Strategic Waiting in the IPO Markets*

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January 2009

*We greatfully acknowledge Social Sciences and Humanities Research Council (SSHRC)'s funding. We would like to thank Don Autore, Gary Benesh, Douglas Cook, Irena Hutton, Toni Whited, and seminar participants at University of Alabama and University of Manitoba for their helpful suggestions. The research assistance of Eric Brisker, Xin Meng, and Adam Smedima was very helpful.

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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&P500 firms.

Keywords: Cycles, Initial Public Offerings, Social Learning, Strategic Waiting, Survival Analysis.

JEL Classification: C41, C72, D82, D83, G20, E32.

1. Introduction

Initial public offering (IPO) is one of the most crucial decisions in the life of a firm. There are managerial and economic reasons for making this decision (see for example, Zingales (1995), Pagano, et al. (1998), Chemmanur and Fulghieri (1999), Stoughton, et al. (2001), Babich and Sobel (2004)). This paper claims that there are some strategic reasons affecting the timing of the IPO decision. Our game theory model shows how some firms that are about to go public will benefit from strategically delaying their issuance. Before issuing, each firm wants to obtain as much information about the aggregate state of the economy, because going public is risky: an IPO during an economic slowdown is more likely to be unsuccessful causing the firm to loose money and reputation.[1] Since earlier IPOs will reveal the aggregate state, each firm has an incentive to wait for another firm to go public first.[2] However, waiting is costly too, because it delays the capital raising that is necessary to implement the firm's valuable projects. Briefly, firms face a trade-off in their timing of issuance.

The "game" in our model captures the behavior of private firms around the periods when the economy is in recession and the IPO market is inactive. The economic conditions and the IPO market have a potential to improve, but there is uncertainty on when they might do so. No single economic actor knows the aggregate state of the economy to the fullest extend. Even the most informed economic actors, like the central banks, can not confirm a recession or an expansion until after it starts. However, each economic agent has a private information about certain part of the whole economy (the car producers about car sales, realtors about the housing sales, investment bankers about 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 conditions i.e., a successful (or failed) IPO is the event that aggregates this privately held information.[3] If the first IPO

[1]We observe that few firms go public during recessions, but many do during the booming periods (see Lowry (2003) and Pastor and Veronesi (2005)). This suggests that the success of initial public offerings depend not only on the quality of the issuing firm, but also on the aggregate state of the economy.

[2]This is sometimes referred to as *strategic waiting*. Hendricks and Kovenock (1989) is one of the first papers in this literature.

[3]This is called *information aggregation* in the economics literature (see Diamond and Verrecchia (1981),

fails, it will incur monetary and reputational costs. If successful, however, it will draw in many more IPOs,[4] due to social learning among firms.[5] In such a game, the informational advantages of delayed issuance causes the private firms to engage in strategic waiting. 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 firms (first the lower-quality firms, then the higher-quality ones will issue). In two closely related prior studies, Hoffmann-Burchardi (2001) and Alti (2005), demonstrate how IPO clustering can occur through information spillovers: early IPOs cause information production about the market's favorable conditions, which in turn originates a wave of new issuances. Neither of them, however, explain how the first issuers, the ones that cause the information spillovers, are determined or selected. They (as well as Benveniste et al. (2002)) implicitly assume that these firms are either exogenously chosen, or are successful firms that can afford to be indifferent to the market conditions.

This study shares another common theme with the above papers: it provides a novel explanation to the IPO clustering phenomenon. Strategic waiting incentives of private firms can lead to such clustering. All the firms have incentives to delay their issuance until the favorable conditions are confirmed. The first IPO (the one that can afford to wait the least) will reveal the state to all the remaining firms. If it is good, these firms will enter the market en mass, because waiting is not optimal anymore.

The importance of first issuers in revealing information has also been emphasized by Benveniste, et al. (2002). They 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. Investment banks

Pesendorfer and Swinkels (1997), and Günay (2008), among others).

[4]According to Lowry and Schwert (2002) and Benveniste et al. (2003), 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.

[5]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.

try to mitigate this free-riding problem. Similarly, Maksimovic and Pitchler (2001) examine the influence of the product market competition on firms' IPO timing. A private firm in possession of a new know-how is facing a trade-off between raising capital and revealing its technology to potential new entrants to its industry. In our model, on the other hand, the strategic and informational reasons are driving the results i.e., a set of competing firms go public in certain order due to strategic (or game-theoretic) reasons. 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 is the one that investigates the composition of firms going public at various market conditions. A seminal paper by Ritter (1984) suggests that the risk composition among IPO firms during "hot issue markets" may be different than the compositions in the other periods. Yung, et al. (2008) demonstrate that this composition change leads to higher asymmetric information and higher adverse selection problem during "hot" IPO markets. The party that strategically benefits the most during such periods are the truly bad firms, who end up raising money despite their lack of valuable projects. Our paper concentrates only on the expanding IPO cycles, and the composition of the issuing firms at its various stages. It has no predictions on what happens during the troughs or the falling parts of it. During the formation and development of a hot IPO market, the strategic waiting by better quality firms could lead to disproportionately more lower quality firms issuing at the early stages of the cycle. Higher quality firms tend to issue in the mid-to-late stages of the cycle, when the market heat is confirmed.

The model we propose has predictions that are in probabilistic terms. It suggests certain pattern of issuance by attaching probabilities to the events. For example, it implies that the probability of lower quality firms issuing first followed by higher quality firms is larger than the probability of the reversed order of issuance. Thus, we are dealing with averages and generalized patterns. Our model does not imply, for example, that good firms will never issue first. All the firms in our model have valuable projects, albeit of different quality (i.e. we have nothing to say about truly bad firms that are the focus of Yung, et al. (2008)). The project's success depends on two factors: the individual firm and the aggregate state of the economy. Both of these factors can bring uncertainty to the agents and to the investors.

We perform several empirical tests to check our model's predictions. Since we want to compare various firms' times of issuance relative to the starting point of the rising IPO cycle,[6] 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 26 and 93 days[7] earlier in the cycle than the higher-quality ones (depending on the technique used to classify high- and low-quality firms). We also report that, on average, firm quality is lower in the early stages of a typical rising IPO cycle in comparison to the second half of the cycle, suggesting that most high-quality firms wait for confirmation of 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&P500 index, are also analyzed to determine any strategic waiting tendencies. We find that the IPOs of future S&P500 firms like to issue in 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 in periods with confirmed market heat. As far as we know, this is the first study to report on issues related to IPOs of S&P500 firms.

At the very minimum, these results imply that the pioneering IPOs in a rising cycle are not always of the best quality, as is assumed or postulated by Hoffmann-Burchardi (2001), Benveniste, et al. (2002), and Alti (2005). 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). What appears as IPO firms' ability to time the market by issuing predominantly during periods of overvaluation in the equity markets or when their cash flows peak, may occur (partially or fully) due to their strategic waiting.[8] 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(s) successfully issues, many

[6]As explained later on, we define a rising cycle as the period of 3 or more back-to-back quarters of increasing IPO activity.

[7]Clearly, we are talking about the days since the beginning of a new rising IPO cycle that are averaged across the firms in each subsample.

[8]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).

of them initiate the IPO process, which can last more than few months.[9] 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 shocks.

While these arguments suggest that strategic waiting 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 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 market is indistinguishable from our strategic waiting hypothesis.

In the next section of the paper we describe our game theory model and its predictions. Section 3 describes our data sources and our sample selection. Section 4 elaborates on the various empirical procedures we employ to test the implications of our model. Section 5 presents the results from the tests and Section 6 concludes the paper. The Appendix provides some extensions of our model.

2. The Model

Two 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 π_{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 $j = g, b$.[10] 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 given state. To be more exact, we have $\pi_{ib} < \pi_{ig}$ with $i = G, B$.

[9] 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.

[10] As long as, π_{Bj} is low enough, our results will hold. By assuming $\pi_{Bj} = 0$, our calculations become simple.

The probability that the 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 $(1-p)$.[11] Note that the signals are correlated with the aggregate state (i.e. it is informative since $p > 0.5$) but imperfect since we assume that $p < 1$. The following table summarizes the signal structure.

	Good Signal	Bad Signal
Good State	p	1-p
Bad State	1-p	p

We assume that the investors and the firms are uninformed about the aggregate state, but the individual firm quality is common knowledge. We will also make the following assumptions, and then discuss how IPOs 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 too many 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.[12] Their demand for equity will not be enough to buy all K that the firm is issuing. At this stage, the firm will withdraw its IPO. In short, IPO will be unsuccessful. Every investor watching the outcome of this event will learn that the state is bad. In other words, the investors will aggregate their privately held information from the result of the IPO (i.e. investors' 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,

[11] These signal structures are taken from Caplin and Leahy (1994).

[12] A continuum of investors are receiving a binary signal; 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.

and everyone will learn that the aggregate state is good.

We assume that the game continues for 2 periods. A firm i will go public by offering a certain percentage of its equity 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.[13] We will denote the action of going public in the first period as IPO1, and waiting in the first period with W1. The expected return of the firm's owner from playing a pure strategy IPO1 will be

$$\frac{1}{2}(\pi_{Gj}X - K) + \frac{1}{2}(-\gamma) \tag{1}$$

If the state is bad, IPO will be unsuccessful because of assumption 1. If the first IPO is successful and the revealed state is good, the other firm will go public in the second period. Since the discount factor is $\delta \in (0, 1)$, the probability of having good state is $\frac{1}{2}$, and the first period payoff from inaction is 0, the total payoff from waiting for firm j will be:

$$0 + \delta\frac{1}{2}(\pi_{Gj}X - K) \tag{2}$$

We will be looking for a symmetric Bayesian Nash equilibrium. In this equilibrium, the investors who receive a good signal will demand the IPO shares in the first period. The ones who receive bad signal will not buy any equities. In the second period, if the state is revealed as good, they will buy the issues.

Next, we discuss the firm owner's behavior. First, there is no pure Nash equilibrium in this game. 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 waiting is not extremely costly). By doing so it will learn the aggregate state from the success/failure of the other firm's IPO, and it will save a reputation 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 anything. Since waiting is somewhat costly ($\delta > 0$), it is better for one firm to deviate to IPO1. The only other remaining symmetric equilibrium is the mixed strategy equilibrium,

[13]This loss includes both financial and reputation costs.

in which firms randomize between IPO1 and W1 strategies. The following proposition shows the outcome of this mixed Bayesian Nash equilibrium.

