Entry and Exit in the Market for IPO Services

PRELIMINARY AND INCOMPLETE

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Abstract

We model entry into and exit from the IPO underwriting business. Specifically, we apply the estimation method for continuous time entry-exit games developed in Arciadiacono, Bayer, Blevins, and Ellickson (2015). Underwriters compete in a potentially collusive auction for IPOs that arrive according to a Poisson process which depends on economic conditions, thus generating an expected flow payoff for being in the market. Expected market share for a given underwriter depends on that underwriter's stochastically evolving reputation and an index of reputation of other active underwriters. Entry choices then identify entry costs, which provides evidence of the extent to which incumbent firms are able to exclude new competition. Our preliminary estimates indicate that entry and exit exhibit patterns that are not consistent with Markov perfect equilibrium behavior by underwriters.

Controversy surrounds the question of whether underwriters collude in the market for IPOs. Some researchers identify the pattern of spreads [Chen and Ritter, 2000; Kang and Lowery, 2014] and the reliance on indirect compensation through underpricing [Kang and Lowery, 2014] as evidence for implicit collusion among underwriters. Others [Hansen, 2001] suggest that efficient contracts can explain the pattern of spreads, while the absence of obvious barriers to entry in the IPO market makes collusion unsustainable.

In this paper, we investigate this question by estimating the entry costs (and exit payoffs) in the IPO market. We proceed by largely following the standard procedure for structural estimation of entry costs developed in the industrial organization literature, with modifications to account for the possibility of price collusion in the market for IPOs. We posit that firms play some (potentially collusive) equilibrium pricing strategy, but that entry and exit decisions follow a Markov perfect equilibrium structure. As noted above, Kang and Lowery [2014] claim that the concentration of spreads at 7% arises because underwriters, who have imperfect information about firm values, collude optimally. This particular form of collusion, however, turns out to permit the estimation of the model with only minor modifications. Spread rigidity eliminates the need for on-equilibrium path punishments, which means that all payoff relevant non-Markov states are degenerate as long as we assume that new entrants follow a strategy that depends only on payoff relevant states and a state summarizing whether the industry has entered a punishment phase.[1] Since punishment phases never occur in equilibrium, it is possible to retain the simplicity of the Markov perfect equilibrium structure under the assumption that entry and exit decisions are Markov in nature.

The approach we take allows us to estimate the cost (or benefit) that potential entrants perceive when deciding whether to enter the IPO market. Determining the exact nature of these costs is beyond the scope of our analysis, but they could represent costs associated with developing the reputational capital necessary to enter the IPO business, or they could represent the "costs" of overcoming barriers to entry erected by incumbent firms. Alternatively, entry into the IPO market

[1]Here, the non-Markovian aspect of the history of the game is the entire history of spread offers and realized IPO proceeds and underpricing. Under imperfect monitoring, this history will determine whether underwriters are in a punishment phase.

might confer a benefit via spillover effects on other parts of the underwriter's business. Interpretation of entry costs or benefits is somewhat more subtle than the standard fixed cost parameter in entry-exit models. The reputation building cost would likely come from hiring, at a premium, top investment bankers from established firms. If, instead, the cost is interpreted as a barrier to entry constructed by incumbent firms, then it is not truly a cost. Lack of entry would be driven by incumbent firms successfully preventing entry by new competitors. By modeling entry as carrying a fixed payoff, we can quantify the ability of incumbent firms to prevent entry by finding the equivalent fixed cost that would generate the same market structure. Further, unlike more traditional sectors, entry into the IPO market may be undertaken in large part as a marketing tool for other banking services, such as debt underwriting and brokerage activity. Thus, entry could in fact carry a benefit, rather than a cost, leaving the only barrier to entry as coming from the lack of an opportunity to start underwriting IPOs.

The primary goal of this paper is to apply the standard industrial organization model of firm entry an exit to the business of underwriting IPOs. We do not necessarily view this approach as appropriate for studying industry dynamics in finance. Indeed, there are strong reasons to believe that some of the fundamental assumptions of this model are significantly violated. Most notably, there is ample if indirect evidence of collusive behavior in the IPO market [Chen and Ritter, 2000; Kang and Lowery, 2014], which calls into question the assumption that firms play a Markov perfect equilibrium with respect to entry and exit decisions. Our goal instead is to develop a benchmark for evaluating the industry under standard assumptions. Further work should then extend the analysis to settings that more explicitly account for collusive behavior.

Even while maintaining the standard assumption of Markov perfect equilibrium, many aspects of our application present challenges that either require adjustments to the standard estimation approach or raise questions about its applicability. We alter the assumptions of the model where possible to address these considerations, but concerns remain. Here, we briefly summarize first the modifications to the model needed to apply the analysis to IPO underwriting, and then we consider the remaining issues with the model that should be addressed in future work.

In contrast to most oligopoly estimation models, we have a large number of players. This apparently contradictory issue arises from one of the more puzzling aspects of the underwriting industry. Many firms appear active in the IPO underwriting market at any given point in time, yet the pricing of underwriting services remains high and exhibits patterns that are unlikely to arise in a competitive equilibrium. This apparent paradox in the market is not driven entirely by the presence of a few very large, dominant firms with a small fringe of small players. In fact, an HHI index based on proceeds never even exceeds the "moderate concentration" threshold used by the government to determine how competitive an industry is.[2]

The number of firms in the market and the need to account for a relatively rich space of economic variables makes full solution methods infeasible in our setting. Indeed, even two-step methods in discrete time are computationally infeasible when trying to account for the large number of players active in the market. Instead, we must use the continuous time version of the two-step estimator as constructed in Arcidiacono et al. [2016]. Such an estimator, however, requires either observations across multiple segmented but otherwise similar markets or strong assumptions of stationarity, such that observations over time can be aggregated. Since the IPO market in the US is a single, large market, we must make such stationarity assumptions, which is a potentially unappealing aspect of the estimation procedure. An alternative approach would be to implement the partially oblivious equilibrium concept of Benkard et al. [2015], which sacrifices precise strategic behavior with respect to smaller firms in favor of a massively lower computational burden. While we take the former approach, a complete analysis of this industry should certainly include analyses following the latter track.

The nature of entry into and exit from the underwriting industry presents both advantages and challenges for estimation. On the positive side, there is effectively continuous data on the timing of IPOs, which naturally maps to the continuous time setting of Arcidiacono et al. [2016]. That is, we can identify exactly the first date on which a particular underwriter first served as a lead manager on an IPO. The structure of the data thus obviates the need to address the aliasing problem [Blevins,

[2]Hatfield et al. [2016] present a model that shows how low industry concentration and oligopoly pricing can exist simultaneously in markets like IPO underwriting where post-competition production is undertaken through syndicates.

2015] that arises when continuous time models are applied to continuously generated but discretely sampled data. On the other hand, a significant drawback of our data is that we observe only the winning lead underwriters. A firm may have chosen to enter the IPO underwriting business but then repeatedly failed to win an underwriting mandate; as such, this firm would not appear in our data as an entrant for some time after its true entry. This issue is a form of the "species sampling problem" or "unseen species problem," Good [1953]. This scenario may lead to a bias in our estimation as the delay between actual entry and the first successful bid for an IPO will likely depend on the state of the IPO market; when there are fewer IPOs, the delay is likely to be longer, which will thus understate the appeal of entry in states where IPOs are infrequent.

To partially address this sampling issue and the general difficulty of identifying the arrival of an entry opportunity, we model arrival opportunities as coming with new IPOs. That is, instead of following directly the assumption in Doraszelski and Judd [2012] that entry opportunities arrive according to a Poisson process, we posit that IPO's arrive following a Poisson process and that each IPO may present an opportunity for a new underwriter to enter the IPO market. The probability that an IPO brings such an opportunity is parameterized; while not fully a normalization, this choice is similar to the implicit assumption in discrete choice estimation that the frequency of move opportunities corresponds with the frequency of data sampling.

