An IPO's Impact on Rival Firms

By

Matthew Spiegel and Heather Tookes [†]

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†Yale School of Management, P.O. Box 208200, New Haven CT 06820-8200. Email: matthew.spiegel@yale.edu and heather.tookes@yale.edu. We would like to thank seminar participants at Yeshiva University for helpful discussions.

Abstract

There is a long literature documenting the process by which firms conduct initial public offerings (IPOs). However, there has been a relative paucity of research into how one firm's decision to switch from being private to public impacts its rivals. This paper uses a structural approach to address that question. We develop a continuous time model in which heterogeneous firms producing heterogeneous goods compete for consumers. Because the model takes place in real time it produces a structure with parameters that can be estimated empirically. Importantly, this allows the empirical work to make meaningful statements about parameter magnitudes as well as signs. In general, when firms conduct IPOs, they are relatively small and their impact on rival values amounts to a few basis points one way or the other. However, we do find that new issues presage a more homogenous product environment which ultimately cuts down on industry profits. The paper's structural model also offers a new way to test for whether an IPO causes these industry changes or simply presages them. Roughly, if the IPO makes the newly public firm stronger, the IPO should benefit the IPO firm and negatively impact its rivals. By comparing forecasts of changes in fundamentals and out-of-sample forecast errors over time, one can see if the IPO firm's future looks fundamentally different from its rivals. Our tests indicate they look the same, implying that IPOs forecast future industry changes but do not cause them.

An initial public offering (IPO) is a major event in the life of any firm. But what does an IPO imply for the industry's future? Does going public signal that competitive pressures will increase or decrease? Pressures may increase if the newly public firm is now a more formidable rival. Alternatively, the IPO firm's now mandatory disclosures may prove useful to rivals that can now better copy its strategy. It is also possible that the firm may decide to go public to take advantage of new opportunities facing the industry, implying greater profitability in the future for it and its rivals. Typically, papers in corporate finance focus on one dimension of problems like this, or they attempt to characterize a dominant effect, to be applied across all industries. This paper takes a structural approach that allows different industries to progress in different ways post IPO. We uncover a great deal of heterogeneity in the data, which improves our understanding of the range of economic forces that are associated with IPO activity. If one is forced to make a sweeping generalization, then this paper finds an IPO augurs in an era of reduced profits and greater consumer mobility within an industry. However, in the upper tail of the interquartile range, industries are forecasted to see higher profits and lower consumer mobility.

If the goal is to see what an IPO may portend for an industry then it seems natural to define an industry as a set of firms that compete with each other for the same customers – as a practical matter those based on 4-digit SIC codes.[1] However, the fact that there are hundreds of 4 digit industries makes it difficult to know what variables should or should not be included. A structural model offers a potential solution. Using one that describes industry dynamics with a relatively small set of variables makes estimation on an industry-by-industry basis feasible. Here, we begin with the Spiegel and Tookes (2013) continuous time model of competition in a heterogeneous product oligopoly. Their model is then modified to allow for a gradual change in the competitive environment over time post IPO. The setting is general enough that the change can be due to a number of factors that play out in a variety of ways. For

[1] It may be that an IPO implies one thing about the IPO firm's rivals. Then another for firms within industries downstream and upstream from it. There is, however, no reason to believe the implications should be the same across all three groups. For example, suppose an IPO leads increased competition in the firm's own industry. That should produce higher profits for its downstream customers along with higher unit sales but overall lower profits for the IPO firm's own industry.

example, information disseminated by the IPO firm may increase or decrease competitive pressures within the industry, leading to changes in spending on customer acquisition. Unlike a purely empirical model, a structural one can be tested on the basis of its dynamic forecasts. If those prove accurate then it at least sets a benchmark against which other explanations (and ultimately forecasts) can be measured. Several tests show that this paper's dynamic model does quite well relative to current alternatives in this regard.

The model generally does well at capturing changes to a firm's profits and values after a rival's IPO. For example, the model yields an in-sample R^2 statistic of nearly 17% when 3 years of profitability data are used and 34% with 5 years of data. To see what this means, compare these values to those found in Hsu, Reed and Rocholl (2010). They have a purely empirical model that seeks to explain operating profitability for rival firms post IPO and report in-sample R^2 statistics of approximately 4%. The data fit from this paper's structural model comes about despite the fact that the empirical model requires only four estimated industry parameters and three firm-specific parameters. When compared with the results typically seen in empirical corporate finance, where far more independent variables are used, the fit produced here is quite good. Beyond this general in-sample comparison, the paper also presents predictive regressions in which the model is used to forecast future changes in profitability and value. While the R^2 naturally declines out-of-sample, the model still performs well compared to the other variables from the literature. We present tables from a horse race between our model's period-ahead forecast and the period-ahead forecasts based on other independent variables seen in the literature. All of them show that, if you have to restrict yourself to one or two independent variables, then our model's predicted values and profits should always be among them. Most of the time, if you are restricted to just one, it would be our model's forecast.

Overall, the model indicates that an IPO is generally bad news for an industry's future profits per unit of market share. Depending on the estimation window used (3, 5 or 10 years of data) the median industry will see a long term drop of between 10% and 25%. However, the estimated heterogeneity across industries is quite large with an interquartile range between −60% and +40%. If forced to provide a broad characterization of what happens, the hypothesis that the information released from an IPO leads firms to a more homogenous form of product competition (and thus lower profits per unit sold) appears to dominate. The parameter estimates indicate that post-IPO it becomes 3 to 4 times easier to lure away a rival's customers. An example of this type of market evolution can be seen in the cell phone industry. As a number of articles have noted, unit sales are up but profits are down.[2] The generally accepted reason is that, as time has passed, the product offerings have become more homogenous, which has increased price pressure.

Unlike a static model or its empirical analog a structural model's parameters produce implications about magnitudes rather than just signs. This permits one to ask a number of questions that are otherwise difficult to address. For example, are the estimates economically "reasonable?" In the case of IPOs it is particularly important to retain some perspective on what is occurring and what role the IPO firm may be playing. As Figure 1 shows, when firms go public they typically have very small market shares.

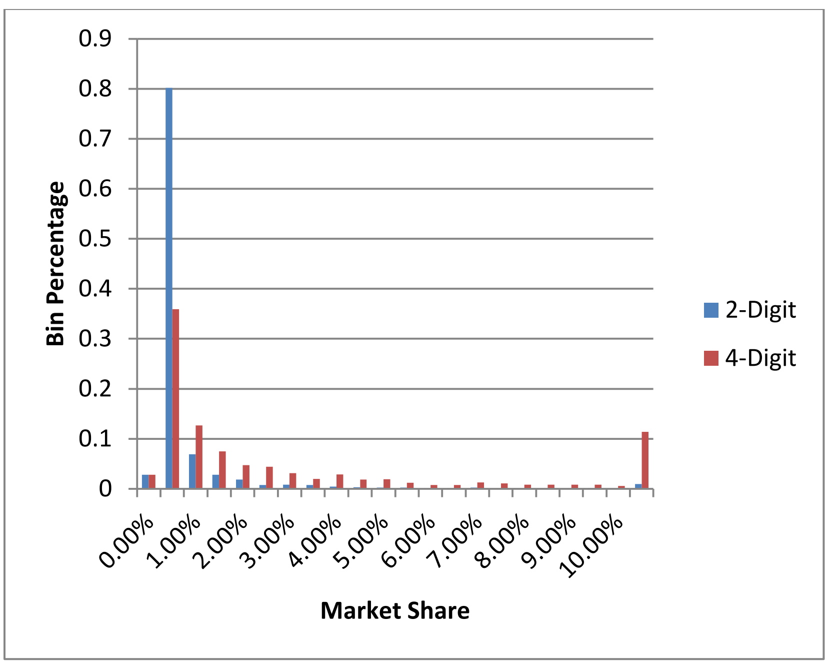

Figure 1: IPO firm's market share.

[2] See, for example, Elmer-DeWitt (2014) and Miller (2014).

The histogram displays the market shares of firms as of their IPO dates using both the 2- and 4-digit Standard Industrial Codes (SIC), since both definitions appear in prior studies. Firms with market shares of more than 10% are relatively rare, comprising less than 1% of all IPO firms using 2-digit industries and fewer than 12% of all IPO firms using 4-digit industries. In fact, the vast majority of IPO firms have market shares that are smaller than 1%. In industries defined at the 2-digit level, over 90% of the firms undertaking an IPO have market shares under 1%. Using 4-digit industries, this figure naturally drops, but still remains at just over 50%.

IPO firms are not only small, but over the three years following the IPO, their market shares do not change very much. As shown in Figure 2, over 90% of the IPO firms see their market shares change in absolute value by less than 1% using 2-digit industries. Even at the 4-digit level, more than 60% see changes in their absolute market share of less than 1% in the subsequent 3 years. This is consistent with the results in Chemmanur, He and Nandy (2010). They find that post-IPO, the newly public firm's sales growth and productivity decline and that its market share changes very little over the next few years.[3]

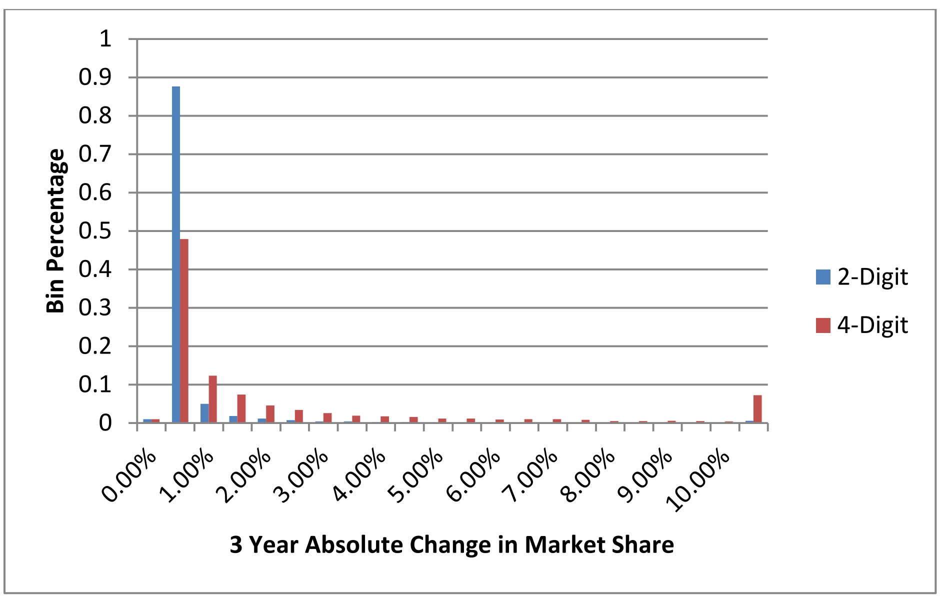

Figure 2: IPO firm growth in the following 3 years.

[3] This rather mundane productivity performance for the IPO firm is also accompanied by long run stock return underperformance (Ritter and Welch, 2002).

The fact that IPO firms are small and grow rather little over the next few years suggests that if one is looking to measure the extent to which a firm's decision to go public changes its competitive stance and impacts other firms then the magnitude should be rather small.[4] Alternatively, if the IPO firm is either a conduit through which the industry changes (via newly released information about the reasons behind the newly public firm's success) or simply a portent (like a canary in a coal mine) then the impact can potentially be much larger. The interquartile range of industry value changes in our sample ranges from −4% to +3% over the long run post-IPO. These results indicate that overall an IPO's impact on an industry's value is quite modest, especially when contrasted with some of the prior results in the literature. However, given the evidence in Figure 1 and Figure 2, these values seem to be more in line with what economic intuition might lead one to expect.

While any model can potentially be judged by whether or not its results are reasonable in magnitude; reasonable may lie in the eye of the beholder. A more concrete test is to determine whether or not the model's estimated parameters tell us anything useful about how an industry evolves post-IPO. That is, can the model forecast industry dynamics out of sample? The short answer, here, is yes. Furthermore, our tests show that forecasting with the model and its estimated parameters does a better job out-of-sample than other empirical variables that have been used in the IPO literature. The out-of-sample performance of the model is particularly important, given the recent criticism that dynamic structural models in corporate finance are not held to high test standards, making them difficult to falsify (Welch, 2013).[5] These forecasts are difficult to structure within empirical work based on static models and offer a unique hurdle that dynamic structural models can potentially clear. Focusing on prediction also offers a natural way to rank various explanations; better ones presumably produce superior forecasts.

[4]Market shares for IPO firms that we observe through year t+3 do increase on average; however, we observe 3,290 IPO firms at date 0 and only 2,569 by the end of year 3 following the IPO. While some of the firms disappear from the sample due to M&A activity, many also disappear because of failure (i.e., market shares approach zero).

[5] Strebulaev and Whited (2013) argue against this claim, pointing out that structural models allow us to glean relationships that are impossible to observe with static reduced form models and that some have predictive power. Hennessy (2013) emphasizes the ability of dynamic structural models to provide quantitative predictions.