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

$$m_g = \frac{(\pi_{Gb}X - K - \gamma)(1-\delta)}{\delta\gamma} \tag{3}$$

$$m_b = \frac{(\pi_{Gg}X - K - \gamma)(1-\delta)}{\delta\gamma} \tag{4}$$

Proof: The bad quality firm should make the good quality firm indifferent between playing the pure strategy of going public in the first period (IPO1), 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.

$$\frac{1}{2}[X\pi_{Gg} - K - \gamma] = \delta m_b[\frac{1}{2}(X\pi_{Gg} - K)] + \delta(1-m_b)[\frac{1}{2}(X\pi_{Gg} - K - \gamma)] \tag{5}$$

If the good quality firm goes public in the first period, then, regardless of how the bad quality firm plays, its payoff will be $\frac{1}{2}[X\pi_{Gg} - K] - \frac{1}{2}\gamma$ since with probability $\frac{1}{2}$ it will be a good state and the firm will get $[X\pi_{Gg} - K]$ and with probability $\frac{1}{2}$, it will be a bad state and the IPO will be unsuccessful resulting in a loss of γ.

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 which will result in a discounted payoff of $\delta m_b[\frac{1}{2}(X\pi_{Gg} - K)]$. If the bad quality does not go public in the first period (which happens with probability $(1-m_b)$), then the discounted payoff of good firm will be

$\delta(1-m_b)[\frac{1}{2}(X\pi_{Gg}-K-\gamma)]$ since the aggregate uncertainty will not be resolved even in the beginning of the second period. 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.

By solving Equation 5, we have the result:

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

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

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

■

We are interested in the relation between the quality of firm π_{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 $m_{Gg} < m_{Gb}$ iff $\pi_{Gg} > \pi_{Gb}$. The latter is true by assumption. ■

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

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

c) The probability that both g and b firms go public in the first period is $m_g.m_b$

d) The probability that neither firms go 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.

We have already shown that bad firm is more likely to go public in the first period (see Proposition 1). 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 other outcomes are also possible. Namely, the good firms may go public in the first period followed by the bad firms 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 (each firm tries to "free ride"). 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 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. In the Appendix, we show that the model can be extended to include 1) three quality types (good, medium, and bad) or 2) two quality types, but with many firms in each type (N good firms and M bad firms).

2.1. 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.

Prediction 2: Around economic slowdowns, 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 and the market conditions. When the economy is in recession, their projects are worth less (π_{Bj} is smaller than π_{Gj}), and the chances that their IPO will be unsuccessful are higher (not enough investors receive "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 (see the Appendix). In that case, our model has 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 mass, because waiting is not optimal anymore for anybody (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.[14]

Prediction 3 has been the focus of several theoretical studies (see Hoffmann-Burchardi (2001), Benveniste, et al. (2002), and Alti (2005)). From the 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 different, previously unexplored, explanation to the IPO clustering phenomenon; strategic waiting incentives of private firms 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 on the type of firms that will issue when the current trough of the IPO cycle is replaced by the

[14]At it its current form our model has no prediction on what causes the rising cycle to end, and what implications this has on IPO failures.

expanding stage.[15] As the new IPO cycle starts to form from the current - almost zero levels of activity - it is probabilistically more likely that mediocre firms will dominate the pioneering cohort of issuers. The really high-quality firms (say future S&P500 firms) will likely issue in the later – confirmed – stages of the rising cycle.

3. Data

Next, we provide some details about our data sources and our sample selection process.

3.1. 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 1970 and 2007 included in the Securities Data Company (SDC)'s database. After eliminating REITs, closed-end funds, ADRs, unit offers, and MLPs, there are 10,655 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 9,238 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)[16] dataset to find common stock, firm-commitment, and CRSP listed IPO firms not reported in any of our previous sources. We find 59 such IPOs. Thus, our combined initial sample is 9,658 IPOs.

In some instances CRSP does not have trading data for the months immediately following

[15] How slow is the IPO activity currently? There were only two IPOs issued in the U.S. for 2008Q4 (see Jay Ritter's website for the IPO activity in 2008). Last time the IPO market slowed this much was in 1974Q3 and Q4.

[16] 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.

the issuance of the new public firm.[17] In extreme situations, the gap between the issuing date and the first date with non-missing trading data can be more than a year. Also, for various reasons CRSP may stop coverage of some firms. In those cases, we require that at least half of the months in the corresponding 3-yr and 5-yr returns are non-missing.[18] Otherwise, we drop the firm from the sample. The above sample selection procedure leaves us with a final sample of 8,249 IPOs (or alternatively, 7,229 IPOs) when 3-year (5-year) returns are used.

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,[19] its industry classification (at 2- and 3-digit SIC level), its offer price, its underpricing,[20] total proceeds it raised, and its founding year used to calculate its age[21] at the time of issuance. The monthly trading data of our sampled IPO firms are obtained from CRSP. The accounting data is from COMPUSTAT.

3.2. The S&P500 Sample

For some of our tests we need to determine which of our sampled IPOs end up being listed in the prestigious S&P500 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&P500 index for each year between 1970 and 2007. We use the dataset available through Wharton Research Data Services (WRDS) that lists the historic S&P500 Index constituents. This data, in turn, was retrieved from COMPUSTAT database. According to this dataset, in December of every year between 1973 and 2007 there are exactly 500 firms listed in S&P500 index. For the years 1970, 1971, and 1972 there are

[17] CRSP NASDAQ begins reporting returns in December of 1972, for example.

[18] The remaining missing return observations are replaced with CRSP value-weighted index's return.

[19] If it is missing, we use assets from COMPUSTAT for the first quarter after the issuance.

[20] If this variable is not available through the above data sources, we rely on CRSP daily data to obtain 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. If the price information is missing for all of those days, we leave the underpricing observation as empty.

[21] To retrieve information about founding dates, we also use another datafile from Jay Ritter's website: "Founding dates for 8,464 IPOs from 1975-2007." When we see inconsistencies between this data and our main data sources, we rely on the former.

fewer than 500 firms listed (489, 491, and 495, correspondingly).[22] During 1970-2007 period, total of 1,261 firms were member of this index at one point or another. When we match these firms with the above IPO sample,[23] we identify 214 IPO firms that ultimately became part of the S&P500 index.

4. 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.

4.1. 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.

As is traditional in the IPO literature, we use the number of IPOs in each quarter as our most relevant measure of market heat. Our 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)[24] 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. *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

[22] In 1973 Standard&Poors Co. started a practice requiring that when a firm is dropped from the index, another firm replaces it immediately, thus keeping the number of index firms at exactly 500 at all times. They did not follow such a rule for the earlier years.

[23] Matching is done in two steps. First, we match with COMPUSTAT (using GVKEY) to retrieve their CUSIPs. Then, we match with our IPO sample using these CUSIPs.

[24] There are about 40% fewer IPOs issued in the 1^{st} quarter of the callendar year than in its 4^{th} quarter. MA(4) controls for this seasonality effect.

expanding) cycles between 1970 and 2007. A typical rising cycle lasts between 5 to 7 quarters (8 of the 12 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).

Within the rising cycles there are total of 5,050 (4,498) issuance events that remain after eliminating the firms with more than half of the returns missing in the 3-year (5-year) return horizon.

4.2. 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 that are issued in the later parts of it.

After identifying each rising cycle, we rank the quarters within each cycle as the 1^{st} quarter, 2^{nd} quarter, ..., n^{th} quarter 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 that are located beyond the 7^{th} quarter.

4.3. Firm Quality

How do we determine an IPO firm's quality? There are various measures used by the literature, but the one that seems 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. 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&P500 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} is 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

$$CAR_{jt} = \sum_{t=1}^{T} AR_{jt} \tag{6}$$

$$BHAR_{jT} = \prod_{t=1}^{T} (1 + R_{jt}) - \prod_{t=1}^{T} (1 + R_{mt}) \,. \tag{7}$$

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.[25] Sorting into deciles within each rising cycle separately, makes little difference in our results.

4.4. 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 time refers to the timespan between the beginning of an up cycle and the date the firms 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.[26]

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

[25] As described in the previous section, in obtaining our final sample, we eliminate firms that have too many missing monthly observations in the CRSP data. This may lead to a sample selection bias. However, the quality classification we describe here alleviates this problem, because we sort the remaining firms *relative* to each other (our high and low quality concepts are in relative terms). As a robustness test, though, 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 the exchanges. Then, we perform the same tests as below. Our results are qualitatively unchanged, suggesting that sample selection problem has a minimal impact on them.

[26] 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 *relative* to it.

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 $t_1 \leq t_2 \leq ... \leq t_k$. Let m_i represent the number of firms that go public at time t_i, where $i = 1, 2, ..., k$. 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[27]

$$\hat{S}(t_i) = \prod_{j=1}^{i} \left(1 - \frac{m_j}{n_j}\right) \tag{8}$$

$\hat{S}(t_i)$ is a right-continuous step function with jumps in the event times. 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.

5. Results

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

5.1. Descriptive Statistics of the Cycles

Before we proceed with our empirical tests, we first describe our 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[28]), 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 $95/3 - 96/4$

[27] It is important to note that the events at t_i are included in the estimate of $S(t_i)$.

[28] For this purpose we use monthly CPI data obtained from Bureau of Labor Statistics website.

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 0.09 for the rising IPO cycles and 0.21 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 the declining cycles. On average, 492 IPOs go public in a rising cycle vs. 312 in a falling cycle. Note that, we had equal number of rising and falling cycles during 1970-2007 period, which is 12.

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 rising cycles. Performing the tests separately for each cycle would be tedious and too overwhelming for this paper. Our model's prediction(s) are general and in probabilistic terms. What matters to us is that it holds on average. 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.[29]

[29] In unreported results, we performed our analyses by removing each one of the cycles at a time, and run our tests. The main conclusions still hold.

5.2. Average IPO Quality Across Stages of a Rising IPO Cycle

After ordering the quarters of an up cycle in the way described earlier, we check the average quality of the firms in each quarter. Our quality measures are 5-yr BHARs and CARs. The returns for all issuing firms in our sample are presorted into deciles. *Figure 2A* plots the mean return decile of issuing firms in each quarter.[30] We observe that as the cycle's heat is rising, the mean quality shows a general upward trend, as well. This result implies that, on average, the firms issuing in the later quarters of an up cycle are performing better in the long-run than the firms issuing in early stages of an up cycle.[31]

As a robustness check, we perform the same test using 3-year BHARs and CARs, and find the same upward trend (*Figure 2B*).

5.3. Survival Analysis of the IPO Quality Groups

In the next test, 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).

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).[32] *Figure 3A* plots the estimated survival functions of high- and low-quality IPO sub-samples when 3-year BHARs are used to rank the firms.[33] 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*

[30]Since there is only one incidence of an up cycle continuing beyond 7 quarters, we concentrate on the typical up cycles (i.e. cycles that last 3 to 7 quarters).