Our approach partially addresses the concern about the sampling problem. When fewer IPOs arrive, fewer opportunities to enter arrive; lower realized IPO entry during periods of time when IPOs are rare can thus be attributed to fewer opportunities, rather than less desire to enter by firms with such an opportunity. This approach partially solves the potential measurement issue with an institutionally reasonable modification to the model; quite often an underwriter does enter the IPO market through an existing connection with a firm that decides to go public [Belfort, 2011; Ljungqvist et al., 2006]. This approach unfortunately does not address the the issue with exit timing, so further work in this direction is warranted.

1 Data

Our primary data source is the SDC database, which provides details for each IPO in the United States. Unless otherwise stated, data on IPOs and underwriters is from this database. For the economic state, we use NBER recessions. Data on venture capital activity is obtained from the National Venture Capital Association 2015 yearbook, which includes the total amount of venture funding raised. Underwriter reputation is based on the Carter-Manaster underwriter reputation measure and is taken from Professor Jay Ritter's website.

We construct our main variable on entry and exit from the SDC database on IPOs. A firm is said to enter the IPO market on the date of its first IPO, assuming that it has at least two total IPOs. A firm is said to exit the market after its last IPO. A potentially important consideration in the underwriting space is that many firms "exit" through mergers, or through spinning off or selling their IPO unit. This complicates the concept of exit. Corwin and Schultz [2005] discuss this issue in the context of their analysis of underwriting syndicates:

> There is a large number of mergers in the securities industry over our sample period. We treat underwriters who change names following a merger as new firms. So, for example, we examine Morgan Stanley Dean Witter separately from either Morgan Stanley or Dean Witter and we study U.S. Bancorp Piper Jaffrey separately from Piper, Jaffrey, and Hopwood. Our reasoning is that different clienteles and financial capabilities after mergers may change the motives for and characteristics of syndicates. See the Appendix for a list of underwriter merger and acquisition events during our sample period and the associated name adjustments applied to the data. A more detailed description of the name adjustments is available from the authors at http://www.nd.edu/ scorwin. Merger and acquisition events are identified using Mergers and Acquisitions (19972002) and the Securities Industry Yearbook (Securities Industry Association (19952002)). It is also likely that some underwriters enter or exit during our sample period for reasons unrelated to mergers. In the analysis to follow

we examine the robustness of the results to this possibility.

We use the Corwin and Schultz database as the starting point for our database of mergers, but we treat the acquiring firm as a continuing entity and the acquired firm as an exiting player on the date of its last IPO. When the direction of the acquisition is unclear, we use hand collected information wherever possible to determine the appropriate continuing entity. Thus, our approach most closely resembles the investment banking lifelines from Morrison et al. [2014].

2 Model

Time is continuous and infinite. At any point in time there are N_I^t incumbent underwriters and N_E^t potential entrants. While the number of potential entrants could vary over time, we model this as a fixed quantity and thus drop the time superscript on the number of potential entrants. IPOs arrive according to a Poisson process with intensity λ_{IPO}^t, which may depend on economic conditions and the number and characteristics of underwriters currently in the market.

One or more lead managers are selected (by nature) to lead manage (or co-lead manage) the IPO. Lead managers and co-lead managers are responsible for completing the IPO and generally receive most of the compensation in the form of spread income. Particularly for larger IPOs, other firms may be invited to join the syndicate, placing some fraction of the shares with their own clients. Such syndicate members generally receive minimal compensation, so we focus only on the lead managers selected for the deal. IPO syndication, and in particular structural models of optimal syndication, is a rich area for analysis and should be the focus of further work, but we abstract from the larger syndicate in this paper. An underwriter's probability of winning and IPO depends on his characteristics and the characteristics of other firms in the market. Lead managers divide the spread income from the IPO evenly.

Whenever an IPO arrives, there is some probability α that the IPO will carry an entry opportunity for one of the N_E^t potential entrants, where each entrant has an equal probability of being selected to have the opportunity. Similarly, each incumbent has an opportunity to exit, where the exit opportunities arrive according to a Poisson process with intensity λ_{exit}. As is common in the literature, when a firm has an opportunity to enter the IPO underwriting industry but declines, we assume the firm has no further entry opportunities and thus receives zero payoffs in the future.[3]

Economic conditions, which influence the arrival rate of IPOs and therefore influence the incentives of firms to enter into or exit from the market, transition between discrete states following a continuous time Markov process with intensity matrix Q.

3 Empirical Implementation

3.1 Flow Payoff

The cost of remaining in the market is assumed to be constant. The flow of profits is determined by the IPO arrival process and the process for selecting underwriters to lead-manage an IPO.

We assume that the arrival time between IPOs is exponentially distributed (i.e. IPOs arrive following a Poisson arrival process) with rate parameter λ_{IPO}^{t}, where

$$\lambda_{IPO}^{t} = \exp\{-(\lambda_0 + x_t^m \lambda_{IPO}^{x} + \lambda_{IPO}^{N} N_t^I)\}. \tag{1}$$

where x_t^m is the vector of macroeconomic conditions, specifically the boom/bust dummy and the venture capital index. We estimate the underlying parameters via maximum likelihood.

We specify the log of the number of lead managers, N_t^{LM}, as a linear function of the economic state as follows:

$$\log N_t^{LM} = x\beta^{LM} + \varepsilon \tag{2}$$

where $x = \{x_0, x_m^t, N_I^t\}$ and x_m includes the boom/recession dummy, the venture capital index, whether the particular IPO is venture backed, and whether the IPO is categorized as high tech. The estimation is via OLS. Note that the predicted number of lead managers will not in general be an

[3] We estimated a version of the model in which potential underwriters would continue as potential entrants after declining an opportunity, but the results of this model indicated that it did not fit the data well.

integer but represents the expected number of lead managers.

Proceeds and spreads are taken directly from the SDC database.

3.2 Economic Condition Transitions

We posit that the arrival of IPOs and the size of IPOs depends on economic conditions, specifically the state of the macroeconomy and the availability of venture capitial funding.

We take the beginning and end dates of NBER recessions as transitions for the boom/recession variable, which gives effectively continuous data on macroeconomic events. We take the start of a recession as the 15th of the month of the event. Data on venture funding are annual, so we must apply simulated maximum likelihood to the transitions between states.

We construct at discrete state of the venture capital market by dividing all periods into periods with low ($<$\$20 billion raised), medium (\$20 to \$40 billion) and high ($>$\$40 billion) venture capital activity. Each individual IPO also has an identifier indicating whether the firm was backed by venture capital.

3.3 Underwriter Reputation

We divide our reputation measure into three bins, high, medium and low. Our measure of underwriter reputation is an index collected over multiple years, with varying window lengths. When reputation differs between two adjacent windows, we treat this as a reputation move that occurs at some point in those windows. We simulate to obtain the date of the transition.

3.4 Proceeds

Proceeds for an IPO, b_t is an outcome determined by market conditions and IPO characteristics. This outcome process is modeled as follows

$$\log(b_t) = \beta_0^v + x_t^m \beta_1^v + x_t^f \beta_2^v + \Phi^v(x_t^u) \tag{3}$$

where x_t^f is IPO specific characteristics (e.g. an indicator for being venture capital backed or for being a high-tech IPO) and Φ^v is defined similarly to Φ^{ipo}[4].

3.5 IPO characteristics

IPO characteristics (high tech and venture capital backing) are estimated using probit models, where the probabilities depend on macroeconomic conditions, the VC index, and the number of incumbents.

3.6 Entry and Exit

Recall that entry opportunities arrive with IPOs with some probability. This probability would be very difficult to identify from the data, so we estimate the model with the value set to several levels. This near-normalization is similar to the implicit assumption that move arrivals coincide with data sampling points in discrete time models, but we are able to evaluate the robustness of our results to different values for this probability. Exit intensity is calibrated such that each underwriter has an opportunity to exit, on average, once a quarter. Realized entry and exit hazard rates are estimated via maximum likelihood.

3.7 Flow Payoff

By incorporating the probability of an IPO arriving and winning the IPO along with the distribution of the number of lead managers, the flow payoff becomes

$$\lambda_t^{ipo}\psi_t^i E[u_{it}]$$

where the expectation is taken over uncertain proceeds (through uncertain VC index, HT index and the number of lead managers) as underwriters do not know the characteristics of the IPOs that will arrive or how many underwriters will be involved in the deal when making entry/exit decisions.