Forecasts not only test a model against the data, but also offer a window into causality. In general, good news for one firm should be bad news for its competitors and vice versa. For example, if going public makes a firm stronger, its forecasted profits per unit of market share should increase and its rivals' profitability should decrease. Alternatively, if the IPO leads to the transmission of formerly private information useful to the firm's rivals, then the opposite should be true. Instead, the paper finds that estimated parameter changes pre- and post-IPO look similar for both the newly public firm and its rivals, indicating the IPO is best described as a "canary in the coal mine" rather than a causal competitive event. Another way to test for causality is to look out of sample. If the IPO causes future changes to the issuer's competitive prospects its forecast errors should be negatively related to those of its rivals. However, we find that this correlation is positive, providing further evidence that an IPO presages events rather than causes them.

To our knowledge, this is the first paper to employ structural parameter change estimates and forecasts as a way to test an event's causal relationship to future changes within an industry. One can think of these tests as structural model analogs to a differences-in-differences (DID) analysis. In a DID test the target or event firm is matched another firm that has similar characteristics along a few dimensions but is not associated with the event. Matching criteria often include selecting from the same industry as the target firm. Unfortunately, matches within 4-digit industries are often impossible frequently leading to the use of 2-digit industry groups.[6] However, as noted earlier, 2-digit industries are rather broad. If the event in question arises from industry specific changes among firms competing with each other, then a match at the 2-digit industry level may not correct for that. The structural test proposed here has the potential advantage of using the firm's own industry as its benchmark. Changes within the set of competitors are thus picked up which can help address the concern that observed effects are due to changes in a specific industry rather than from the event being studied.

[6] DID tests have appeared in the IPO literature since there is little or no pre-event data on the issuing firm. However, it has proven useful in other contexts where there is both pre-event data and researchers have been willing to use broad industry definitions in order to find reasonably close matches along various dimensions. Recent papers using 2-digit SIC codes include Agrawal and Nasser (2012), Almeida, et al. (2011) and Gormley and Matsa (2011).

While the IPO literature is voluminous (see Ritter and Welch (2002) and Ljungqvist (2008) for excellent surveys), we are only aware of three other articles that explore empirically how a firm's decision to go public impacts the values of other firms in its industry. One is Hsu, Reed and Rocholl (HRR) (2010). Their paper looks at 2-digit SIC industries and asks how well they perform after a very large IPO in the industry. We are interested in IPO events more generally, so we include both large and small IPO firms in our sample. As discussed and shown in Figure 1 above, the vast majority of issuers are relatively small, especially at the 2-digit level. A second paper that examines an IPO's impact on its rivals is Chod and Lyandres (2011).[7] Like us, they examine 4-digit SIC industries. The Chod and Lyandres (CL) paper begins with the development of a static model that they use to motivate a subsequent regression analysis. In their model, when firms go public the founders can diversify their portfolios and then take a more aggressive (riskier) stand in the product market. As with any static model, the best one can do is verify whether or not the regression parameters are consistent with it. CL find that a measure developed in Sundaram, John and John (1996) that examines cross firm demand elasticities produces estimates in the direction their model indicates it should. Because the Sundaram, John and John (1996) measure is related to some of ideas developed here, the text contains fuller discussion and includes a comparison of it with the procedures employed here. The third paper to look at how an IPO impacts its industry is Chemmanur and He (CH) (2011). They begin with a static model in which going public allows a firm to obtain lower cost external financing. This becomes preferable to financing growth internally if there is a productivity shock. The goal of their paper is to help explain why we see IPOs waves within industries. As part of their analysis, they look at market share growth post IPO across firms in the industry and find that those that go public gain relative to their private rivals.

[7]Maksimovic and Pichler (2001) also examine IPOs in competitive settings, but their focus is on explaining the timing of offerings and IPO waves within industries. An empirical paper in this area is De Jong, Huijgen, Marra and Roosenboom (2012). They find that those in industries with lower entry barriers (as measured by capital intensity) tend to go public earlier. A fully dynamic model of when a single firm should go public can be found in Pastor and Veronesi (2005). Even though they do not explicitly model a firm's competitors, we mention it here because they discuss how particular elements of an industry's structure might affect the economic environment they model. From this, they then draw some conclusions regarding IPO decisions across industries. An explicit dynamic oligopoly model within the IPO literature can be found in Kang and Lowery (2014). Their paper looks at the pricing of IPO services. Here the focus is on how the IPO affects the IPO firm's own industry.

In addition to its contribution to the IPO literature, this paper adds to the growing body of structural corporate finance research. Prominent examples include Hennessy and Whited (2005, 2007), Strebulaev (2007), and Riddick and Whited (2009), which focus on capital structure and investment dynamics.[8] These papers provide tests of quantitative predictions, in addition to qualitative analyses (i.e., tests of dominant effects) found in more common reduced form estimation. Like these papers, ours is clear about the objective functions of firms and the ways in which the firms' choices over time impact future dynamics. Our contributions lie not only in the IPO application, but also in the model's ability to characterize the value dynamics of entire industries.

The paper is structured as follows: Section I presents the structural model. Section II contains the empirical estimates. Section III concludes.

I. The Model

The model begins with the basic structure found in Spiegel-Tookes (2013). Consider an industry containing n firms that produce a heterogeneous product. Firm i competes with its rivals for market share (m_i) by spending funds $u_i(t)$ at time t on customer acquisition. Here customer acquisition should be construed quite broadly. Advertising is perhaps the most obvious way firms acquire market share. But so is research and development on improved product design. In some industries customer acquisition may include capital expenditures that create outlets closer to where customers shop: McDonalds and Starbucks are two examples of firms that compete for market share in this way. The model assumes that market share evolves over time via:

$$dm_i(t) = \phi\left[\frac{s_i u_i(t)}{\sum_{j=1}^{n} s_j u_j(t)} - m_i(t)\right]dt \tag{1}$$

[8] See Strebulaev and Whited (2012) for a survey.

Of course, some firms are more efficient at customer acquisition than others. This heterogeneity is captured through the variable s_i. Higher values of s_i imply a firm achieves a greater "bang for its buck" when trying to gain market share. The variable ϕ represents customer loyalty with high values indicating that it is relatively easy to lure away a rival's customers.

To allow for a richer comparison with the prior IPO literature it is useful to add a stochastic industry size component to the basic Spiegel-Tookes (2013) model. Let ς represent an industry's size measure and assume it follows the law of motion

$$d\varsigma = g dt + \sigma dz \tag{2}$$

where dz is a standard Brownian motion. In the model, all else equal, instantaneous corporate profits are proportional to industry size and are given by

$$\pi_i(t) = e^{\varsigma t}\left[\alpha_i m_i(t) - u_i(t) - f_i\right] \tag{3}$$

The parameter α_i translates a unit of market share into corporate profits gross of its spending on customer acquisition and its fixed operating costs f_i. Firms seek to maximize their expected present discounted value $E\left[\int_{t=0}^{\infty} e^{(\varsigma - r)t}\pi_i(t)\,dt\right]$, where r (assumed to be greater than ς) is the discount rate. Letting δ equal $r-g-\varsigma$ the HJB equation for this problem can be written as

$$\max_{u_i} \quad \alpha_i m_i - f_i - u_i + V_i'\phi\left[\frac{u_i s_i}{\sum_{j=1}^{n} u_j s_j} - m_i\right] - \delta V_i + \frac{1}{2}V_i\sigma^2 = 0 \quad . \tag{4}$$

The formulation of (4) incorporates the solution to the Spiegel-Tookes (2013) model along with the "guess" that the addition of the stochastic term in (3) will produce a value function V(ς) of the form $e^{\varsigma}V$

along with a term arising from the Brownian motion process. Not too surprisingly, this guess will indeed work and produce a solution to (4).

A. Gradual Incorporation of Information from an IPO

The primary objective of this paper is to apply the basic Spiegel-Tookes (2013) model given above to the question of how an IPO impacts its industry. When a firm conducts an IPO, it is forced to release quite a bit of information about its sales and operations. While this information may help investors, it also may prove to be of use to rival firms that can to work towards incorporating the newly gleaned information into their own strategies and product offerings. (This, presumably, is why the information was hidden prior to the IPO.) Alternatively, anticipated changes in industry structure (due to new production technologies, consumer preferences or other factors) may induce successful firms to go public. In this case, the IPO contains information about the industry rather than firm-specific competitive information. The Spiegel-Tookes (2013) framework allows for both of these possibilities. Assume that, prior to the IPO, firms are endowed with a set of parameter values for their profits per unit of market share $\alpha^* = (\alpha_1^*, \ldots, \alpha_n^*)$, spending efficiency $s^* = (s_1^*, \ldots, s_n^*)$ and fixed operating costs $f^* = (f_1^*, \ldots, f_n^*)$. For simplicity assume firm *n* conducts the IPO. Over time, the industry will adapt to the information the IPO firm is forced to release eventually leading to new parameter sets $\alpha = (\alpha_1, \ldots, \alpha_n)$, $s = (s_1, \ldots, s_n)$ and $f = (f_1, \ldots, f_n)$. These new parameters may be favorable relative to existing parameters. They may also imply losses. The overall impact on value will depend on consumer demand and on the competitive responses of all firms in the industry. Assume that the transition to the new parameter occurs at an exponential rate ψ so that at time *t* a firm's actual profits per unit of market share, spending efficiency, and fixed costs are given by $\breve{\alpha}$, $\breve{s}$ and $\breve{f}$:

$$\begin{aligned} \breve{\alpha} &= \mathrm{e}^{-\psi t} \alpha^* + \left(1 - \mathrm{e}^{-\psi t}\right)\alpha \\ &= \alpha + e^{-\psi t} \Delta\alpha, \end{aligned} \tag{5}$$

$$\begin{aligned}\breve{s} &= \mathrm{e}^{-\psi t} s^{*} + \left(1-\mathrm{e}^{-\psi t}\right) s \\ &= s + e^{-\psi t}\Delta s,\end{aligned} \tag{6}$$

and

$$\begin{aligned}\breve{f} &= \mathrm{e}^{-\psi t}\ f^{*} + \left(1-\mathrm{e}^{-\psi t}\right) f \\ &= f + e^{-\psi t}\Delta f\end{aligned} \tag{7}$$

where $\Delta\alpha = \alpha^{*} - \alpha$, $\Delta s = s^{*} - s$ and $\Delta f = f^{*} - f$. Under this specification the HJB equation can be written as

$$0 = \max_{u_i}\ \left(\alpha_i + e^{-\psi t}\Delta\alpha_i\right) m_i - f_i - e^{-\psi t}\Delta f_i - u_i + V_i^{m}\phi\left[\frac{\breve{s}_i u_i}{\sum_{j=1}^{n}\breve{s}_j u_j} - m_i\right] - \delta V_i + V_i^{t} \tag{8}$$

where superscripts on the value function V indicate partial derivatives with respect to market share (m_i) and time (t).

To solve (8) assume V_i has the form:

$$V_i\left(m_i, t\right) = a_i\left(t\right) + b_i\left(t\right) m_i\left(t\right). \tag{9}$$

Under this assumption, the first order condition for the optimal u_i and the resulting HJB equation has the same form as in Spiegel-Tookes (2013). After defining

$$\hat{\alpha}_i = \left(\phi + \delta + \psi\right)\alpha_i + \left(\phi + \delta\right)\Delta\alpha_i e^{-\psi t} \tag{10}$$

and

$$\hat{z} = \sum_{j=1}^{n}\frac{1}{\hat{\alpha}_j \breve{s}_j} \tag{11}$$

Following the steps in Spiegel-Tookes (2013) one can write the solution to u_i as

$$u_i = \frac{\hat{\alpha}_i \phi (n-1)\left[b_i \breve{s}_i \hat{z} - (n-1) \right]}{(\phi + \delta + \psi)(\phi + \delta)(\hat{\alpha}_i \breve{s}_i \hat{z})^2}. \tag{12}$$

Using (12) and (9) in (8) and the applying some additional algebra, the problem comes down to solving two equations; one for a_i and one for b_i. In Spiegel-Tookes (2013), these equations are algebraic. In this case, they are the ODEs for a_i

$$0 = -e^{-\psi t}\Delta f_i - f_i - \frac{b_i \phi (n-1)\left[b_i \breve{s}_i \hat{z} - (n-1) \right]}{\left\{ 1 + (n-1)\left[b_i \breve{s}_i \hat{z} - (n-1) \right]^{-1} \right\}^2} + \frac{b_i^2 s_i \phi \dfrac{b_i \phi (n-1)\left[b_i \breve{s}_i \hat{z} - (n-1) \right]}{\left\{ 1 + (n-1)\left[b_i \breve{s}_i \hat{z} - (n-1) \right]^{-1} \right\}^2}}{\sum_{k=1}^{n} \dfrac{b_i \phi (n-1)\left[b_k \breve{s}_k \hat{z} - (n-1) \right]}{\left\{ 1 + (n-1)\left[b_k \breve{s}_k \hat{z} - (n-1) \right]^{-1} \right\}^2}} - \delta a_i + a_i^t \tag{13}$$

and for b_i

$$0 = e^{-\psi t}\Delta \alpha_i + \alpha_i - (\phi + \delta) b_i + b_i^t. \tag{14}$$