[31]Note that we are not comparing the composition of hot vs. cold IPO markets, like in Yung, et al. (2008). Instead, we are comparing the composition of IPOs within the expanding IPO cycle: IPOs issued in the early stages vs. IPOs issued during the late stages of the cycle. To be more specific, we are more concerned with the signaling aspect of the first few quarters of an expanding IPO market, and what it implies for the order of the issuance *within* such a rising cycle. Early quarters of an expanding IPO cycle may or may not be classified as hot quarters, depending on how low the rising cycle begins (see *Figure 1*). Our model's predictions require us to concentrate on the the entire expanding cycle, rather than on its hot quarters only.

[32]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.

[33]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.

3B-3D 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.

5.4. IPOs in Each Quarter with Positive Post-Issuance Abnormal Returns

In the previous test we divided all the returns into deciles, and sorted the IPOs from the best to worst quality ones. Obviously, this locates equal number of IPOs in each decile. For our next test we need to define the term "good" IPO. We want to find out what percentage of IPOs issued in a particular quarter are truly good, in the sense that they reward their long-term investors with positive abnormal returns. So, we define as good IPOs the firms that have positive BHAR and CAR for the 3-year (or 5-year) post-issuance period. The rest of the IPOs are "Bad." Then, we compare the firm composition (in terms of good vs. bad IPOs) across each quarter located on the rising cycle.

Table 3 shows the percentage of "good" IPOs in each quarter of an up cycle. On average, only 26.14% (43.05%) of IPOs issued during the first few quarters of a typical rising cycle have positive BHARs (CARs). When the "good" private firms observe that the lesser quality firms were able to raise money, they decide to issue as well. So, in the later stages of a typical rising cycle (quarters 4 through 7) the proportion of "good" quality firms rises. 30.07% (47.56%) of the IPOs issued in those quarters are, on average, "good" according to the BHAR (CAR) criteria. Similar conclusions can be derived for the case when we use 5-year BHAR and CAR returns. Thus, this test supports the model's prediction that good quality firms can afford to, and thus it is likely that they will, wait to receive confirmation of a favorable issuance market.[34]

[34] 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.

5.5. Evidence from S&P500 Firms

Next, we investigate when in the rising IPO cycle, the future S&P500 firms are going public. The IPOs that are later on included in the S&P500 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 214 IPOs issued between 1970 and 2007 that were subsequently listed in the S&P500 index. Of these IPOs, 124 (or 58%) are issued during a rising IPO cycle. Using this sample of 124 S&P500 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 113 IPOs that were issued in a quarter located from the 1^{st} in line to the last (7^{th}) in line of a rising cycle.

Table 4 presents the results of this test. In comparison to the earlier two quarters, the mean number of firms per cycle per location is much higher for quarters 3 through 5. The mean issuance jumps from 2.25 in the second quarter to 3.43 in the fifth quarter: a 52% jump. Similarly, we have a total of 24 IPOs issued in the fifth quarter, which is 33% higher than the corresponding number in the first quarter, 18. This is despite the fact that not all of our rising cycles last until the fifth quarter. All of them, of course, have at least three quarters. In short, mid quarters (quarters 3 through 5) are the most active quarters for future S&P500 firms.

In the second test we ask "Were the S&P500 firms first to issue within their industry?" For each rising cycle (remember that there are 12 of them), within each 2-digit (or alternatively 3-digit) industry, we order all the issuing firms from 1^{st} 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&P500 firm within their industry. *Table 5* shows that for 2-digit SIC sorting, mean issuance order is changing from 3.88 to 31.84 from cycle to cycle. So, the evidence suggests that S&P500 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&P500 firms will issue first are increasing, of course, but still for majority of the cycles (7 out of 10 cycles with an S&P500 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&P500 firm individually, and find that 68% of them were not the first to issue in their 3-digit SIC industry. For example, Genentech was 5^{th}, Microsoft was 18^{th}, and Starbucks was 15^{th} to issue in 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&P500 firms) are not the first issuers even in their own industry.

For reference, we also report the issuance order of S&P500 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&P500 firms.

Thus, based on the results from this subsection, we conclude that S&P500 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, but not too late in the cycle (usually, between the 3^{rd} and the 5^{th} quarter after the start of the cycle).

5.6. 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[35]

[35] We define cash flows as [*Income Before Extraordinary Items* + *Depreciation&Amortization* − *Dividends* (Preferred + Common)] / *Assets*. In an alternative definition, we use *Sales* as a scaling variable in the

of each firm during the first 3 years (or alternatively, 5 years) of its public trading. There are total of 3,795 (or 3,804) 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.

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 3E* and *3F*, and *Table 2, Panel C*, our results from this robustness test confirm that high quality firms (decile 10) wait, on median, 37 to 48 days longer than the low quality ones (decile 1) before issuing.

6. 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&P500 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. Many models explicitly or implicitly assume that pioneering IPOs are usually of the best quality, and all the followers are of lower quality (see Alti (2005) and Hoffmann-Burchardi (2001)). We show, both theoretically and empirically, that not only this assumption is shaky, but also that the reverse order is more likely to happen.

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))

previous equation; our qualitative results do not change.

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 on rise, 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.

Further work of this kind 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 show two generalizations of our model. First one shows what happens when there are three quality types among the issuing firms, and the second one demonstrates that it is possible to have many firms within the quality types (N good and M bad firms).

The Model With Three Firm Types

In this version of the model, there are three types of firms, one good type, one medium type, and one bad type, with the project success probabilities in the order of $\pi_{Gb} < \pi_{Gm} < \pi_{Gg}$. All three firm-types have valuable (positive NPV) projects. For the same reasons as before, we focus on Bayesian Nash mixed strategy equilibrium. In this equilibrium, we will use the notation m_j to denote the probability of playing IPO1 for firm j, $j = b, m, g$. The assumptions in the proposition below guarantee that m_g and m_b are between zero and 1. For example, the first assumption makes sure that the cost of a failed IPO is high enough. Otherwise, all the firms will go public in the first period with probability 1 (i.e. no incentive to wait).

Proposition 4 *Assume that* $\gamma > (X\pi_{Gb} - K)(1-\delta)$

$$0 < \sqrt{\frac{[\gamma - (X\pi_{Gm} - K)(1-\delta)][\gamma - (X\pi_{Gb} - K)(1-\delta)]}{[\gamma - (X\pi_{Gg} - K)(1-\delta)]\delta\gamma}} < 1$$

$$0 < \sqrt{\frac{[\gamma - (X\pi_{Gg} - K)(1-\delta)][\gamma - (X\pi_{Gm} - K)(1-\delta)]}{[\gamma - (X\pi_{Gb} - K)(1-\delta)]\delta\gamma}} < 1$$

$$0 < \sqrt{\frac{[\gamma - (X\pi_{Gm} - K)(1-\delta)][\gamma - (X\pi_{Gb} - K)(1-\delta)]}{[\gamma - (X\pi_{Gg} - K)(1-\delta)]\delta\gamma}} < 1$$

The bad quality firm is more likely to go public in the first period. Specifically, we have $m_g < m_m < m_b$.

Proof: Each firm will solve the following equations in equilibrium when playing the mixed strategy.

$$\delta\frac{1}{2}[1-(1-m_m)(1-m_b)](X\pi_{Gg} - K) + \delta[(1-m_m)(1-m_b)]$$
$$[\frac{1}{2}(X\pi_{Gg} - K) + \frac{1}{2}(-\gamma)] = \frac{1}{2}(X\pi_{Gg} - K - \gamma) \tag{9}$$

$$\delta\frac{1}{2}[1-(1-m_g)(1-m_b)](X\pi_{Gm} - K) + \delta[(1-m_g)(1-m_b)]$$
$$[\frac{1}{2}(X\pi_{Gm} - K) + \frac{1}{2}(-\gamma)] = \frac{1}{2}(X\pi_{Gm} - K - \gamma) \tag{10}$$

$$\delta\frac{1}{2}[1-(1-m_g)(1-m_m)](X\pi_{Gb}-K)+\delta[(1-m_g)(1-m_m)]$$
$$[\frac{1}{2}(X\pi_{Gb}-K)+\frac{1}{2}(-\gamma)]=\frac{1}{2}(X\pi_{Gb}-K-\gamma) \tag{11}$$

First, we find the following three reduced form equations by removing the constant term $\frac{1}{2}$ and the common terms.

$$\delta[X\pi_{Gg}-K-(1-m_m)(1-m_b)\gamma]=X\pi_{Gg}-K-\gamma \tag{12}$$

$$\delta[X\pi_{Gm}-K-(1-m_g)(1-m_b)\gamma]=X\pi_{Gm}-K-\gamma \tag{13}$$

$$\delta[X\pi_{Gb}-K-(1-m_g)(1-m_m)\gamma]=X\pi_{Gb}-K-\gamma \tag{14}$$

Second, we rearrange equation 12 to equation 14.

$$(1-m_m)(1-m_b)\delta\gamma=\gamma-(X\pi_{Gg}-K)(1-\delta) \tag{15}$$

$$(1-m_g)(1-m_b)\delta\gamma=\gamma-(X\pi_{Gm}-K)(1-\delta) \tag{16}$$

$$(1-m_g)(1-m_m)\delta\gamma=\gamma-(X\pi_{Gb}-K)(1-\delta) \tag{17}$$

Third, we find m_b and m_m in terms of m_g and all the parameters by dividing equation 15 by equation 18 and dividing equation 15 by equation 16.

$\frac{1-m_m}{1-m_g}=\frac{\gamma-(X\pi_{Gg}-K)(1-\delta)}{\gamma-(X\pi_{Gm}-K)(1-\delta)}\Longrightarrow(1-m_m)=\frac{\gamma-(X\pi_{Gg}-K)(1-\delta)}{\gamma-(X\pi_{Gm}-K)(1-\delta)}(1-m_g)$

$\frac{1-m_b}{1-m_g}=\frac{\gamma-(X\pi_{Gg}-K)(1-\delta)}{\gamma-(X\pi_{Gb}-K)(1-\delta)}\Longrightarrow(1-m_b)=\frac{\gamma-(X\pi_{Gg}-K)(1-\delta)}{\gamma-(X\pi_{Gb}-K)(1-\delta)}(1-m_g)$

And then substituting $(1-m_m)$ and $(1-m_b)$ into equation 15, we have the mixed strategy of good-type firm, m_g,

$(1-m_g)^2=\frac{[\gamma-(X\pi_{Gm}-K)(1-\delta)][\gamma-(X\pi_{Gb}-K)(1-\delta)]}{[\gamma-(X\pi_{Gg}-K)(1-\delta)]\delta\gamma}\Longrightarrow$

$1-m_g=\sqrt{\frac{[\gamma-(X\pi_{Gm}-K)(1-\delta)][\gamma-(X\pi_{Gb}-K)(1-\delta)]}{[\gamma-(X\pi_{Gg}-K)(1-\delta)]\delta\gamma}}\Longrightarrow$

$$m_g=1-\sqrt{\frac{[\gamma-(X\pi_{Gm}-K)(1-\delta)][\gamma-(X\pi_{Gb}-K)(1-\delta)]}{[\gamma-(X\pi_{Gg}-K)(1-\delta)]\delta\gamma}} \tag{18}$$

Symmetrically, the mixed strategies of medium-type and bad-type firms, m_m and m_b, are given by the following equations,

$$m_m=1-\sqrt{\frac{[\gamma-(X\pi_{Gg}-K)(1-\delta)][\gamma-(X\pi_{Gb}-K)(1-\delta)]}{[\gamma-(X\pi_{Gm}-K)(1-\delta)]\delta\gamma}} \tag{19}$$

$$m_b=1-\sqrt{\frac{[\gamma-(X\pi_{Gg}-K)(1-\delta)][\gamma-(X\pi_{Gm}-K)(1-\delta)]}{[\gamma-(X\pi_{Gb}-K)(1-\delta)]\delta\gamma}} \tag{20}$$

From equation 18 to equation 20, we also find that $m_b > m_m > m_g$, when $\pi_{Gg} > \pi_{Gg} > \pi_{Gb}$.

