Identifying An IPO's Impact on Rival Firms

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Abstract

We use the IPO setting to demonstrate how the forecasts generated by a dynamic oligopoly model can help researchers overcome empirical challenges associated with establishing causality and identify appropriate control firms. Both of these are common issues in the empirical corporate finance literature. Recent papers report deteriorating performance by rivals following an IPO in the industry. Authors have attributed this to the competitive advantages a firm acquires by going public. When we reexamine this issue via a dynamic structural model, the results indicate that the value reductions across the industry primarily arise from an increased commoditization of the product market post-IPO. Based on the structural model, the paper develops a new causality test analogous to the difference-in-differences methodology and concludes that IPOs forecast future industry changes but do not cause them.

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Traditional corporate finance models typically take place over one or two dates. Their implications are testable, but often only against the sign of a regression coefficient. There is rarely any basis, within the model, to say if a regression parameter should be 10 or 10,000. Empirically, it can be difficult to differentiate across models because many carry with them features that should yield identical signs across the regression coefficients of interest. As Strebulaev and Whited (2013) and Hennessy (2013) argue, the recent literature in structural corporate finance provides predictions regarding economic magnitudes that, in part, overcome these limitations. This paper demonstrates that structural oligopoly models can offer another benefit: industry-wide forecasts that can produce causality tests analogous to those in the differences-in-differences (DD) literature. Using an oligopoly model, changes across industry rivals, along with adjustments based on the model's structure, act as controls. This paper uses the initial public offering (IPO) setting to demonstrate this technique.

Applying the model based DD analog, we investigate whether firms that undertake IPOs lead to changes in their industries or just presage them. This question is interesting because earlier research (Hsu, Reed and Rocholl (HRR) (2010), Chemmanur and He (CH) (2011) and Chod and Lyandres (CL) (2011)) reports substantial deterioration in rival firms' performance post-offering. This could be due to the competitive strength of the IPO firm. It could also be that the IPO event and post-IPO trends that rivals experience are due to a common unobserved industry-wide shock. Our technique helps us disentangle these two competing hypotheses.

The DD approach begins with matching treatment firms, which have been subject to an economic shock, with a set of control firms that have not been impacted by the change. If the matching is successful, then observed differences in the outcome variable's evolution within pairs can be attributed to the treatment. This lets researchers deduce causality. But characteristic matching is not always practical. Adding characteristics to help guarantee that firms are similar and that the crucial parallel trends assumption holds (i.e., that pre-event trends in the outcome variable are the same for treatment and control firms) can quickly exhaust the pool of potential matches. For example, matching on both size and industry can be problematic at the 4-digit Standard Industrial Classification Code (SIC) level since many

4-digit SIC codes contain just a few firms. Consider a 4-digit industry with five firms and market shares of 5%, 15%, 20%, 20% and 40%. Suppose there is an event associated with one of the 20% market share firms. In this case, matching on size is simple. What if the 15% firm triggers the event? Is 20% close enough? The question becomes even more acute if the treatment firm is either the one with a 5% or a 40% share. Two-digit SIC industries are an option, but these are broad and often encompass firms in very different lines of business.

We show how a structural oligopoly model's forecasts allows researchers to overcome the matching problem. It produces a DD-type of analysis within narrow industry definitions by using data from all of a treatment firm's rivals as the control. Even when, as in the examples above, the closest match within the industry is much larger or smaller than the treatment firm, the structural oligopoly model's forecasts adjust for these disparities. By construction, it forecasts future changes across all firms in the industry. Furthermore, it is possible to test how well a structural model adjusts for observed factors and to compare this performance with other models.

Forecasts from a dynamic oligopoly model also offer a window into causality based on empirically testable magnitudes, something static models rarely produce. In a static setting, tests typically revolve around a cross-sectional analysis of model attributes, assuming the model accurately captures the causal mechanism. A dynamic model can be agnostic regarding the causal mechanism at work and still address the causality issue. It does this by producing model statistics that, along with basic economics, can be used to interpret outcomes. In our application, the model is forced to create parameter forecasts consistent with a null hypothesis that all firms in an industry change over time at the same rate, in proportion to their pre-IPO values. That is, if a profitability parameter for firm i transitions from a_i to ka_i then all firms in the industry must see the same transition; a_j to ka_j. We apply the economic intuition that, if going public makes the IPO firm a stronger competitor, its profitability should increase and the profitability of its rivals 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. Both of these scenarios would violate the assumptions forced on the model's forecasts and one can therefore conduct straightforward tests of the model's null hypothesis. If going public triggers an industry's change, forecasts restricted to treating all firms in the same manner should yield biased forecast errors for IPO firms. Our analysis indicates this is not the case. Forecast errors for the IPO firms look like those of their rivals. The conclusion: IPOs foreshadow future industry changes rather than cause them.

Prior work by HRR, CH and CL reveals that the value and performance of an IPO firms' rivals decline post offering. The CL paper uses a model to guide the interpretation of this result and is most similar to ours in methodology. CL use a static Cournot model to motivate a set of cross-sectional tests on 6-digit NAICS and 4-digit SIC industries. They focus on variables that, based on their model, will induce cross-sectional variation in an IPO's impact on rival firms. Their evidence leads them to conclude that IPOs make newly public firms more aggressive and this leads to lower valuations in rival firms. Like CL, our paper begins with a model. But ours is dynamic. By design, the model offers industry forecasts that can help disentangle industry trends from those induced by an IPO in ways a static model cannot. The resulting forecast errors can indicate if an industry's progression through time differs from what would be expected if IPOs have a minimal impact on rival firms. When the variables used by both HRR and CL are included in our analysis as controls, the main results and interpretation are unchanged.

How well does the model capture industry dynamics? Our findings are relevant only if the model captures a substantial fraction of the variation in observed changes to corporate profits and values before and after a rival's IPO. We find strong evidence that it does. For example, in the case of profitability, it yields an in-sample R^2 statistic of more than 32% when 3 years of data are used and 23% with 5 years of data. To see what this means, compare these values to those found in HRR. Their variable list for explaining operating profitability for public rival firms post-IPO produces an R^2 statistic of approximately 4%. The fit from our paper's model comes about despite the fact that it requires only four estimated industry parameters and three firm-specific parameters. When compared with the results typically seen in empirical corporate finance, where many more independent variables are used, the fit produced here is very good. Period-ahead forecast tests indicate that, if you have to restrict yourself to one or two independent variables, then the structural 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 the structural 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 or 5 years of data) the median industry will see a long-term drop in rivals' profitability of between 10% and 20%. However, the estimated heterogeneity across industries is quite large, with an interquartile range between −45% and +40%. If forced to provide a broad characterization of what happens, the hypothesis that the information released from an IPO portends a more homogenous form of product competition (and thus lower profits per unit sold) appears to dominate. The industry 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.[1] The generally accepted reason is that the product offerings have become more homogenous, leading to increased price pressure.

Although the main goal of this paper is to use the dynamic structural model to help answer the question of whether IPOs cause deterioration in performance of rival firms within industries, the methodology also allows us to offer some insights into why IPO firms go public in the first place. As noted above, we find that customer loyalty declines substantially following IPOs. This increased commoditization can reduce the value of maintaining competitive secrecy via private financing. If IPO firms go public in response to the anticipated changes in demand, then one would expect them to go public earlier when the shifts in consumer responsiveness are larger. This is precisely what we find in the data. Within industries, firms go public with smaller market shares when the post-IPO change in consumer responsiveness is bigger. The estimated impact is economically large. In the median industry, the increased commoditization following an IPO reduces the estimated market share at which the next

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

firm in the industry goes public by about 20%. This evidence is consistent with the idea that the IPO event is a response to anticipated industry changes, not their cause.

The paper is structured as follows: Section I discusses the parallels between tests using forecasts from a structural model and those conducted with a DD analysis. Section II presents the structural model. Section III contains the empirical estimates. Section IV reviews the literature in the context of this paper's findings. Section V concludes.

I. Structural Forecasts – An Analog to Difference-in-Differences

The difference-in-differences (DD) methodology has been used to help determine causality in a large number of applications in economics and finance. The basic idea is to compare a change in outcome variable X within population A that undergoes a treatment with the change in the same outcome variable within a control population B that does not. Assuming that populations A and B are well-matched on traits other than the treatment, the difference in their changes can reasonably be attributed to the treatment.

While the DD methodology is extremely valuable, data limitations can restrict its use. For some applications, finding a control group may not be easy. The number of attributes on which a study can match to find an appropriate control is necessarily limited by the size of the available pool. This can force compromises that may result in inadequate matches across unobservable attributes. A structural model produces forecasts that, by necessity, adjust for underlying attributes. As the next subsection discusses, the resulting forecast errors can be used to create a DD type of analysis.

A. Forecast Error Models and DD with Pre- and Post- Treatment Data

In this paper "forecast error model" means a test conducted on the difference between an outcome variable and the model's forecast. With this broad definition, one can think of DD models as a subset of forecast error models. Consider a typical DD model in corporate finance. At some date 0 an event (‘treatment”) occurs. In this paper, it is a firm deciding to go public. At the beginning of date 0 the value of some variable y_{i0} is recorded. This captures the value of y prior to the treatment. At some future date, call it date 1, the same variable has its value y_{i1} noted and the difference $\Delta y_i = y_{i1} - y_{i0}$ recorded. The question is then whether the firm’s action causes Δy_i or if the action takes place in response to unobserved forces that induce Δy_i. Endogeneity. A DD analysis looks for a control group of firms that did not undergo the treatment but likely also faced the same unobserved forces as the treatment firm.

A typical individual level DD model is based around a specification of the following form:

$$y_{it} = x_{it}\beta_i + \tau w_{it} + z_{it}\gamma + u_{it},\ t = \{0,1\}. \tag{1}$$

Time, t, is recorded as date 0 for the pre-treatment data and 1 for post treatment. The x_{it} are observable variables across time periods and individuals. Some may be common to the whole industry, others specific to individuals. The vector β_i represents the parameters associated with the observable variables. w_{it} is an indicator variable equal to 1 if subject i is in the treatment group (e.g., a firm that took the action in question) and τ is the estimated parameter. The z_{it} are unobservable variables. These are responsible for the potential endogeneity problems of concern to researchers: variables correlated with the treatment and y_{it}. Like the x_{it} , they may be specific to individuals or common across subjects. The γ are the associated parameter values. Finally, u_{it} is a random error term.

Based on equation (1) and letting $\Delta v_i = v_{i1} - v_{i0}$ for some variable v, first differencing across time periods yields

$$\Delta y_i = \Delta x_i \beta_i + \tau w_{i1} + \Delta z_i \gamma + \Delta u_i. \tag{2}$$

Multiple periods can be handled by including time periods among the x_{it} and creating treatment dummies across time periods.[2] The DD model for pairs i and j, with j as the untreated control (i.e., w_{j1}=0), can be written as

$$\Delta y_i - \Delta y_j = \Delta x_i \beta_i - \Delta x_j \beta_j + \tau w_i + \gamma \left(\Delta z_i - \Delta z_j \right) + \Delta u_i - \Delta u_j . \tag{3}$$

If the matching process has been successful, the Δz terms in (3) that also induce the treatment to take place cancel. This eliminates the endogeneity bias. Standard panel data procedures can then be used to see if τ is economically and statistically different from zero.

Operationally, an empirical model based on equation (3) is a forecast error model. In this case, the "forecast" is that y_i will remain unchanged from periods 0 to 1 absent changes in the x_i.[3] The error term contains the unobserved changes in the z_i and an idiosyncratic error. Structural forecasts provide another route to an equation operationally analogous to (3). Consider a forecast y_{i1}^f of the value for y_{i1} based on data available in period 0. Letting $\Delta y_i^f = y_{i1} - y_{i1}^f$ represent the forecast error for subject i one can then produce a regression equation identical to (3) with Δy_i^f replacing Δy_i for both i and j. As in the standard DD setting, if the firms are well matched, differences in the errors caused by omitted variables that are correlated with the treatment and y_{i2} will cancel. The estimated value of τ is then the forecast error due to the treatment, i.e., from the model's viewpoint it is the unexpected change in the treatment group's future performance.[4]

One can easily nest the standard DD model into one with forecast errors by simply leaving y_{i0} in (2) and (3) in order to run

[2] There are innumerable variants on this specification. For example, one can remove linear time trends by comparing the change in growth rates pre- and post- treatment. In this case the independent variables include $y_{i0}-y_{i,-1}$.
[3] This does not mean the DD forecast of y_i is time-invariant. The x_i can include time trends.
[4] In Mora and Reggio's (2012) parlance, this is a variant of the parallel growth assumption.

$$\Delta y_i - \Delta y_j = y_{i0} - y_{j0} + \Delta x_i \beta_i - \Delta x_j \beta_j + \tau w_i + \gamma \left(\Delta z_i - \Delta z_j \right) + \Delta u_i - \Delta u_j . \tag{4}$$

So long as the Δz terms cancel, the estimated value of τ will be unbiased.