Equation (14) yields a solution for b_i of

$$b_i = \frac{\alpha_i}{\phi + \delta} + \frac{\Delta \alpha_i e^{-\psi t}}{\phi + \delta + \psi} + k e^{(\phi + \delta)t} \tag{15}$$

where k is an arbitrary constant of integration. Since the solution to b_i at t goes to infinity must approach the solution where $\Delta\alpha$ equals 0, this implies k=0. Thus the solution for b_i is

$$b_i = \frac{\alpha_i}{\phi + \delta} + \frac{\Delta \alpha_i e^{-\psi t}}{\phi + \delta + \psi}. \tag{16}$$

In general, there does not appear to be a closed form solution for the a's. However, after plugging (16) in for the b_i in (13) one can write the non-linear ODE for solving a_i as

$$0 = -e^{-\psi t}\Delta f_i - f_i + \frac{\hat{\alpha}_i\phi\left[\left(\hat{\alpha}_i\breve{s}_i\hat{z}\right)-\left(n-1\right)\right]^2}{\left(\phi+\delta+\psi\right)\left(\phi+\delta\right)\left(\hat{\alpha}_i\breve{s}_i\hat{z}\right)^2} - \delta a_i + a_i^t. \tag{17}$$

The above does not, in general, admit a closed form solution because the $\hat{\alpha}_i\breve{s}_i\hat{z}$ terms vary over time. However, if one assumes that $\hat{\alpha}_i = \left(\left(\phi+\delta+\psi\right)\alpha_i + \left(\phi+\delta\right)e^{-\psi t}\Delta\alpha_i\right) = \alpha_i\left(\left(\phi+\delta+\psi\right)+\left(\phi+\delta\right)k_\alpha e^{-\psi t}\right)$ and $\breve{s}_i = s_i\left(1+k_s e^{-\psi t}\right)$ for industry wide constants k_α and k_s (implying each firm experiences a proportional change to its profits per unit of market share and marketing capabilities post-IPO) then it is easy to show that the $\hat{\alpha}_i\breve{s}_i\hat{z}$ terms reduce to the constant

$$\hat{\alpha}_i\breve{s}_i\hat{z} = \alpha_i s_i z \tag{18}$$

where z^* is defined as $\sum_j 1/\left(\alpha_j s_j\right)$. Plugging this into (17) it becomes

$$0 = -e^{-\psi t}\Delta f_i - f_i + \frac{\alpha_i\left(\left(\phi+\delta+\psi\right)+\left(\phi+\delta\right)k_\alpha e^{-\psi t}\right)\phi\left[\left(\alpha_i s_i z\right)-\left(n-1\right)\right]^2}{\left(\phi+\delta+\psi\right)\left(\phi+\delta\right)\left(\alpha_i s_i z\right)^2} - \delta a_i + a_i^t. \tag{19}$$

The solution to (19) has the same form as that for (16)

$$a_i = -\frac{f_i}{\delta} + \frac{\alpha_i\phi\left[\left(\alpha_i s_i z\right)-\left(n-1\right)\right]^2}{\delta\left(\phi+\delta\right)\left(\alpha_i s_i z\right)^2} + e^{-\psi t}\left[\frac{\alpha_i k_\alpha\phi\left[\left(\alpha_i s_i z\right)-\left(n-1\right)\right]^2}{\left(\delta+\psi\right)\left(\phi+\delta+\psi\right)\left(\alpha_i s_i z\right)^2} - \frac{\Delta f_i}{\delta+\psi}\right]. \tag{20}$$

The solutions given by (9), (16) and (20) can be readily applied to industry data near IPO events. Doing so can help inform us about the economic forces driving the value and profit dynamics of rival firms that follow public offerings.

II. EMPIRICAL ANALYSIS OF THE COMPETITIVE EFFECTS OF IPOS

Dealing with data covering a wide variety of 4-digit SIC industries can potentially require an empirical model that includes so many controls the results become nearly meaningless. One potential solution is to reduce the number of industries by simply switching to 2-digit groupings.[9] While 2-digit codes reduce the problem's dimensionality, the resulting estimates are now based on groupings comprising relatively broad sectors. Often this is harmless and, better yet, such an analysis can be uniquely informative. But, if the goal is to see how one firm's actions affect its competitors then it is important to recognize that 2-digit industries include firms that are not in fact competitors. As an example, consider the 2-digit SIC industry labeled 28. This represents firms in chemical and allied products. It includes firms that make plastic materials and resins (2821), diagnostic substances (2835) and perfumes and cosmetics (2844). It is difficult to imagine that firms in these three areas consider each other competitors.

To get a better idea of just what types of firms populate the SIC 28 two digit industry, consider Advanced Polymer Systems[10], which is in industry 2821. It 1997 10-K describes its business as,

> Advanced Polymer Systems, Inc. and subsidiaries ("APS" or the "Company") is using its patented Microsponge(R) delivery systems and related proprietary technologies to enhance the safety, effectiveness and aesthetic quality of topical prescription, over-the-counter ("OTC") and personal care products.

Compare APS with Guest Supply (2844) whose 1997 10-K filing included the statement that,

> The Company operates principally as a manufacturer, packager and distributor of personal care guest amenities, housekeeping supplies, room accessories and textiles to the lodging industry. The Company also manufactures and packages personal care products for major consumer products and retail companies.

It seems extremely unlikely that in 1997 APS and Guest Supply saw each other as competitors. [11] If they had any relationship, it likely involved Guest Supply as a customer of APS. While large aggregations of firms into 2-digit industries may be useful for some applications, if we hope to explore how IPOs impact a firm's rivals then one needs to use at least 4-digit industries.

[9] This is likely why HRR used 2-digit Standard Industrial Codes in their analysis.
[10] Which became AP Pharma and is now Heron Theraputics.
[11] Both Advanced Polymer Systems and Guest Supply are part of the paper's IPO database.

A. Estimation

An important advantage of the model is that it characterizes the value dynamics resulting from changes in the competitive structure of the industry in a way that is amenable to empirical estimation and testing. In this section, we present results from estimates of the key model parameters. The paper focuses on innovations in profitability per unit market share (α) and changes in consumer loyalty (ϕ) , but, as shown in the previous section, the model can easily be extended to investigate other potential shocks (e.g., to the fixed costs of operations) as well.

The profitability equation provides a structure for estimating both firm-specific and industry-wide parameter values. Recall that the basic profit function is given by: $\pi_i(t) = \mathrm{e}^{gt}(\alpha_i m_i(t) - u_i(t) - f_i)$. Following Spiegel and Tookes (2013) let $\pi_i(t) + \mathrm{e}^{gt}\, u_i(t) \equiv \hat{\pi}_i(t)$ = (Revenue – Cost of Goods Sold). This can then be adapted to the pre-spending profitability equation to incorporate the slow information revelation underlying the model. To keep the empirical problem manageable, with the data at hand, the focus here is on the transition from α_i^* to α_i (for simplicity, set $f_i^* \equiv f_i$). Under the assumption that, for every firm i, $\alpha_i = k\alpha_i^*$, the model estimates:

$$\pi_i(t) - \mathrm{e}^{gt}\, u_i(t) = \mathrm{e}^{gt} \ \left((k - (k-1)e^{-t\psi})\alpha_i^*\right)m_i(t) - f_i^* \ . \tag{21}$$

Using only data on revenue and costs of goods sold, we can use non-linear least squares to obtain estimates for $\psi, g, \alpha_i^*, \alpha_i$, and f_i^*. Recall that ψ defines the transition rate from the pre-IPO α_i^* to the new α_i . Call this the transition rate and the associated "information revelation" in broad terms. For example, the IPO decision could be the result of IPO-firm's desire to obtain public financing in order to take advantage of an impending positive industry-wide shock (that will take time to fully impact the firms in the industry). The IPO decision could also be the result of the IPO firm's managers' assessment of an impending negative shock that will decrease the benefits associated with remaining private.

In order to estimate model-implied values, we also need estimates for consumer responsiveness and competitive strength (ϕ and $\alpha_i s_i z$, respectively). Recall that, because profitability evolves at the common rate ψ, then the transition from α_i^* to α_i has no impact on $\alpha_i s_i z$. Letting $\bar{m}_i$ equal firm i's steady state market share, one can follow Spiegel and Tookes (2013) and use the equation $dm = \phi(\bar{m}_i - m_i(t))dt,$ which has a solution for $m_i(t)$ of :

$$m_i(t) = \bar{m}_i + (m_i(0) - \bar{m}_i)e^{-t\phi}. \tag{22}$$

Equation (22) can be estimated via non-linear least squares and provides estimates for each firm's $\bar{m}_i$ as well as the industry parameter ϕ. It also gives firm-specific competitive strength $\alpha_i s_i z$ since, in steady state, $\bar{m}_i = 1 - \dfrac{n-1}{\alpha_i s_i n\bar{z}}$. The empirical model estimates pre and post IPO consumer responsiveness parameters (ϕ_0 and ϕ respectively) by allowing it to change as of the IPO date. Using data from the pre and post IPO period then allows equation (22) to generate estimates of ϕ_0 and ϕ. Following Spiegel and Tookes (2013), the only restriction that we impose is that ϕ is non negative and less than 25 (in our quarterly estimation, this would correspond to a customer half-life of just 2.5 days).

B. Data and Summary Statistics

The model is estimated for each IPO event using quarterly Compustat and CRSP data for all rival firms that share the IPO firms' 4-digit SIC codes as recorded by Compustat.[12] The initial sample of IPO events are from Securities Data Corporation New Issues Database and includes the IPOs of U.S. publicly listed stocks from 1983 through 2011.[13] Because we are interested in oligopolistic competition, only the 3,290 IPO events that occurred in industries with 50 or fewer competitors are included in the initial sample. All publicly traded rival firms for which we have market share data at the beginning of the estimation period are included in the estimation. We begin the estimation at the IPO quarter and estimate

[12] Prior work indicates Compustat's SIC codes do a better job than those generated by CRSP when it comes to indicating which firms view themselves as belonging to the same industry. For example see Guenther and Rosman (1994).

[13] We exclude financials and utilities (SIC codes 6000-6999 and 4900-4999).

the model over horizons that include data through 3, 5 and 10 years post-IPO (i.e., using a total of 24, 32 and 52 quarters of data for each firm respectively). Parameter estimates are shown in Table 1. We obtain estimates for between 726 and 843 events, depending on the estimation horizon.[14] The median estimated ψ ranges between 0.182 to 0.382. This implies that, following the median IPO event, between 17% and 32% of the transition from the old to new profitability regime occurs in the first quarter. At the end of four quarters the transition is between 52% and 78% complete. By the end of the second year between 77% and 95% has occurred. There is however substantial cross-sectional variation in ψ. For example, the interquartile range of estimates using data for the 10-year horizon is 0.089 to 0.474. This implies that, for slower transition industries, only 9% of the profitability change occurs in the first quarter. For fast ones, this value is 38%.

Table 1 also provides estimates of the value of the profitability shock *k*, where $\alpha_i = k\alpha_i^*$. Across all of the estimation horizons, the median estimated value of the profitability shock *k* is less than 1. This implies that IPO events are more often than not followed by a reduction in industry-wide profits per unit of market share. However, as in the case of ψ, there is substantial cross-sectional variation. The interquartile range for the estimated value of *k* using data over the 10-years following the IPO is 0.405 to 1.333. This implies that rival firms experience between a 59.5% drop and a 33.3% increase in profit per unit market share following the IPO. There are some IPO events for which estimated parameters are not reasonable (for example, the maximum estimate for *k* for the 3-year estimation horizon is 740,827); however, most are quite plausible. As noted earlier, no model can be expected to fit every industry and the one in this paper is no exception.

While industry profitability tends to decrease following IPOs, the industries are still growing. The median estimated quarterly real industry growth rate is near 0.5% per quarter under all specifications.

[14] The model convergence rate is approximately 20-25%. As mentioned in the introduction, we do not claim that the model is suitable for all industries. For example, the model is not intended for industries for which $r<g$.

This quarterly growth parameter varies within a reasonable range (for example, based on the estimates using data for the 10-year window, we obtain estimates with an interquartile range of −0.6% to 2.1%).

The median consumer responsiveness parameter pre-IPO (still using the 10-year estimation horizon as an example) of 0.021 implies that, for the median industry, it would take a competitor about 33vquarters to lose half of its customers if it completely stopped spending to attract them. (For expositional purposes, call this the market share half-life.) Post-IPO it appears the median industry transitions to a state where consumers are much more willing to switch brands. The median ϕ is 0.059 which implies a market share half-life of only 12 quarters. Median pre-IPO consumer responsiveness in the IPO sample is more than 50% slower than in the broad industry sample in Spiegel and Tookes (2013). Post-IPO the median values in the two studies look very similar. Economically, this seems to imply that industries with impending IPOs contain firms producing products that consumers view as relatively unique, at least when compared with the typical industry in the overall economy. Post-IPO, the industry transitions to a state where consumers are about as loyal to a particular product as elsewhere in the economy.

The ϕ parameter in this model has a similar interpretation to the Competitive Strategy Measure (CSM) developed by Sundaram, John and John (1996) and employed by Chod and Lyandres (2011). In Chod and Lyandres (CL) the CSM is used to proxy for the degree of competitive interaction among firms in an industry. Using this paper's notation, CSM for firm *i* can be written as

$$CSM_i = corr\left[\frac{\Delta\pi_i}{\Delta S_i}, \Delta S_{-i}\right] \tag{23}$$

where ΔS_i equals the change in firm *i*'s sales and ΔS_{-i} the change in the sales of its rivals. The idea is to provide a simple way to capture the degree to which firms in an industry pull away each other's customers. While the intuition is useful, one immediate issue that needs to be dealt with when comparing the CSM to our ϕ parameter is that the first variable in Equation (23) is unit free while the second is not.