$m_b > m_m > m_g \iff$

$1 - \sqrt{\frac{[\gamma-(X\pi_{Gm}-K)(1-\delta)][\gamma-(X\pi_{Gg}-K)(1-\delta)]}{[\gamma-(X\pi_{Gb}-K)(1-\delta)]\delta\gamma}} > 1 - \sqrt{\frac{[\gamma-(X\pi_{Gg}-K)(1-\delta)][\gamma-(X\pi_{Gb}-K)(1-\delta)]}{[\gamma-(X\pi_{Gm}-K)(1-\delta)]\delta\gamma}} >$
$1 - \sqrt{\frac{[\gamma-(X\pi_{Gb}-K)(1-\delta)][\gamma-(X\pi_{Gm}-K)(1-\delta)]}{[\gamma-(X\pi_{Gg}-K)(1-\delta)]\delta\gamma}}$

Removing the constant term and changing the greater-than sign.

$\iff \sqrt{\frac{[\gamma-(X\pi_{Gm}-K)(1-\delta)][\gamma-(X\pi_{Gg}-K)(1-\delta)]}{[\gamma-(X\pi_{Gb}-K)(1-\delta)]\delta\gamma}} < \sqrt{\frac{[\gamma-(X\pi_{Gg}-K)(1-\delta)][\gamma-(X\pi_{Gb}-K)(1-\delta)]}{[\gamma-(X\pi_{Gm}-K)(1-\delta)]\delta\gamma}} <$
$\sqrt{\frac{[\gamma-(X\pi_{Gb}-K)(1-\delta)][\gamma-(X\pi_{Gm}-K)(1-\delta)]}{[\gamma-(X\pi_{Gg}-K)(1-\delta)]\delta\gamma}}$

Removing the square root, we get:

$\iff \frac{[\gamma-(X\pi_{Gm}-K)(1-\delta)][\gamma-(X\pi_{Gg}-K)(1-\delta)]}{[\gamma-(X\pi_{Gb}-K)(1-\delta)]} < \frac{[\gamma-(X\pi_{Gg}-K)(1-\delta)][\gamma-(X\pi_{Gb}-K)(1-\delta)]}{[\gamma-(X\pi_{Gm}-K)(1-\delta)]} <$
$\frac{[\gamma-(X\pi_{Gb}-K)(1-\delta)][\gamma-(X\pi_{Gm}-K)(1-\delta)]}{[\gamma-(X\pi_{Gg}-K)(1-\delta)]}$

$\iff [\gamma - (X\pi_{Gg} - K)(1-\delta)]^2 < [\gamma - (X\pi_{Gm} - K)(1-\delta)]^2 < [\gamma - (X\pi_{Gb} - K)(1-\delta)]^2$

$\iff [\gamma - (X\pi_{Gg} - K)(1-\delta)] < [\gamma - (X\pi_{Gm} - K)(1-\delta)] < [\gamma - (X\pi_{Gb} - K)(1-\delta)]$

$\iff (X\pi_{Gg} - K)(1-\delta) > (X\pi_{Gm} - K)(1-\delta)] > (X\pi_{Gb} - K)(1-\delta)$

Removing the positive constant term $(1-\delta)$ and not changing the sign.

$\iff (X\pi_{Gg} - K) > (X\pi_{Gm} - K) > (X\pi_{Gb} - K)$

$\iff \pi_{Gg} > \pi_{Gm} > \pi_{Gb}$

■

The Model With Many Firms in Each Type

Next, we will show that our model allows for multiple number of firms in each type. Suppose that there are N good-type firms and M bad-type firms. Everything else is the same as in the main model, except that we have to adjust our assumptions for this case.

Assumptions:

1) $(1-p)R < K$

2) $pR > (M+N)K$.

Again, the assumptions within the proposition are for tractability of the model. They assure that m_g and m_b are between zero and 1.

Proposition 5 *Assume that* $\gamma > (X\pi_{Gb} - K)(1-\delta)$ *and*

$$0 < \exp[\frac{M\ln(\gamma - (X\pi_{Gb} - K)(1-\delta)) - (M-1)\ln(\gamma - (X\pi_{Gg} - K)(1-\delta)) - \ln\delta\gamma}{M+N-1}] < 1$$

$$0 < \exp[\frac{N\ln(\gamma - (X\pi_{Gg} - K)(1-\delta)) - (N-1)\ln(\gamma - (X\pi_{Gb} - K)(1-\delta)) - \ln\delta\gamma}{M+N-1}] < 1$$

In a symmetric mixed strategy Bayesian Nash equilibrium, bad quality firm is more likely to go public in the first period compared to a good quality firm. That is $m_b > m_g$.

Proof: We are looking for a symmetric equilibrium. That is, all good type firms will play IPO1 with probability m_g, and all bad quality firms will play IPO with probability m_b. All the firms must be indifferent between playing IPO1 and W1 in this equilibrium. That is, each firm will solve the following equations in equilibrium when playing the mixed strategy. In equation 21, a good type of firm is indifferent between playing IPO1 and W1. In equation 22, a bad type of firm is indifferent between two pure strategies. The only difference is that if a good firm waits, then the probability that at least one firm plays IPO1 and reveals the aggregate state is $[1-(1-m_g)^{N-1}(1-m_b)^M]$.

$$\delta\frac{1}{2}[1-(1-m_g)^{N-1}(1-m_b)^M](X\pi_{Gg}-K)+\delta[(1-m_g)^{N-1}(1-m_b)^M]$$
$$[\frac{1}{2}(X\pi_{Gg}-K)+\frac{1}{2}(-\gamma)]=\frac{1}{2}(X\pi_{Gg}-K)-\frac{1}{2}\gamma \tag{21}$$

$$\delta\frac{1}{2}[1-(1-m_g)^{N}(1-m_b)^{M-1}](X\pi_{Gb}-K)+\delta[(1-m_g)^{N}(1-m_b)^{M-1}]$$
$$[\frac{1}{2}(X\pi_{Gb}-K)+\frac{1}{2}(-\gamma)]=\frac{1}{2}(X\pi_{Gb}-K)-\frac{1}{2}\gamma \tag{22}$$

First, we find the following two reduced form equations by removing the constant term $\frac{1}{2}$ and the common term $\delta(1-m_g)^{N-1}(1-m_b)^M](X\pi_{Gg}-K)$ and $\delta(1-m_g)^N(1-m_b)^{M-1}](X\pi_{Gb}-K)$.

$$\delta[X\pi_{Gg}-K-(1-m_g)^{N-1}(1-m_b)^M\gamma]=X\pi_{Gg}-K-\gamma \tag{23}$$

$$\delta[X\pi_{Gb}-K-(1-m_g)^{N}(1-m_b)^{M-1}\gamma]=X\pi_{Gb}-K-\gamma \tag{24}$$

Second, by rearranging equation 23 and equation 24, we get the following.

$$(1-m_g)^{N-1}(1-m_b)^M\delta\gamma=\gamma-(X\pi_{Gg}-K)(1-\delta) \tag{25}$$

$$(1-m_g)^{N}(1-m_b)^{M-1}\delta\gamma=\gamma-(X\pi_{Gb}-K)(1-\delta) \tag{26}$$

Third, we divide equation 25 by equation 26.
$\frac{1-m_b}{1-m_g}=\frac{\gamma-(X\pi_{Gg}-K)(1-\delta)}{\gamma-(X\pi_{Gb}-K)(1-\delta)} \Longrightarrow (1-m_b)=\frac{\gamma-(X\pi_{Gg}-K)(1-\delta)}{\gamma-(X\pi_{Gb}-K)(1-\delta)}(1-m_g)$
And then substituting $1-m_b$ into equation 25 we have,
$(1-m_g)^{M+N-1}(\frac{\gamma-(X\pi_{Gg}-K)(1-\delta)}{\gamma-(X\pi_{Gb}-K)(1-\delta)})^M\delta\gamma=\frac{\gamma-(X\pi_{Gg}-K)(1-\delta)}{\delta\gamma} \Longrightarrow$

$$(1-m_g)^{M+N-1}=\frac{[\gamma-(X\pi_{Gb}-K)(1-\delta)]^M}{[\gamma-(X\pi_{Gg}-K)(1-\delta)]^{M-1}\delta\gamma} \tag{27}$$

Finally, we take the natural log of both sides of equation 27, and find the mixed strategies of the good type, m_g.

$(M+N-1)\ln(1-m_g) = M\ln(\gamma-(X\pi_{Gb}-K)(1-\delta)-(M-1)\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-\ln\delta\gamma \Longrightarrow$

$$m_g = 1-\exp[\frac{M\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))-(M-1)\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-\ln\delta\gamma}{M+N-1}] \tag{28}$$

Symmetrically, the mixed strategies of bad type firms, m_b, is given by the following equation,

$$m_b = 1-\exp[\frac{N\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-(N-1)\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))-\ln\delta\gamma}{M+N-1}] \tag{29}$$

From equation 28 and equation 29, we also find that $m_b > m_g$, when $\pi_{Gg} > \pi_{Gb}$.

If $m_b > m_g$ and we substitute the results, we have

$1-\exp[\frac{N\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-(N-1)\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))-\ln\delta\gamma}{M+N-1}] >$
$1-\exp[\frac{M\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))-(M-1)\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-\ln\delta\gamma}{M+N-1}]$

Removing the constant term and changing the greater-than sign,

$\Longleftrightarrow \exp[\frac{N\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-(N-1)\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))-\ln\delta\gamma}{M+N-1}] <$
$\exp[\frac{M\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))-(M-1)\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-\ln\delta\gamma}{M+N-1}]$

Remove the exponential function and keep the same sign, because it is an increasing function.