A forecast error model can also be used to create out-of-sample tests of various kinds. These can further alleviate endogeneity concerns by restricting the data used to produce the forecasts. One method is to estimate the model parameters using only data from the control firms. Forecasts based on the estimated parameters are then created for all firms in the database. The resulting forecast errors are then compared as in (3). By design, the industry parameters are influenced only by control firm data, making the treatment firm's forecast out-of-sample. This necessarily means the forecast excludes the treatment-specific effect which should show up as part of the treatment firm's forecast error. Thus the forecast error for the control firms equals $u_i(t)$ while it equals $\tau w_i(t) + u_i(t)$ for the treatment firm. We refer to tests of this sort as pseudo out-of-sample since the parameter estimates use data across all time periods. The tests cannot be duplicated in real time. It is only in the cross-section that the out-of-sample forecasting takes place. To create an out-of-sample test that can also be conducted in real time, it is necessary to create rolling parameter estimates. In this case, data from the control group is used up to time t to estimate the industry parameters. After that, forecasts for the outcome variable at time t+1 are created and differenced from the actual outcomes to create true real time forecast errors. From there, the analysis proceeds as above.

As noted above, a standard DD model is a forecast model in which the forecast is that the future value of the dependent variable will equal its current value, up to the impact of the control variables x. The question then is the degree to which a better forecast helps to distinguish among hypotheses. There are two situations in which it seems likely to help: (1) if the structural model does a much better of forecasting y_{i1} than the empirical model; and (2) if the structural model indicates that the treatment firm will see changes that differ from others in its industry or control group. For example, a structural model might indicate that if a control (industry rival) firm sees a drop of 10 then the treatment firm (absent the treatment) will drop by 2. If the treatment firm drops 5, a standard DD approach would indicate that the treatment increased the value of the treatment firm (since its value dropped by less than 10). In contrast, the structural model would indicate the treatment did not add value to the treatment firm (since the treatment did not leave the firm better off given the observed changes to its industry rival).

B. Forecast Error Tests and General Causality Questions

There are several forms of endogeneity discussed in the corporate finance literature: omitted variables, simultaneity, measurement error and reverse causality. As noted above, forecast error and DD models can potentially overcome the omitted variable issue. To the degree simultaneity is a problem and appears as an omitted variable then that too is addressed by both the forecast error and DD models. By design, structural models create forecasts based on every agent in the represented economy. How effective a model will be at handling simultaneous equation issues that do not manifest themselves as an omitted variable depends on the setting. If the model explicitly contains the equation in question then it can be used to estimate the parameters. Naturally, if the model does not include an equation that played an important role in the data generation process, then it cannot help in this regard.

Measurement error is an issue in any model and can lead to misattributed causality findings. It is often the case that an important independent variable is inaccurately measured. How critical this problem is depends on the application. Because poorly measured variables lead to poor forecasts, they provide a useful test of the measurement issue's importance. Models that are better at handling the measurement error issue should yield better forecasts. Finally, there is the reverse causality issue. In terms of this paper's question, do IPO's cause the subsequent changes we observe in an industry or does the IPO occur in anticipation of those changes? As noted in the introduction, this issue can be addressed directly using a forecast error model. A firm will only trigger an event if doing so provides it with a benefit. This implies that triggering firms should have forecast errors that indicate that the future changes for them were unexpectedly good. It is also possible that forces outside the issue in question (but related to the observed industry changes in the data) induced the trigger. If the triggering firm does have unexpectedly good forecast errors then analysis can consider the forecast errors of its rivals. When one firm in an industry becomes relatively stronger, that is a cost to its rivals. Changes in rival statistics should indicate that they are hurt by the trigger and the model can predict the magnitude of this cost given the industry's structure.

II. Model

The goal of the model is to provide a structural framework that can be used to forecast industry variables. Its structure and solution are based on Spiegel-Tookes (2013). To maintain this paper's focus on the empirical work, the model's solution is relegated to the appendix.

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[5]:

$$dm_i(t) = \phi\left[\frac{s_i u_i(t)}{\sum_{j=1}^{n} s_j u_j(t)} - m_i(t)\right]dt \tag{5}$$

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 that a firm achieves a greater "bang for its

[5] At the limit, where every firm spends zero on customer acquisition, the ratio becomes undefined. Those for whom this seems problematic can just assume that firms are endowed with a small free level of customer acquisition. This is equivalent to assuming a firm's product has a subset of very loyal customers. Ultimately, one can show that adding this to the model does not materially alter any of the model's results.

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

$$d\varsigma = gdt + \sigma dw \tag{6}$$

where dw is a standard Brownian motion.[6] In the model, all else equal, instantaneous corporate profits are proportional to industry size and are given by

$$e^{\varsigma}\pi_i(t) = e^{\varsigma}\left[\alpha_i m_i(t) - u_i(t) - f_i\right] \tag{7}$$

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. Each firm seeks to maximize its expected present discounted value $V_i(m,\varsigma,t) = E\left[\int_{t=0}^{\infty} e^{\varsigma - rt}\pi_i(t)dt\right]$, where r (assumed to be greater than g) is the discount rate. In principle V_i can be a function of the vector m. However, we will guess that it is just a function of m_i and then confirm that this guess is a solution to the value function. As the appendix shows, a change in the probability measure lets one further simplify the problem by writing the value function as $V_i(m_i,t)$, which drops the ς term and with it the second order terms in the HJB equation that determines the solution to the optimal control problem.

[6] In the model, corporate spending on customer acquisition does not influence the overall industry's growth rate. Because of this assumption, the model better describes a mature oligopoly than a new and rapidly growing one. For example, if a company develops a better refrigerator, it is unlikely that many households will then add an additional refrigerator to their house. Instead, sales are more likely to come at the expense of rivals. Many industries appear to function like this. It is clearly possible to add an interaction between the u_i and ς, but this comes at the cost of a closed-form solution.

When a firm conducts an IPO, it is forced to release information about its sales and operations. While this information may help investors, it may also be of use to rival firms that can work towards incorporating the newly gleaned information into their own strategies, product offerings and customer appeals.[7] (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. Assume that, prior to the IPO, firms are endowed with a set of parameter values for their profits per unit of market share $\alpha^* = \left(\alpha_1^*, \ldots, \alpha_n^*\right)$, spending efficiency $s^* = \left(s_1^*, \ldots, s_n^*\right)$ and fixed operating costs $f^* = \left(f_1^*, \ldots, f_n^*\right)$. For simplicity, assume that firm n conducts the IPO. Over time, the industry will adjust to the new post-IPO parameter sets $\alpha = \left(\alpha_1, \ldots, \alpha_n\right)$, $s = \left(s_1, \ldots, s_n\right)$ and $f = \left(f_1, \ldots, f_n\right)$. These new parameters may reflect the effects of the information the IPO firm is forced to release now that it is public, or information about changes in the industry structure. They could also reflect the competitive effects of the new, stronger, publicly-financed IPO firm.

The model does not take a stand regarding the industry's progression following the IPO. Parameters may evolve in ways favorable to industry profits. They may also imply future hardship. The overall impact on value will depend on consumer demand and on the competitive responses of all firms in the industry. Nor does the model directly address the empirical endogeneity issue. That is, forthcoming industry changes may have triggered the IPO or the IPO may have triggered the industry changes. The model is a vehicle for creating forecasts whose errors can be used to test for causality. As previously noted, if we observe a parameter transition and the new parameter set leaves the IPO firm worse off, then

[7] People generally think of production secrets in situations like this. However, customer secrets can be important as well. Suppose firm A's sales are flat but B's are up. Firm A may conclude that B's customers are doing well and increase its marketing to them. In the model, this is equivalent to an increase in B's value of s_i relative to A's.

it is unlikely that the IPO was used to trigger the industry changes. This observation will prove central to the causality tests later on in the paper.

Whether or not the IPO triggers an industry's evolution, assume that the transition to the new parameter set 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 $\breve{f}$:

$$\breve{\alpha} = \alpha + e^{-\psi t} \Delta \alpha, \tag{8}$$

$$\breve{s} = s + e^{-\psi t} \Delta s, \tag{9}$$

and

$$\breve{f} = f + e^{-\psi t} \Delta f \tag{10}$$

where $\Delta \alpha = \alpha^* - \alpha$, $\Delta s = s^* - s$ and $\Delta f = f^* - f$. This lets the model incorporate all three elements into the $-\delta V_i$ term in the HJB equation. To reduce notational clutter further, let $\delta = r - g - \frac{1}{2}\sigma^2$ so that we can write the problem of finding the optimal amount to spend on consumer acquisition as:

$$0 = \max_{u_i} \left(\alpha_i + e^{-\psi t} \Delta \alpha_i\right) m_i - f_i - e^{-\psi t} \Delta f_i - u_i + V_i^m \phi \left[\frac{\breve{s}_i u_i}{\sum_{j=1}^{n} \breve{s}_j u_j} - m_i \right] - \delta V_i + V_i^t. \tag{11}$$

In equation (11) superscripts on the value function V indicate partial derivatives with respect to market share (m_i) and time (t). Like most papers that employ continuous time game theoretic models, the above setup seeks to find a Markov equilibrium. There may be, and likely are, other non-Markovian equilibria.[8]

[8] See Dockner, Jorgensen, Van Long and Sorger (2000) for a discussion of Markov and non-Markov equilibria in continuous time game theoretic models.

To solve (11) assume V_i has the form:

$$V_i\left(m_i,t\right)=a_i\left(t\right)+b_i\left(t\right)m_i\left(t\right). \tag{12}$$

Interested readers can find details regarding the solution procedure in the appendix. For empirical purposes, all that is necessary is the solution itself so that forecasts can be created. The empirical work that follows is based upon the following equations. Define

$$\hat{\alpha}_i=\left(\phi+\delta+\psi\right)\alpha_i+\left(\phi+\delta\right)\Delta\alpha_i e^{-\psi t} \tag{13}$$

and

$$\hat{z}=\sum_{j=1}^{n}\frac{1}{\hat{\alpha}_j\breve{s}_j} \tag{14}$$

Then the solution to u_i is

$$u_i=\frac{\hat{\alpha}_i\phi\left(n-1\right)\left[b_i\breve{s}_i\hat{z}-\left(n-1\right)\right]}{\left(\phi+\delta+\psi\right)\left(\phi+\delta\right)\left(\hat{\alpha}_i\breve{s}_i\hat{z}\right)^2}. \tag{15}$$

The solution for b_i is

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

Finally, the solution to a_i comes in the form of non-linear ODE. While it does not in general admit a closed form solution, it does so 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. These constraints imply that each firm experiences a proportional change to its profits per unit of market share and marketing capabilities post-IPO. In this case, one can show that the $\hat{\alpha}_i\breve{s}_i\hat{z}$ terms reduce to the constant $\hat{\alpha}_i\breve{s}_i\hat{z}=\alpha_i s_i z$, where z is defined as $\sum_j\left(\alpha_j s_j\right)^{-1}$. This then leads to the closed form solution for the a_i of

$$a_i = -\frac{f_i}{\delta} + \frac{\alpha_i \phi\left[\alpha_i s_i z - (n-1)\right]^2}{\delta(\phi+\delta)(\alpha_i s_i z)^2} + e^{-\psi t}\left[\frac{\alpha_i k_\alpha \phi\left[\alpha_i s_i z - (n-1)\right]^2}{(\delta+\psi)(\phi+\delta+\psi)(\alpha_i s_i z)^2} - \frac{\Delta f_i}{\delta+\psi}\right]. \tag{17}$$

III. EMPIRICAL ANALYSIS: COMPETITIVE EFFECTS OF IPOS

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. While the empirical analysis focuses on innovations in profitability per unit market share (α) and changes in consumer loyalty (ϕ) 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).

A. Profitability Transition

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: $\pi_i(t) = e^{\varsigma(t)}(\alpha_i m_i(t) - u_i(t) - f_i)$.

Following Spiegel and Tookes (2013), let $\pi_i(t) + e^{\varsigma(t)} u_i(t) \equiv \hat{\pi}_i(t) =$ (Revenue – Cost of Goods Sold). This can 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 $f_i^* \equiv f_i$ and $s_i^* \equiv s_i$). Under the assumption that, for every firm i, $\alpha_i = k\alpha_i^*$, the model estimates

$$\pi_i(t) - e^{\varsigma(t)} u_i(t) = e^{\varsigma(t)}\left(((k-(k-1)e^{-\psi t})\alpha_i^*) m_i(t) - f_i^*\right). \tag{18}$$

Using only data on revenue and costs of goods sold, non-linear least squares can be used 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 . This transition rate and the associated "information revelation rate" are terms that should be broadly construed. For example, the IPO decision could be the result of the private 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 result from management's assessment that an impending economic shock will decrease the benefits associated with remaining private.