[4]We impose log to the firm value to take care of the wide dispersion of the firm value.

That is,

$$\begin{aligned}\lambda_t^{ipo}\psi_t^i E[u_{it}] &= \lambda_t^{ipo}\psi_t^i \textstyle\sum_{l\in\{1,\ldots,\bar{N}_{LM}\}}\sum_{m\in\{0,1\}}\sum_{n\in\{0,1\}} Pr(N_{LM}=l|VC_t=m,HT_t=n)\\ &\quad\times Pr(VC_t=m)Pr(HT_t=n)E[u_{it}|N_{LM}=l,VC_t=m,HT_t=n]\end{aligned}$$

where the expectation of u_{it} is taken over the uncertain number of lead managers, N_{LM}, and b_t which we obtain through simulations through the empirical distributions of error terms in eq. (2) and eq. (3).

3.8 Instantaneous Payoffs

When an incumbent underwriter i makes an exit choice ($j = 1$), a scrap value κ_{it}^{ex} is incurred. Similarly, an entry cost κ_{it}^{en} is incurred when a potential entrant enters the IPO market ($j = 2$). To summarize,

$$\nu_{ijt} = \begin{cases} \kappa_{it}^{ex} & \text{if } j = 1 \\ \kappa_{it}^{en} & \text{if } j = 2 \end{cases}$$

3.9 CCP representation

This section documents how to express the value function as a function of data, model parameters and CCPs. Two special choices are considered to derive the expression: a terminal choice and a continuation choice. Once chosen, a terminal choice makes a player's future choice irrelevant as it terminates the game from the player's perspective. A continuation choice, when chosen, does not change the state. In our application, exiting the market is a terminal choice. Once an underwriter exits the IPO market we assume he gets a constant payoff afterwards where we normalized to zero. If an underwriter neither exits nor enters the IPO market, a state change does not happen as a result of the underwriter's decision. Hence, doing nothing (remaining in the market if the firm is an incumbent and remaining out of the market if the firm is a potential entrant) is a continuation action. Note that the arrival of an IPO does not change the state; specifically, we do not account for the effect on an underwriter's reputation from a successfully completed IPO. The continuation choice yields a zero instantaneous payoff (i.e. the underwriter incurs neither an entry cost nor a scrap value): $\nu_{ijt} = 0$ if $j \notin \{1, 2\}$.

In an infinite time horizon, a state at any time t can be described by one state k in a finite state space $\bar{K} = \{1, 2, \ldots, K\}$.[5] For small time increments h, the value function an underwriter $i \in \{1, 2, \ldots, N\}$ in state k is

$$\begin{aligned} V_{ik}(\varsigma_i) &= \frac{1}{1+\rho h}[\lambda_k^{ipo}\psi_k^i E[u_{ik}]h + \sum_{l \neq k} q_{kl} h V_{il} + \sum_{m \neq i} \lambda h \sum_j \varsigma_{imjk} V_{i,l(m,j,k)}(\varsigma_i) \\ &+ \lambda h E \max_{j,0}\{\nu_{ijt} + \varepsilon_{ij} + V_{i,l(i,j,k)}(\varsigma_i)\} \\ &+ (1 - \sum_{l \neq k} q_{kl} h - \sum_{m \neq i} \lambda h \sum_j \varsigma_{imjk} - \lambda h) V_{ik}(\varsigma_i) + o(h)] \end{aligned}$$

where ρ is a discount rate per unit time, q_{kl} is the hazard rate for nature moving the state from k to l, ς_i is i's beliefs regarding actions (j) of each rival (m) for each state (k) of which ς_{imjk} is a particular element. We define $l(m, j, k)$ to be the new state reached when m chooses action j in state k.[6] [7] ε_{ij} is an error term associated with each discrete action that is distributed independently across underwriters and actions. We assume that ε_{ij} follows the Extreme Type I distribution. The first two lines of the above expression relate to the cases where a state moves away from k while the last line represents the case where the state remains at k.[8] The continuous time framework enables us to ignore one strategic element of the value function which is relevant in discrete time models, as almost surely only one move occurs during a small instantaneous time interval h.[9]

[5]Hence, we use the k subscript instead of the t subscript from now on. Note that dropping the t subscript is appropriate because of our strong assumptions about the stationarity of the market, which is necessary for identification when there is only a single large market instead of many separate markets as in Arcidiacono et al. [2016].

[6]The new state l is a deterministic result of i's action at k. This assumption is not very different from a general conditional (on actions) state transition in discrete time models. This is because the stochastic feature of a state move can be achieved by nature's move after i's action. In other words, i's action moves the state deterministically to l, but once reaching l the state change is stochastic, with its evolution determined by the intensity matrix.

[7]Note that j does not include the continuation action as such an action does not change the state.

[8]For a Poisson process with parameter λ, λh is the probability that an event occurs for a time interval h.

[9]In other words, we only have to trace how the state changes based on one player's choice. In discrete time, the l function would be a mapping from $[J^I \times K]$ to K instead of a mapping from $[I \times J \times K]$ to K.

Rearranging the above equation gives[10]

$$V_{ik}(\varsigma_i) = \frac{\lambda_k^{ipo}\psi_k^i E[u_{ik}] + \sum_{l\neq k} q_{kl}V_{il} + \sum_{m\neq i}\lambda\sum_j \varsigma_{imjk}V_{i,l(m,j,k)}(\varsigma_i) + \lambda E\max_{j,0}\{\nu_{ijt}+\varepsilon_{ij}+V_{i,l(i,j,k)}(\varsigma_i)\}}{\rho+\sum_{l\neq k} q_{kl} + \sum_{m\neq i}\lambda\sum_j \varsigma_{imjk}+\lambda}$$

Assuming Markov perfect equilibrium, $\varsigma_{imjk} = \sigma_{mjk}$ for all $i \neq m$ where σ_{mjk} is a best response probability of m playing Markov strategy. Then the above equation becomes

$$V_{ik} = \frac{\lambda_k^{ipo}\psi_k^i E[u_{ik}] + \sum_{l\neq k} q_{kl}V_{il} + \sum_{m\neq i}\lambda\sum_j \sigma_{mjk}V_{i,l(m,j,k)} + \lambda E\max_{j,0}\{\nu_{ijt}+\varepsilon_{ij}+V_{i,l(i,j,k)}\}}{\rho+\sum_{l\neq k} q_{kl} + \sum_{m\neq i}\lambda\sum_j \varsigma_{imjk}+\lambda} \tag{4}$$

Incorporating the feature of the model that there are two sets of underwriters, incumbents and potential entrants, the above equation can be expressed as

$$\begin{aligned} V_{ik}\left(\rho+\sum_{l\neq k} q_{kl} + \sum_{m\neq i, m\in N_I}\lambda\sigma_{m1k} + \sum_{m\neq i, m\in N_E}\lambda\sigma_{m2k}\right) &= \lambda_k^{ipo}\psi_k^i E[u_{ik}] + \sum_{l\neq k} q_{kl}V_{il} \\ &+ \sum_{m\neq i, m\in N_I}\lambda\sigma_{m1k}V_{i,l(m,1,k)} \\ &+ \sum_{m\neq i, m\in N_E}\lambda\sigma_{m2k}V_{i,l(m,2,k)} \\ &+ \lambda E\max_{j\in\{J_I(i),J_E(i),0\}}\{\nu_{ijt}+\varepsilon_{ij}+V_{i,l(i,j,k)}\} \end{aligned} \tag{5}$$

where N_I (N_E) is the number of players, $J_I = \{0,1\}$ ($J_E = \{0,2\}$) is the choice set of incumbents (entrants) and $J_I(i)$ ($J_E(i)$) is the choice set of an incumbent (entrant) i.[11]

Incumbents: We first illustrate how to represent the value function of incumbents with CCPs and model primitives. From Proposition 2 of Arcidiacono et al. [2016]

$$E\max_j\{\nu_{ijk}+\varepsilon_{ij}+V_{i,l(i,j,k)}\} = \nu_{ij'k} + V_{i,l(i,j',k)} + \Gamma_i(j',\sigma_{ik}) \text{ for all } j' \tag{6}$$

where $\sigma_{ik} = \{\sigma_{i1k}, \sigma_{i2k}, \ldots, \sigma_{iJk}\}$. By the property of the distribution of ε, $\Gamma_i(j',\sigma_{ik}) = -\ln\sigma_{ij'k}+$

[10]Note that $\sum_j \varsigma_{imjk} \neq 1$ as j does not include continuation action, and hence the term $\sum_{m\neq i}\lambda\sum_j \varsigma_{imjk}+\lambda \neq N\lambda$.