Nevertheless, since sales map into market shares Equation (23) can be reformulated to fit this paper's model. The algebra is carried out in the appendix but the end result is the following expression

$$CSM_{it} = corr\left\{ \frac{\left(e^{g}-1\right)\left(u_i - f_i\right)}{\left[m_{it+1}\left(e^{g}-1\right)+\left(m_{it+1}-m_{it}\right)\right]S_0}, \left[m_{it+1}\left(e^{g}-1\right)+\left(m_{it+1}-m_{it}\right)\right]S_0 e^{gt} \right\} \tag{24}$$

where S_0 is initial aggregate sales. Given the complexity of the above measure, it is perhaps not surprising that the correlation between the estimated values of *CSM* and ϕ are near zero. Some of the problem lies in the denominator of (23) and thus (24). The change in sales is not strictly positive or negative. Values near 0 therefore blow up the left hand term and, when sales flip sign, the change in the left hand side can be dramatic (as illustrated in Figure 3). In contrast, the estimates of ϕ using (22) do not have similar problems. This comparison shows how a structural model can help produce parameter estimates of interest that may be more stable than those using an estimator based on economic intuition.

The final input to the firm value function is δ, the cost of capital minus the growth rate . We define δ as the long-run (1926 through period *t*) historical market risk premium plus the risk-free rate minus the long-run GDP growth rate.

While the changes in profits per unit of market share (*k*) and consumer responsiveness (φ_0 versus φ) in Table 1 may seem large, the actual estimated long-run change in market value for the industry post-IPO is actually quite modest. To see this, we begin by plugging the estimated parameters into Equations (9), (16) and (20) with *t* set to zero and infinity to get the pre and post IPO firm values, respectively. We then calculate the ratio of the post to pre IPO industry market values. Firms which have an estimated value change in excess of a factor of 100 are dropped (post/pre of less than 0.01 or greater than 100). Next, for each industry and date, the firm median, value weighted mean and equally weighted mean ratios are calculated. Finally, the mean or median value across all dates is calculated for each IPO event. The results from this exercise are in Table 2. For the median industry, the value change post-IPO is near zero. However, the cross section exhibits considerable variability. The median firm in the median industry on the median date has interquartile range between 96% and 101% using a 3 year estimation horizon to a range of 96% and 113% using a 10 year estimation horizon. Given how small most IPOs firms are, these are figures in the range one might expect. They also show that there is quite a bit of variability across industries.

Although the HRR paper focuses on 134 large IPOs at the 2-digit industry level, it is worth using their results as a benchmark. They report that, within days of an IPO, the industry sees a loss in market value of somewhere between 0.5% and 1.0%. This is broadly consistent with the average value changes that we find in Table 2 using a broader sample of IPOs and analyzing rivals at the 4-digit industry level. HRR credit this change to the competitive advantages the IPO firm sees from going public. However, as noted in the introduction, even for large IPOs, the market shares of IPO firms are generally small, especially at the 2-digit level (the 63 firms with the largest market shares at the 2-digit level in our sample have a median market share of 5.5%). Given their small size, the observed value effect on rival firms may be due to forces other than the IPO firms inducing large expected losses on a broad group of competitors. This is especially true when using 2-digit SIC codes since industries will include any combination of an IPO firm's suppliers, customers and others with which it has no meaningful business relationship.

C. In-Sample Estimates

Table 1 and Table 2 indicate that an empirical model that simply says industries lose value post IPO may be missing some important heterogeneity in the data, even if that is the median result. Of course, like any structural model, the one estimated here was clearly unable to fit some industries. Not too surprisingly, this resulted in some very implausible forecasted value changes. Because our focus is on industries for which the model is relevant and because it is unlikely that a forecaster would use extreme or unreasonable estimates for prediction, we remove extreme value observations from our sample. These are defined as observations in which: (1) IPO events with estimated ψ, k, g or φ that are less than the 1st percentile of all estimates or greater than the 99th percentile; (2) model implied or actual changes in firm value (log ratio of values) that are less than −1 or greater than +1; and (3) model-implied or actual changes in profitability that is greater (in absolute value) than the value of beginning-of-period assets.

The parameter estimates $\psi, g, \alpha_i^*, \alpha_i, f_i^*, \bar{m}_i$ and ϕ and market share data (m_{it}) can be plugged into the value and profitability equations to generate model-implied changes in them. The model-implied change in value is calculated as the log ratio: $\ln\left(\frac{V(m_t,t)}{V(m_{t-1},t-1)}\right)$, where $V(m_t,t)$ is the value function defined earlier.[15] The actual value V_t is in 2011 dollars and is defined as the market value of equity, plus the book value of assets, minus the book value of equity and deferred taxes at the end of quarter *t*. Actual value change is calculated as: $\ln\left(\frac{V_t}{V_{t-1}}\right)$. To test the model, actual changes in firm value are regressed on the model-implied changes. Test statistics are calculated using pooled data (all IPO events and all rival firms) and clustered standard errors at the IPO event level. Results are shown in Table 3. In all cases, the model implied value changes predict those in the actual market. The coefficients on the model implied changes are all statistically significant and range between 0.0213 and 0.0350. Roughly, this implies that a 10% increase in model-implied value is associated with an increase in actual value of between 0.57% and 0.35% in those industries for which reasonable estimates were obtained. The adjusted R^2 values range between 0.001 and 0.003, which is expected given returns are the dependent variable.

Similar to the value change regressions, the table also includes tests to see whether model-implied changes in profitability explain actual changes. Let $\pi_a(m_t)$ equal model-implied profitability as given in Equation (21), divided by total assets at time *t* zero. Next, define model-implied change in profitability as $\pi_a(m_t) - \pi_a(m_{t-1})$. Actual profitability is calculated as revenue minus cost of goods sold (in 2011 dollars) during quarter *t*, divided by *t* zero assets. Actual change in profitability is the first difference of

[15] Observations in which model-implied $V(m_t,t)$ are less than or equal to zero are missing. The model assumes that the industry and firm parameters are such that there is no exit. Thus, these observations are analogous to cases in which the model does not converge. We do not claim that the model is appropriate for all industries and these are examples of the cases in which the model does not do a good job in characterizing industry and firm dynamics.

quarterly profitability. Table 3 presents the results from regressing actual profitability changes on model implied changes. An immediate observation from the table is that the explanatory power of the model is even greater for profits than it is for firm value. The R^2 statistic ranges from 17% to 34%. This may not seem surprising at first, given that the profit function is used to estimate key model parameters. However, note that the parameters are estimated in a regression based on profit levels, not changes.[16] Estimated coefficients on model-implied changes in profitability are all highly significant and range from 0.4550 and 0.8453. These imply that a 10% increase in model-implied profitability is associated with between a 4.55% and 8.45% increase in actual profitability.

Under the model's assumptions, the model-implied changes in value and profitability are the only relevant explanatory variables in the value and profitability regressions, respectively. The findings in Table 3 confirm that these are important; however, in order to assess marginal impact of the model, it is useful to study other variables from the literature as well. Table 4 adds the explanatory variables from HRR. These are the lagged change in value (and profitability, for the profitability equation), the natural log of total assets, industry market-to-book value, the annual level of IPO underpricing, firm age, an IPO dummy equal to one if period *t* occurs during years 0, 1, 2, or 3 relative to the IPO, and IPO event fixed effects. Since HRR's analysis was not proscribed by an underlying model, presumably they selected the variables for their regression equations because they seemed likely to offer the greatest chance of empirically describing the data. This naturally leads to the question of whether the model estimates produced here add anything to what they have already documented.

One potential advantage of a dynamic structural model is that it can point to particular specifications that are not obvious from the intuition one might get from a static model. Table 4 looks into this issue with regard to this paper's model. The results indicate that the structural model's implied changes help explain post-IPO changes to an industry beyond what can be said with the variables used in other papers. Note that the estimated coefficients on the model implied changes are similar in magnitude and statistical significance to those in the analysis from Table 3, which excluded the HRR controls.

[16] To sharpen the interpretation, we also perform out-of-sample tests, as will be discussed later.

However, the HRR controls add insights of their own: (1) age is generally negatively related to changes in profitability, (2) recent IPO underpricing is positively related to value changes and profits and (3) industry market to book is negatively related to value and positively to profit changes.[17] None of the above three results from the HRR controls would have been predicted by the structural model. This indicates that, even though the structural model captures quite a bit of the data's variability, it does not explain all of it.

CL predict that going public increases an IPO firms' risk-taking incentives. To test this hypothesis, the authors link rivals' returns near IPOs to the competitive strategy (CSM) measure defined in Equation (23), industry demand uncertainty and the systematic portion of demand uncertainty. Because competition in their model is characterized by strategic substitutes, they include only those industries in which industry CSM is negative and they use the absolute value of CSM in their regressions.[18] In Table 5, we repeat the extended HRR regressions from Table 4, and we add the CL variables. The sample size is substantially smaller than in previous tables because, for comparability with CL, we limit our attention to those industries in which estimated CSM is negative. The results indicate that the absolute value of CSM, demand uncertainty and the systematic component of demand uncertainty are all positively related to rivals' value changes.[19] CL do not estimate profitability regressions; however, we include them in Table 5 to maintain consistency with the earlier tables. In the case of profitability, the coefficients on the CL variables are more mixed, but overall they appear to be negatively related to changes in profitability. Importantly, the model-implied changes in value and profitability remain highly significant, both statistically and economically, in all regressions.

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[17] The other control variables are not as consistent in their signs and statistical significance.

[18] Chod and Lyandres (2011) use 20 rolling quarters of historical data to generate all three of these measures. They calculate CSM for each firm according to Equation 22. Industry CSM is defined as the median of the firm-by-firm estimates. Demand uncertainty in quarter t is the standard deviation of seasonally adjusted industry sales growth during the prior 20 quarters. The systematic portion of demand uncertainty is the ratio of the variance of the predicted values from a regression of seasonally adjusted industry sales growth on the seasonally adjusted sales growth of all Compustat firms. See Chod and Lyandres (2011) for seasonal adjustment and further estimation details. In our sample, the distributions of all 3 of these variables are comparable to those reported in their paper.

[19] Chod and Lyandres (2011) find that rivals' value changes are positively related to systematic uncertainty, negatively related to total uncertainty and insignificantly related to CSM. The positive and significant estimated coefficient on the demand uncertainty in Table 5 is inconsistent with their findings; however, if we repeat the analysis using only the Chod and Lyandres (2011) variables, this coefficient becomes statistically insignificant.

D. Out-of-Sample Tests

The results in Table 3, Table 4 and Table 5 provide strong evidence of the model's empirical validity. In-sample tests like these are the standard assessment tools in the empirical corporate finance literature. They help us to understand the degree to which various variables and models fit the historical data and potentially explain what occurred. While these tests are valuable, it is also useful to know how well a model handles data out-of-sample. This not only allows one to see if over fitting has occurred, but also offers another avenue for assessing each model's relative explanatory power.

Comparing a dynamic model's ability to forecast out-of-sample changes with the static models others have estimated is naturally problematic. Nevertheless, this is an important issue. Dynamic structural models have the potential to advance beyond the limits of static models by, in part, offering a way to predict future events. However this does beg the question of how to implement a forecast using a static model in order to compare the approaches. The following sections employ two methodologies towards this end. Section II.D.1 examines what might be called pseudo forecasts. In it, a period t+1 projection comes from the parameter set estimated with data up to time t, as in standard out-of-sample tests. However, data from time t+1 is then used to forecast the dependent variable's period t+1 value. The procedure is designed to give the static model its best chance of producing a superior forecast to the dynamic one developed here. Absent the use of period t+1 data the static model forecasts a constant value for the dependent variable going forward; due to the use of constant parameter values along with fixed independent variables. The pseudo forecast thus lets the static model produce a more dynamic projection, albeit one that cannot be conducted in real time. To see how the dynamic and static models do in real time. Section II.D.2 conducts a set of true out-of-sample tests. In it, a period t+1 forecast is made solely on the basis of data available as of period t. Unlike the pseudo forecasts, these can be created in real time.

1. Pseudo Out-of-Sample Tests

The left-hand-side panel in Table 6 repeats the univariate tests shown in Table 3, but instead of in-sample regressions, it uses the parameters estimated over the initial 3 and 5 year horizons, along with real-time market share data to predict quarterly value and profitability changes over the next 3 and 5 years, respectively. As noted above, while the parameter estimates are based only on historical data the forecasts then employ them with data concurrent in time with the dependent variable.

From Table 6 it is clear that the model performs well, even when out-of-sample parameter estimates are used in the forecasts.[20] All of the regressions produce positive and significant coefficients on model-implied value changes. Not too surprisingly, the model does a better job of explaining how profits evolve over time than how market values change.