B. Consumer Responsiveness and Competitive Strength

In order to estimate model-implied values, estimates for consumer responsiveness and competitive strength (ϕ and $\alpha_i s_i z$, respectively) are also required. Recall that, because profitability evolves at the common rate ψ and given the common factor k scaling α_i^* relative to α_i, 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 use the equation $dm = \phi(\bar{m}_i - m_i(t))dt$, which has a solution for $m_i(t)$ of :

$$m_i(t) = \bar{m}_i + (m_i(0) - \bar{m}_i)e^{-t\phi}. \tag{19}$$

Equation (19) can be estimated via non-linear least squares and provides estimates for each firm's $\bar{m}_i$ as well as for the industry parameter ϕ. It also gives firm-specific competitive strength $\alpha_i s_i z$ since, in steady state, $\bar{m}_i = 1 - \frac{n-1}{\alpha_i s_i z}$. The empirical model estimates pre- and post-IPO consumer responsiveness parameters (ϕ_0 and ϕ respectively) by allowing consumer behavior to change as of the IPO date. Data from the pre- and post-IPO period then allows equation (19) 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).

C. 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.[9] The initial sample of IPO events is from Securities Data Corporation New Issues Database and includes the IPOs of U.S. publicly listed stocks from 1983 through 2012.[10] Because we are interested in oligopolistic competition, only the 3,299 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 3 years prior to the IPO quarter. We estimate the model over horizons that include data through 3 and 5 years post-IPO, using a total of 24 and 32 quarters of data for each firm, respectively. Parameter estimates are shown in Table 1, Panel A. We obtain estimates for between 741 and 855 IPO events, depending on the estimation horizon.[11] The median estimated ψ ranges from 0.304 to 0.387. This implies that, following the median IPO event, between 26% 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 70% and 78% complete. By the end of the second year between 91% and 95% has occurred. However, there is substantial cross-sectional variation in ψ .

Table 1 also provides estimates of the value of the profitability shock *k*, where $\alpha_i = k\alpha_i^*$. Across both 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 profitability per unit of market share. However, as in the case of ψ , there is substantial cross-sectional

[9] Prior work indicates Compustat's SIC codes do a better job than those generated by CRSP when it comes to capturing related firms. For example, see Guenther and Rosman (1994).
[10] We exclude financials and utilities (SIC codes 6000-6999 and 4900-4999). The IPO issue sample ends in 2012 so that there are a sufficient number of post-IPO quarters for model estimation. The financial data from CRSP and Compustat are through December 31, 2014.
[11] 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*.

variation. The interquartile range for the estimated value of k using data over the 5 years following the IPO is 0.54 to 1.40. This implies that rival firms experience between a 46% drop and a 40% increase in profit per unit market share (α_i) 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 305,260); 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 0.6% per quarter under all specifications. This quarterly growth parameter varies within a reasonable range (for example, based on the estimates using data for the 5-year window, we obtain estimates with an interquartile range of −1.0% to 2.1%).

The median consumer responsiveness parameter pre-IPO (still using the 5-year estimation horizon as an example) of 0.04 implies that, for the median industry, it would take a competitor about 17 quarters to lose half of its customers if it completely stopped spending to attract them. For expositional purposes, call this the market share half-life. [12] Post-IPO it appears the median industry transitions to a state where consumers are much more willing to switch brands. The median ϕ is 0.129, which implies a market share half-life of only 5.3 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 become about as loyal to a particular product as elsewhere in the economy.

The ϕ parameter in this model has an interpretation that is closely related 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

[12] The market share half-life is defined as $\log(2)/\phi$.

interaction among firms in an industry. Because the CSM measure is related to some of the ideas developed here, it is useful to compare it with the procedures we employ. Using this paper's notation, the CSM for firm i can be written as

$$CSM_i = corr\left[\frac{\Delta\pi_i}{\Delta S_i}, \Delta S_{-i}\right] \tag{20}$$

where ΔS_i equals the change in firm i's sales and ΔS_{-i} the change in the sales of its rivals. The CSM provides a simple way to capture the degree to which firms in an industry pull away each other's customers (the authors use it as a proxy for the second derivative of firm i's profits with respect to firm i's sales and rivals' sales). While the intuition behind the CSM is useful, there are two issues that may complicate the interpretation. First, the ratio $\Delta\pi_i / \Delta S_i$ in Equation (20) is unit-free while ΔS_{-i} is not. Second, the CSM measure may be less reliable when sales are relatively stable. Estimates of ϕ using (19) do not have these issues. In the Appendix, we reformulate Equation (20) to fit this paper's model and we compare our ϕ to the CSM measure. In this case, the structural model helps to produce parameter estimates of interest that are more robust and stable over time.

The final input to the firm value function is δ, the cost of capital minus the growth rate. We follow Spiegel and Tookes (2013) and 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. This is value is identical for all firms for a given time period.[13]

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. As Equation (15) shows, firms will optimally respond to industry developments by changing their spending patterns. Thus, the equilibrium impact on firm value is smaller

[13] We make this simplification to reduce the noise in the industry level cost of capital and growth estimates. We also do not include the $.5\sigma^2$ term, as doing so should not impact the cross-sectional tests.

than it would be in the absence of strategic response. To see this, we begin by plugging the estimated parameters into Equations (12), (16) and (17) with *t* set to zero and infinity to obtain the pre- and post-IPO rival firm values, respectively. We then calculate the ratio of the post- to pre-IPO industry market values. Firms that 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 IPO event, the rival firm median, value weighted mean and equally weighted mean ratios are calculated. The results of this exercise are in Table 1 Panel B. For the median industry, we find that the model-implied value change post-IPO is near zero. This may seem surprising since the estimated value of *k* is between 0.8 and 0.9 for the median IPO in Table 1 Panel A. Competition for market share reconciles the seeming contradiction. Before the IPO suppose one unit of market share (a customer) is worth $10. Firms will react by spending up to $10 in customer acquisition activities to draw in additional units of market share. After the IPO the same unit of market share sees its value reduced to $8.50. Firms react by reducing their customer acquisition spending accordingly. The overall impact on profits is just the degree to which the value of *k* alters what amounts to a firm's local monopoly over consumers that prefer its product.

All industries are not the same and there is some variability regarding their evolution post IPO. Some intuition can be garnered from the interquartile ranges reported in Table 1 Panel B. Using the median value as an example, the interquartile range of the ratio is between 98% and 101% using a 3-year estimation horizon and between 96% and 101% using a 5-year estimation horizon. Given how small most IPO firms are these are figures in the range one might expect.[14]

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%. These short-run results are broadly consistent with the median value changes that we find in Table 1 Panel B using a broader sample of IPOs and analyzing

[14] Ritter (2016) reports that during the years 1980 to 2015 the median IPO firm had sales of $47 million during the 12 months prior to the IPO and at-issue market capitalization of $178 million (2005 dollars).

rivals at the 4-digit industry level. HRR credit this change to the competitive advantages the IPO firm sees from going public. The next section uses the model's forecast errors to reexamine this interpretation.

D. Filtering Implausible Model Estimates

Table 1 indicates 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 is clearly unable to fit some industries. This results 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 the: (1) IPO events with estimated ψ, k, g or φ that are less than the 1st percentile or greater than the 99th percentile of all estimates; (2) model-implied or actual quarterly changes in firm value (log ratio of values) that are less than -1 or greater than $+1$; or (3) model-implied or actual quarterly changes in profitability that is greater (in absolute value) than the value of beginning-of-period assets.

E. Are IPO Firms Catalysts or Canaries?

Recent studies, including this one, find that industries undergo significant changes after an IPO takes place. It is certainly possible that IPOs induce large changes within an industry. For example, Table 1 shows that, post-IPO, customers generally become easier to steal. Pre-IPO, the up-and-coming firm may have successfully hidden critical information about its production, profits and customers that competitors seeking entry into its product space needed.[15] Because public status requires significant disclosure of information, the IPO could facilitate copying, making products in the industry more homogenous. Of course, it is also possible that IPOs do not catalyze industry changes but instead just presage them. If firms in an industry have discovered that one particular product characteristic mix is optimal, they all may

[15] 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. Even after the IPO, newly public firms seek to maintain some degree of secrecy. Boone, Floros and Johnson (2015) report that nearly 40% of IPO firms redact information from their SEC registration filings.

move in the same strategic 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; that movement is the proximate cause for customers' 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.

The empirical model forces estimates of the firm specific parameters to transition at the same rate ψ and change by the same proportion k for all firms in the industry. This forces the model to treat the IPO firm no differently than its rivals. The null hypothesis is that this is indeed the case: the IPO firm, like the rest of the industry, is affected by outside changes to the competitive environment. The alternative hypothesis is that the IPO firm causes the observed changes in the industry in order to prop up its own value. Assuming the IPO firm is value-maximizing, this should imply that the IPO firm outperforms its rivals relative to the restricted model forecasts.

We examine the "canary" hypothesis empirically by constructing a time series of model-implied performance and comparing it to actual firm performance. The parameter estimates $\psi, g, \alpha_i^*, k, f_i^*, \overline{m}_i \text{ and } \phi$ from Table 1 and market share data (m_{it}) can be plugged into the value and profitability equations to generate model-implied changes in firm performance. The industry-level parameters $\psi, g, k \text{ and } \phi$ are estimated using data for all rivals. That is, the IPO firm is excluded so that industry parameter estimates are influenced only by control firm data. The model-implied change in value is then calculated for all firms in the industry (including the IPO firm). The value change is defined as the log value 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.[16] The actual

[16] Observations in which model-implied $V(m_t,t)$ are less than or equal to zero are eliminated. 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.

firm value V_t is in 2014 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*. Each firm's actual value change is then calculated as: $\ln\left(V_t/V_{t-1}\right)$. For profitability, let $\pi_a(m_t)$ equal model-implied profitability as given in Equation (18), divided by total assets at time t_0. Define the 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 2014 dollars) during quarter *t*, divided by t_0 assets. Realized change in profitability is the first difference of quarterly profitability.

Table 2 begins our examination of the causality question. For the IPO firms and their rivals, we compare the realized changes in firm values and profitability to the changes forecast by the model. The forecast errors are defined as the realized value change minus the forecasted change, so that positive values are associated with better-than-forecasted performance. We know from prior work that rival firms in the industry see their values drop following IPOs. The interpretation in prior papers is that this drop in rivals' values is induced by the increased competitive strength of the newly public IPO firm. If that is true, then if one regresses all of the firms' forecast errors on an *ipo_firm* dummy (equal to one if firm *i* is the one conducting the IPO and zero otherwise) and a constant, the coefficient on the *ipo_firm* dummy should be positive. That is because the null hypothesis is that the IPO firm's value evolves in the same manner as the other firms in its industry. As discussed in Section I, this approach is essentially a DD test in which the forecast errors replace the raw differences between each firm's value on the IPO date and future period.

Table 2 shows results from regressing the in-sample forecast errors for changes in firm value on the *ipo_firm* dummy as well as a variety of control variables based on those in HRR and CL. The coefficient on the *ipo_firm* dummy is insignificant in all specifications. The results indicate that IPO firms do not outperform their rivals during the 3- and 5- years after going public. If anything, they may even do worse. These results hold whether or not the controls from the HRR or CL papers are included. In some cases, some subset of the variables proposed in those articles are significant. However, the inclusion of those variables does not change the insignificant effect of the *ipo_firm* dummy. Table 3 repeats the analysis using out of sample forecasts beginning 3- and 5- years following the IPO. The model parameters are rolling, estimated with quarterly revenue and costs of goods sold data from the IPO quarter through quarter *t*-1.[17] The period-ahead market shares used in the estimation also use data through quarter *t*-1 and are forecast from rolling 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. Predictions are then differenced from out-of-sample data in quarters 12-24 (3-year horizon) and from 20 through 40 (5-year horizon). As in the in-sample tests, the statistically insignificant coefficients on the IPO firm dummy indicate that the IPO firm does no worse than the model would have predicted given the data available at the time the forecast is made. Overall, neither Table 2 nor Table 3 offers any evidence that IPO firms outperform their rivals after going public. If rival firms are seeing their values decline because the IPO firm becomes a stronger rival, it is not showing up in the IPO firm's post issue value.

Table 4 and Table 5 repeat the forecast error tests but this time examine the forecast errors for changes in corporate profits. As in Table 2 and Table 3, the *ipo_firm* dummy is insignificant in all tests. Indeed, so are many of the control variables used in prior studies. There again appears to be no evidence that the overall decline in industries post-IPO is due to the IPO firm's becoming a stronger competitor. If that were true, then, compared to its rivals, the IPO firm would outperform against the model forecast. The IPO firms do not appear to be doing so.