[11]We observe N_I in the data while N_E is unobserved. Also note that N_I and N_E can vary across data periods.

γ where γ is an Euler constant. Furthermore if j' is a terminal action of exiting ($j' = 1$), $V_{i,l(i,j',k)} = 0$. Then

$$E \max_j \{\nu_{ijt} + \varepsilon_{ij} + V_{i,l(i,j,k)}\} = \nu_{i1k} - \ln \sigma_{i1k} + \gamma. \tag{7}$$

Now suppose an underwriter $m \neq i$ makes a choice of j resulting in a state move from k to k' and let j^* be a continuation action. Then $l(m, j, k) = k' = l(i, j^*, k')$ and $\nu_{ij^*k} = 0$. Since eq. (6) applies to any action,

$$\begin{aligned} \nu_{ij^*k} + V_{i,l(i,j^*,k)} + \Gamma_i(j^*, \sigma_{ik}) &= \nu_{i1k} + V_{i,l(i,1,k)} + \Gamma_i(1, \sigma_{ik}) \\ 0 + V_{i,l(i,j^*,k)} - \ln \sigma_{ij^*k} + \gamma &= \nu_{i1k} + 0 - \ln \sigma_{i1k} + \gamma. \end{aligned}$$

Therefore, i's value function when $m \neq i$ makes a choice j in state k is

$$V_{i,l(m,j,k)} = V_{ik'} = V_{i,l(i,j^*,k')} = \nu_{i1k'} - \ln \sigma_{i1k'} + \ln \sigma_{ij^*k'}. \tag{8}$$

Now consider that the nature moves the state from k to $\dot{l}(k)$ and again define j^* to be the continuation action of i. That is, $l(i, j^*, \dot{l}(k)) = \dot{l}(k)$. Similarly to the above argument for the state change by opponents,

$$V_{i,\dot{l}(k)} = \nu_{i1\dot{l}(k)} - \ln \sigma_{i1\dot{l}(k)} + \ln \sigma_{ij^*\dot{l}(k)}. \tag{9}$$

Substituting eq. (7), eq. (8) and eq. (9) into eq. (5) gives a CCP representation of an incumbent's value function as follows:

$$\begin{aligned} V_{ik}\left(\rho + \sum_{l \neq k} q_{kl} + (N_I + N_E)\lambda\right) &= \lambda_k^{ipo} \psi_k^i E[u_{ik}] + \sum_{l \neq k} q_{kl} \{\nu_{i1l} - \ln \sigma_{i1l} + \ln \sigma_{ij^*l}\} \\ &+ \sum_{m \neq i, m \in N_I} \lambda \sum_{j \in J_I} \sigma_{mjk} \{\nu_{i1k'} - \ln \sigma_{i1k'} + \ln \sigma_{ij^*k'}\} \\ &+ \sum_{m \neq i, m \in N_E} \lambda \sum_{j \in J_E} \sigma_{mjk} \{\nu_{i1k'} - \ln \sigma_{i1k'} + \ln \sigma_{ij^*k'}\} \\ &+ \lambda\{\nu_{i1k} - \ln \sigma_{i1k} + \gamma\} \end{aligned} \tag{10}$$

where $\dot{l} = \dot{l}(k)$ and $k' = l(m,j,k)$.

[12]

The above derivation is completed assuming the scale parameter of the distribution of the error term (which henceforth we refer to as the standard deviation of the choice specific error term) is 1. If this standard deviation of ε is not one but σ_ε: by the property of the distribution of ε, $\Gamma_i(j', \sigma_{ik}) = -\sigma_\varepsilon \ln \sigma_{ij'k} + \sigma_\varepsilon \gamma]$

$$
\begin{aligned}
V_{ik}\left(\rho + \sum_{\dot{l}\neq k} q_{k\dot{l}} + (N_I + N_E)\lambda\right) \quad = \quad & \lambda_k^{ipo}\psi_k^i E[u_{ik}] + \sum_{\dot{l}\neq k} q_{k\dot{l}}\{\nu_{i1\dot{l}} - \sigma_\varepsilon \ln \sigma_{i1\dot{l}} + \sigma_\varepsilon \ln \sigma_{ij^*\dot{l}}\} \\
+ \quad & \sum_{m\neq i, m\in N_I} \lambda \sum_{j\in J_I} \sigma_{mjk}\{\nu_{i1k'} - \sigma_\varepsilon \ln \sigma_{i1k'} + \sigma_\varepsilon \ln \sigma_{ij^*k'}\} \\
+ \quad & \sum_{m\neq i, m\in N_E} \lambda \sum_{j\in J_E} \sigma_{mjk}\{\nu_{i1k'} - \sigma_\varepsilon \ln \sigma_{i1k'} + \sigma_\varepsilon \ln \sigma_{ij^*k'}\} \\
+ \quad & \lambda\{\nu_{i1k} - \sigma_\varepsilon \ln \sigma_{i1k} + \sigma_\varepsilon \gamma\} \qquad (11)
\end{aligned}
$$

Potential Entrants: Since a potential entrant cannot exit the market yet, we cannot apply the same derivation as above using a terminal action. However once entered, the underwriter becomes an incumbent enabling us to exploit the terminal action.

Setting $j' = 2$ in eq. (6) and exploiting the property of ε's distribution,

$$
E \max_j \{\nu_{ijk} + \varepsilon_{ij} + V_{i,l(i,j,k)}\} = \nu_{i2k} + V_{i,l(i,2,k)} - \ln \sigma_{i2k} + \gamma. \qquad (12)
$$

Unlike the incumbents' problem, we cannot set the value function on the right hand side ($V_{i,l(i,2,k)}$) to be zero as potential entrants cannot take the terminal action of exiting. However, note that i in $V_{i,l(i,2,k)}$ is no longer a potential entrant but an incumbent. Therefore we can apply eq. (8) to $V_{i,l(i,2,k)}$. Letting $k_2 = l(i,2,k)$ and j^* be a continuation action,

$$
V_{i,l(i,2,k)} = V_{i,k_2} = \nu_{i1k_2} - \ln \sigma_{i1k_2} + \ln \sigma_{ij^*k_2}
$$

[12]Note that in eq. (11) N_I is state specific: that is, an incumbent in state k faces a different number of market participants than in state k'. Hence to be exact, N_I should be indexed by state as well, N_{I_k}.

and eq. (12) becomes

$$E \max_j \{\nu_{ijk} + \varepsilon_{ij} + V_{i,l(i,j,k)}\} = \nu_{i2k} + [\nu_{i1k_2} - \ln \sigma_{i1k_2} + \ln \sigma_{ij^*k_2}] - \ln \sigma_{i2k} + \gamma. \tag{13}$$

Note that the above expression involves two states, k and k_2 while the counterpart for incumbents (eq. (7)) only has one state.