The middle and right-hand-side panels of Table 6 compare the model's out-of-sample performance relative to the real time HRR and CL variables. The model continues to perform well, even after the inclusion of these additional explanatory variables. In all cases, the dynamic model's forecasts remain statistically significant. For the value change estimates, the coefficients on the model-implied forecasts actually increase in magnitude with variables from HRR and CL are added, implying it is not simply a proxy for the information they contain. While the HRR and CL variables add considerably to the R^2 statistics when explaining value changes, they add little to the profit change regressions. In the latter, by itself, the dynamic model yields an R^2 of 0.14 when using a 3-year model and 0.26 when using a 5 year model. Adding in both the HRR and CL variables only increases these values by less than 0.015. These modest increases occur despite the fact that the dynamic model alone has just one independent variable in the regression while the HRR and CL models combined have 9.

2. Predictive Regressions

[20] We use the term "pseudo" because the tests use real time market share data. In the next section, we conduct out-of-sample analysis in which all explanatory variables are out-of-sample forecasts. The pseudo out-of-sample analysis is particularly useful when we compare the model's performance to the HRR and CL variables which come from static models and are based on real time data.

As noted above, a true forecast can only use data available to investors at time *t* to make a projection about some value as of time *t*+1 or further into the future. In a dynamic model this is a straight forward exercise. Table 7 begins with the model-implied changes based on the same out-of-sample parameter estimates used in Table 6. Now, however, the real time market share data is replaced with period-ahead market share forecasts. These forecasts are generated from regressions of market share changes on model-implied changes in market shares (based on Spiegel and Tookes (2013), Equation 19), one-quarter lagged changes in market share, and one-quarter lagged market share levels (using data through *t*-1). From Table 7, it is clear that the model-implied forecasts remain significant in all of the univariate regressions. Not too surprisingly, the R^2 statistics are lower than those in Table 6. But this corresponds to what one expects when going from the pseudo forecasts that were conducted in the prior subsection of the paper to the true out-of-sample forecasts in this subsection.

Relative to a dynamic model, constructing a set of forecasts for a static model is a challenging task. A static model by design combines current period's parameter and explanatory variables to produce an expected value of the current period's dependent variable. To work around this problem, we take the following approach: for every period t, we use data through period t-1 to estimate regressions of profitability and value (levels) on the variables from HRR. We then interpret the period *t-1* residual as the predicted change in value from period t-1 to period t. The basic idea is that, if the HRR variables imply that actual profitability in period t-1 is higher-than-predicted, we should expect profitability decrease in the next period (i.e., the HRR residuals are expected to have a negative sign in period-ahead predictive regressions). We construct similar predictions based on the measures proposed by CL. Results are in Table 7. In the case of value changes (Panel A), the model-implied changes are the only statistically significant predictor. In the case of profitability, both the model-implied changes and changes implied by the HRR variables are statistically significant, with the expected signs. The CL variable is only marginally significant but it too has the expected sign. As expected, the R^2 statistics for all of the predictive regressions decline relative to the earlier tables.

In addition to examining the significance of various regression coefficients, another way to compare the candidate variables is to perform a model selection analysis. Table 8 and Table 9 use the Schwarz Bayesian Information Criterion to do this. Table 8 considers in-sample which regressors add the most explanatory power. In each case, the model-implied changes in value and profitability rank either first (in 10 specifications) or second (2 specifications) across all seven variables. Table 9 repeats the analysis but this time compares each regressor's value in the pseudo and true out-of-sample tests. In the pseudo out-of-sample tests (Panel A), the model forecast is either first (5 specifications), second (2 specifications) or third (1 specification). In the true out-of-sample tests, the model forecast is either first (6 specifications) or second (2 specifications). No other single variable performs as well. With the exception of the market-to-book ratio, the test suggests excluding all of the other regressors in one or more specifications.

As noted earlier, the model in the CL paper indicates that demand uncertainty should result in lower competitor values post IPO if the idiosyncratic demand uncertainty is high and higher values if the systematic component is high. To the degree the out of sample results yield significant results, our analysis comes to a similar conclusion. However, the results are rather weak. When pitted against other possible explanatory variables in Table 9, both idiosyncratic and systematic demand uncertainty are often placed by the Schwarz-Bayesian information criterion in the "exclude" category.

E. IPOs and an Industry's Future

Given the strong performance of the model in explaining the dynamics of both value and profitability, what can we learn about the mechanisms driving the impact of IPOs on rival firms? As shown by HRR, the evidence points to large economic implications of IPOs for rival firms. However, the evidence does not always point to the idea that newly public firms exhibit competitive advantages relative to their peers. In fact, our results suggest that the mechanisms driving rivals' responses vary in important ways across industries. In many industries, competition becomes more intense, lowering profitability per unit market share, *k*. In other industries, rival firm profitability increases following IPOs, perhaps because rivals observe once private information about their newly public competitors and use what they observe to increase the efficiency of providing goods and services to their current customers. These differences would be very difficult to identify in a purely empirical model.

Our analysis of pre- and post- IPO consumer loyalty suggests important shifts in customer demand. In most IPO industries, consumers are becoming easier to steal. This shift in consumer demand can increase competition, increase the attractiveness of cheaper public financing and decrease the relative advantages associated with staying private. Thus, shifts in industry-wide dynamics can explain at least some of the previous findings that IPOs have important implications for rival firms.

As a start towards understanding the cross-sectional variation in the industry shifts that occur near IPO events, we run tests to see how the change in ϕ pre and post IPO responds to the ratio of profits per unit of market share on market value. The ratio can be thought of as the model's analog of the earnings price ratio. For ease of exposition, we will refer to it as the model's E/P analog. Table 10 reports the estimates of this relationship. Define $\alpha_t / V_{mkt,t} = n^{-1} \sum_{i=1}^{n} \alpha_{i,t} / V_{i,mkt,t}$ where V_{mkt} is firm *i*'s market value as of date *t* and $\alpha_{i,t}$ is the firm's estimated profit per unit of market share as of time *t*. The table displays the results from regressing $\phi - \phi_0$ on $\alpha_t / V_{mkt,t}$ and a constant. Time *t*=0 is defined as the quarter in which the IPO takes place and *t=12* is thus 3 years after the IPO date. In all of the regressions, the estimated coefficient on the $\alpha_t / V_{mkt,t}$ term is negative. However, only at time *t*=0 is it statistically significant. Furthermore, the parameter estimate at *t*=12 is only half that of the estimate at *t*=0. What seems to be happening is that when an IPO occurs in an industry with a high model E/P analog (i.e. presumably high growth) that presages a smaller change in future consumer responsiveness. This is good for the industry's profits. When consumers are harder to steal then firms spend less trying to do s0.

1. Are IPO Firms Catalysts or Canaries?

Numerous studies, including this one, find that industries undergo significant changes after an IPO takes place. However, as noted in the introduction, IPO firms are typically very small players with market shares of 1% or less. Can such small firms really impact other firms in their industry to the degree documented in CH, CL, and HRR?

It is certainly possible to construct scenarios under which IPOs induce large changes within an industry. For example, Table 1 and Table 10 show that, post IPO, customers generally become easier to steal. Pre-IPO, the up-and-coming firm may have been able to hide critical information regarding its production process and profits needed by competitors if they are going enter its product space.[21] Of course, it is also possible that IPOs do not catalyze industry changes but instead just presage them. If an industry has discovered that one particular characteristic mix in a product is optimal, then everybody may move in that direction for reasons having nothing to do with the IPO firm's newly public status. Imagine the industry is moving towards a more homogeneous product line; the proximate cause for why customers are becoming easier to steal. A change like this may reduce the value of keeping a firm's information hidden, spurring private firms to go public. In this case an IPO is not a catalyst but rather a forewarning – a canary in the coal mine.

A structural industry model offers a way to test for whether a particular event is a catalyst or canary. Structural models produce dynamic forecasts across a number of performance measures for each firm in an industry. More importantly, the model itself restricts how various estimates across firms and over time must behave, both relative to each other and, in some cases, in absolute magnitude. In the case of an IPO, if the event is a competitive catalyst, then positive impacts on the IPO firm should imply negative ones for its rivals and vise-versa. For example, if the IPO makes a firm a stronger competitor (as

[21] Indeed hiding, much of the information contained in a 10-K must be valuable to firms. Private firms have the option to release this information. The fact that they do not indicates there is a competitive advantage to keeping it secret.

hypothesized in CH and CL) then the event should increase the IPO firm's future profits, value and market share. At the same time, the opposite should be true of its competitors. Furthermore, the magnitudes of these changes should make sense within the model, if it is properly specified. By contrast, if the IPO firms are simply signals of industry changes to come, the IPO firm should look similar to the rest of the industry. Looking out of sample, one can also test to see whether forecast errors move in the same or different directions. If the IPO event itself is a cause, then using industry parameter estimates should yield systematically biased forecast errors for the IPO firm. If not, then the forecast errors for the IPO firm should be unbiased.

While there seems to be considerable heterogeneity in how IPO industries change post-issue, on average, the data reveals two broad patterns. First, rival firms see substantial reductions in profitability per unit of market share post-IPO. Second, it becomes more difficult for rivals to maintain their customers. Are these changes occurring because rivals are now facing stronger IPO firms? Or are the IPOs "canaries in coal mines" that signal impending industry shifts? The paper conducts two tests in order to examine these possibilities. The first estimates the IPO firms' profitability transitions (i.e., the k parameter specific to the IPO firm) and compares them to the same transitions for their rivals. If the IPO firm becomes a stronger competitor post-event these correlations should be negative. If the IPO firm is just a portent then they should be positively correlated.[22] Table 11 Panel A shows that the correlations in the estimated k's are positive and significant over all three estimation horizons. In other words, we find strong similarities in the evolution of firm fundamentals across IPO firms and rivals post-IPO implying the IPOs are canaries.

Another test in Table 11 for whether IPOs cause subsequent changes in an industry or just presage them can be found in Panel B. This panel examines the hypothesis that forecast errors in the IPO firms' values and profitability are unrelated to those observed in the rival firms. This is accomplished by

[22] Uncorrelated value changes would either indicate a lack of power, model misspecification or some other missing factor in the estimates.

first re-estimating the model to generate the parameters given in Table 1. Unlike the main analysis, the data now includes every firm within the industry – meaning the IPO firm too. Next, actual value and profitability changes are regressed on model-implied changes. From this, a time series of residuals for rival firms is constructed (i.e., for each quarter, calculate the average residual for all firms in the industry, excluding the IPO firm) as well as for the IPO firm. Finally, the correlation between the IPO firms' residuals and those of the rival firms is computed. If the IPO firm is causing a competitive disruption, its fundamentals should vary in ways that are negatively related to its rivals. Instead, we find that the opposite is true. The residual correlations based on in-sample data are shown in the top half of Table 11's Panel B. They are positive and significant at all estimation horizons.

The bottom half of Table 11's Panel B repeats the analysis of residual correlations described above, but it uses the residuals from period-ahead forecasts instead (analogous to those described in Table 7). This out-of-sample test has the potential to provide what is perhaps the most convincing evidence of whether IPOs lead to future changes among competitors or just presage events to come. Out-of-sample, the model estimates cannot "cheat" by taking into account future industry trends and weaving a set of parameter estimates around them. If the IPO firm is behaving differently from its rivals then such differences should appear in this test. However, consistent with the results in Table 11 Panel A and the in-sample Panel B tests, the out-of-sample results reveal that innovations in the IPO firms' fundamentals move with those of its rivals. Taken together, the evidence is most consistent with the idea that that IPO firms are canaries that signal significant changes to come in the industry rather than their catalyst.

2. Structural Model Tests Compared with DID Tests

Corporate finance papers often look to untangle cause and effect issues like those examined here with a difference-in-difference (DID) test.[23] But that is typically not practical in an IPO setting where issuer data pre-offering may be sparse. Beyond that, finding matches for the event related firm can also

[23] See Roberts and Whited (2012) for a review of the technique and literature.

be problematic no matter what topic is under study. If a match is to include several characteristics like size, book-to-market and volatility then it is unlikely a close pairing will exist in the target firm's own 4-digit SIC code. Thus papers like Agrawal and Nasser (2012), Almeida, et al. (2011) and Gormley and Matsa (2011) use 2-digit industry code groups for their matches. In many cases this is enough to provide a good control sample. However, if a situation arises where effects pertaining to a set of competitors may be driving a result, then two firms in the same 2-digit but separate 4-digit industries are likely to be poor controls for each other. A structural model like the one used here offers a potential mechanism for circumventing this difficulty. Assuming the model's forecasts prove useful, then the estimated parameter changes and out-of-sample errors offer a means with which to use a firm's direct competitors as its control group. Then, if there is something unique about the target firm relative to its rivals, this should be reflected in both changes to the estimated parameters as well as the forecast errors.

III. Conclusion

Initial public offerings have been of long standing interest to academics. The interesting patterns associated with them have generated a wealth of theoretical models and empirical investigations. However, the literature has only recently turned its attention to the issue of how an IPO might impact competitors in the same industry. This paper contributes the first structural model to tackle that question. Estimates from the model do indeed help explain what happens to non-IPO firms in an industry. On average, their values decline. This seems to occur because profits get squeezed on a per unit basis and because their products (in the view of consumers) become less unique; making it easier for one firm to steal another's customers. Overall, the model explains up to about a third of the in-sample variation in industry profit changes and also has predictive-power out-of sample. Adding additional variables that have been suggested in the prior literature improves explanatory power but, overall, the model remains the most important predictor of post-IPO changes in both profitability and value. Relative to the various purely empirical models that have been estimated in the past, the one based on the structural model in this paper does quite well.

