the first quarter of that cycle. Each rising cycle is described by its beginning (exp: 75/3, which shows the third quarter of 1975) and the end of the cycle (exp: 76/4). The columns show (1) the total number of IPOs issued in each cycle; (2) the total number of future S&P 500 firms that are issued in that cycle; (3) among all the firms, what was the mean (median) issuance order of the S&P 500 firms in that cycle; (4) and (5) within their 2-digit or 3-digit SIC industry, what was the mean (median) issuance order of the S&P 500 firms in that cycle. Under each column we show the results for our main IPO sample of all the future S&P 500 firms, and for a subsample of these IPOs that were not involved in any Mergers and Acquisitions before their inclusion in the index.

<table>
<thead>
<tr>
<th>The Rising Cycle</th>
<th>(1) Total # of IPOs</th>
<th>(2) Total # of S&amp;P 500 Firms</th>
<th>(3) Mean (Med.) Issuance Order All Firms</th>
<th>(4) Mean (Med.) Issuance Order 2-Digit SIC</th>
<th>(5) Mean (Med.) Issuance Order 3-Digit SIC</th>
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<td>Subsample</td>
<td>Main Sample</td>
<td>Subsample</td>
<td>Main Sample</td>
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<tr>
<td>75/3 – 76/4</td>
<td>41</td>
<td>5</td>
<td>5</td>
<td>24.50 (24)</td>
<td>24.50 (24)</td>
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<tr>
<td>78/2 – 81/3</td>
<td>453</td>
<td>16</td>
<td>12</td>
<td>190.13 (167.75)</td>
<td>169.67 (167.75)</td>
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<tr>
<td>83/1 – 84/1</td>
<td>751</td>
<td>17</td>
<td>8</td>
<td>320.59 (299.5)</td>
<td>289.06 (201.75)</td>
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<td>85/3 – 87/1</td>
<td>832</td>
<td>26</td>
<td>10</td>
<td>386.81 (361.25)</td>
<td>347.55 (262.25)</td>
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<tr>
<td>89/4 – 90/2</td>
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<td>52.17 (73)</td>
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<tr>
<td>91/2 – 92/2</td>
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<td>325.11 (402.75)</td>
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<tr>
<td>93/3 – 94/2</td>
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<td>–</td>
<td>–</td>
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<tr>
<td>06/4 – 07/4</td>
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<td>0</td>
<td>0</td>
<td>–</td>
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Table VI: The Determinants of Waiting Days

The table presents the results from the OLS regressions estimating the variables affecting the waiting days of the sampled firms. The dependent variable is \( \text{WaitingDays} \), which measures the timespan (in days) between the start of the rising cycle and the issuance date of the IPO. In the right-hand-side we use seven different \textit{Quality} measures: 1) a dummy variable indicating whether or not the firm was ultimately included in the S&P 500 index; 2) the 3-year CAR ranking of the firm among all the sampled IPOs (in deciles); 3) the 3-year BHAR decile ranking of the firm; 4) the 3-year averaged cash flows (scaled by assets) decile ranking of the firm; 5) the 5-year CAR decile ranking of the firm; 6) the 5-year BHAR decile ranking of the firm; and 7) the 5-year averaged cash flows (scaled by assets) decile ranking of the firm. The remaining regressors are \textit{Age} (which is defined as logarithm of one plus age of the firm at the time of its IPO), \textit{HiTech} (a dummy variable which takes a value of 1 if the IPO firm is in a hi-tech industry; 0 otherwise), \textit{Leverage} (total debt divided by total assets), \textit{NI/Sales} (is the net income of the firm divided by its first-year’s sales), \textit{OfferPrice} (the price the issue was offered to public), \textit{Reputation} (underwriter’s reputation ranking), \textit{ROA} (is the return-on-assets of the firm, again in the first year of public trading), \textit{Size} (defined as logarithm of one plus \textit{Sales}), \textit{Underpricing} (first day return), and \textit{VC} (dummy variable indicating whether or not the issue is backed by a venture capitalist). The numbers in the parentheses below the coefficients are the \( p \)-values, which are calculated using standard errors that are robust to clustering in time and to heteroskedasticity (Huber-White). At the bottom of the table the number of observations with non-missing data and the adjusted \( R^2 \) are also shown.

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>(0.0001)</td>
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