In interpreting the results in Table 2 through Table 5, one might be concerned that the power of the test is insufficient to detect a true difference in IPO firm performance. To examine this potential issue, we repeated the analyses but replaced actual IPO firm performance values with ones that were 1%, 2% and 3% greater than their true values (i.e., generated false over-performance). We then estimated 12

[17] If there is non-convergence or if the parameter estimates for period t are in the 1st or 99th percentile of all parameter estimates, then the usable estimates for the nearest period t-k are used.

sets of regressions: in-and out of sample tests for the 3- and 5-year horizons, using 1%, 2% and 3% over-performance levels. For profitability, over-performance was detected in all 12 cases. For value change, we rejected the null in 10 cases: all 6 of the out-of sample tests and 4 of the 6 in-sample tests (i.e., in all but the 1% over-performance case). Thus, the evidence that IPO firms do not out-perform is not likely to be due to low statistical power in the tests.

Another way to clarify the overall interpretation is to ask how changes in the industry relate to the timing of a firm's IPO. This paper finds that consumer responsiveness ϕ tends to increase following going-public events. Reductions in consumer loyalty can reduce the value of maintaining competitive secrecy via private financing.[18] As a start towards addressing the question of why firms go public in the first place, we examine the relationship between the change in ϕ following the IPO and the market share of the IPO firm at issuance. If IPO firms use anticipated changes in their competitive environments to time their IPOs, we expect IPO firms to go public earlier (i.e., when their market shares are smaller) when the anticipated increase in ϕ is larger.

Table 6 presents results from regressing the *t=0* market share of the IPO firms on $\phi-\phi_0$, 4-digit SIC code fixed effects, industry sales growth over the previous year, industry size, as well as control variables from HRR and CL. Given the 4-digit SIC code fixed effects, the coefficient on $\phi-\phi_0$ captures, within industry, the impact of larger changes in consumer responsiveness on the size of the IPO firm at issue. All of the estimated coefficients on $\phi-\phi_0$ in Table 6 are negative and, when the 3-year estimation horizon is used, all are statistically and economically significant. For example, consider the estimated coefficient of 0.0142 from the first column of Table 6. In the median industry the change in ϕ is −0.168 post IPO. Multiplying these two values together implies that following the i^{th} IPO, if the industry sees the median change in ϕ then IPO firm i+1 will go public with a market share about 24 basis points smaller

[18] The idea that IPO timing may be endogenous is discussed formally in Appendix VII.B. In the model, the consumer mobility parameter undergoes an increase at some time in the future due to increased product homogenization across firms. The trigger date for this is determined by a Poisson process.

than the i^{th} firm did. This is substantial considering the sample average at-issuance market share is 116 basis points. The weaker results for the 5-year horizon line up with the intuition that changes in consumer demand are easier for firms to forecast over shorter periods. Overall, the evidence in Table 6 sharpens the overall interpretation of the paper: IPO firms go public in response to impending commoditization in the product market.

Naturally, data on IPOs only exist in those cases where an IPO took place. Table 2 through Table 5 all indicate that after an IPO the newly public firm does not outperform its rivals relative to model expectations. As noted earlier, an IPO should only take place if it aids the firm in question. If the IPO triggers a decline in industry value and the IPO firm does not outperform the industry as a whole, then conducting an IPO is counterproductive, assuming the firm is seeking to maximize its value. However, there is an alternate possibility that these tests may not account for: the IPO firm may choose to go public at the expense of the industry in order to avoid even larger losses that it would face if it remained private. Suppose that, absent the IPO, the industry as a whole would not see its value drop. But if the firm contemplating the IPO remains private, its value will decline by X%. The IPO, however, will cause it and its industry all to decline by Y%. Assuming Y<X, then our tests would indicate the IPO firm does not outperform the industry as a whole and yet deliberately triggers the industry's decline, all the while maximizing its own value. In theory, this could be the case. However, it begs the question of why larger rivals do not simply purchase firms before they go public.

In general, if an IPO leads to the industry's subsequent decline in value, Table 7 indicates the largest firm can likely profit by purchasing the nascent IPO firm prior to its going public. In the median industry in our sample, the largest firm is more than 20 times the size of the IPO firm. Restricting attention to just those industries where post IPO profits decline (those where purchasing the target would prevent the value losses under the hypothesis that IPOs cause the industry to change), results in similar ratios. HRR report in their Figure 1 an average long-run post IPO value decline per industry of just under 2%. A 20 to 1 size difference means that the largest company in an industry can purchase the still-private firm, lose almost 40% on the transaction and remain better off. At the 75th percentile of this size ratio, the largest firm is 70 times bigger than the IPO firm. In this case the larger company can purchase and shut down the nascent IPO firm and retain value relative to letting the IPO trigger a decline in industry value. At the 25th percentile, the largest firm is 7 times bigger than the IPO firm and can lose up to 14% on the transaction and still profit relative to allowing the IPO to go through. Now, consider again the argument that IPOs trigger declines in industry value and are conducted because the IPO firm would otherwise be even worse off if it remained private. If true, then one now has to ask why most of the observed IPOs in the data were not short-circuited by vastly larger rivals through acquisitions of firms prior to their going public.

F. Model Verification and Comparison with Prior Models

Given our reliance on model estimation errors to infer causality, it is useful to ask how well the model fits the post-IPO performance data. Does it produce results superior to those of models that employ simple linear structures to explain rivals' post-IPO performance? The HRR, CH and CL models all analyze post-IPO data of rival firms using regressions unrestricted by a model. The next sections show that, both in- and out-of-sample, this paper's structural model's forecasts are superior in a number of dimensions to fits based on the independent variables that other papers use.

1. In-Sample Tests

To test the model, actual changes in rival firm value are regressed on the model-implied changes. Test statistics are calculated using pooled data (all IPO events and all rival firms) and standard errors are double-clustered at the IPO event and calendar quarter level. Results are shown in Table 8. The coefficients on the model-implied value changes range between 0.086 and 0.093 and are all statistically significant. Intuitively, a 10% increase in model-implied value is associated with an increase in actual value of between 0.86% and 0.93% in those industries for which reasonable estimates were obtained. The adjusted R^2 values range between 0.47% and 0.65%, which is expected given that returns are the dependent variable.

As with the value change regressions, Table 8 also includes tests to see whether model-implied changes in rival firm profitability explain actual changes. To test this, actual profitability changes are regressed 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 23% to 32%. 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, but the tests are on changes.[19] Estimated coefficients on model-implied changes in profitability are highly significant and range from 0.544 and 0.697. These indicate that a 10% increase in model-implied profitability is associated with a 5.44% to 6.97% increase in actual profitability.

Under the model's assumptions, the changes in value and profitability are the only relevant explanatory variables in the value and profitability regressions, respectively. The findings in Table 8 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 9 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. HRR selected control variables that were previously found to describe firm performance since these variables are 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 HRR have already documented.

One potential advantage of a dynamic structural model is that it can point to particular specifications that are not obvious from a static model's analysis. Table 9 examines 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 using the variables used in other papers. The

[19] To sharpen the interpretation out-of-sample tests are also carried out. These are discussed later.

estimated coefficients on the model-implied changes are similar in magnitude, with slightly higher statistical significance compared to those in the analysis from Table 8, which excludes the HRR controls. The HRR controls do add useful insights of their own: (1) age is generally negatively related to changes in profitability, (2) changes in profitability are positively correlated with firm size; (3) industry market to book is negatively related to value and positively to profit changes.[20] 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.

Note that the HRR variables include the lagged dependent variable. Thus, nested in the HRR analysis is the possibility that changes in firm value and profitability simply follow first-order autoregressive processes. Indeed, there is evidence of first-order autocorrelation; however, the results in Table 9 indicate that the model-implied changes are even more significant. The model is not just mimicking an AR process. Instead, the structure is itself helping to forecast an industry's progression.

CL predict that going public increases an IPO firm's risk-taking incentives. To test this hypothesis, the authors link rival returns near IPOs to the competitive strategy measure (CSM) defined in Equation (20), industry demand uncertainty and the systematic portion of demand uncertainty. Because competition in their model is characterized by strategic substitutes, CL include only those industries in which industry CSM is negative and they use the absolute value of CSM in their regressions.[21]

In Table 10, we repeat the extended HRR regressions from Table 9 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 the estimated CSM is negative. While none are significant statistically, the estimated coefficients on the absolute value of CSM, demand uncertainty and the

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

[21] 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.

systematic component of demand uncertainty are all positive in the rivals' value change regressions.[22] CL do not estimate profitability regressions; however, we include them in Table 10 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.

G. Out-of-Sample Tests

The results in Table 8, Table 9 and Table 10 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 the variables and models fit the historical data and can potentially explain some of the patterns that we observe. 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 raise 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 III.G.1 examines what we refer to as 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

[22] 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 sign on the estimated coefficient on the demand uncertainty in Table 10 is inconsistent with their findings; however, our regressions include the model-implied changes as well as the HRR variables.

procedure is designed to give the static model its best chance of producing a forecast superior 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 perform in real time, in Section III.G.2 we conduct 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 columns in Table 11 repeat the univariate tests shown in Table 8, but instead of in-sample regressions, Table 11 uses the parameters estimated with dates through period *t-1*, along with real-time market share data, to predict quarterly value and profitability changes over the next period. The out-of-sample tests begin at 12 and 20 quarters following the IPO (3- and 5-year horizons, respectively). As noted above, while the parameter estimates are based only on historical data, we use them with data concurrent in time with the dependent variable.

From Table 11 it is clear that the model performs well, even when out-of-sample parameter estimates are used in the value change forecasts. All the regressions produce positive and significant coefficients on model-implied value changes. Given the in-sample findings, it is not surprising that the findings in Table 11 also reveal that model does a better job of explaining how profits evolve over time than how market values change.

The middle and right panels of Table 11 compare the model's out-of-sample performance 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 when variables from HRR and CL are added, implying that the model-implied forecasts are not simply a proxy for the information these variables 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 case, the dynamic model alone yields an R^2 of 25.25% when using a 3-year model and 24.03% when using a 5-year model. Adding the additional HRR and CL variables, including IPO event fixed effects, increases these values by only 5 to 6%. These increases are particularly modest considering that the dynamic model has just one independent variable in the regression while the HRR and CL models combined have 9.

2. Predictive Regressions

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 straightforward exercise. Table 12 begins with the model-implied changes based on the same rolling out-of-sample parameter estimates used in Table 11. 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 12, it is clear that the model-implied forecasts remain significant in all of the univariate regressions, particularly at the 3-year estimation horizon. At the five-year horizon (which examines data from 5 years to 10 years post-IPO), the coefficients are still significant but only at the 10% level. This might be expected, as other developments are likely impact the industry by year 10 following an IPO. Also not surprising, the R^2 statistics are lower than those in Table 11. But this corresponds to what one expects when going from the pseudo forecasts 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 challenging. A static model by design combines the 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 to 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 12. In the case of value changes (Panel A), the model-implied changes are the only statistically significant predictor. In the case of profitability, the model-implied changes and changes implied by the HRR and CL variables are statistically significant, with the expected signs. Again, as expected, the R^2 statistics are lower than those in Table 11.

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 13 and Table 14 use the Schwarz Bayesian Information Criterion to do this. Table 13 asks which regressors add the most explanatory power in-sample. In each case, the model-implied changes in value and profitability rank first across all nine potential explanatory variables. Table 14 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 (4 specifications), second (3 specifications) or third (1 specification). In the true out-of-sample tests, the model forecast is always first. No other single variable performs as well. In fact, the test suggests excluding all the other regressors in one or more specifications. This is true of the lagged dependent variable as well. Thus, there is little support for the alternative hypothesis that the value and profitability changes that we observe are predictable simply because they follow first-order autoregressive processes.

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 that the out-of-sample tests 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 14, both idiosyncratic and systematic demand uncertainty are often placed by the Schwarz-Bayesian information criterion in the "exclude" category.

IV. Literature Review

While the IPO literature is voluminous (see Ritter and Welch (2002) and Ljungqvist (2008) for surveys), we are aware of only three other articles--HRR, CH and CL--that explore empirically how a firm's decision to go public impacts the values of other firms in its industry. In each case, the authors conclude that IPOs create stronger firms that then lead to lower rival values. Our results indicate that IPOs simply presage changes in an industry; they do not induce them. Beyond the statistical evidence presented here, the idea that IPOs cause rival firm values to drop by even 1 or 2 percent requires a model that can lead very small firms to cause relatively large changes in their competitors. When firms conduct an IPO they are small and stay small over the next several years.