To form a value function resulting from an opponent's action, consider the two actions, $j = 2$ (entry) and j^* (continuation action), and a new state achieved by opponent m's action j, $k' = l(m, j, k)$. Using eq. (6),

$$\begin{aligned} \nu_{ij^*k'} + V_{i,l(i,j^*,k')} + \Gamma_i(j^*, \sigma_{ik'}) &= \nu_{i2k'} + V_{i,l(i,2,k')} + \Gamma_i(2, \sigma_{ik'}) \\ 0 + V_{i,l(i,j^*,k')} - \ln \sigma_{ij^*k'} + \gamma &= \nu_{i2k'} + V_{i,l(i,2,k')} - \ln \sigma_{i2k'} + \gamma. \end{aligned} \tag{14}$$

Applying eq. (8) to $V_{i,l(i,2,k')}$ and denoting $k'_2 = l(i, 2, k')$ gives

$$V_{i,l(i,2,k')} = \nu_{i1k'_2} - \ln \sigma_{i1k'_2} + \ln \sigma_{ij^*k'_2}.$$

By substituting the above expression to eq. (14) we reach the following expression:

$$V_{i,l(m,j,k)} = V_{i,k'} = V_{i,l(i,j^*,k')} = \nu_{i2k'} + [\nu_{i1k'_2} - \ln \sigma_{i1k'_2} + \ln \sigma_{ij^*k'_2}] - \ln \sigma_{i2k'} + \ln \sigma_{ij^*k'}. \tag{15}$$

Similarly to the opponents' case, a value function in a state $\dot{l}(k)$ that is reached from k by the nature can be expressed as

$$V_{i,\dot{l}(k)} = V_{i,l(i,j^*,\dot{l}(k))} = \nu_{i2\dot{l}(k)} + [\nu_{i1\dot{k}} - \ln \sigma_{i1\dot{k}} + \ln \sigma_{ij^*\dot{k}}] - \ln \sigma_{i2\dot{l}(k)} + \ln \sigma_{ij^*\dot{l}(k)}. \tag{16}$$

where $\dot{k}$ is a state reached from $\dot{l}(k)$ by i's entry, i.e. $\dot{k} = l(i, 2, \dot{l}(k))$.

Substituting eq. (13), eq. (15) and eq. (16) into eq. (5) gives a CCP representation of a potential entrant's value function as follows

$$
\begin{aligned}
V_{ik}\left(\rho+\sum_{l\neq k} q_{kl}+N\lambda\right) &= \sum_{\dot{l}\neq k} q_{k\dot{l}}\{\nu_{i2\dot{l}}+[\nu_{i1\dot{k}}-\ln\sigma_{i1\dot{k}}+\ln\sigma_{ij^*\dot{k}}]-\ln\sigma_{i2\dot{l}}+\ln\sigma_{ij^*\dot{l}}\} \\
&+ \sum_{m\neq i, m\in N_I}\lambda\sum_{j\in J_I}\sigma_{mjk}\{\nu_{i2k'}+[\nu_{i1k_2'}-\ln\sigma_{i1k_2'}+\ln\sigma_{ij^*k_2'}]-\ln\sigma_{i2k'}+\ln\sigma_{ij^*k'}\} \\
&+ \sum_{m\neq i, m\in N_E}\lambda\sum_{j\in J_E}\sigma_{mjk}\{\nu_{i2k'}+[\nu_{i1k_2'}-\ln\sigma_{i1k_2'}+\ln\sigma_{ij^*k_2'}]-\ln\sigma_{i2k'}+\ln\sigma_{ij^*k'}\} \\
&+ \lambda\{\nu_{i2k}+[\nu_{i1k_2}-\ln\sigma_{i1k_2}+\ln\sigma_{ij^*k_2}]-\ln\sigma_{i2k}+\gamma\} \qquad (17)
\end{aligned}
$$

where $\dot{l}=\dot{l}(k)$, $\dot{k}=l(i,2,\dot{l}(k))$, $k'=l(m,j,k)$, $k_2=l(i,2,k)$ and $k_2'=l(i,2,k')$. Note that the above equation does not include a flow payoff unlike eq. (11) for incumbents as the flow payoff is defined for market participants. We set the flow payoff of potential entrant who has not yet entered the market to be zero. Current flow payoffs enter the decision of the potential entrant through the value of selecting to become a market participant.

If instead the the standard deviation of ε is not one but σ_ε: by the property of the distribution of ε, $\Gamma_i(j',\sigma_{ik})=-\sigma_\varepsilon\ln\sigma_{ij'k}+\sigma_\varepsilon\gamma]$

$$
\begin{aligned}
V_{ik}\left(\rho+\sum_{l\neq k} q_{kl}+N\lambda\right) &= \sum_{\dot{l}\neq k} q_{k\dot{l}}\{\nu_{i2\dot{l}}+[\nu_{i1\dot{k}}-\sigma_\varepsilon\ln\sigma_{i1\dot{k}}+\sigma_\varepsilon\ln\sigma_{ij^*\dot{k}}]-\sigma_\varepsilon\ln\sigma_{i2\dot{l}}+\sigma_\varepsilon\ln\sigma_{ij^*\dot{l}}\} \\
&+ \sum_{m\neq i, m\in N_I}\lambda\sum_{j\in J_I}\sigma_{mjk}\{\nu_{i2k'}+[\nu_{i1k_2'}-\sigma_\varepsilon\ln\sigma_{i1k_2'}+\sigma_\varepsilon\ln\sigma_{ij^*k_2'}]-\sigma_\varepsilon\ln\sigma_{i2k'}+\sigma_\varepsilon\ln\sigma_{ij^*} \\
&+ \sum_{m\neq i, m\in N_E}\lambda\sum_{j\in J_E}\sigma_{mjk}\{\nu_{i2k'}+[\nu_{i1k_2'}-\sigma_\varepsilon\ln\sigma_{i1k_2'}+\sigma_\varepsilon\ln\sigma_{ij^*k_2'}]-\sigma_\varepsilon\ln\sigma_{i2k'}+\sigma_\varepsilon\ln\sigma_{ij} \\
&+ \lambda\{\nu_{i2k}+[\nu_{i1k_2}-\sigma_\varepsilon\ln\sigma_{i1k_2}+\sigma_\varepsilon\ln\sigma_{ij^*k_2}]-\sigma_\varepsilon\ln\sigma_{i2k}+\sigma_\varepsilon\gamma\} \qquad (
\end{aligned}
$$

3.10 Estimation

We employ a two-step estimation approach similar to Arcidiacono et al. [2016]. In the first step we estimate hazard rates. The remaining model parameters are estimated in the second step.

Likelihood: By exploiting the property of Poisson processes,[13] the probability that state k changes during an interval of length τ is

$$1 - \exp\Big[-\tau\big(\sum_{l\neq k} q_{kl} + \sum_{i\in N_I} \lambda\sigma_{i1k} + N_E\lambda\sigma_{i_E 2k}\big)\Big] \tag{19}$$

where N_I is the number of incumbents and N_E is the number of potential entrants. Note that since we do not know the characteristics of potential entrants, we assume all potential entrants have the same distribution of characteristics as the set of actual entrants. This result follows from the assumption that entrants do not observe their own characteristics prior to entering the market. Also note that the continuation choice ($j = 0$) is excluded as the choice does not change the state. Then the density of duration until the next change is

$$\big(\sum_{l\neq k} q_{kl} + \sum_{i\in N_I} \lambda\sigma_{i1k} + N_E\lambda\sigma_{i_E 2k}\big)\exp\Big[-\tau\big(\sum_{l\neq k} q_{kl} + \sum_{i\in N_I} \lambda\sigma_{i1k} + N_E\lambda\sigma_{i_E 2k}\big)\Big]. \tag{20}$$

Given a state change, the probability that the state change is due to an incumbent i making an exit choice ($j = 1$) is[14]

$$\frac{\lambda\sigma_{ijk}}{\sum_{l\neq k} q_{kl} + \sum_{i\in N_I} \lambda\sigma_{i1k} + N_E\lambda\sigma_{i_E 2k}}. \tag{21}$$

The likelihood of a state change during an interval of τ that results from incumbent i's action $j = 1$ is a multiplication of eq. (20) and eq. (21), or

$$\lambda\sigma_{ijk}\exp\Big[-\tau\big(\sum_{l\neq k} q_{kl} + \sum_{i\in N_I} \lambda\sigma_{i1k} + N_E\lambda\sigma_{i_E 2k}\big)\Big]. \tag{22}$$

Now given a state changes, the probability that the state change is by an event of entry is

$$\frac{N_E\lambda\sigma_{i_E 2k}}{\sum_{l\neq k} q_{kl} + \sum_{i\in N_I} \lambda\sigma_{i1k} + N_E\lambda\sigma_{i_E 2k}}. \tag{23}$$

[13]When there are more than one Poisson process, the waiting time until any event follows the exponential distribution with rate that is the sum of each process' rate.