$\Longleftrightarrow N\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-(N-1)\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))-\ln\delta\gamma < M\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))-(M-1)\ln(\gamma-(X\pi_{Gg}-K)(1-\delta))-\ln\delta\gamma$

$\Longleftrightarrow (N+M-1)\ln(\gamma-(X\pi_{Gg}-K)(1-\delta)) < (N+M-1)\ln(\gamma-(X\pi_{Gb}-K)(1-\delta))$

$\Longleftrightarrow \ln(\gamma-(X\pi_{Gg}-K)(1-\delta)) < \ln(\gamma-(X\pi_{Gb}-K)(1-\delta))$

Remove the logarithmic function and keep the same sign, because it is an increasing function.

$\Longleftrightarrow -(X\pi_{Gg}-K)(1-\delta) < -(X\pi_{Gb}-K)(1-\delta) \Longleftrightarrow (X\pi_{Gg}-K) > (X\pi_{Gb}-K)$

$\Longleftrightarrow \pi_{Gg} > \pi_{Gb}$. By assumption, this is true; hence, $m_b > m_g$.

■

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Figure 1: IPO Activity Over Time (Quarterly)

This figure plots the quarterly number of IPOs and its four-quarter moving average (i.e. MA(4)). Timespan is between 1970 and 2007. For referense, the quarters when the U.S. economy was in a recession, as defined by NBER, are also shown with circles on the horizontal axis.

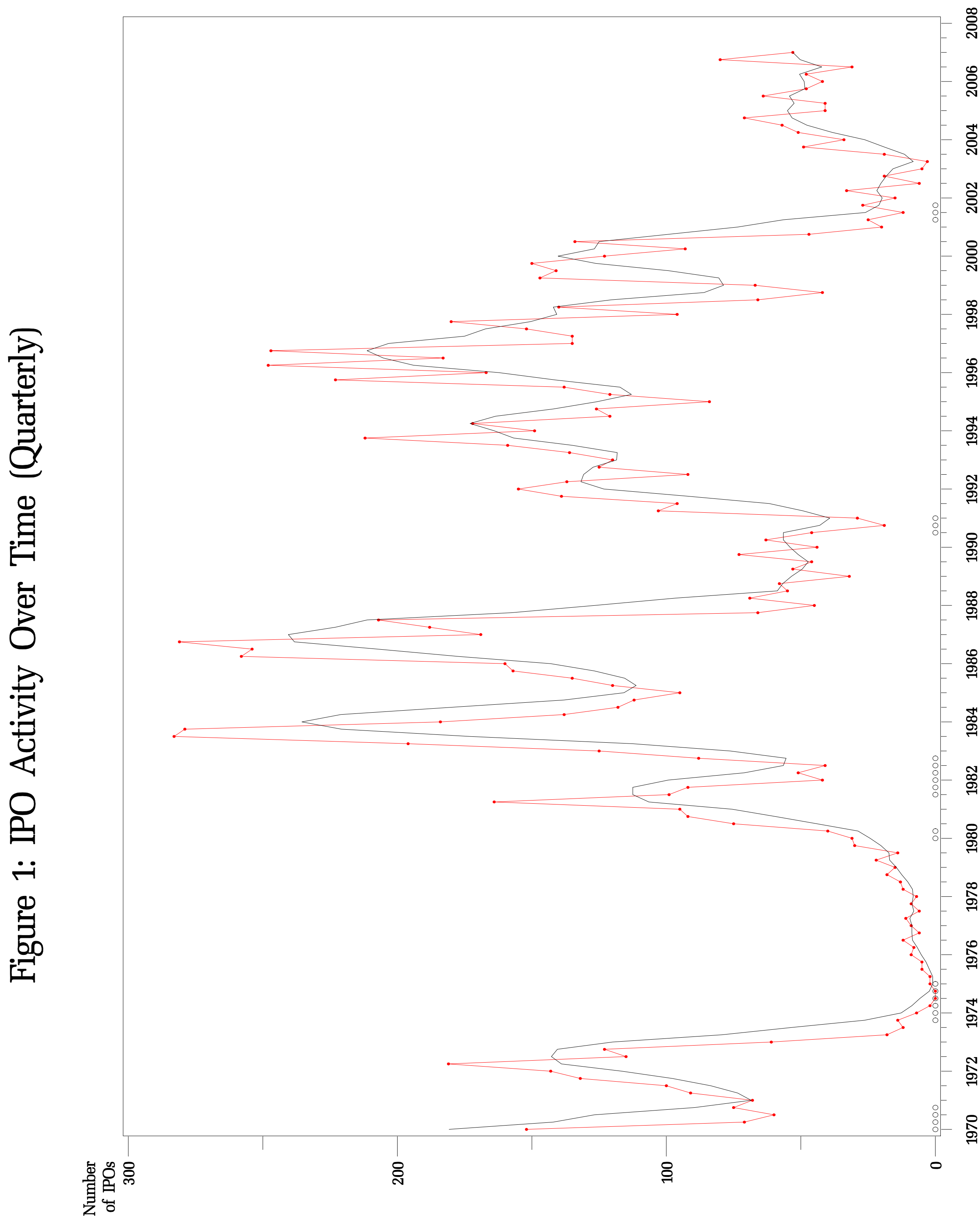

Figure 2: IPO Quality Across Quarters of the Rising Cycle

Figures 2A and 2B plot the average quality decile of the IPOs issued in each quarter of a rising cycle. The quality of an IPO is measured by its BHAR or CAR, and the return horizons considered are 3-year and 5-year. BHARs and CARs are presorted into deciles (largest returns are in decile 10). A rising cycle is the one for which MA(4) of quarterly number of IPOs has been rising for at least 3 quarters. The quarters in each rising cycle are ordered as 1^{st}, 2^{nd},..., 7^{th} since the beginning of the cycle.

Figure 2A: Mean Quality Rank Across Quarters (3 − Year Returns)

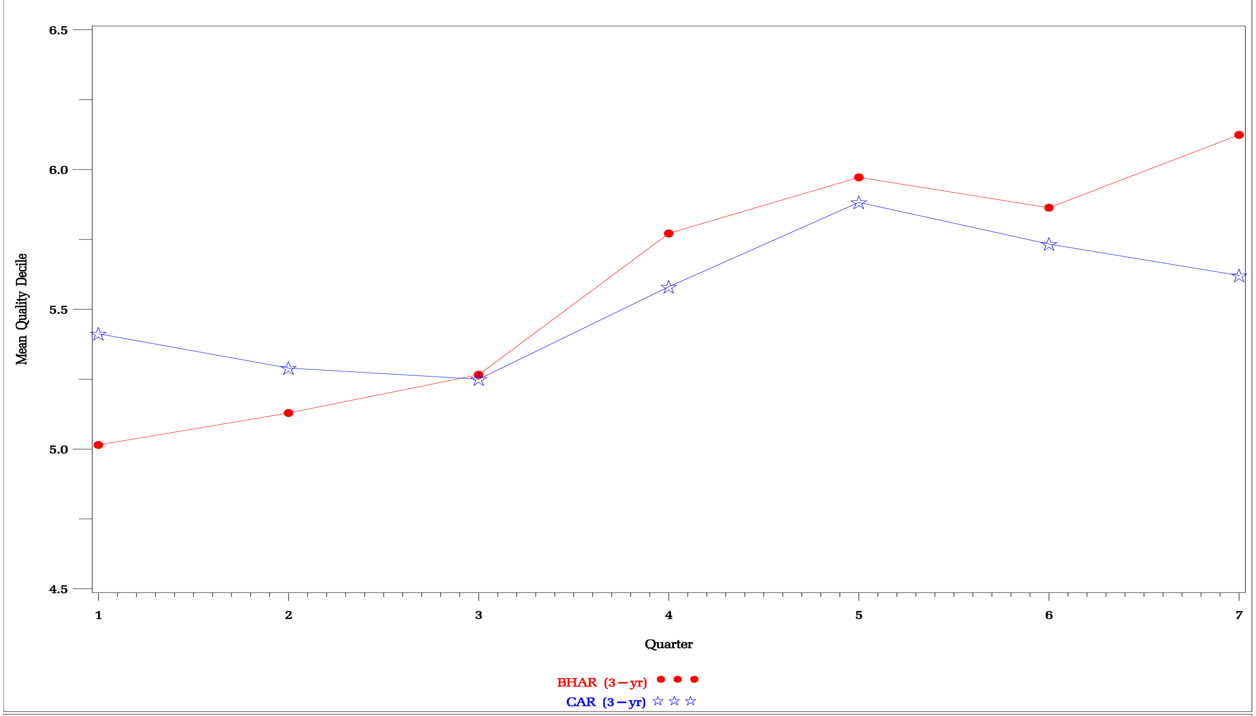

Figure 2B: Mean Quality Rank Across Quarters (5 − Year Returns)

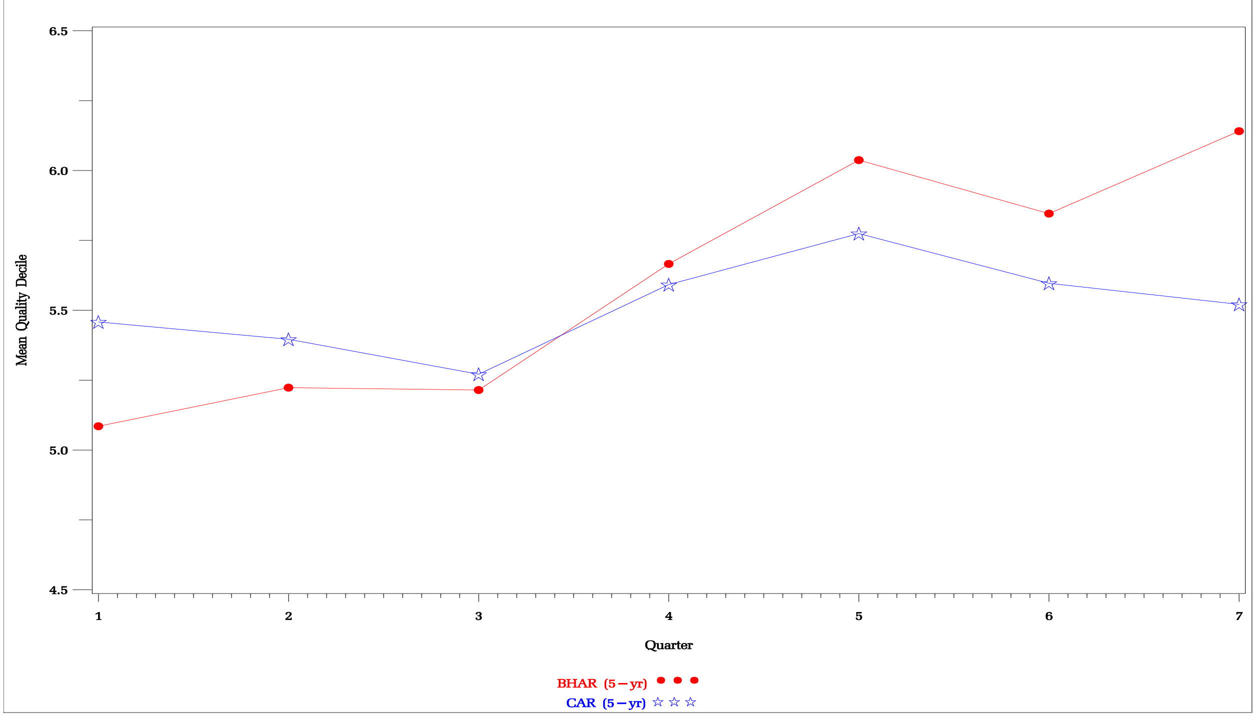

Figure 3: Survival Function by Quality Groups

Figures 3A-3F 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.