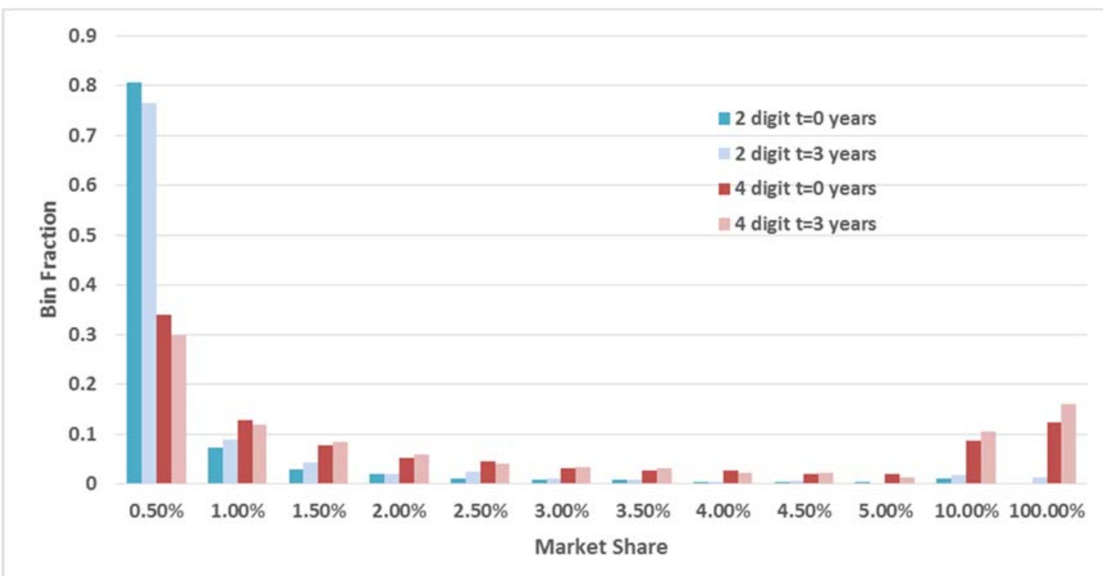

Figure 1: IPO firm market share.

The figure displays the IPO firm's Compustat market share as of its IPO date and three years following the IPO. Industry is defined according to both 2- and 4-digit Standard Industrial Codes (SIC), since both definitions appear in prior studies. Bin labels represent the upper bound. Thus, the bars in the 0.50% bin represent firms that went public with market shares less than or equal to 0.50%. Figure 1 reveals that market shares of more than 10% are relatively rare, comprising 1.1% of all IPO firms using 2-digit industries and 12.2% of all IPO firms using 4-digit industries. At the other end of the spectrum, small firms are rather common. In industries defined at the 2-digit level, 92% of the firms undertaking an IPO have market shares under 1.5%. Using 4-digit industries, this figure naturally drops, but still comes in at 57%. Three years later the IPO firms remain small; indeed, 20.5% of those in our sample disappear from the public markets. (This is consistent with Bharath and Dittmar (2010) who find that IPO firms often return to private ownership within a few years.) Of the survivors, 90% have market shares under 1.5% at the 2-digit industry level. At the 4-digit industry level, 51% of the surviving IPO firms have market shares under 1.5%.

The data in Figure 1 parallel the results in Chemmanur, He and Nandy (2010). They find that post-IPO, newly public firms' sales growth and productivity decline and that their market shares change very little over the next few years.[23] Our data displays a similar pattern. Over the three years following an IPO, 94% 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 shares of less than 1% in the subsequent 3 years. The fact that IPO firms are small and grow rather little over the years following the IPO suggests that a firm's decision to go public has a rather modest practical impact on its competitive stance, limiting the firm's direct impact on rivals.[24] Given the evidence in Figure 1 the results of our forecast error test seem to be more in line with what economic intuition might lead one to expect.

As noted previously, Hsu, Reed and Rocholl (HRR) (2010) look at 2-digit SIC industries and ask how well publicly-traded rivals perform after a very large IPO by one of their members. We are interested in IPO events more generally, so we include both large and small IPO firms in our sample. As discussed

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

[24] Market shares for IPO firms that we observe through year t+3 do increase on average; however, we observe 3,299 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).

and shown in Figure 1 above, the vast majority of issuers are relatively small, especially at the 2-digit level, which is among the reasons we focus on 4-digit industries. Another reason we focus on 4-digit industries is that, if the main economic question is how a firm's actions impact its competition, then 2-digit industries are likely to be too broad to answer it.[25] 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 the heterogeneity of firms within a 2-digit industry, consider the types of firms that populate the SIC 28 2-digit industry. Advanced Polymer Systems[26] is in industry 2821. Its 1997 10-K describes its business this way:

> 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.[27] 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, we need to narrow the lens to at least the 4-digit industry level.

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[25] As noted in Section I, DD type tests can run into difficulties when using 4-digit SIC industries. With a narrow set of potential controls, comparisons with the treatment firm may prove problematic. One possible solution is to increase the number of potential control firms by simply switching to 2-digit groupings. This is likely why HRR use 2-digit SIC codes in their analysis. Often this is harmless and, better yet, because 2-digit codes reduce the problem's dimensionality, such an analysis can be uniquely informative.

[26] Advanced Polymer Systems became AP Pharma and is now Heron Therapeutics.

[27] Both Advanced Polymer Systems and Guest Supply are part of this paper's IPO database.

A second paper that examines an IPO's impact on its rivals is Chod and Lyandres (2011).[28] Like us, they examine 4-digit SIC industries. CL begin 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. The analysis in CL does this by showing that a cross-firm demand elasticity measure developed in Sundaram, John and John (1996) produces estimates in the direction their model indicates it should.

A third paper that looks at an IPO's impact on its industry is Chemmanur and He (CH) (2011). They develop a three date 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 different from ours in that their paper aims to help explain why we see IPO waves within industries. However, 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 do gain relative to their private rivals.

Our paper is also related to the substantial empirical literature documenting intra-industry spillover effects of firm-level announcement events outside of the IPO context, including: mergers and acquisitions (Eckbo (1983, 1992), Song and Walking, (2000), Fee and Thomas (2004), and Shahrur (2005)); dividend announcements (Laux, Starks, and Yoon (1998)); bankruptcies (Lang and Stulz (1992)); corporate security offerings (Szewczyk (1992)); and cash policy (Fresard (2010)). As in Spiegel

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[28] 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. 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.

and Tookes (2013), the advantage of the model in this paper is that it produces a testable structure for examining the mechanisms driving these spillover effects.

In addition to its contribution to the IPO and intra-industry spillover literatures, 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.[29] 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.

V. Conclusion

There has been recent growth in the structural corporate finance literature. In part, the goal is to create and test models that produce magnitudes rather than just parameters' signs in a regression. This paper shows how an oligopoly model can also be used to test for causality within a structure that is analogous to a DD model. In a DD model pairs are compared before and after some event. In the tests proposed here the focus is on measuring differences in the forecast errors.

Recently, papers in the literature have concluded that going public significantly strengthens a firm's competitive position, which leads to significant performance losses for its competitors. Our results indicate that the industry losses are due to industry trends. The IPO is just a portent of those trends. Consistent with prior findings, post-IPO industry values do decline on average. However, prior studies are based on static models, making it difficult to know how to control for trends. The dynamic model used here indicates that post-IPO changes do not occur because the newly public firm is stronger. Rather, the changes arise because profits get squeezed as consumers increasingly view the industry's products as less unique, making it easier for one firm to steal another's customers. Overall, the model explains up to about

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

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 the statistical 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.

While it is important to document the changes in rivals' performance following an IPO, traditional empirical approaches make the drivers of these changes difficult to identify. 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 suggests 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 its profits per unit of market share and value going forward.

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VII. Appendix

A. Derivation of Equation (11)

Write the value function as

$$V(m,\zeta,t) = E_P\left[\int_0^\infty e^{-(rt-\zeta_t)}\pi_i(t)\,dt\right] \tag{21}$$

under some probability measure P. This can be changed to an equivalent measure Q using the Radon-Nikodym density $e^{-\left(\frac{1}{2}\sigma^2 t-\sigma W_t\right)}$ to transform (21) to

$$E_P\left[\int_0^\infty e^{-\left(r-g-\frac{1}{2}\sigma^2\right)t} e^{-\left(\frac{1}{2}\sigma^2 t-\sigma W_t\right)}\pi_i(t)\,dt\right] = E_Q\left[\int_0^\infty e^{-\left(r-g-\frac{1}{2}\sigma^2\right)t}\pi_i(t)\,dt\right]. \tag{22}$$

This drops creates an equivalent value function without the ζ term, effectively just changing the discount rate from r to $r-.5\sigma^2$ in the HJB equation.

B. Modeling the IPO Decision

This section analyzes a version of the model in which the private firm in the industry endogenously decides when to go public. A firm presumably transitions from private to public when the benefits of the latter outweigh the former. For this to happen within the model's confines it must be that the private financing costs and benefits in terms of α, *s* and *f* yield a lower value relative to those from going public at some point in time. There are numerous economic motivations for this. In favor of remaining private, regulatory costs will be lower and information can be more effectively hidden from competitors. Public financing, in contrast, may be less expensive and it may encourage (now better diversified) executive/owners to take on high-risk but *ex ante* profitable projects.[30] Furthermore, as the

[30] This is the hypothesis tested in CL.

private firm grows larger its competitors are likely to become better at offsetting whatever advantages the private firm's secrets provide.[31]

The above list includes the idea that going public gives a firm better access to capital and that strengthens its competitive position. In the model, this is equivalent to assuming that $\alpha_{ip} \leq \alpha_i^*$ and that $s_{ip} \leq s_i^*$, where the subscript p stands for the parameter's value while the firm is private. While every firm might like to become a stronger competitor via lower-cost financing and better diversification of its managerial team, the fixed regulatory costs of going public are not trivial.[32] To represent this assume it costs F to go public and that the instantaneous fixed operating costs are lower if the firm is private rather than public, $f_{ip} \leq f_i^*$ and $f_{ip} \leq f_i$. Offsetting these advantages to public financing is that private firms are better able to keep their competitive advantages secret. For algebraic simplicity, assume this means the industry parameters α, s and f remain unchanged while the firm is private. In the main text, mathematically this corresponds to the case where ψ equals 0.

While firm specific factors may induce a firm to go public, a viable alternative explanation is that some industry-wide change triggers the decision. For example, over time firms are likely to copy each other's more successful product lines and production processes. Even though this increased homogenization makes it easier for firms to acquire each other's customers it simultaneously reduces the value of doing so. To model this mathematically, assume that a Poisson process with parameter λ triggers: (1) the consumer mobility parameter to increase from φ_λ to φ; (2) the profit parameter to drop from α_λ to α^* (i.e. $\alpha_\lambda > \alpha^*$) and (3) the difference between α^* and α to shrink (using subscript λ to represent pre-shock values one has $\left\|\alpha_\lambda^* - \alpha_\lambda\right\| < \left\|\alpha^* - \alpha\right\|$).[33]

[31] As noted in Footnote 15 revealed preference indicates that firms prefer to keep the material in a typical 10-K private.

[32] According to the SEC (2011) these costs come to about $2.5 million for the initial public offering followed by another $1.5 million per year thereafter.

[33] The shock can be thought of as arising from a patent expiration or the start of a new product cycle. Of course, there are numerous other ways to model this homogenization process as well. For example, a gradual increase in

To calculate the value function for the initially private firm there are several cases to consider. Is the firm private or public when the industry becomes more homogeneous? After the industry changes, if the firm is still private how long until it goes public? Will the firm ever go public prior to the industry's changing? What about after? The algebra needed to cover every situation is extensive. To keep this Appendix section down to a manageable length it only details a situation where the firm never goes public unless the going-public conditions are satisfied. The solutions in this setting, with some minor notational changes, also cover situations where the private firm never goes public and where it goes public even if the industry never becomes more homogenous. Empirically, these cases include those where an IPO is due to a firm's desire to become a stronger competitor and those where industry changes are the primary catalyst.

Solving for the case where a firm is private unless the industry changes requires several steps. The first is to find the value function after the industry shock occurs and before the private firm goes public. With the assumptions given above the HJB equation has the same form as (11) with $\Delta\alpha_i$ and Δf_i set to zero. The value function is again affine in m_i and of the form $V_i(t)=a_{ip}(t)+b_{ip}(t)m_i$. Dropping the assumptions required to set $\hat{\alpha}_i\breve{s}_i\hat{z}$ to the constant $\alpha_i s_i z$ for all t post IPO the solution to a_i is given implicitly as the solution to the ODE, where $a_i^t = da_i/dt$,

$$0=-e^{-\psi t}\Delta f_i - f_i - \frac{b_i\phi(n-1)\left[b_i\breve{s}_i\hat{z}-(n-1)\right]}{\left\{1+(n-1)\left[b_i\breve{s}_i\hat{z}-(n-1)\right]^{-1}\right\}^2}$$
$$-\left[1-\frac{b_i^2 s_i\phi}{\sum_{k=1}^{n}\frac{b_i\phi(n-1)\left[b_k\breve{s}_k\hat{z}-(n-1)\right]}{\left\{1+(n-1)\left[b_k\breve{s}_k\hat{z}-(n-1)\right]^{-1}\right\}^2}}\right]-\delta a_i + a_i^t \tag{23}$$

product and production uniformity. But these alternatives produce additional algebraic complexity that seems excessive in an Appendix like this.