[14]Conditional on arrival of any event, the probability that the event is a particular event is given by the ratio of the particular event's rate and the sum of all processes' rate.

and the likelihood of a state change during an interval of τ that results from an entry event is

$$N_E \lambda \sigma_{i2k} \exp\Big[-\tau\big(\sum_{l \neq k} q_{kl} + \sum_{i \in N_I} \lambda \sigma_{i1k} + N_E \lambda \sigma_{i_E 2k}\big)\Big]. \tag{24}$$

Similarly, the contribution of nature moving state k to l to the likelihood is

$$q_{kl} \exp\Big[-\tau\big(\sum_{l \neq k} q_{kl} + \sum_{i} \{\lambda \sigma_{i1k} + N_E \lambda \sigma_{i2k}\}\big)\Big]. \tag{25}$$

Assume that there are a total of N state changes and let subscript n be an index for those state changes, $n \in \{1, 2, \ldots, N\}$. Also let k_n be the state prior to n-th state change and τ_n be the interval between $(n-1)$-th and n-th state changes. Then the likelihood of state changes observed in the data is

$$\begin{aligned} L &= \prod_{n=1}^{N} \Big[\exp\Big[-\tau_n\big(\sum_{l \neq k_n} q_{k_n l} + \sum_{i \in N_I} \lambda \sigma_{i1k_n} + N_E \lambda \sigma_{i_E 2k_n}\big)\Big] \prod_{l \neq k_n} q_{k_n l}^{I_n(l)} \prod_{i \in N_I} (\lambda \sigma_{i1k_n})^{I_n(i,1)} (N_E \lambda \sigma_{i_E 2k_n})^{I_n(2)} \Big] \\ &\cdot \ \exp\Big[-\tau_{N+1}\big(\sum_{l \neq k_{N+1}} q_{k_{N+1} l} + \sum_{i \in N_E} \lambda \sigma_{i2k_{N+1}} + N_E \lambda \sigma_{i_E 2k_{N+1}}\big)\Big] \end{aligned} \tag{26}$$

where $I_n(l)$ is an indicator that the n-th state change to l is by nature and $I_n(i,1)$ is by incumbent i's action of exiting. The second line is the probability that the state change does not happen between the last state change observed and the last time period in the data. The corresponding log-likelihood is

$$\begin{aligned} l &= \sum_{n=1}^{N} \Big[-\tau_n\big(\sum_{l \neq k_n} q_{k_n l} + \sum_{i \in N_I} \lambda \sigma_{i1k_n} + N_E \lambda \sigma_{i_E 2k_n}\big) \\ &+ \sum_{l \neq k_n} I_n(l) \ln q_{k_n l} + \sum_{i \in N_I} I_n(i,1) \ln(\lambda \sigma_{i1k_n}) + I_n(2) \ln N_E \lambda \sigma_{i_E 2k_n} \Big] \\ &- \tau_{N+1}\big(\sum_{l \neq k_{N+1}} q_{k_{N+1} l} + \sum_{i \in N_I} \lambda \sigma_{i2k_{N+1}} + N_E \lambda \sigma_{i_E 2k_{N+1}}\big). \end{aligned} \tag{27}$$

Note how the terms enter differently for incumbents and potential entrants. Also note that incumbents other than actual exiting firms are included in estimating exit hazard as can be seen in the first summation over $i \in N_I$. For these cases τ is defined using the exiting dates by actual exiting firms.

To consider a case where the number of players (underwriters) changes over time, we segment the time line whenever exit/entry happens and rewrite the likelihood accordingly as follows

$$\begin{aligned} L &= \prod_{m=1}^{M} \prod_{n_m=1}^{N_m} \Big[\exp\Big[-\tau_{n_m}\big(\sum_{l \neq k_{n_m}} q_{k_{n_m} l} + \sum_{i \in N_I} \lambda \sigma_{i1k_{n_m}} + N_E \lambda \sigma_{i_E 2 k_{n_m}} \big) \Big] \\ &\cdot \prod_{l \neq k_{n_m}} q_{k_{n_m} l}^{I_n(l)} \prod_{i \in N_I} (\lambda \sigma_{i1k_{n_m}})^{I_{n_m}(i,1)} (N_E \lambda \sigma_{i_E 2 k_{n_m}})^{I_{n_m}(2)} \Big] \\ &\cdot \exp\Big[-\tau_{N+1}\big(\sum_{l \neq k_{N+1}} q_{k_{N+1} l} + \sum_{i \in N_E} \lambda \sigma_{i2k_{N+1}} + N_E \lambda \sigma_{i_E 2 k_{N+1}} \big) \Big] \end{aligned} \quad (28)$$

where m is an index for exit/entry events (including the end of the data), N_m is the total number of events which change the state, either by nature or by the players, between $(m-1)$th and mth entry/exit events. As before N indexes the total number of events.[15] The first two lines are an equivalent expression for the first line of eq. (26) except the timing is now segmented further by the exit/entry events. The second line is the same quantity as the last line of eq. (26). The corresponding log-likelihood is

$$\begin{aligned} l &= \sum_{m=1}^{M} \sum_{n_m=1}^{N_m} \Big[-\tau_{n_m}\big(\sum_{l \neq k_{n_m}} q_{k_{n_m} l} + \sum_{i \in N_I} \lambda \sigma_{i1k_{n_m}} + N_E \lambda \sigma_{i_E 2 k_{n_m}} \big) \\ &+ \sum_{l \neq k_{n_m}} I_n(l) \ln q_{k_{n_m} l} + \sum_{i \in N_I} I_{n_m}(i,1) \ln(\lambda \sigma_{i1k_{n_m}}) + I_n(2) \ln N_E \lambda \sigma_{i_E 2 k_{n_m}} \Big] \\ &- \tau_{N+1}\big(\sum_{l \neq k_{N+1}} q_{k_{N+1} l} + \sum_{i \in N_I} \lambda \sigma_{i2k_{N+1}} + N_E \lambda \sigma_{i_E 2 k_{N+1}} \big). \end{aligned} \quad (29)$$

Pre-estimation summary

– Estimate Poisson process of IPO arrival (eq. (1), MLE)

– IPO winning probability (probit)

– Number of lead managers distribution (eq. (2), Poisson)

[15] The point representing the end of the data is the event where $N_m = N$, i.e. the last "event."

– Proceeds equation (eq. (3), OLS)

– IPO characteristic distribution (probit)

First-step - Hazard rates: We estimate hazard rates, $c_{i1k} = \lambda\sigma_{i1k}$ for incumbents and $c_{i2k} = N_E\lambda\sigma_{i2k}$ for entrants, empirically by maximizing eq. (27) with respect to hazards. Instead of estimating c_{ijk} nonparametrically, we specify a reduced form logit function with observed variables, $c_{i1k}(\theta_{cI})$ and $c_{i2k}(\theta_{cE})$. Then we estimate θ_{cI} and θ_{cE} as follows:

$$\begin{aligned} \hat{\theta_{cI}} &= \arg\max_{\theta_{cI}} \sum_{n=1}^{N} \Big(-\tau_n \sum_{i \in N_I} c_{i1k_n}(\theta_{cI}) + \sum_{i \in N_I} I_n(i,1) \ln c_{i1k_n}(\theta_{cI}) \Big) \\ &- \tau_{N+1} \sum_{i \in N_I} c_{i1k_{N+1}}(\theta_{cI}). \end{aligned} \tag{30}$$

$$\begin{aligned} \hat{\theta_{cE}} &= \arg\max_{\theta_{cE}} \sum_{n=1}^{N} \Big(-\tau_n c_{i2k_n}(\theta_{cE}) + I_n(2) \ln c_{i_E 2k_n}(\theta_{cE}) \Big) \\ &- \tau_{N+1} \sum_{i} c_{i_E 2k_{N+1}}(\theta_{cE}). \end{aligned} \tag{31}$$

Note that N_E cannot be separately estimated at this stage.