Figure 3A: Ranking with 3 – year BHAR

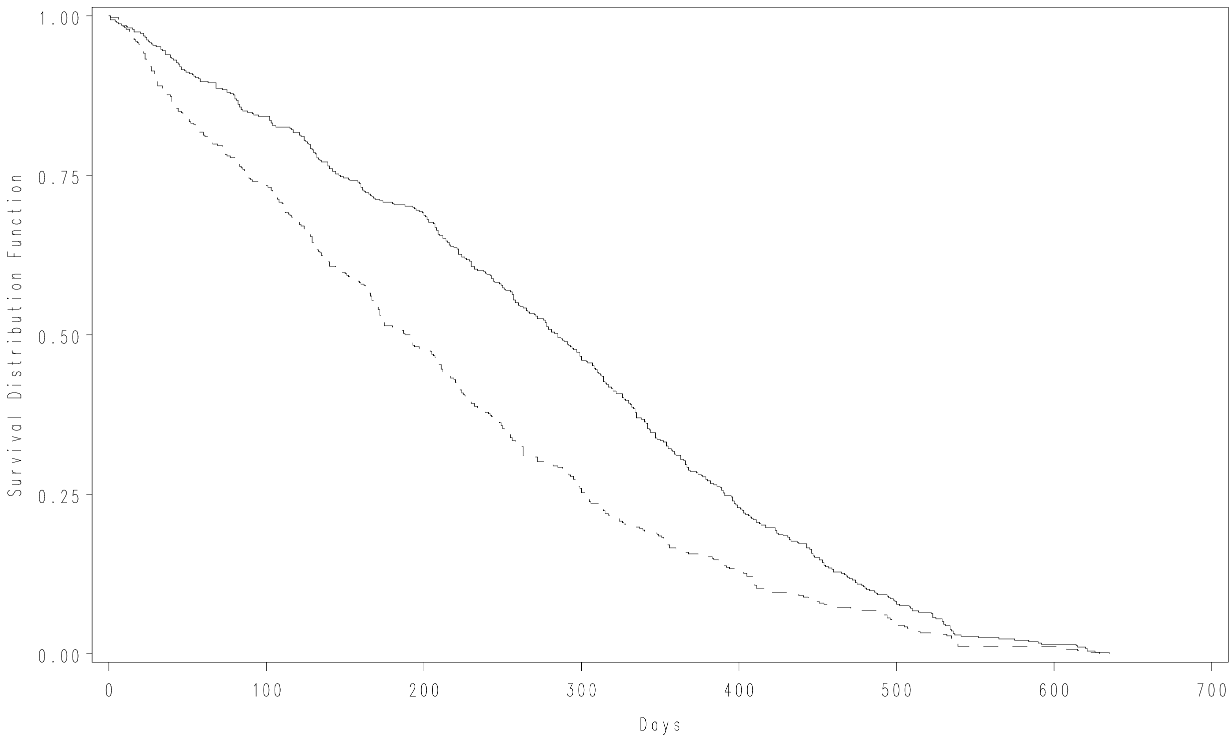

Figure 3B: Ranking with 5 – year BHAR

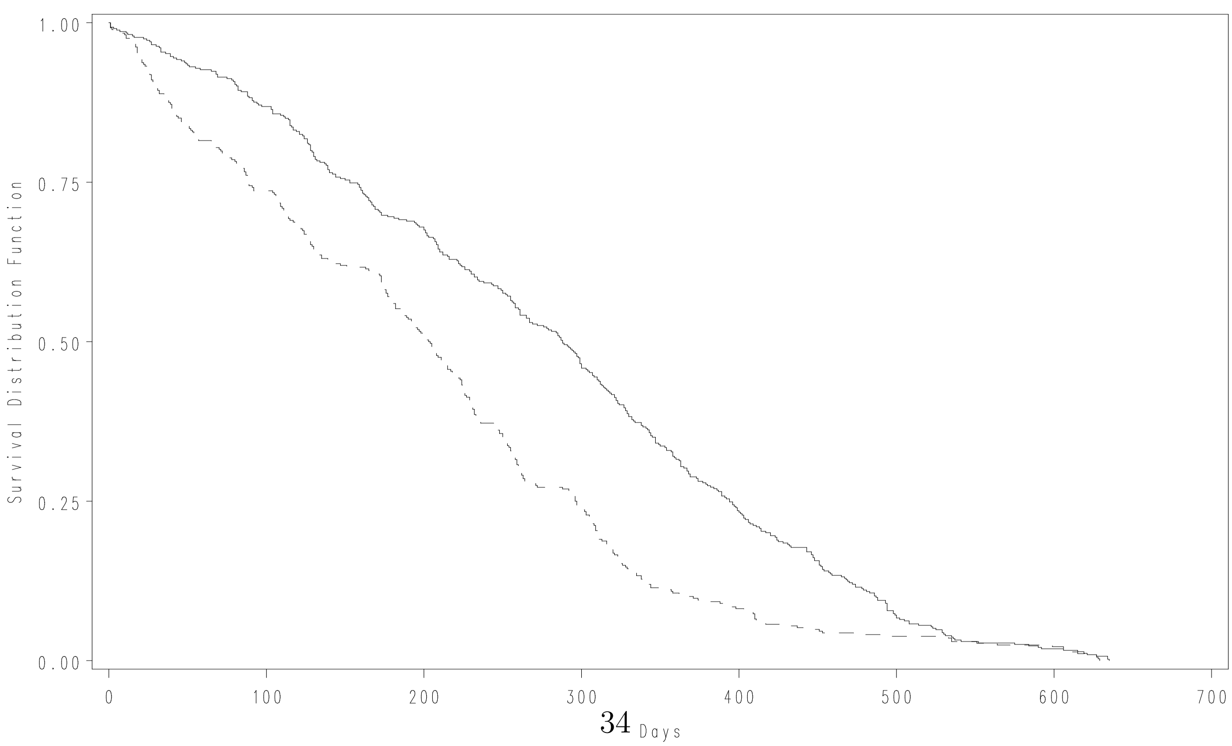

Figure 3C: Ranking with 3 − year CAR

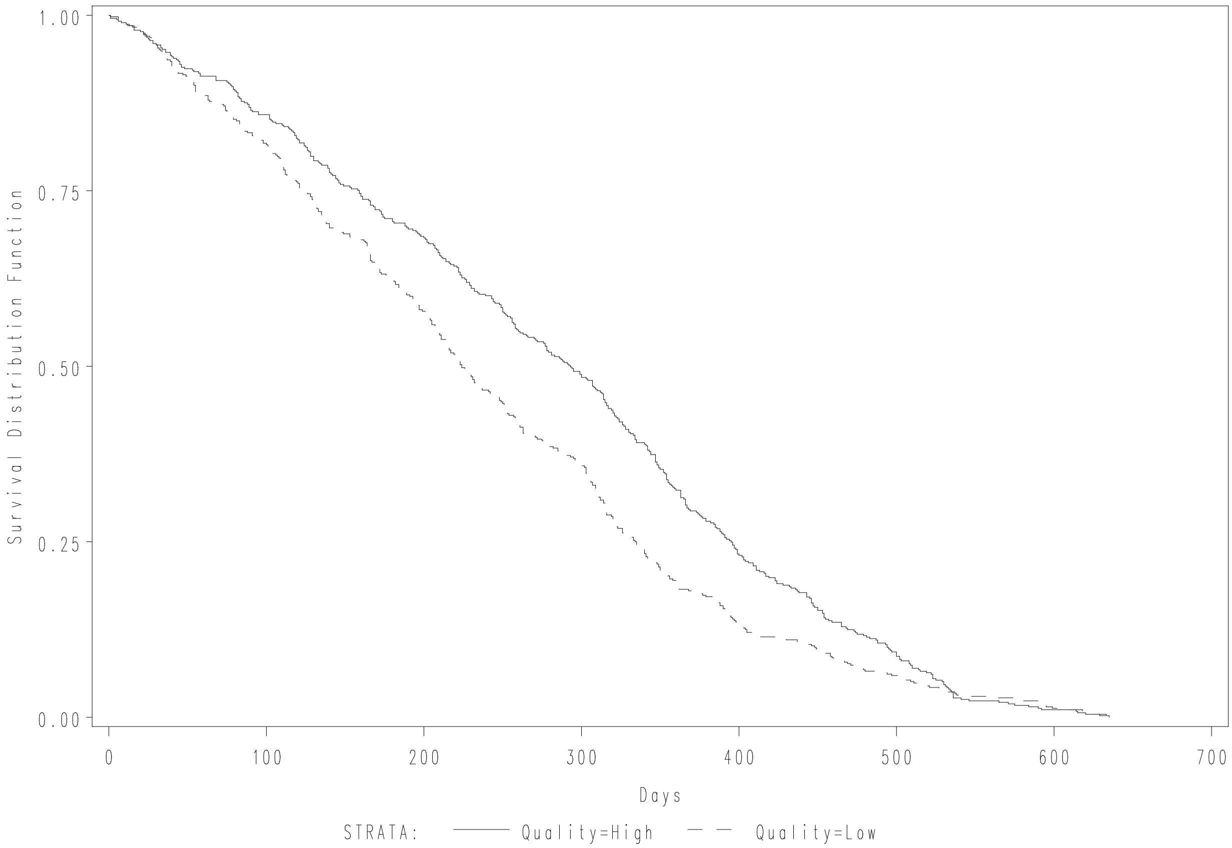

Figure 3D: Ranking with 5 − year CAR

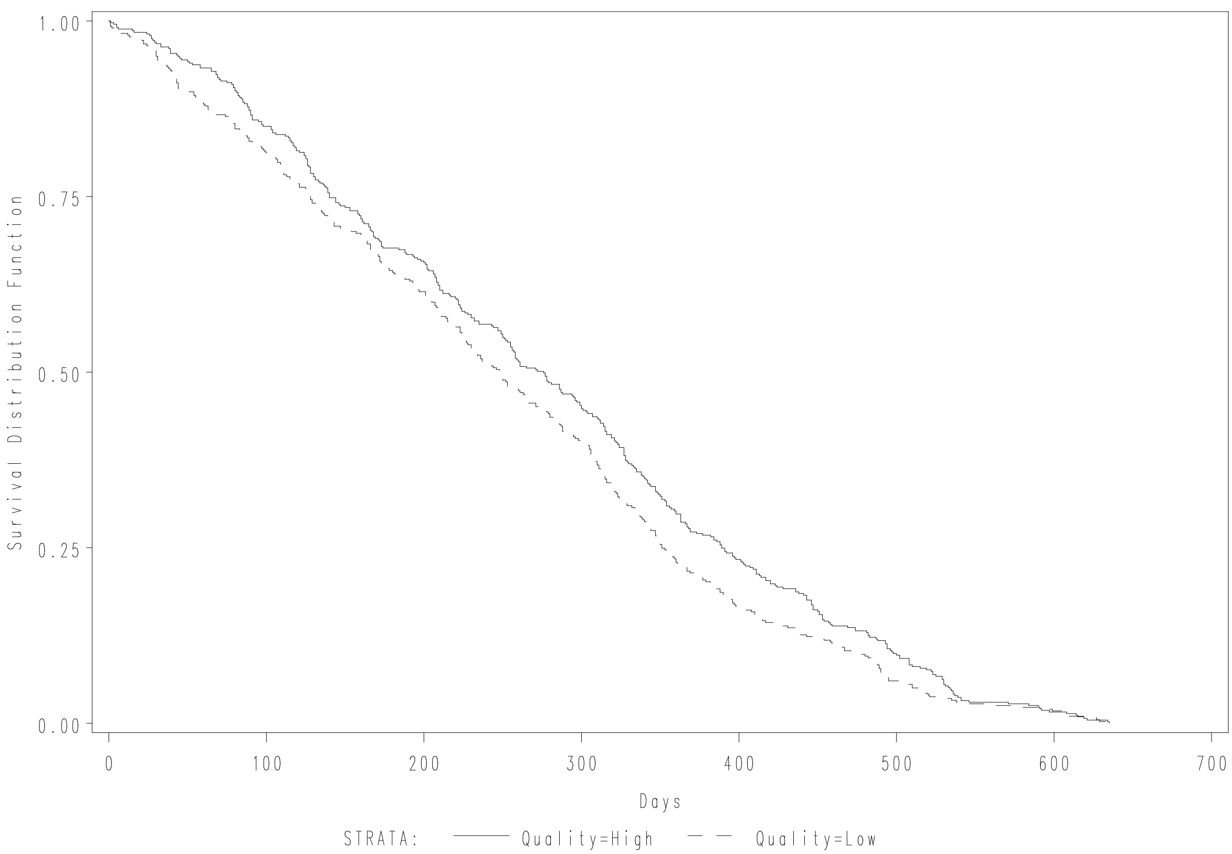

Figure 3E: Ranking with Average Cash Flows (3 Years)