In this case the terminal value sets the solution to a_{ip} and b_{ip}, equal to their value in (23) and (16) at the IPO date, t^*, with an adjustment for the fixed cost F of going public. Some algebra shows that the solution to b_{ip} is

$$b_{ip} = \frac{\alpha_{ip}}{\phi+\delta} + \left[\frac{\alpha_i - \alpha_{ip}}{\phi+\delta} + \frac{\Delta a_i}{\phi+\delta+\psi}\right] e^{-(\phi+\delta)\left(t^*-t\right)}. \tag{24}$$

Since the solution to a_i in the main text does not, have a general closed form solution, it is not possible to produce an equation like (24) for a_{ip} without additional restrictions to the model. Instead, let a_i^* equal the value of a_i on the firm's IPO date, which is given implicitly as the solution to (23). For the pre-IPO period the ODE governing a_{ip} has the same form as (23) with k_α, k_s and ψ all set to zero. Let $z_p = 1/\sum s_{ip}\alpha_{ip}$ then the solution to this ODE can be written as

$$a_{ip} = \left[1-e^{\left(t-t^*\right)}\right]\left\{-\frac{f_{ip}}{\delta} + \frac{\phi\alpha_{ip}\left[\alpha_{ip}s_{ip}z_p - (n-1)\right]^2}{\delta(\phi+\delta)\left(\alpha_{ip}s_{ip}z_p\right)^2}\right\} + e^{\left(t-t^*\right)}\left[a_i\left(t^*\right)+F\right]. \tag{25}$$

To find the IPO date differentiate $a_{ip}+b_{ip}m_i$ with respect to t^*, set the result equal to zero and solve for t^*. (Note that the optimal time includes the changes in the firm's market share since m_i also depends on t^* through (5).) Without going through all of the algebra to get a final solution, it is easy to show that the smaller the firm is on the day the industry shock hits the longer it will wait to conduct an IPO. Since the private firm becomes a stronger competitor if it goes public it is straightforward to show that both db_{ip}/dt^* and da_{ip}/dt^* are negative (the latter if f_i is not too large relative to f_{ip}). Thus, the firm will only remain private if $d(b_{ip}m_i)/dt^*$ is positive. For an initially small market share this may be true as m_i will grow through time. However, as m_i approaches its steady state value dm_i/dt goes to zero. Thus, for the appropriate parameter values, there is an optimal IPO date. Not too surprisingly, increasing the regulatory costs of going public implies that firms will be larger in size when they finally conduct their IPO. The comparative static examined in Table 6 is that reducing the difference in profits per unit of market share pre and post IPO reduces the optimal size at which a firm goes public. That is, $dt^* / d\alpha_{ip} > 0$ for $\alpha_{ip} > \alpha_i$.

To complete the analysis of the case where the firm remains private unless there is a change to the industry after which it will, at some point, go public, begin by considering the value function prior to the change. To keep the solution as simple as possible, assume the private firm reaches its steady state market share prior to the date of the industry shock. In this case the appropriate guess for the value function is that it is time independent. This leads to an HJB equation of the form

$$0 = \max_{u_i} \; \alpha_{i\lambda} m_i - f_{i\lambda} - u_i + V_{i\lambda}^m \phi_\lambda \left[\frac{s_i u_i}{\sum_{j=1}^{n} s_j u_j} - m_i \right] - \delta \left[\lambda \left(a_{ip} + b_{ip} m_i \right) + \left(1 - \lambda \right) V_{i\lambda} \right]. \tag{26}$$

The subscript λ indicates a parameter's value prior to the industry shock.[34] In (26) the a_{ip} and b_{ip} terms equal their value immediately post shock; this occurs at time t=0 in (24) and (25). Next, guess that the value function in (26) has the form $V_{i\lambda} = a_{i\lambda} + b_{i\lambda} m_i$ where $a_{i\lambda}$ and $b_{i\lambda}$ are both time independent. Quite a bit of algebra then yields solutions of

$$a_{i\lambda} = \frac{\lambda - 1}{\lambda} a_{ip} - \frac{f_{i\lambda}}{\delta\lambda} + \frac{\phi \left[\alpha_{i\lambda} \left(\phi + \delta \right) - \alpha_i^* \delta \left(1 - \lambda \right) \right]}{\delta\lambda \left(\phi + \delta \right) \left(\phi + \lambda\delta \right)} \left[\frac{\left(\alpha_{i\lambda} \left(\phi + \delta \right) - \alpha_i^* \delta \left(1 - \lambda \right) \right) s_{i\lambda} z_\lambda - \left(n - 1 \right)}{\left(\alpha_{i\lambda} \left(\phi + \delta \right) - \alpha_i^* \delta \left(1 - \lambda \right) \right) s_{i\lambda} z_\lambda} \right]^2 \tag{27}$$

and

[34] If the private firm has not yet reached its equilibrium market share then (32) needs to be adjusted for the fact that the time between when the industry shock happens and the firm goes public depends on when the shock occurs. If the private firm has already reached its steady state market share the time between these two events is a constant.

$$b_{i\lambda} = \frac{\alpha_{i\lambda} - \delta(1-\lambda) b_{ip}}{\phi + \lambda\delta}. \tag{28}$$

In the above equations, $z_\lambda = 1 / \sum\left(\alpha_{i\lambda}(\phi+\delta) - \alpha_i^* \delta(1-\lambda)\right) s_i$.

Given the above set of solutions, with sufficient pre-IPO period data it is now possible to investigate the degree to which the model does or does not explain IPO activity. Besides fitting the model to the data with explicit parameter estimates, there are a number of comparative statics that can be examined.

C. Data Note

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 the 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.

D. A Derivation of the CSM Measure

From Equation (25) in CL, the CSM measure for firm *i* is given by (20). In this paper's model, sales do not exist as an independent variable but they do map to market shares. 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. Using pre-IPO data, period *t* market share equals

$$m_{it} = \frac{S_{it}}{S_t}. \tag{29}$$

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

$$S_{it} = m_{it} S_t. \tag{30}$$

Recall that profits, sales and other industry values grow at the stochastic exponential rate given by (6). Market shares can also move around randomly (more on this below). These random attributes should capture the basic idea behind the *CSM* measure, which is designed to capture cross-firm demand elasticity. With the above in mind, aggregate sales at time *t* equal

$$S_t = S_0 e^{\varsigma(t)}. \tag{31}$$

It helps to convert the ΔS_i terms into market share changes to allow for a stochastic element in line with the intuition behind the *CSM* measure. Equations (30) and (31) do this, resulting in

$$S_{it+h} - S_{it} = m_{it+h} S_{t+h} - m_{it} S_t = \left(m_{it+h} e^{\varsigma(t+h)-\varsigma(t)} - m_{it} \right) S_0 e^{\varsigma(t)}. \tag{32}$$

Now plug this along with (29) into (20) in order to write the measure in terms of our model's variables:

$$CSM_{it} = corr\left\{ \frac{\left(\alpha_i m_{it+h} - u_i - f_i\right) e^{\varsigma(t+h)} - \left(\alpha_i m_{it} - u_i - f_i\right) e^{\varsigma(t)}}{\left(m_{it+1} e^{\varsigma(t+h)-\varsigma(t)} - m_{it} \right) S_0 e^{\varsigma(t)}}, \left[\left(1 - m_{it+h}\right) e^{\varsigma(t+h)} - \left(1 - m_{it}\right) \right] S_0 e^{\varsigma(t)} \right\}. \tag{33}$$

Some rearranging then produces

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

Since only market shares and industry size 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 (34) to

$$CSM_{it} = corr\left\{ \frac{-\left(e^{\varsigma(t+h)-\varsigma(t)}-1\right)\left(u_i+f_i\right)}{\left(m_{it+h}e^{\varsigma(t+h)-\varsigma(t)}-m_{it}\right)S_0}, \left[\left(e^{\varsigma(t+h)-\varsigma(t)}-1\right)-\left(m_{it+h}e^{\varsigma(t+h)-\varsigma(t)}-m_{it}\right)\right]S_0 e^{\varsigma t} \right\}. \qquad (35)$$

One feature of Equation (35) that deserves mention is that the left hand term in the correlation lacks the $e^{\varsigma(t)}$ term that appears in the right term. This is because the change in profits divided by the change in sales (the left term) is unitless while the change in sales (the right term) is not.

Another addition that can be made to the basic model so that its properties are similar to the intuition behind the CSM measure is to add a random term to the change in market share. 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

$$m_{it+1} - m_{it} = \frac{\phi\left[(1-m_i)u_i s_i - m_i \sum_{j\neq i} u_j s_j\right]}{\sum_{j=1}^{n} u_j s_j} + \sigma_m \sqrt{m_i} \sum_{j\neq i} \iota_{ij} \sqrt{m_j} \qquad (36)$$

where ι is an indicator variable equal to +1 if $i<j$ and −1 if $i>j$ while σ_m is the standard deviation that presumably arises from the underlying Weiner process governing market shares.

Since the *CSM* is in variables that contain units, they grow over time. By contrast, market shares are unitless. The *CSM* measure depends 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, too. Another potential consideration, as noted in the main text, is that the denominator of (20) can both change sign and take on values near zero. In these cases, the CSM measure is difficult to interpret.

Table 1: Summary Statistics

In Panel A 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 (8). Consumer responsiveness ϕ is estimated via Equation (19) from Spiegel and Tookes (2013). Estimates for pre- and post-IPO are labeled ϕ_0 and ϕ respectively. IPO firm rivals are defined as those firms in the same Compustat 4-digit SIC code as the IPO firm. We use quarterly Compustat revenue and costs of goods sold data from the IPO quarter *t*-12 through quarters 12 and 20 following the IPO (3-year and 5-year post-IPO estimation horizons, respectively). IPO events are taken from SDC from January 1, 1983 through December 31, 2012 in industries with fewer than 50 publicly traded competitors. In Panel B, the estimated model parameters are plugged into Equations (16) and (17) with *t*=0 and t=∞ to calculate the ratio of values post IPO to pre. Firms with a forecasted value change greater than a factor of 100 (ratio greater than 100 or less than 0.01) are removed. Estimates are aggregated across the sample of IPO events. First, for each IPO calculate the median, equally weighted mean (EWmean) or value weighted mean (VWmean) value ratio. Second, take the median or mean of this series.

Panel A: Estimated Parameter Values												
Variable	Mean	5th Pctl	10th Pctl	25th Pctl	Med.	75th Pctl	90th Pctl	95th Pctl	Min	Max	Std Dev	N
3 Year Estimation Horizon												
ψ	0.674	0.065	0.101	0.187	0.387	0.882	1.561	2.169	0.000	9.021	0.806	741
k	1115	0.223	0.361	0.646	0.893	1.359	1.977	3.007	0.000	305,260	14754	741
g	0.006	-0.042	-0.028	-0.010	0.006	0.022	0.041	0.053	-0.152	0.243	0.033	741
Φ_0	0.132	0.005	0.012	0.031	0.063	0.121	0.264	0.417	0.000	3.137	0.270	741
Φ	0.451	0.017	0.038	0.116	0.256	0.531	1.050	1.710	0.000	4.775	0.594	741
5 Year Estimation Horizon												
Ψ	0.591	0.049	0.075	0.142	0.304	0.745	1.419	1.932	0.000	11.208	0.866	855
k	264	0.137	0.274	0.543	0.818	1.401	2.103	3.304	0.000	129,194	4770	855
g	0.008	-0.035	-0.024	-0.010	0.006	0.021	0.039	0.053	-0.118	0.483	0.034	855
Φ_0	0.102	0.002	0.006	0.017	0.040	0.085	0.181	0.317	0.000	3.797	0.285	855
Φ	0.263	0.014	0.025	0.061	0.129	0.273	0.592	1.044	0.000	4.327	0.410	855
Panel B: Post IPO/Pre IPO Value Ratios												
3 Year Estimation Horizon												
median	1.080	0.869	0.931	0.980	0.998	1.009	1.049	1.120	0.523	56.891	2.070	732
EWmean	1.116	0.814	0.893	0.962	0.996	1.018	1.120	1.328	0.523	56.891	2.093	732
VWmean	1.102	0.807	0.902	0.976	0.997	1.013	1.083	1.230	0.286	56.891	2.099	732
5 Year Estimation Horizon												
median	0.988	0.707	0.821	0.956	0.996	1.013	1.076	1.158	0.188	5.395	0.249	848
EWmean	1.021	0.663	0.787	0.928	0.993	1.025	1.134	1.283	0.188	11.159	0.534	848
VWmean	0.992	0.627	0.783	0.944	0.994	1.021	1.100	1.251	0.214	9.201	0.383	848