The intensity matrix of natures move is also estimated at this stage. We nonparametrically estimate the quantities by maximizing eq. (27) with the FOC

$$\sum_{n=1}^{N} \Big(-\tau_n + \frac{I_n(l)}{q_{k_n l}} \Big) I(k_n = a, l = b) - \tau_{N+1} I(k_{N+1} = a, l = b)|_{\hat{q}_{(k_n = a, l = b)}} = 0 \tag{32}$$

where $I(k_n = a, l = b)$ indicates that the stage prior to n-th state change is a and that the state moves to b. By noting $\frac{I_n(l)}{q_{k_n l}} I(k_n = a, l = b) = \frac{I_n(l)}{q_{ab}} I(k_n = a, l = b)$,

$$\hat{q}_{ab} = \frac{\sum_{n=1}^{N} I_n(l) I(k_n = a, l = b)}{\sum_{n=1}^{N+1} \tau_n I(k_n = a, l = b)}. \tag{33}$$

A similar argument applies when the likelihood is segmented as in eq. (28). The FOC from eq. (29 becomes

$$\sum_{m=1}^{M}\sum_{n_m=1}^{N_m}\Big(-\tau_{n_m}+\frac{I_{n_m}(l=b)}{q_{k_{n_m}l}}\Big)I(k_{n_m}=a,l=b)-\tau_{N+1}I(k_{N+1}=a,l=b)|_{\hat{q}(k=a,l=b)}=0 \quad (34)$$

which yields

$$\hat{q}_{ab}=\frac{\sum_{m=1}^{M}\sum_{n_m=1}^{N_m}I_{n_m}(l)I(k_{n_m}=a,l=b)}{\sum_{m=1}^{M}\sum_{n_m=1}^{N_m}\tau_{n_m}I(k_{n_m}=a,l=b)+\tau_{N+1}I(k_{N+1}=a,l=b)}. \quad (35)$$

One of the states that nature moves is the reputation level. Unlike other states, these changes are player specific. Within an m-th segment of $n_m=\{1,\dots,N_m\}$, where the number of players is fixed at N_m^I, there is an N_m^I sequence of $\{\tau\}_{n_m}$, one sequence for each player. When calculating $\sum_{n_m=1}^{N_m}I_{n_m}(l)I(k_{n_m}=a,l=b)$ and $\sum_{n_m=1}^{N_m}\tau_{n_m}I(k_{n_m}=a,l=b)$ of eq. (35), we average the quantities over all N_m^I players. That is,[16]

$$\begin{aligned}\sum_{n_m=1}^{N_m}I_{n_m}(l)I(k_{n_m}=a,l=b) &= \frac{\sum_i^{N_m^I}\sum_{n_m^i=1}^{N_m^i}I_{n_m^i}(l)I(k_{n_m^i}=a,l=b)}{N_m^I}\\ \sum_{n_m=1}^{N_m}\tau_{n_m}I(k_{n_m}=a,l=b) &= \frac{\sum_i^{N_m^I}\sum_{n_m^i=1}^{N_m^i}\tau_{n_m^i}I(k_{n_m^i}=a,l=b)}{N_m^I}.\end{aligned}$$

Note that N_m^I is constant within a particular m but varying over m as the number of players changes. This variation of N_m^I is the reason why the likelihood needs to be segmented. If N_m^I is fixed over m, then all that would be necessary would be to sum all sequences over players without segmenting.

When we impose that reputation change is an independent process across all players[17] and from other variables, then an element of the intensity matrix can be estimated similarly to eq. (33) as

[16]Note that due to the summation over m, the averaging factor of N_m^I will not cancel each other even though one affects the numerator and the other the denominator.

[17]The construction of the reputation measure may call this assumption into question; reputation is to some degree a relative measure as the level of reputation is determined by the frequency of appearing at different positions in tombstone listings. Since reputation measures aggregate data over a number of years, the relative effect is likely limited.

follows:

$$\hat{q}_{ab} = \frac{\sum_i^{N^I} \sum_{n_i=1}^{N_i} I_{n_i}(l) I(k_{n_i} = a, l = b)}{\sum_i^{N^I} \sum_{n_i=1}^{N_i+1} \tau_{n_i} I(k_{n_i} = a, l = b)} \tag{36}$$

where N^I is the total number of players who are ever in the market, n_i indicates the event (reputation change) happening to player i and N_i is the number of such events.[18]

Second-step: Let $\tilde{c}_{ijk}$ be the estimated hazards. Then the empirical CCP can be expressed as $\tilde{c}_{ijk}/\lambda$. The distribution of the choice specific error term gives the following model implied CCPs:

$$\begin{aligned}
\sigma_{i1k} &= \frac{\exp(\kappa^{ex} + V_{i,l(i,1,k)})}{\exp(V_{i,l(i,0,k)}) + \exp(\kappa^{ex} + V_{i,l(i,1,k)})} \text{ if } i\text{: incumbents} \\
\sigma_{i2k} &= \frac{\exp(\kappa^{en} + V_{i,l(i,2,k)})}{\exp(V_{i,l(i,0,k)}) + \exp(\kappa^{en} + V_{i,l(i,2,k)})} \text{ if } i\text{: potential entrants.}
\end{aligned} \tag{37}$$

Note that $V_{i,l(i,1,k)} = 0$ for incumbents; exiting is the terminal action. Also, we assume a potential entrant has the option of declining to enter and waiting until another entry opportunity arises to enter. After a firm does enter, it is immediately replaced with another potential entrant, $V_{i,l(i,0,k)} \neq 0$ for entrants. It is clear from eq. (11) and eq. (18) that the value functions in the above specification can be constructed from the model primitives (θ_s), the estimated intensity matrix for nature's moves, and the estimated CCPs. Let $\tilde{V}_{ijk}$ be such constructed values. Then the model implied CCPs also become functions of θ_s, $\tilde{q}_{kl}$ and $\tilde{c}_{ijk}/\lambda$ when said $\tilde{V}_{ijk}$s are substituted into the above equation. Let $\hat{\sigma}_{ijk}$ be such quantities. To recover the structural parameters, note that the likelihood is now a function of observable data, pre-estimated CCPs, and θ_s. Hence, maximizing eq. (27) with respect to θ_s delivers the estimates of the structural parameters.

3.11 Discrete data

We treat the business cycle and entry/exit decisions as continuously observed in the data while aggregate venture capital funding (VC macro index) and the reputation level of each underwriter

[18] In fact, this is assuming qs are the same for all players. The equation can be seen in that way using the property of the mediant (freshman sum).

are observed at discrete intervals.[19] To understand the issue with discrete data, consider an example of the reputation levels of three underwriters that are different from the previous observation. In this case, we know that the state has moved as these reputation levels have changed, but we do not observe precisely when these changes occurred. We address this issue by simulating when the state change happens.[20] This approach is similar to Arcidiacono et al. [2016] except that our data feature *both* continuous and discrete observations. In their paper, they simulate R times between each equispaced data observation period and average the simulations to obtain the likelihood at each data point. This procedure is appropriate because they do not have any continuously observed data. In contrast, our one simulation applies to the whole sequence of events and generates the intervals between events, $\tau_n^{(r)}$, so that we can determine how continuously *observed* data and continuously *simulated* data are ordered. Then we average R such simulations to get the likelihood as a whole. Hence, the likelihood that a state change is observed is

$$L = \ln\left(\frac{1}{R}\sum_{r=1}^{R} L_r\right) \tag{38}$$

[19]We do not control directly for the state of the IPO market, which is often described as alternating between hot and cold markets. In our setting, the intensity of IPO arrivals is an endogenous variable, and thus dividing the market based on the observed number of IPOs would be inappropriate. Instead, to account for the persistence of IPO activity, it would be necessary to model the IPO arrival rate as also depending on the intensity of an unobservable market state. We would then need adopt an EM algorithm to account for the unobserved heterogeneity in IPO arrival determinants. We leave this problem for future research.