In the end, our paper finds that post IPO industry profits per unit of market share decline and customers become easier to steal. The structural model presented here offers a new way to test for whether these changes to an industry are induced by the competitive effects of the IPO or if the IPO simply presages them. Dynamic structural models constrain the relative direction and magnitudes of the model's estimates. If an IPO makes a firm stronger, that should be bad news for its rivals. However, looking at both the estimated relative changes in profits per unit share (changes in k) and forecast errors across firms, the evidence suggest that when industries are becoming more competitive, private firms go public. Overall, if an IPO takes place, every firm in the industry will likely see a decline in it profits per unit of market share and value going forward.

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V. Appendix

A. Data Notes

In order to construct industry market shares using quarterly data, it is important to align the reported values by firms that may have heterogeneous fiscal end dates. To do so, we implement the following smoothing rule. Where fiscal quarter end date does not equal calendar quarter end date, we use data from the last report date preceding the calendar quarter end as well as the first quarter following quarter end. Fiscal quarters are transformed to calendar quarters via weighting the consecutive fiscal quarter values by the distance to the calendar quarter end date.

B. A Derivation of the CSM Measure

From equation (25) in CL the CSM measure for firm *i* in their notation is given by (23). In this paper's model, while sales do not exist as an independent variable, they do map into market share. In what follows, assume that the CSM_i measure is estimated pre-IPO. This lets one ignore the impact of time and *k* on the system. Given the use of pre-IPO data, period *t* market share equals

$$m_{it} = \frac{S_{it}}{S_t}. \tag{25}$$

where the firm specific subscript has been dropped to indicate aggregate sales. Next rearrange the above to

$$S_{it} = m_{it} S_t. \tag{26}$$

Recall that profits grow at an exponential rate, presumably because the industry does and thus equal:

$$\pi_{it} = \left(\alpha_i m_{it} - u_{it} - f_i\right) e^{gt}. \tag{27}$$

The way the model is structured sales need to grow deterministically to get a closed form solution. However, market shares can move around randomly (more on this later) which should capture the basic idea behind the *CSM* measure which is supposed to indicate cross firm demand elasticity. With the above in mind aggregate sales at time *t* equal

$$S_t = S_0 e^{gt}. \tag{28}$$

One can add a stochastic process to the law of motion for market share (Equation (1)) without altering the model's solution (see Spiegel and Tookes (2013) for an explanation). Thus, it helps to convert the ΔS_i terms into market share changes to allow for a stochastic element in line with what seems to be the intuition behind the *CSM* measure. Equations (26) and (28) do this resulting in

$$S_{it+1} - S_{it} = m_{it+1} S_{t+1} - m_{it} S_t = \left(m_{it+1} e^{g} - m_{it}\right) S_0 e^{gt}. \tag{29}$$

Now plug this in along with (27) into (23) in order to put the measure in terms of our model's variables yielding

$$CSM_{it} = corr\left\{ \frac{(\alpha_i m_{it+1} - u_i - f_i) e^{g(t+1)} - (\alpha_i m_{it} - u_i - f_i) e^{gt}}{\left(m_{it+1} e^{g} - m_{it}\right) S_0 e^{gt}}, \left[(1 - m_{it+1}) e^{g} - (1 - m_{it})\right] S_0 e^{gt} \right\}. \tag{30}$$

Some rearranging then produces

$$CSM_{it} = corr\left\{ \frac{\alpha_i \left(m_{it+1} e^{g} - m_{it}\right) - (u_i + f_i)\left(1 - e^{g}\right)}{\left(m_{it+1} e^{g} - m_{it}\right) S_0}, \left[\left(e^{g} - 1\right) - \left(m_{it+1} e^{g} - m_{it}\right)\right] S_0 e^{gt} \right\}. \tag{31}$$

Since only market shares are random in the model, terms that are independent of market share are deterministic. From basic statistics, these non-random terms have no impact on the correlation coefficient which makes it possible to simplify (31) to

$$CSM_{it} = corr\left\{ \frac{\left(e^{g}-1\right)\left(u_i - f_i\right)}{\left(m_{it+1}e^{g} - m_{it}\right)S_0}, \left(m_{it+1}e^{g} - m_{it}\right)S_0 e^{gt} \right\}. \tag{32}$$

Equation (32) looks odd because the left hand term in the correlation lacks an e^{gt} term that appears in the right term. This is because change in profits over change in sales is unitless (the left term) while change in sales is not (the right term).

Using the notation from Spiegel and Tookes (2013) for the case where market share changes include a stochastic term and then translating it (roughly) into discrete time yields

$$m_{it+1} - m_{it} = \frac{\phi\left[(1-m_i)u_i s_i - m_i \sum_{j\neq i} u_j s_j\right]}{\sum_{j=1}^{n} u_j s_j} + \sigma\sqrt{m_i}\sum_{j\neq i}\iota_{ij}\sqrt{m_j} \tag{33}$$

where ι is an indicator variable equal to +1 if $i<j$ and −1 if $i>j$ while σ is the standard deviation that presumably arises from the underlying Weiner process. Since the *CSM* measure is in variables that contain units, they grow over time. By contrast, market shares are unitless. The e^{g} terms have to be dropped so that one can sensibly use (33) in (32). Add and subtract m_{it+1} terms to the terms containing market share changes in (32) to get

$$CSM_{it} = corr\left\{ \frac{\left(e^{g}-1\right)\left(u_i - f_i\right)}{\left[m_{it+1}\left(e^{g}-1\right) + \left(m_{it+1} - m_{it}\right)\right]S_0}, \left[m_{it+1}\left(e^{g}-1\right) + \left(m_{it+1} - m_{it}\right)\right]S_0 e^{gt} \right\}. \tag{34}$$

Clearly, the *CSM* measure will depend on a firm's current market share. This in turn means the average across firms (to get an industry cross elasticity) will depend on the distribution of market shares.

Another issue, pointed out in the main text, is that the denominator of (23) can both change sign and take on values near zero. A graph of the measure's output across negative and positive sale changes (if changes in the firm's profits do not change sign with the change in sales) produces the following:

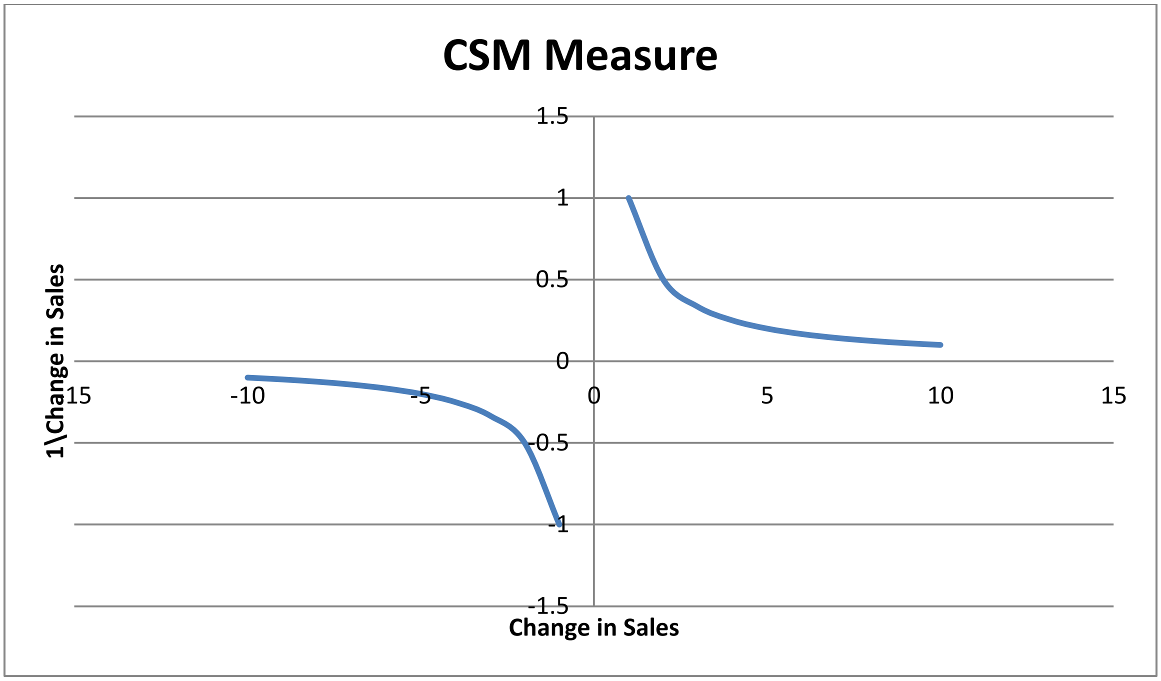

Figure 3: Illustration of the impact a change in sales near 0 has on the CSM .

If you now draw a line through the data, to represent the average over time as sales change, you get a small positive slope, but it is not clear what it means.

Table 1: Summary Statistics – Estimated Parameter Values

This table presents summary statistics for the estimated parameter values. The model is estimated separately for each IPO event. Estimates for ψ, k and g are from the profitability equation under slow information revelation, given by Equation (5). We use Equation (19) from Spiegel and Tookes (2013) to estimate the consumer responsiveness parameter, ϕ. This parameter is allowed to vary pre and post IPO (ϕ_0 and ϕ respectively). All rival firms, defined as those firms with the same 4-digit SIC code as the IPO firm, are included in the estimation. We use quarterly Compustat revenue and costs of goods sold data from the IPO quarter t-12 through quarters 40, 20 and 12 following the IPO (these 10-year, 5-year and 3-year post-IPO estimation horizons, respectively). IPO events are taken from SDC and include all IPOs from January 1, 1983 through December 31, 2011 which occurred in industries with fewer than 50 publicly traded competitors.

Variable	Mean	1st Pctl	5th Pctl	10th Pctl	25th Pctl	Med.	75th Pctl	90th Pctl	95th Pctl	99th Pctl	Min	Max	Std Dev	N
						3 Year Estimation Horizon								
ψ	0.618	0.000	0.046	0.080	0.162	0.382	0.764	1.484	2.036	3.757	0.000	4.192	0.720	726
k	4423	0.026	0.224	0.376	0.599	0.902	1.403	2.260	3.730	64646	0.006	740827	47446	726
g	0.006	-0.095	-0.044	-0.030	-0.012	0.005	0.021	0.041	0.057	0.110	-0.152	0.332	0.037	726
Φ_0	0.160	0.001	0.007	0.011	0.031	0.064	0.128	0.282	0.479	2.006	0.000	14.240	0.600	726
Φ	0.466	0.005	0.021	0.042	0.118	0.282	0.562	1.040	1.588	3.602	0.000	4.994	0.612	726
						5 Year Estimation Horizon								
Ψ	0.572	0.008	0.045	0.068	0.120	0.265	0.699	1.449	2.129	4.186	0.000	6.292	0.786	843
k	424	0.019	0.126	0.247	0.530	0.839	1.420	2.215	3.412	25.904	0.000	151056	7381	843
g	0.007	-0.064	-0.036	-0.023	-0.010	0.005	0.020	0.040	0.058	0.103	-0.290	0.478	0.036	843
Φ_0	0.102	0.001	0.004	0.008	0.019	0.042	0.091	0.199	0.306	0.960	0.000	3.748	0.273	843
Φ	0.296	0.007	0.018	0.030	0.068	0.144	0.306	0.668	1.065	2.391	0.001	6.792	0.511	843
						10 Year Estimation Horizon								
Ψ	0.456	0.009	0.031	0.045	0.089	0.182	0.474	1.243	1.825	2.982	0.000	23.669	1.030	791
k	303	0.010	0.059	0.116	0.405	0.735	1.333	2.568	4.237	16.024	0.000	141333	6084	791
g	0.008	-0.049	-0.026	-0.018	-0.006	0.006	0.021	0.036	0.051	0.097	-0.290	0.249	0.028	791
Φ_0	0.061	0.000	0.001	0.003	0.008	0.021	0.055	0.106	0.176	0.723	0.000	3.416	0.199	791
Φ	0.160	0.003	0.006	0.010	0.023	0.059	0.139	0.291	0.487	1.611	0.000	6.998	0.497	791

Table 2: Summary Statistics – Estimated Steady State Value Post IPO/Estimated Steady State Value Pre IPO

Based on the estimated parameter values, this table presents summary statistics for the estimated ratio of firm values post-IPO/pre-IPO. The estimated model parameters are plugged into equation (16) and (20) with t=0 and t=∞ to calculate the values pre and post IPO (steady state). Firms with a forecasted value change greater than a factor of 100 (post/pre <.01 or >100) are dropped. The table presents results from aggregating the estimates in various ways. Each row presents the results from a two-step process. In the first step for each IPO the median (med), equally weighted mean (EWmean) or value weighted mean (VWmean) value ratio is calculated on each date. Then the median or mean of this time series value is calculated and recorded as one observation representing the results from a particular IPO. The columns then list the various summary values and percentiles based on the statistics calculated through the row's procedure.