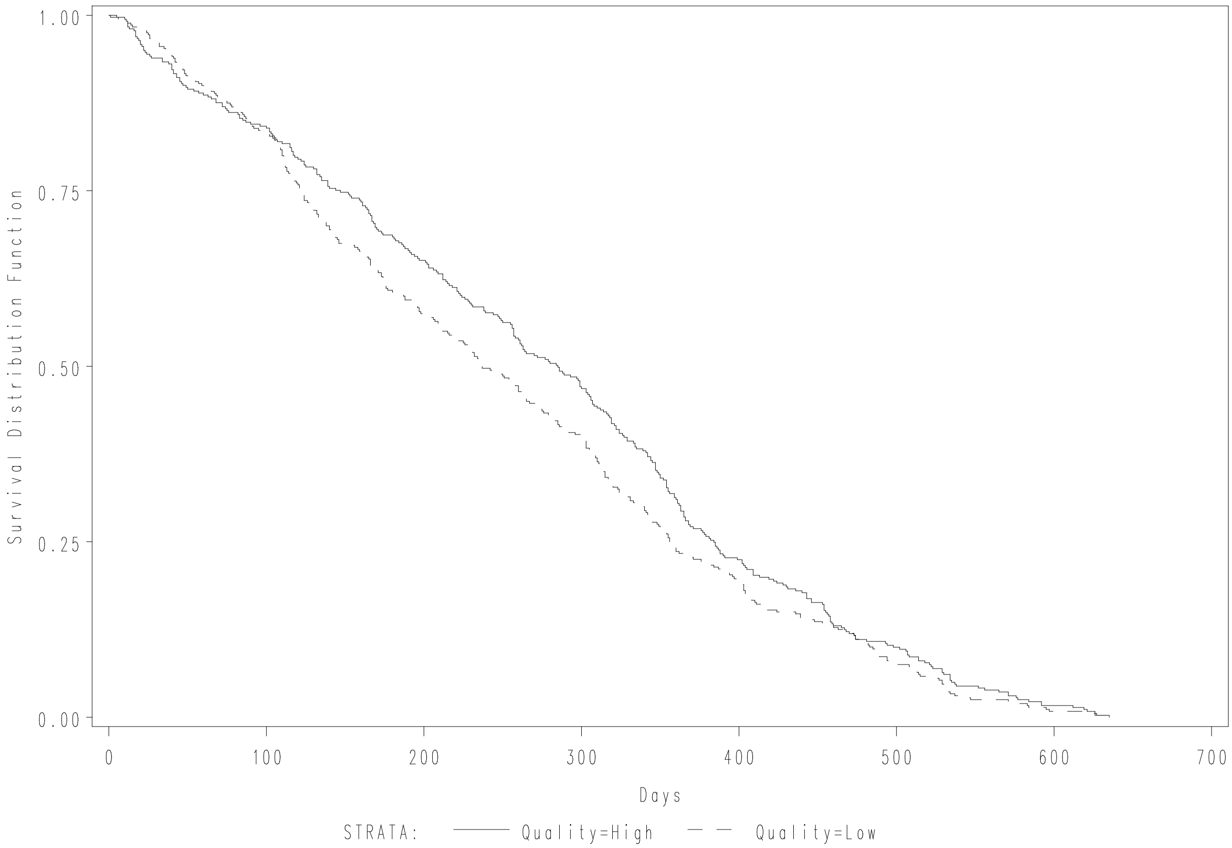

Figure 3F: Ranking with Average Cash Flows (5 Years)

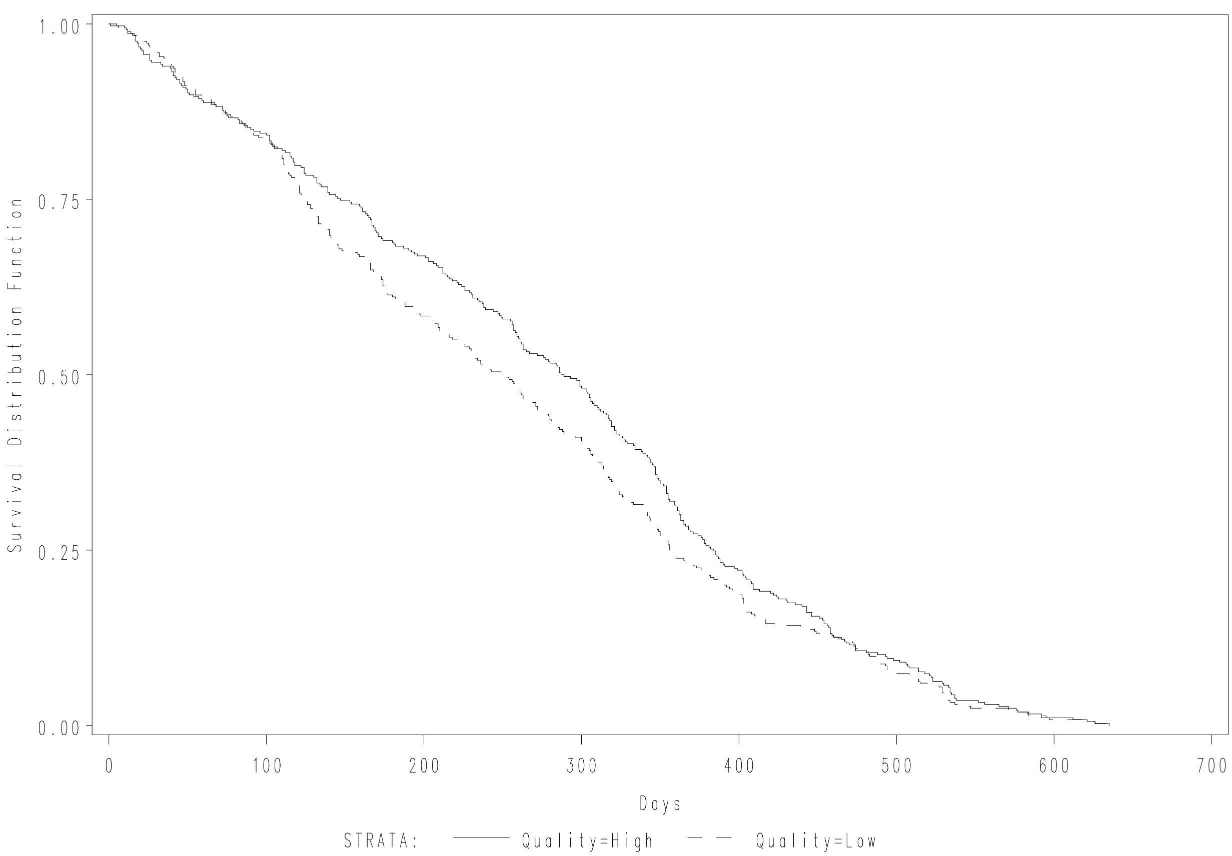

Table 1: Descriptive Statistics of the Cycles

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 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 $s; 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 $s; in million $s).