Table 2: Post-IPO Error Causality Tests on Firm Value: In-Sample Evidence

This table shows the parameter estimates from forecast error tests based on the formulation in Equation (2). The dependent variable is the in-sample forecast error in changes in firm value V (positive values imply the firm did better than expected). We use data from the IPO quarter t through quarters 12 and 20 (3-year and 5-year post-IPO estimation horizons, respectively). The independent variables are: *Ipo_firm* , a dummy equal to 1 if the firm is the one that conducts the IPO; *lag_ind_error_v*, the lagged industry forecast error (sum of all firms' forecast errors); *log_at*, the natural log of total assets; *ind_mb*, the median industry market to book ratio in the previous year; *underprice*, the annual level of underpricing in year t; *age*, the number of years since the firm's first trading day in CRSP; *csm*, the absolute value of the competitive strategy measure (CSM from Equation (20)); *d_uncertain*, the standard deviation of seasonally adjusted sales growth; and *s_uncertain*, the systematic component of demand uncertainty. Following CL, the regressions using *csm* include only the subsample of industries with a negative CSM. All regressions are pooled, with standard errors double-clustered by IPO event and calendar quarter end date. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

3-year horizon								
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
Intercept	0.0022	0.20	0.0023	0.21	0.0000	0.00	-0.0350**	-1.97
ipo_firm	-0.0042	-0.90	-0.0038	-0.80	-0.0084	-1.50	-0.0004	-0.05
lag_ind_error_v			-0.0360	-0.77	-0.0970**	-2.09	-0.0303	-0.60
log_at					0.0016	1.13	-0.0003	-0.19
ind_mb					-0.0180	-1.37	-0.0088	-0.60
underprice					0.0762	0.64	0.0314	0.25
age					0.0006	0.19	0.0061*	1.68
csm							0.1505*	1.70
d_uncertain							0.2599**	2.22
s_uncertain							0.1272	1.63
Adj. R^2	0.002%		0.052%		0.695%		1.134%	
N	54,751		54,728		54,703		28,338	
5-year horizon								
Intercept	-0.0003	-0.02	-0.00025	-0.02	0.0000	0.00	-0.0231	-1.38
ipo_firm	-0.0044	-1.16	-0.00442	-1.17	0.0004	0.08	-0.0002	-0.03
lag_ind_error_v			-0.03319	-0.71	-0.0670	-1.44	-0.0114	-0.23
log_at					-0.0002	-0.12	0.0002	0.15
ind_mb					-0.0118	-1.10	-0.0127	-1.12
underprice					0.0684	0.67	0.0715	0.67
age					0.0041	1.16	0.0055	1.27
csm							0.1467	1.36
d_uncertain							0.2078*	1.71
s_uncertain							0.0308	0.44
Adj. R^2	0.002%		0.041%		0.359%			
N	83,996		83,980		83,880		44,077	

Table 3: Post-IPO Error Causality Tests on Firm Value: Out-of-Sample Evidence

This table shows the parameter estimates from forecast error tests based on the formulation in Equation (2). The dependent variable is the out-of-sample forecast error on changes in firm value V (positive values imply the firm did better than expected). We use data from the IPO quarter t+12 through t+24 and from quarter t+20 to t+40 (3-year and 5-year estimation horizons, respectively). The independent variables are: *Ipo_firm* , a dummy equal to 1 if the firm is the one that conducts the IPO; *lag_ind_error_v*, the lagged industry forecast error (sum of all firms' forecast errors); *log_at*, the natural log of total assets; *ind_mb*, the median industry market to book ratio in the previous year; *underprice*, the annual level of underpricing in year t; *age*, the number of years since the firm's first trading day in CRSP; *csm*, the absolute value of the competitive strategy measure (CSM from Equation (20)); *d_uncertain*, the standard deviation of seasonally adjusted sales growth; and *s_uncertain*, the systematic component of demand uncertainty. Following CL, the regressions using *csm* include only industries with a negative CSM. All regressions are pooled, with standard errors double-clustered by IPO event and quarter end date. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

	3-year horizon							
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
Intercept	-0.0194	-1.58	-0.0174	-1.44	0.0000	0.00	-0.0090	-0.47
ipo_firm	0.0020	0.35	0.0031	0.54	0.0095	1.38	0.0095	0.75
lag_ind_error_v			0.0877***	2.72	0.0063	0.22	0.1023***	3.15
log_at					-0.0049**	-2.33	0.2292	2.04
ind_mb					-0.0284**	-2.17	0.0080	0.05
underprice					0.1110	1.15	-0.1089	-1.45
age					0.0085**	1.96	-0.0061**	-2.45
csm							-0.0246*	-1.74
d_uncertain							0.0036	0.03
s_uncertain							0.0085	1.21
Adj. R^2	0.000%		0.360%		0.453%		0.906%	
N	37,421		36,093		36,019		18,848	
	5-year horizon							
Intercept	-0.0217*	-1.72	-0.0188	-1.47	0.0000	0.00	-0.0338*	-1.74
ipo_firm	0.0028	0.59	0.0024	0.50	0.0055	0.90	0.0030	0.35
lag_ind_error_v			0.0932**	2.39	0.0347	0.97	0.0864**	2.46
log_at					-0.0027	-1.71	-0.0015	-0.81
ind_mb					-0.0044	-0.33	-0.0089	-0.63
underprice					0.0495	0.53	-0.0486	-0.53
age					0.0089	1.76	0.0090	1.46
csm							0.0655	0.45
d_uncertain							0.1848	1.02
s_uncertain							-0.0107	-0.14
Adj. R^2	0.001%		0.445%		0.131%		0.715%	
N	60,376		59,023		58,766		31,424	

Table 4: Post-IPO Error Causality Tests on Profits: In-Sample Evidence

This table shows the parameter estimates from forecast error tests based on the formulation in Equation (2). The dependent variable is the in-sample forecast error on changes in firm profitability (positive values imply the firm did better than expected). We use data from the IPO quarter t through quarters 12 and 20 (3-year and 5-year post IPO estimation horizons, respectively). The independent variables are: *Ipo_firm* , a dummy equal to 1 if the firm is the one that conducts the IPO; *lag_ind_error_p*, the lagged industry forecast error (sum of all firms' forecast errors); *log_at*, the natural log of total assets; *ind_mb*, the median industry market to book ratio in the previous year; *underprice*, the annual level of underpricing in year t; *age*, the number of years since the firm's first trading day in CRSP; *csm*, the absolute value of the competitive strategy measure (CSM from Equation (20)); *d_uncertain*, the standard deviation of seasonally adjusted sales growth; and *s_uncertain*, the systematic component of demand uncertainty. Following CL, the regressions using *csm* include only the subsample of industries with a negative CSM. All regressions are pooled, with standard errors double-clustered by IPO event and calendar quarter end date. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
3-year horizon								
Intercept	0.0025	1.33	0.0020	1.02	0.0000	0.00	0.0074**	2.46
ipo_firm	-0.0013	-1.08	-0.0008	-0.67	-0.0033	-1.41	-0.0016	-0.48
lag_ind_error_v			0.2047***	8.91	0.1775***	6.85	0.1196***	3.92
log_at					0.0002	0.64	-0.0003	-0.59
ind_mb					0.0054***	3.17	0.0075	2.99
underprice					-0.0015	-0.10	-0.0102	-0.58
age					-0.0018*	-1.88	-0.0006	-0.48
csm							-0.0165	-0.62
d_uncertain							-0.0638***	-2.98
s_uncertain							0.0026	0.26
Adj. R^2	0.001%		2.590%		1.810%		1.161%	
N	81,334		81,247		80,992		43,140	
5-year horizon								
Intercept	0.0017	1.20	0.0017	1.01	0.0017	0.00	0.0031***	2.60
ipo_firm	0.0009	-0.58	0.0010	-0.32	0.0016	-1.42	0.0021	-0.23
lag_ind_error_v			0.0311***	4.07	0.0333***	3.07	0.0404*	1.88
log_at					0.0005	0.20	0.0006	-0.97
ind_mb					0.0017**	2.55	0.0022***	3.00
underprice					0.0137	0.70	0.0148	-0.08
age					0.0009	-1.46	0.0012	0.39
csm							0.0290*	-1.89
d_uncertain							0.0199***	-3.48
s_uncertain							0.0081	-0.63
Adj. R^2	0.000%		0.716%		0.534%		0.770%	
N	117,332		117,292		116,780		61,482	

Table 5: Post-IPO Error Causality Tests on Profits: Out-of-Sample Evidence

This table shows the parameter estimates from forecast error tests based on the formulation in Equation (2). The dependent variable is the in-sample forecast error on changes in firm profitability (positive values imply the firm did better than expected). We use data from the IPO quarter t+12 through t+24 and from quarter t+20 to t+40 (3-year and 5-year estimation horizons, respectively). The independent variables are: *Ipo_firm* , a dummy equal to 1 if the firm is the one that conducts the IPO; *lag_ind_error_p,* the lagged industry forecast error (sum of all firms' forecast errors); *log_at*, the natural log of total assets; *ind_mb*, the median industry market to book ratio in the previous year; *underprice*, the annual level of underpricing in year t; *age*, the number of years since the firm's first trading day in CRSP; *csm*, the absolute value of the competitive strategy measure (CSM from Equation (20)); *d_uncertain*, the standard deviation of seasonally adjusted sales growth; and *s_uncertain*, the systematic component of demand uncertainty. Following CL, the regressions using *csm* include only the subsample of industries with a negative CSM. All regressions are pooled, with standard errors double-clustered by IPO event and calendar quarter end date. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

				3-year horizon				
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
Intercept	-0.0004	-0.16	-0.0005	-0.20	0.0000	0.00	0.0094	3.02
ipo_firm	0.0007	0.46	0.0004	0.25	-0.0023	-1.03	-0.0024	-0.80
lag_ind_error_v			-0.0881**	-2.57	-0.1449***	-4.51	-0.1657***	-4.03
log_at					0.0000	0.05	-0.0009	-1.07
ind_mb					0.0093***	2.74	0.0132***	2.71
underprice					0.0246	1.02	0.0171	0.75
age					-0.0019	-1.19	-0.0009	-0.46
csm							0.0455	1.50
d_uncertain							-0.0832***	-3.57
s_uncertain							-0.0106	-1.21
Adj. R^2	0.000%		0.253%		0.859%		1.682%	
N	54,150		53,846		53,386		28,263	
				5-year horizon				
Intercept	-0.0004	-0.15	-0.0005	-0.18	0.0000	0.00	0.0073	1.58
ipo_firm	0.0008	0.51	0.0009	0.61	0.0002	0.11	0.0003	0.08
lag_ind_error_v			-0.0715**	-2.26	-0.1012***	-3.13	-0.1058***	-3.01
log_at					-0.0004	-0.46	0.0971	1.73
ind_mb					0.0048	1.51	-0.0708**	-2.13
underprice					-0.0025	-0.12	-0.0019	-0.15
age					-0.0002	-0.08	-0.0009	-1.00
csm							0.0013	0.30
d_uncertain							-0.0224	-0.88
s_uncertain							0.0010	0.35
Adj. R^2	0.000%		0.165%		0.360%		0.684%	
N	80,042		79,816		78,717		42,240	

Table 6: IPO Firm Size at Issuance and Change in Consumer Responsiveness

This table shows results from regressing the market share of the firm at IPO quarter t=0: on the estimated change in consumer responsiveness, industry fixed effects, industry growth and control variables based on HRR and CL. The change in consumer responsiveness is defined as the difference between ϕ estimated using data from the 12- and 20-quarters following the IPO event (3- and 5- year horizons, respectively) and ϕ_0, estimated using data from the 12 calendar quarters preceding the IPO. All t-statistics are based on standard errors clustered by year. 4-digit SIC code fixed effects are estimated but not reported. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

	Estimate	t Value	Estimate	t Value	Estimate	t Value
3-Year horizon						
Intercept	0.0000	0.00	0.0000	0.00	0.0000	0.00
$\varphi - \varphi_0$	-0.0142***	-3.62	-0.0144***	-3.65	-0.0168**	-2.07
g	0.0770	1.09	0.0675	0.91	-0.0081	-0.08
ind_size	-0.0134	-7.32***	-0.0133***	-7.04	-0.0177***	-3.84
ind_mb			0.0026	0.84	0.0010	0.14
underprice			-0.0121	-1.10	0.0176	0.67
csm					0.0735	1.02
d_uncertain					-0.0336	-0.86
s_uncertain					0.0135	0.59
N	701		701		343	
Adj. RSQ	6.645%		6.818%		8.008%	
5-year horizon						
Intercept	0.0000	0.00	0.0000	0.00	0.0000	0.00
$\varphi - \varphi_0$	-0.0084	-1.31	-0.0087	-1.30	-0.0033	-0.55
g	0.0724	1.77	0.0624	1.45	0.0506	1.04
ind_size	-0.0051**	-2.45	-0.0044*	-1.64	-0.0077***	-2.47
ind_mb			0.0037*	1.89	0.0067***	3.17
underprice			-0.0237	-1.40	0.0157	0.63
csm					0.0097	0.25
d_uncertain					-0.0048	-0.15
s_uncertain					0.0358	1.56
N	806		806		403	
Adj. RSQ	1.328%		1.771%		2.684%	

Table 7: Market Value Ratio per Industry – Largest Firm to IPO Firm

This table shows the ratio of the enterprise value of the largest firm in an industry to that of the IPO firm. All industries are included in the tabulation. The row labeled Profitability Declines Post IPO are those industries in which aggregate profitability declines after the IPO is conducted.