Variable	Mean	1st Pctl	5th Pctl	10th Pctl	25th Pctl	Med.	75th Pctl	90th Pctl	95th Pctl	99th Pctl	Min	Max	Std Dev	N
3 Year Estimation Horizon														
med-med	1.028	0.418	0.745	0.868	0.963	0.994	1.014	1.128	1.345	2.228	0.025	7.372	0.393	709
med-mean	1.033	0.480	0.748	0.855	0.952	0.990	1.013	1.153	1.360	2.616	0.022	11.613	0.513	709
EWmean-med	1.063	0.418	0.720	0.823	0.923	0.988	1.039	1.304	1.674	3.156	0.025	7.372	0.486	709
EWmean-mean	1.120	0.480	0.745	0.838	0.931	0.991	1.080	1.463	1.881	3.764	0.022	11.613	0.643	709
VWmean-med	0.943	0.061	0.247	0.616	0.912	0.982	1.003	1.078	1.208	2.228	0.026	6.266	0.385	709
VWmean-mean	0.947	0.068	0.252	0.630	0.909	0.979	1.002	1.073	1.222	2.227	0.022	7.980	0.421	709
5 Year Estimation Horizon														
med-med	1.054	0.440	0.805	0.871	0.961	0.998	1.031	1.233	1.493	2.463	0.016	8.823	0.415	835
med-mean	1.077	0.453	0.802	0.873	0.950	0.997	1.049	1.289	1.628	2.647	0.030	7.961	0.474	835
EWmean-med	1.104	0.533	0.781	0.851	0.933	0.997	1.080	1.349	1.821	3.377	0.020	8.823	0.536	835
EWmean-mean	1.208	0.514	0.813	0.872	0.953	1.013	1.186	1.658	2.284	4.691	0.030	7.961	0.673	835
VWmean-med	1.030	0.272	0.831	0.887	0.960	0.995	1.034	1.173	1.350	2.210	0.013	4.560	0.298	835
VWmean-mean	1.035	0.384	0.820	0.879	0.953	0.992	1.038	1.176	1.410	2.284	0.016	6.495	0.331	835
10 Year Estimation Horizon														
med-med	1.182	0.389	0.785	0.853	0.955	1.008	1.133	1.604	2.092	4.139	0.050	10.296	0.672	789
med-mean	1.237	0.402	0.792	0.858	0.955	1.011	1.156	1.657	2.331	5.014	0.121	18.952	0.973	789
EWmean-med	1.320	0.519	0.789	0.842	0.950	1.039	1.310	2.092	2.770	5.976	0.050	14.036	0.950	789
EWmean-mean	1.470	0.598	0.825	0.878	0.970	1.085	1.484	2.422	3.289	6.894	0.121	18.952	1.249	789
VWmean-med	1.154	0.323	0.813	0.895	0.967	1.012	1.181	1.601	1.882	3.548	0.050	6.487	0.490	789
VWmean-mean	1.188	0.342	0.817	0.896	0.968	1.015	1.189	1.609	1.925	3.509	0.116	18.952	0.823	789

Table 3: Model fit in sample – Actual and model implied changes in rival firm value and profitability

This table presents results from regressing quarterly changes in rival firm value (Δ*value*) and profitability (Δ*profit*) on model-implied changes (*model*_Δ). Value changes are defined as the log of the value in quarter t, divided by the value in period $t-1$. Profit changes are defined as profit in period t minus profit in period $t-1$, divided by the t=0 value of assets. Model-implied values are given by the slow-leak model value functions in Equations (16) and (20). Model-implied profitability is based on the profitability equation given in Equation (10) and estimates for ψ, k, g, α_i and f_i derive from it. The ϕ parameter is estimated from Spiegel and Tookes (2013), Equation 19. The discount rate net of growth variable δ is defined as the long-run (1926 through period t) historical market risk premium plus the risk-free rate minus the long-run GDP growth rate. Market-wide δ_t is identical for all firms. All rival firms, defined as those firms with the same 4-digit SIC code as the IPO firm are included in the estimation. We use quarterly Compustat revenue and costs of goods sold data from the IPO quarter t through quarters 40, 20 and 12 (10-year, 5-year and 3-year post IPO estimation horizons, respectively). All regressions are pooled, with standard clustered at the IPO event level.

Est. Hor.	3-Year			5-year			10-year		
Dep. Var.	Est.	Std. Err	t-val.	Est.	Std. Err	t-val.	Est.	Std. Err	t-val.
				Dependent Variable: Δ*V*					
Intercept	0.0112	0.0014	7.8	0.0098	0.0009	11.25	0.0086	0.0006	14.85
*model*_Δ	0.0213	0.0037	5.72	0.0268	0.0030	8.85	0.0350	0.0024	14.32
N	66,497			135,081			251,378		
Adj. R^2	0.001			0.002			0.003		
				Dependent Variable: Δ*profit*					
Intercept	0.0036	0.0003	11.79	0.0017	0.0002	9.29	0.0017	0.0002	10.92
*model*_Δ	0.4550	0.0220	20.66	0.8183	0.0173	47.39	0.8453	0.0196	43.18
N	95,393			184,340			305,458		
Adj. R^2	0.171			0.341			0.322		

Table 4: In Sample Fit – Extended Specification

This table presents results of regressing quarterly changes in rival firm value (Δ*value*) and profitability (Δ*profit*) on model-implied changes (*model_*Δ) as well as the explanatory variables from Hsu, Reed and Rocholl (2010). See Table 3 for a detailed explanation of each variable and column heading appearing there. In addition, *lag_dependent_var* is the one-quarter lag of Δ*value* or Δ*profit*; *log_at* is the natural log of total assets; *ind_mb* variable is the median industry market to book ratio in the previous year; *underprice* is the annual level of underpricing in a given year *t*; *age* is the number of years since the firm's first trading day in CRSP; *ipo dummy* is an indicator equal to 1 if the quarter occurs in the IPO year or in years 1, 2 or 3 following the IPO.

Est. Hor.	3-Year			5-year			10-year		
Dep. Var.	Est.	Std. Err	t-val.	Est.	Std. Err	t-val.	Est.	Std. Err	t-val.
				Δ*V*					
Intercept	-0.0014	0.0007	-2.03	0.0004	0.0004	1.02	0.0009	0.0002	4.02
*model_*Δ	0.0764	0.0066	11.59	0.0671	0.0042	15.91	0.0549	0.0029	18.92
lag dep. var.	-0.0198	0.0072	-2.73	-0.0037	0.0052	-0.71	-0.0093	0.0031	-2.98
log_at	-0.0003	0.0006	-0.53	-0.0002	0.0003	-0.64	-0.0005	0.0003	-1.89
ind_*mb*	-0.0340	0.0041	-8.35	-0.0198	0.0017	-11.38	-0.0114	0.0010	-11.57
underprice	0.1633	0.0327	5	0.0958	0.0190	5.04	0.1028	0.0098	10.49
age	0.0010	0.0015	0.63	0.0014	0.0011	1.3	-0.0002	0.0008	-0.19
ipo dummy				0.0034	0.0028	1.21	-0.0032	0.0015	-2.16
N	61,835			129,447			245,557		
Adj. R^2	0.015			0.010			0.008		
				Δ*profit*					
Intercept	0.0057	0.0020	2.88	0.0000	0.0001	0.25	0.0000	0.0001	0.06
*model_*Δ	0.8329	0.0150	55.6	0.8097	0.0176	45.96	0.8384	0.0197	42.5
lag dep. var	0.0001	0.0002	0.37	-0.0961	0.0065	-14.84	-0.0668	0.0071	-9.41
log_at	-0.0005	0.0002	-2.52	0.0006	0.0001	4.66	0.0005	0.0001	4.73
ind_mb	0.0059	0.0013	4.66	0.0044	0.0006	7.78	0.0047	0.0004	10.99
underprice	-0.0059	0.0082	-0.72	0.0145	0.0045	3.21	0.0138	0.0029	4.85
age	-0.0027	0.0004	-6.76	-0.0029	0.0004	-8.12	-0.0028	0.0003	-8.13
ipo dummy				0.0002	0.0007	0.33	-0.0011	0.0004	-3.02
N	56,231			174,477			295,607		
Adj. R^2	0.452			0.354			0.330		

Table 5: In Sample Fit – Negative CSM subsample based on Chod and Lyandres (2011)

This table presents results of regressing quarterly changes in rival firm value (Δ*value*) and profitability (Δ*profit*) on model-implied changes (*model_*Δ) as well as the explanatory variables from Hsu, Reed and Rocholl (2010). See Table 3 and Table 4 for detailed explanations of each variable and column heading appearing there. In addition, *csm* is absolute value of the competitive strategy measure (*CSM* from Equation (23)), *d_uncertain* is the standard deviation of seasonally adjusted sales growth, and *s_uncertain*, the systematic component of demand uncertainty. These measures are calculated using 20 rolling quarters of historical data. Following Chod and Lyandres (2011), we focus only on the subsample of industries with negative *CSM*.

Est. Hor.	3-Year			5-year			10-year		
Dep. Var.	Est.	Std. Err	t-val.	Est.	Std. Err	t-val.	Est.	Std. Err	t-val.
				Δ*V*					
Intercept	-0.0027	0.0011	-2.51	-0.0005	0.0006	-0.85	0.0010	0.0003	3.16
*model_*Δ	0.0680	0.0090	7.57	0.0702	0.0059	11.94	0.0380	0.0028	13.61
lag dep. var.	-0.0314	0.0127	-2.48	-0.0234	0.0081	-2.88	-0.0202	0.0038	-5.26
log_at	-0.0009	0.0009	-0.97	-0.0009	0.0005	-1.74	-0.0013	0.0003	-3.89
ind_*mb*	-0.0354	0.0053	-6.62	-0.0150	0.0029	-5.16	-0.0055	0.0013	-4.33
underprice	0.1212	0.0490	2.47	0.0524	0.0254	2.06	0.0913	0.0145	6.29
age	0.0025	0.0026	0.97	0.0025	0.0015	1.66	-0.0012	0.0010	-1.24
ipo dummy				0.0076	0.0041	1.89	-0.0047	0.0022	-2.09
csm	0.0411	0.0497	0.83	0.0432	0.0326	1.33	0.0424	0.0172	2.46
d_uncertain	0.0320	0.0353	0.91	0.0941	0.0248	3.8	0.0044	0.0034	1.29
s_uncertain	0.0844	0.0506	1.67	0.1052	0.0303	3.47	0.0172	0.0135	1.28
N	26,987			62,055			164,577		
Adj. R^2	0.016			0.011			0.006		
				Δ*profit*					
Intercept	-0.0014	0.0004	-3.62	-0.0006	0.0002	-2.72	0.0004	0.0002	2.57
*model_*Δ	0.4737	0.0283	16.72	0.8311	0.0192	43.28	0.8803	0.0166	53.00
lag dep. var	-0.0001	0.0000	-1.16	-0.0005	0.0003	-1.76	-0.0001	0.0000	-2.57
log_at	-0.0002	0.0003	-0.61	0.0005	0.0002	2.63	0.0004	0.0001	3.88
ind_mb	0.0064	0.0012	5.26	0.0066	0.0010	6.58	0.0063	0.0006	10.45
underprice	0.0066	0.0129	0.51	0.0090	0.0064	1.4	0.0143	0.0045	3.2
age	-0.0025	0.0008	-3.10	-0.0025	0.0005	-5.37	-0.0035	0.0003	-10.35
ipo dummy				-0.0004	0.0012	-0.38	-0.0006	0.0005	-1.03
csm	0.0223	0.0215	1.03	-0.0337	0.0157	-2.14	-0.0074	0.0067	-1.11
d_uncertain	-0.1217	0.0194	-6.29	-0.1323	0.0133	-9.95	-0.0186	0.0084	-2.23
s_uncertain	0.0369	0.0171	2.16	0.0202	0.0097	2.09	-0.0023	0.0051	-0.44
N	38,305			82,045			197,170		
Adj. R^2	0.193			0.368			0.367		

Table 6: Pseudo Out-of-Sample Tests

This table presents results from regressing the quarterly change in rival firm value (Δ*value*) or profitability (Δ*profit*) on model-implied changes as well as variables suggested by Hsu, Reed and Rocholl (2010) and Chod and Lyandres (2011). Model parameters ψ, k, g, ϕ, α_i and f_i are estimated in the same manner as in Table 3. We use quarterly revenue and costs of goods sold data from the IPO quarter through quarters 20 and 12 (5-year and 3-year estimation horizons, respectively) following the IPO. These parameters are then used to estimate quarterly model-implied changes (*model_Δ*) from quarter 20 to 40 (5-year horizon) and from quarter 12 to 24 (3-year horizon). *Δvalue* is defined as the log of the value in quarter *t*, divided by the value in period *t-1*. *Δprofit* is profit in period *t* minus profit in period *t-1*, divided by the t=0 value of assets. *lag_dependent_var*, *log_at* , ind_mb, *underprice*, *age*, *ipo dummy*, *csm*, *demand uncertainty* and *systematic uncertainty* are defined in Table 4 and Table 5. Regressions are "pseudo" out-of-sample because the HRR and CL variables are all based on real time data, as are the market shares used in calculating Δ*value* and Δ*profit*. All regressions are pooled, with standard clustered at the IPO event level and IPO event fixed effects. For consistency with Chod and Lyandres (2011), only industries in which csm is negative are considered when *csm*, demand uncertainty and systematic uncertainty are included in the regressions.