	(1) Duration (qtrs)	(2) # of IPOs	(3) % with +'ve 5yr BHAR(CAR)	(4) Mean 5yr BHAR (CAR)	(5) Mean(Med.) Underp.	(6) Mean(Med.) Proceeds	(7) Mean(Med.) Age	(8) Mean (Med.) Size
Rising Cycles:								
71/2 – 72/3	6	425	15.06(31.76)	–29.81(+ 1.08)	+142.53(+142.53)	$ 19.73($12.44)	14.15(7)	$ 84.62($ 49.67)
75/3 – 76/4	6	41	26.83(36.59)	–23.66(–19.43)	+ 0.38(– 0.75)	$ 27.56($17.52)	25.57(11)	$ 15.37($ 82.13)
78/2 – 81/3	14	453	17.00(34.00)	–73.16(–38.67)	+ 13.80(+ 4.08)	$ 18.33($10.94)	10.71(7)	$ 56.00($ 21.34)
83/1 – 84/1	5	751	27.56(42.34)	– 2.34(– 1.18)	+ 9.17(+ 1.56)	$ 31.49($15.37)	16.16(8)	$ 200.38($ 29.79)
85/3 – 87/1	7	832	23.80(38.94)	– 8.67(– 8.15)	+ 14.23(+ 2.24)	$ 39.59($14.72)	19.61(7)	$ 339.33($ 27.96)
89/4 – 90/2	3	142	21.83(38.03)	–14.05(–20.34)	+ 14.31(+ 5.88)	$ 34.98($20.74)	15.24(8)	$ 271.42($ 50.93)
91/2 – 92/2	5	552	24.64(45.29)	–38.15(–13.14)	+ 10.96(+ 5.67)	$ 54.86($30.24)	18.62(9)	$ 222.48($ 55.75)
93/3 – 94/2	4	658	26.29(42.10)	+23.58(– 1.24)	+ 9.68(+ 4.46)	$ 55.27($26.25)	13.05(8)	$ 311.33($ 48.53)
95/3 – 96/4	6	1,044	16.57(40.61)	–27.02(+22.19)	+ 19.89(+ 11.63)	$ 51.41($31.18)	11.86(8)	$ 202.00($ 48.88)
99/2 – 00/1	4	498	04.02(26.71)	–138.58(–31.05)	+ 78.26(+ 44.01)	$101.04($59.85)	9.81(5)	$1745.93($ 93.90)
03/3 – 05/1	7	297	26.60(38.72)	–16.94(–17.68)	+ 10.91(+ 6.00)	$145.19($85.74)	18.55(9)	$ 726.68($213.01)
06/4 – 07/4	5	216	——(——)	——-(——-)	+ 14.40(+ 6.87)	$144.04($80.70)	16.97(10)	$ 756.99($135.29)
Total	72	5,909	19.78(37.21)	–26.90(– 5.96)	+ 19.54(+ 5.98)	$ 54.88($25.04)	14.86(8)	$ 435.59($ 53.15)
Falling Cycles:								
70/1 – 71/1	5	133	11.28(18.05)	–19.33(–14.64)	–29.03(+ 2.20)	$14.58($ 8.79)	16.55 (16)	$108.84($ 56.62)
72/4 – 75/2	11	140	12.86(31.43)	–52.37(– 4.49)	– 2.44(+ 0.31)	$24.56($10.26)	23.46 (6)	$610.22($ 43.91)
77/1 – 78/1	5	29	31.03(44.83)	+11.58(+ 1.63)	+ 5.56(– 0.43)	$15.24($11.48)	9.68 (8.5)	$ 50.29($ 25.36)
81/4 – 82/4	5	174	20.11(34.48)	–33.98(–29.41)	+ 6.99(+ 1.19)	$19.13($ 9.92)	11.36 (7)	$ 55.33($ 21.05)
84/2 – 85/2	5	305	22.30(38.69)	–10.39(– 8.45)	– 0.21 (0)	$17.86($ 8.82)	17.33 (10)	$ 72.68($ 20.52)
87/2 – 89/3	10	594	21.55(43.60)	+ 2.30(+15.02)	+29.47(+ 2.66)	$34.11($12.32)	19.39 (7)	$479.21($ 31.06)
90/3 – 91/1	3	83	16.87(39.76)	–96.21(– 7.40)	+10.66(+ 7.29)	$42.11($19.83)	14.71 (8)	$227.94($ 49.06)
92/3 – 93/2	4	443	24.38(41.31)	–24.78(–13.68)	+10.89(+ 6.25)	$59.35($27.33)	17.07 (9.5)	$667.57($ 50.19)
94/3 – 95/2	4	368	18.21(39.67)	–15.63(+11.63)	+16.58(+ 8.33)	$41.66($26.05)	12.82 (8)	$150.85($ 45.65)
97/1 – 99/1	9	861	14.63(39.02)	–45.30(+19.24)	+20.54(+ 9.09)	$68.68($35.71)	14.69 (8)	$579.05($ 75.20)
00/2 – 03/2	13	397	16.12(37.78)	–69.24(– 4.44)	+52.07(+11.07)	$155.73($69.05)	14.76 (8)	$2717.36($130.22)
05/2 – 06/3	6	222	00.91(0.91)	–23.29(–44.47)	+ 8.49(+ 3.99)	$127.80($82.01)	22.51 (10)	$677.97($192.12)
Total	80	3,749	17.44(36.49)	–30.78(+ 2.87)	+20.70(+ 5.19)	$61.16($25.29)	16.13 (8)	$700.84($ 60.27)

Table 2: 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*) and one likelihood ratio test ($-2Log(LR)$) 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.

Panel A: BHAR Returns						
	3 years			*5 years*		
Quality	Mean (Days)	Median (Days)	# of IPOs	Mean (Days)	Median (Days)	# of IPOs
High	278.37	285.00	472	279.96	288.00	420
Low	211.82	192.00	472	207.70	207.50	420
Tests						
Log-Rank	0.0001			0.0001		
Wilcoxon	0.0001			0.0001		
-2Log(LR)	0.0001			0.0001		

Panel B: CAR Returns						
	3 years			*5 years*		
Quality	Mean (Days)	Median (Days)	# of IPOs	Mean (Days)	Median (Days)	# of IPOs
High	283.11	293.00	472	276.46	274.00	420
Low	240.95	224.00	472	254.62	248.00	420
Tests						
Log-Rank	0.0001			0.0382		
Wilcoxon	0.0001			0.0467		
-2Log(LR)	0.0133			0.1331		

Panel C: Cash Flows						
	3 years			*5 years*		
Quality	Mean (Days)	Median (Days)	# of IPOs	Mean (Days)	Median (Days)	# of IPOs
High	276.15	285.00	361	277.87	288.00	366
Low	253.74	237.00	360	255.40	251.00	365
Tests						
Log-Rank	0.0263			0.0375		
Wilcoxon	0.0403			0.0390		
-2Log(LR)	0.0843			0.1573		

Table 3: Percentage of Good IPOs in Each Quarter of a Rising Cycle

The table presents the percentage of "good" IPOs issued in each quarter of a rising cycle. 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^{st} quarter, 2^{nd} quarter, ...,7^{th} quarter since the beginning of the rise. "Good" IPOs are the firms that deliver *positive* 3-year (or 5-year) post-issuance abnormal returns. The rest are considered to be low-quality IPOs. The columns under "BHAR" and "CAR" present the percentage of good IPOs within the cohort of IPOs issued in that quarter when the quality classification is done using BHAR or CAR, correspondingly. The columns under "Numb." present the total number of IPOs (summed across rising cycles) issued in each quarter. The row "Avg." tabulates the average percentage of good IPOs in the first part (first 3 quarters) or in the last part (last 4 quarters) of a rising cycle.

	3-Year Returns			*5-Year Returns*		
Quarter Count	BHAR	CAR	Numb.	BHAR	CAR	Numb.
1^{st}	27.84%	45.21%	679	24.92%	48.87%	622
2^{nd}	24.56%	42.26%	859	24.44%	48.61%	757
3^{rd}	26.03%	41.67%	876	23.65%	46.14%	778
Avg.	**26.14%**	**43.05%**		**24.34%**	**47.87%**	
4^{th}	30.95%	48.31%	1037	28.57%	51.34%	931
5^{th}	32.25%	50.77%	648	31.44%	53.64%	563
6^{st}	29.64%	46.06%	469	26.65%	49.63%	409
7^{th}	27.45%	45.10%	153	30.28%	48.59%	142
Avg.	**30.07%**	**47.56%**		**29.24%**	**50.80%**	

Table 4: Evidence from S&P500 Firms

The table displays some information about issuance patterns of IPOs that are ultimately included in the S&P500 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^{st} quarter, 2^{nd} quarter, ...,7^{th} quarter since the beginning of the rise. The columns show (1) the mean number of future S&P500 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.

Quarter Count	(1) Mean Number of IPOs Per Cycle Per Quarter	(2) Total Number of IPOs	(3) Number of Up Cycles That Have IPOs Issued in The Quarter
1^{st}	2.57	18	7
2^{nd}	2.25	18	8
3^{rd}	3.13	25	8
4^{th}	3.00	21	7
5^{th}	3.43	24	7
6^{st}	2.33	7	3
7^{th}	0.00	0	0
$(8^{th} - 14^{th})$	1.83	11	1

Table 5: S&P500 Firms' Order of Issuance Within Their Industries

The table presents issuance order of IPOs that are ultimately included in the S&P500 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 (1^{st} firm to issue in their industry, 2^{nd},...,n^{th}) . 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: 71/2, which shows the second quarter of 1971) and the end of the cycle (exp: 72/3). The columns show (1) the total number of IPOs issued in each cycle; (2) the total number of future S&P500 firms that are issued in that cycle; (3) among all the firms, what was the mean (median) issuance order of the S&P500 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&P500 firms in that cycle.

The Rising Cycle	(1) Total # of IPOs	(2) Total # of S&P500 Firms	(3) Mean (Med.) Issuance Order All Firms	(4) Mean (Med.) Issuance Order 2-Digit SIC	(5) Mean (Med.) Issuance Order 3-Digit SIC
71/2 – 72/3	425	14	166.64 (95.5)	5.86 (4.5)	1.96 (1)
75/3 – 76/4	41	5	24.50 (24)	3.88 (3)	2.67 (2)
78/2 – 81/3	453	16	190.13 (167.75)	8.55 (4)	5.65 (3)
83/1 – 84/1	751	17	320.03 (298.5)	15.68 (6.5)	9.05 (5)
85/3 – 87/1	832	20	343.38 (304.5)	11.97 (11.5)	5.75 (3)
89/4 – 90/2	142	5	75.00 (73)	4.63 (5)	2.63 (2.75)
91/2 – 92/2	552	22	319.23 (302)	9.79 (6)	6.22 (3)
93/3 – 94/2	658	8	409.56 (346.25)	19.63 (14)	5.79 (2)
95/3 – 96/4	1,044	12	510.33 (490.5)	31.84 (16)	17.53 (7)
99/2 – 00/1	498	5	181.20 (115.5)	14.40 (4)	12.40 (3)
03/3 – 05/1	297	0	–	–	–
06/4 – 07/4	216	0	–	–	–