Group (3-year horizon)	10%	25%	50%	75%	90%
All Industries	2.69	6.60	22.29	71.29	242.14
Profitability Declines Post IPO	3.25	7.55	24.79	86.51	298.14
Group (5-year horizon)	10%	25%	50%	75%	90%
All Industries	2.69	7.02	21.84	69.29	224.45
Profitability Declines Post IPO	3.26	8.15	23.69	78.45	258.75

Table 8: 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 (17). Model-implied profitability is based on the profitability equation given in Equation (13) 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 12 and 20 (3-year and 5-year post IPO estimation horizons, respectively). All regressions are pooled, with standard errors double-clustered by IPO event and calendar quarter end date. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

Est. Hor.	3-Year			5-year		
Dep. Var.	Est.	Std. Err	t-val.	Est.	Std. Err	t-val.
	Dependent Variable: Δ*V*					
Intercept	0.0091	0.0080	1.13	0.0081	0.0079	1.03
*model*_Δ	0.0861***	0.0293	2.94	0.0928***	0.0195	4.75
N	62,497			118,499		
Adj. R^2	0.470%			0.652%		
	Dependent Variable: Δ*profit*					
Intercept	0.0043**	0.0017	2.53	0.0047***	0.0017	2.83
*model*_Δ	0.6971***	0.0243	28.71	0.5438***	0.0247	21.99
N	91,353			165,008		
Adj. R^2	32.39%			22.99%		

Table 9: 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 8 for a detailed explanation of each variable and column heading. 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. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

Est. Hor.	3-year			5-year		
Dep. Var.	Est.	Std. Err	t-val	Est.	Std. Err	t-val.
	Dependent Variable: Δ*V*					
Intercept	0.0000	0.0074	0.00	0.0000	0.0075	0.00
*model_*Δ	0.0910***	0.0276	3.30	0.0936***	0.0184	5.09
lag dep. var.	-0.0254	0.0188	-1.35	0.0018	0.0198	0.09
log_at	0.0013	0.0014	0.90	-0.0004	0.0014	-0.30
ind_*mb*	-0.0236**	0.0098	-2.40	-0.0201**	0.0083	-2.43
underprice	0.0597	0.0891	0.67	0.0165	0.0792	0.21
age	-0.0002	0.0030	-0.05	0.0016	0.0030	0.55
ipo dummy				0.0023	0.0050	0.46
N	62,346			118,240		
Adj. R^2	1.124%			1.059%		
	Dependent Variable: Δ*profit*					
Intercept	0.0001	0.0016	0.04	0.0000	0.0016	0.01
*model_*Δ	0.7054***	0.0241	29.23	0.5449***	0.0250	21.82
lag dep. var	-0.0784***	0.0142	-5.53	-0.0742**	0.0120	-6.19
log_at	0.0008**	0.0004	2.03	0.0007	0.0005	1.60
ind_mb	0.0041**	0.0020	2.02	0.0062***	0.0017	3.62
underprice	0.0039	0.0149	0.26	0.0079	0.0142	0.56
age	-0.0037***	0.0008	-4.36	-0.0044***	0.0008	-5.17
ipo dummy				0.0007	0.0013	0.56
N	90,764			163,896		
Adj. R^2	35.350%			25.530%		

Table 10: 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 8 and Table 9 for detailed explanations of each variable and column heading. In addition, *csm* is the absolute value of the competitive strategy measure (*CSM* from Equation (20)), *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*. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

Est. Hor.	3-Year			5-year		
Dep. Var.	Est.	Std. Err	t-val.	Est.	Std. Err	t-val.
	Dependent Variable: Δ*V*					
Intercept	0.0000	0.0071	0.00	0.0000	0.0074	0.00
*model*_Δ	0.0952***	0.0219	4.36	0.1060***	0.0133	7.95
lag dep. var.	-0.0308	0.0191	-1.62	-0.0143	0.0191	-0.75
log_at	-0.0007	0.0016	-0.41	-0.0008	0.0016	-0.53
ind_*mb*	-0.0132	0.0120	-1.10	-0.0146*	0.0087	-1.69
underprice	0.0156	0.0758	0.21	-0.0023	0.0696	-0.03
age	0.0039	0.0033	1.19	0.0038	0.0033	1.15
ipo dummy			.	0.0044	0.0067	0.66
csm	0.0828	0.0779	1.06	0.0858	0.0811	1.06
d_uncertain	0.0716	0.0736	0.97	0.0766	0.0822	0.93
s_uncertain	0.0228	0.0738	0.31	0.0447	0.0554	0.81
N	32,967			65,203		
Adj. R^2	0.928%			25.530%		
	Dependent Variable: Δ*profit*					
Intercept	0.0000	0.0017	0.00	-0.0016	0.0018	-0.89
*model*_Δ	0.7436***	0.0267	27.84	0.5241***	0.0326	16.05
lag dep. var	-0.0824***	0.0175	-4.70	-0.0809***	0.0187	-4.34
log_at	0.0001	0.0006	0.25	0.0001	0.0006	0.22
ind_mb	0.0050	0.0031	1.60	0.0076***	0.0024	3.10
underprice	-0.0060	0.0160	-0.38	-0.0008	0.0150	-0.06
age	-0.0024**	0.0012	-2.04	-0.0033***	0.0012	-2.75
ipo dummy	0.0000	0.0000	.	0.0014	0.0022	0.64
csm	-0.0094	0.0262	-0.36	-0.0164	0.0250	-0.65
d_uncertain	-0.1300***	0.0242	-5.37	-0.1247***	0.0232	-5.36
s_uncertain	0.0154	0.0209	0.74	0.0070	0.0140	0.50
N	48,396			88,533		
Adj. R^2	38.270%			28.960%		

Table 11: 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 8. 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 quarters 20 to 40 (5-year horizon) and from quarters 12 to 24 (3-year horizon). The variable *Δvalue* is defined as the log of the value in quarter *t*, divided by the value in period *t-1*. The variable *Δprofit* is profit in period *t* minus profit in period *t-1*, divided by the t=0 value of assets. Finally, *lag_dependent_var*, *log_at* , *ind_mb*, *underprice*, *age*, *ipo dummy*, *csm*, *demand uncertainty* and *systematic uncertainty* are defined in Table 9 and Table 10. 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 errors clustered by IPO event and calendar quarter end date. IPO event fixed effects are included in the HRR and CL regressions. 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	0.0054	0.60	0.0073	0.86	0.0000	0.00	0.0000	0.00	0.0000	0.00	0.0000	0.00
model_Δ	0.0432***	5.30	0.0362***	3.92	0.0474***	5.03	0.0360***	3.81	0.0517***	4.99	0.0362***	3.70
lag dependent var					-0.0198	-0.80	-0.0326	-1.30	-0.0379	-1.43	-0.0492**	-2.25
log_at					-0.0015	-0.78	-0.0009	-0.69	-0.0018	-0.91	-0.0003	-0.22
ind_mb					-0.0308***	-2.86	-0.0204**	-2.14	-0.0209*	-1.80	-0.0166	-1.60
underprice					0.0675	0.81	-0.0087	-0.12	0.0201	0.27	-0.0479	-0.74
age					0.0008	0.24	-0.0009	-0.28	0.0027	0.62	-0.0018	-0.43
ipo dummy					0.0069	1.31			0.0120**	2.02	0.0000	.
csm									-0.0055	-0.07	0.0316	0.36
demand uncertainty									0.0328	0.48	0.0351	0.43
systematic uncertainty									-0.0043	-0.05	0.0503	0.80
N	50,379		84,060		50,303		83,957		26,290		46,341	
Adj. RSQ	0.267%		0.202%		1.392%		0.816%		1.133%		0.985%	

Table 11 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	
	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value	Est.	t-value
Intercept	0.0017	0.77	0.0026	1.10	0.0000	-0.01	0.0000	0.01	0.0000	0.00	0.0000	0.00
model_Δ	0.6118***	26.91	0.5761***	25.89	0.6239***	27.11	0.5863***	25.94	0.6533***	21.56	0.6062***	19.70
lag dependent var					-0.0101	-0.63	-0.0223**	-2.23	0.0031	0.16	-0.0171	-1.51
log_at					0.0003	0.32	0.0006	0.75	-0.0008	-0.91	0.0001	0.12
ind_mb					0.0070**	2.30	0.0044*	1.66	0.0085**	2.27	0.0026	0.73
underprice					0.0235	1.08	-0.0081	-0.39	0.0203	1.04	-0.0199	-0.89
age					-0.0035**	-2.32	-0.0042**	-2.22	-0.0024	-1.34	-0.0042	-1.63
ipo dummy					0.0001	0.06			0.0014	0.53	0.0000	.
csm									-0.0184	-0.68	0.0556	1.27
demand uncertainty									-0.1779***	-5.63	-0.1561***	-3.44
systematic uncertainty									0.0159	0.50	0.0248	1.01
N	70,790		108,268		70,355		107,655		37,798		59,212	
Adj. RSQ	25.25%		24.03%		27.39%		25.8%		30.31%		29.55%	

Table 12: 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 8. 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 quarters 20 through 40 (5-year horizon) and from quarters 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 9. *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 10. All regressions are pooled, with standard errors clustered by IPO event and calendar quarter end date. IPO event fixed effects are included in the HRR and CL regressions. For consistency with Chod and Lyandres (2011), only industries in which csm is negative are included in the regressions in which the CL variables are included. Significance levels are: '***' 0.01 '**' 0.05 '*' 0.10.

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	0.0048	0.53	0.008	0.92	0.0000	0.00	0.000	0.00	0.0000	0.00	0.000	0.00
model_Δ	0.0258***	3.61	0.014*	1.67	0.0319***	4.05	0.016*	1.83	0.0409***	4.39	0.026***	3.08
HRR					-0.0117	-0.31	-0.030	-0.95	-0.0174	-0.47	-0.014	-0.43
CL									-0.0137	-0.83	-0.025	-0.95
N	46,148		83,916		45,933		80,298		24,470		44,119	
Adj. RSQ	0.096%		0.030%		0.150%		0.103%		0.260%		0.204%	
Panel B: Dependent Variable = Δprofit												
Intercept	0.0051**	2.34	0.0062***	2.61	0.0036	1.60	0.0057**	1.97	-0.0001	0.0000	0.0000	0.00
model_Δ	0.0879***	4.83	0.0656***	3.90	0.1029***	5.41	0.0844***	4.77	0.0710	0.0974	0.0777***	3.48
HRR					-0.0560**	-2.40	-0.060***	-3.05	-0.1067	-0.0353	-0.0094	-0.34
CL									-0.0148	-0.0203	-0.0435*	-1.90
N	65,160		107,725		64,147		102,273		34,861		56,669	
Adj. RSQ	0.597%		0.292%		0.957%		0.808%		0.822%		0.674%	

Table 13: 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 9 and Table 10. All regressions are estimated in-sample, using quarterly Compustat revenue and costs of goods sold data from the IPO quarter *t* through quarters 20 and 12 (5-year and 3-year post IPO estimation horizons, respectively).

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

Table 14: 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 11. 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 9 and Table 10. 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 *CL*, respectively. These variables are defined in Table 12.

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	2	1	1	2	3	1	1
lag dependent var	3	3	4	2	3	2	exclude	3
log_at	exclude	exclude	exclude	exclude	exclude	exclude	exclude	exclude
ind_mb	1	1	3	4	1	1	exclude	exclude
underprice	4	exclude	5	exclude	exclude	4	exclude	5
age	exclude	exclude	2	3	exclude	exclude	3	4
ipo_dummy	5	n/a	exclude	n/a	4	n/a	exclude	n/a
csm	n/a	n/a	n/a	n/a	exclude	exclude	exclude	6
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	1	1	1	1	1	1
HRR	exclude	2	2	2	exclude	exclude	2	exclude
CL	n/a	n/a	n/a	n/a	exclude	2	exclude	2