Panel A: Dependent Variable = Δvalue

	Model				**HRR Variables**				**HRR and CL Variables (Neg. CSM Sample)**			
Estimation Horizon	3-year		5-year		3-year		5-year		3-year		5-year	
	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value
Intercept	0.0059	3.93	0.0080	9.71	0.0028	3.71	0.0020	4.71	0.0027	2.21	0.0019	2.93
model_Δ	0.0486	7.05	0.0371	7.72	0.0667	10.03	0.0455	9.34	0.0713	7.73	0.0526	8.36
lag dependent var					-0.0334	-3.77	-0.0148	-2.54	-0.0573	-3.61	-0.0506	-4.98
log_at					-0.0006	-0.92	-0.0013	-3.19	-0.0006	-0.67	-0.0005	-0.92
ind_mb					-0.0321	-8.55	-0.0170	-8.23	-0.0253	-4.58	-0.0121	-4.37
underprice					0.1904	7.55	0.1359	7.73	0.2004	5.51	0.1293	4.64
age					0.0002	0.13	0.0012	0.95	-0.0003	-0.13	0.0007	0.43
ipo dummy					0.0034	0.9			0.0006	0.11		
csm									0.0793	1.54	0.0716	2.25
demand uncertainty									0.0492	1.28	-0.0250	-0.92
systematic uncertainty									0.1786	3.62	0.0718	2.2
N	55,817		92,104		50,800		86,815		23,536		44,863	
Adj. RSQ	0.0021		0.0018		0.0152		0.0082		0.0167		0.0113	

Table 6 Panel B: Dependent Variable = Δprofit

	Model				HRR Variables				HRR and CL Variables (Neg. CSM Sample)			
Estimation Horizon	3-year		5-year		3-year		5-year		3-year		5-year	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
Intercept	0.0018	3.36	0.0004	0.96	-0.0001	-0.46	0.0000	0.01	-0.0001	-0.13	-0.0001	-0.47
model_Δ	0.3990	20.19	0.6434	36.1	0.3984	20.00	0.6472	35.85	0.4108	14.41	0.6374	32.28
lag dependent var					-0.0486	-4.62	-0.0269	-3.82	-0.0317	-3.13	-0.0256	-4.67
log_at					0.0006	1.89	0.0002	0.65	0.0008	1.66	0.0008	2.19
ind_mb					0.0067	5.79	0.0038	4.14	0.0087	3.98	0.0057	4.02
underprice					0.0347	4.01	0.0184	2.81	0.0433	3.05	-0.0085	-0.75
age					-0.0049	-5.59	-0.0027	-3.73	-0.0063	-4.88	-0.0053	-4.5
ipo dummy					-0.0002	-0.18			0.0012	0.65		
csm									0.0089	0.32	-0.0006	-0.03
demand uncertainty									-0.1741	-7.68	-0.1683	-7.85
systematic uncertainty									0.0103	0.57	-0.0077	-0.6
N	76,775		118,972		69,811		112,018		32,840		57,788	
Adj. RSQ	0.1369		0.2588		0.1431		0.2627		0.1527		0.2728	

Table 7: Does the model have predictive power? Out-of-sample tests

This table presents results of period-ahead predictive regressions of quarterly changes in rival firm value (*Δvalue*) and profitability (*Δprofit*) on model-implied changes (*model_Δ*), as well as the predicted changes based on the explanatory variables from Hsu, Reed and Rocholl (2010) and Chod and Lyandres (2011). Model parameters ψ, k, g, ϕ, α_i and f_i are estimated in the same manner as in Table 3. We use quarterly revenue and costs of goods sold data from the IPO quarter through quarters 20 and 12 following the IPO (5-year and 3-year estimation horizons, respectively). Predictive regressions are then estimated using out-of-sample data from quarter 20 through 40 (5-year horizon) and from quarter 12-24 (3-year horizon). The period-ahead market shares used in the estimation are forecast from regressions of market share changes on model-implied changes in market shares, one-quarter lagged changes in market share, and one-quarter lagged market share levels. *HRR* represents the quarter *t-1* residuals from regressions in which the dependent variables are firm value and profitability and the explanatory variables are: *lag_dependent_var, log_at, ind_mb, underprice, age and ipo dummy*. These variables are defined in Table 4. *CL* represents the quarter *t-1* residuals from regressions in which the dependent variables are firm value and profitability and the explanatory variables are: csm, demand uncertainty and systematic uncertainty. These variables are defined in Table 5. All regressions are pooled, with standard errors clustered at the IPO event level and include IPO event fixed effects. For consistency with Chod and Lyandres (2011), only industries in which csm is negative are included in the regressions in which the CL variable is included.

Est. Horizon	3-year		5-year		3-year		5-year		3-year		5-year	
	Est.	t-val.	Est.	t-val.	Est.	t-val.	Est.	t-val.	Est.	t-val.	Est.	t-val.
Panel A: Dependent Variable = Δvalue												
Intercept	0.0061	4.08	0.0076	9.18	0.0061	4.07	0.0076	9.15	0.0044	2.02	0.0064	4.25
model_Δ	0.0240	4.16	0.0178	4.68	0.0252	4.34	0.0186	4.86	0.0221	2.77	0.0243	4.63
HRR					-0.0139	-1.43	-0.0052	-0.78	0.0157	0.96	-0.0242	-1.96
CL									-0.0137	-0.83	0.0074	0.61
N	55,486		92,185		55,340		91,936		29,204		50,581	
Adj. RSQ	0.0005		0.0004		0.0007		0.0004		0.0005		0.0010	
Panel B: Dependent Variable = Δprofit												
Intercept	0.0040	7.87	0.0044	10.09	0.0002	1.72	0.0000	0.14	-0.0001	-0.14	-0.0007	-1.85
model_Δ	0.0620	5.99	0.0930	6.59	0.0729	7.02	0.1089	7.61	0.0710	5.36	0.1166	6.4
HRR					-0.0944	-7.67	-0.0582	-5.11	-0.1067	-6.39	-0.0294	-2.05
CL									-0.0148	-1.37	-0.0264	-3.17
N	76,088		118,250		75,893		117,934		40,628		64,966	
Adj. RSQ	0.0033		0.0051		0.0121		0.0102		0.0163		0.0110	

Table 8: Explanatory Variable Ranks (In-Sample Model Selection)

This table summarizes the ranks of each explanatory variable using model selection based on the Schwarz Bayesian Information Criterion. In Panel A, candidate variables are model-implied changes in firm value and profitability, as well as those variables identified in Hsu, Reed and Rocholl (2010). Panel B includes the variables from Chod and Lyandres (2011) for the subsample of industries with negative csm. All variables are defined in Table 4 and Table 5. All regressions are estimated in-sample, using quarterly Compustat revenue and costs of goods sold data from the IPO quarter *t* through quarters 40, 20 and 12 (10-year, 5-year and 3-year post IPO estimation horizons, respectively).

Dependent Variable		ΔV			Δprofit	
Estimation Horizon	3 Year	5 Year	10 Year	3 Year	5 Year	10 Year
HRR Variables						
model_Δ	2	1	1	1	1	1
lag dependent var	4	exclude	4	2	2	exclude
log_at	exclude	exclude	exclude	exclude	5	exclude
ind_mb	1	2	3	exclude	3	2
underprice	3	3	2	exclude	exclude	4
age	exclude	exclude	exclude	3	4	3
ipo dummy	n/a	exclude	exclude	n/a	exclude	exclude
HRR and CL Variables (Negative CSM Subsample)						
model_Δ	2	1	1	1	1	1
lag dependent var	4	5	3	exclude	exclude	exclude
log_at	exclude	exclude	5	exclude	exclude	exclude
ind_mb	1	2	4	3	3	2
underprice	3	6	2	exclude	exclude	5
age	exclude	exclude	exclude	exclude	exclude	4
ipo_dummy	n/a	7	6	n/a	exclude	exclude
csm	exclude	exclude	7	exclude	4	exclude
demand uncertainty	exclude	3	exclude	2	2	3
systematic uncertainty	exclude	4	exclude	exclude	exclude	exclude

Table 9: Explanatory Variable Ranks (Out-Of-Sample Model Selection)

This table summarizes the ranks of each of the explanatory variables using model selection based on the Schwartz Bayesian Information Criterion. Panel A shows results from the pseudo out-of-sample tests described in Table 6**Error! Not a valid result for table.**. Candidate variables (*model_Δ, lag_dependent_var, log_at, ind_mb, underprice, age, ipo_dummy, csm, demand uncertainty, and systematic uncertainty*) are defined in Table 4 and Table 5. Panel B shows results from period-ahead predictive regressions in which the candidate variables are model-implied changes in firm value and profitability, as well as the changes predicted by the variables in Hsu, Reed and Rocholl (2010) and Chod and Lyandres (2011). These are *model_Δ*, *HRR* and *C*L, respectively. These variables are defined in in Table 7.

Panel A: Pseudo Out of Sample Regressions

	HRR Variables				HRR and CL Variables (Negative CSM Subsample)			
Dep. Var.	ΔV		Δprofit		ΔV		Δprofit	
Est. Horizon	3 Year	5 Year	3 Year	5 Year	3 Year	5 Year	3 Year	5 Year
model_Δ	2	3	1	1	2	1	1	1
lag dependent var	4	4	2	2	3	2	3	3
log_at	exclude	exclude	exclude	exclude	exclude	exclude	exclude	exclude
ind_mb	1	1	3	3	1	4	4	4
underprice	3	2	4	4	4	3	6	exclude
age	exclude	exclude	5	5	exclude	exclude	5	5
ipo_dummy	exclude	n/a	exclude	n/a	exclude	n/a	exclude	n/a
csm	n/a	n/a	n/a	n/a	exclude	exclude	exclude	exclude
demand uncertainty	n/a	n/a	n/a	n/a	exclude	exclude	2	2
systematic uncertainty	n/a	n/a	n/a	n/a	5	5	exclude	exclude

Panel B: Out of Sample Predictive Regressions

model_Δ	1	1	2	1	1	1	2	1
HRR	exclude	exclude	1	2	exclude	2	1	2
CL	n/a	n/a	n/a	n/a	exclude	exclude	3	3

Table 10: Changes in Consumer Responsiveness

This table reports the results from regressing the change in the industry estimated value of φ post IPO minus pre IPO on the equally weighted average profit per unit of market share over firm value. Define $\alpha_t / V_{mkt,t} = n^{-1} \sum_{i=1}^{n} \alpha_{i,t} / V_{i,mkt,t}$ where V_{mkt} is firm *i*'s market value as of date *t* and $\alpha_{i,t}$ is the firm's estimated profit per unit of market share as of time *t*. The results report on a regression of the form $\phi - \phi_0 = constant + \beta \alpha_t / V_{mkt,t} + \varepsilon$. Time *t*=0 is defined as the quarter in which the IPO takes place and *t=12* is thus 3 years after the IPO date. Significance: ***=1%, **=5% and *=10%, *t*-statistics are in parenthesis.

t	0	3	6	9	*12*
Intercept	0.348	0.324	0.320	0.342	0.3340
	(10.666)***	(10.319)***	(10.852)***	(9.744)***	(9.879)***
$\bar{\alpha}_t / V_{mkt,t}$	-0.514	-0.309	-0.271	-0.390	-0.254
	(-2.123)**	(-1.343)	(-1.287)	(-1.457)	(-1.019)
R^2	0.006	0.003	0.003	0.003	0.002
N	691	691	691	691	691

Table 11: Post-IPO Correlations between the IPO Firm and Its Rivals

Panel A shows the correlations between the estimated *k* parameters for the IPO firms and their rivals. For each IPO event, the IPO firm's *k* is estimated from the profitability equation under slow information revelation (Equation (5)) using data over 3-, 5-, and 10-year horizons that begin at IPO quarter 0. The transition rates for each IPO event are set equal to those obtained in Table 1. Rival firm *k*'s are the same as those shown in Table 1. Panel B shows the distributions of the correlations of surprises in IPO firms' and rival firms' fundamentals. In the top half of Panel B, surprises are calculated from the residuals of regressions of firm value and profitability on model-implied changes using in-sample data. Estimation details are given in Table 3. We use data for all firms in the industry (including the IPO firm). The bottom half of Panel B shows the correlations of the period-ahead forecast errors using out-of-sample data, as described in Table 7.

Panel A: Estimated Profitability Transitions of IPO firms and Rivals

	Estimated k	
Est. Horizon	Correlation	*t*-stat
3-Year	0.309	7.62
5-year	0.415	11.85
10-year	0.454	13.30

Panel B: Correlations – IPO Firm and Rival Residuals

	ΔValue		Δprofit	
Est. Horizon	Correlation	*t*-stat	Correlation	*t*-stat
		In-Sample		
3-Year	0.269	12.49	0.281	18.55
5-year	0.282	18.56	0.320	25.24
10-year	0.288	18.91	0.277	22.5
		Out-Of-Sample		
3-Year	0.274	11.64	0.193	8.27
5-year	0.284	14.4946	0.181	9.59