[20]We assume there is only one change for VC macro index or one change for individual reputation for a relevant time period. To guarantee that there is only one move in an interval we draw the timing of state changes associated with the VC macro index and the reputation levels from uniform distributions.

where the r-th simulated likelihood L_r is defined as

$$\begin{aligned}
L_r &= \prod_{n(r)=1}^{N} \Bigg\{ \sum_{j\in J_{BC}} I_{n(r)}(0,j)q_j + \sum_i \sum_{j\in J_i, j\neq 0} I_{n(r)}(i,j)\lambda p_{ijk_{n(r)}} + \sum_{j\in J_{VC}} I^{(r)}_{n(r)}(0,j)q_j \\
&+ \sum_{w_{n(r)}=1}^{W_{n(r)}} \sum_{j\in J_{rep}} I^{(r)}_{w_{n(r)}}(0,i,j)q_{rep} \Bigg\} \\
&\times \exp\left(-\tau^{(r)}_{n(r)} \left(\sum_{j\in J_{BC}} q_j + \sum_i \sum_{j\in J_i, j\neq 0} \lambda p_{ijk_{n(r)}} + \sum_{j\in J_{VC}} q_j + W_{n(r)} \sum_{j\in J_{rep}} q_j \right)\right) \\
&\times \exp\left(-\tau^{(r)}_{N+1} \left(\sum_{j\in J_{BC}} q_j + \sum_i \sum_{j\in J_i, j\neq 0} \lambda p_{ijk_{N+1}} + \sum_{j\in J_{VC}} q_j + \sum_{j\in J_{rep}} q_j \right)\right) \qquad (39)
\end{aligned}$$

where $n(r)$ is an order of all events that are the union of continuously simulated and continuously observed events. This order might change depending on the simulation r. J_x is a set of actions that can change the state of x. For example, $J_{BC} = \{-1, +1\}$ where -1 represents booming to recession while $+1$ the reverse. Similarly, $J_i = \{0, 1\}$ where 0 represents "do nothing" and 1 "exit (enter)" if i is an incumbent (entrant). Sometimes multiple reputation changes occur within one time interval. We denote $W_{n(r)}$ to be the number of reputation changes recorded at $n(r)$-th observation and $w_{n(r)}$ be the index for the changes. Since we do not know the order of these multiple reputation changes, we randomly assign $\{w_{n(r)}\}$ to the changes. $I_{n(r)}(i,j)$ indicates that i moves the state by action j at the $n(r)$-th observation. $I^{(r)}_{w_{n(r)}}(0,i,j)$ indicates that nature moves the reputation of an underwriter i by j levels, and this move is the $w_{n(r)}$-th event out of $W_{n(r)}$ events. When the indicators are superscripted by (r), they are the results of simulation. The first two summations in the first line are for the continuously observed events of business cycle changes and entry/exit decisions and we do not have to simulate these terms, except that the order of these events relative to the simulated events can change due to the simulation. The rest of the two summations in the first line are for the simulated events of VC macro index change and reputation changes. The last line captures that no event happened during $\tau^{(r)}_{N+1}$ (the period between the last event we observe and the end of the data).

Another difference between our approach and the approach in Arcidiacono et al. [2016] is that some data used in our pre-estimation step is discretely observed. All of the pre-estimation regressions include at least one discretely observed variable. For example, the amount of proceeds is a function of the VC index, which is only observed annually. Suppose an IPO happens in November 1985 and the VC macro index is recorded in July of every year. In this case it is not clear whether we should use the VC macro index in 1985 or in 1986 as a regressor, as we do not know when VC macro index moves from its 1985 level to 1986 level. To address this problem, we again utilize simulations. In principle, we can construct the joint likelihood of state moves and observing a set of IPO related variables that are independent variables in the pre-estimation regressions (IPO arrival, proceeds, VC or HT index and winning underwriter). This joint likelihood is then averaged across simulations so that a maximum likelihood estimation of parameters can be executed. Given our assumption that the errors of IPO related observables are independent of the state transition process, we can still utilize a pre-estimation approach using a conditional MLE. Note that the likelihood associated with the pre-estimation regressions do not contain the rest of the structural parameters. Hence we perform MLE on the average of the simulated partial likelihood that is relevant to IPO related observables. Then we apply the pre-estimated parameters to the likelihood of state moves and construct the average of the simulated likelihood. We then perform MLE. To summarize, the estimation proceeds as follows:

1. For each interval between discrete observations of the VC macro index, draw when the change occurs from an uniform distribution, $U[0, 1]$ (see footnote 20.) This procedure produces a single simulation draw.

2. Form a likelihood of observing IPO related variables. For example, one can form a likelihood of observing IPO arrivals with a Poisson parameter that is a function of the VC macro index that has been simulated. Repeat this R times to obtain an averaged likelihood over the simulations. Save the simulation seeds for later use.

3. Estimate pre-estimation equations using the averaged likelihood.[21]

4. Utilize the saved seeds to construct the average likelihood of state moves across simulations as in eq. (39).

5. Perform MLE to estimate the remaining structural parameters.

4 Pre-estimates

In order to recover the structural parameters of the model, it is first necessary to estimate the hazard rates from the data for both the endogenous state changes of entry and exit and the exogenous state changes which drive the entry and exit decisions. Entry and exit hazards serve to replace value function differences in the continuous value functions, while the other hazards determine the changes of the underlying state that affect the static and dynamic incentives for firms to enter or exit the market.

4.1 IPO arrivals and value

In order to recover the expected flow payoff to active underwriters, we posit that IPOs arrive according to a Poisson process, where the rate parameter is determined by macroeconomic conditions, the venture capital index, and the number of IPO underwriters active at the time. We assume the arrival rate parameter is a linear function of these variables. At this stage, we assume that all variables that determine the IPO arrival rate are observable, which allows us to take the number of underwriters as given when estimating the arrival rate even though the number of underwriters is endogenous. Our results indicate that IPOs arrive at a higher rate during economic booms, when venture capital funding is more common, and when there are more underwriters active. This last result indicates, as expected, that underwriters play a role in recruiting firms into the IPO market; they are not simply passive bidders in an auction market.

[21]For linear regressions as in the case of proceeds equation in eq. 3), it is equivalent to assign the VC macro index with a weighted sum of the two adjacent VC macro indices and perform the regression. The weight is determined by how close the IPO date is to the annual observation date (assumed to be July 2nd) of the VC macro index.

The results on the IPO arrival rate, presented in Table 1, are consistent with conventional wisdom and our modeling assumptions. For example, if the economic condition improves from recession to boom, on average, we would see 1.08 more IPO arrivals per day, a difference of about 270 IPOs per year based on trading days. While this figure may seem high, it is in line with the differences in the number of IPOs per year between hot IPO markets and cold IPO markets, which tend to line up fairly closely with boom and bust periods.

As for the effect of entry on IPO arrival, our results show that ten more incumbents in the market leads to 0.2 more IPOs arrivals per day. If the venture capital index is higher (medium), 1.07 (0.72) more IPOs arrive daily.

Table 1: Arrival Rate for IPOs. Time unit is days.

IPO Arrival			
	Estimate	S.E.	T-stat
Constant	4.586729	0.064853	70.72517
I_Boom	-1.19873	0.055978	-21.4143
I_VC_high	-1.18757	0.025385	-46.7828
I_VC_mid	-0.79528	0.019628	-40.5172
Num_Players	-0.02511	0.000271	-92.6724

The second input needed to determine the flow payoff to a particular underwriter is the probability that a firm will choose the particular underwriter out of all active underwriters. Underwriter reputation is the only underwriter specific variable being used, so we model the probability of winning as a function of one's own reputation and the average reputation of other active underwriters. A probit model is used, pooling all IPOs to give the "probability" of winning as a function of underwriter characteristics. The probability of winning a particular IPO is then calculated by normalizing this "probability" of winning by the sum of the "probability" that any firm currently in the market wins the IPO. Thus, the probability that some firm wins the IPO is 1 for each IPO.

Table 2 presents the results. Having a high reputation has an extremely large effect on the probability of winning an IPO, approximately quintupling the probability of winning an IPO. A medium reputation has a trivial (and, in fact, negative) effect on the probability of winning relative

Table 2: Determinants of the probability of winning an IPO.

IPO Win Probability			
	Estimate	S.E.	T-stat
Const	-2.11945	0.088571	-23.9293
Num_Players	-0.00347	0.000257	-13.5039
I_Rep_high_myself	0.577972	0.010489	55.10055
I_Rep_mid_myself	-0.02039	0.012829	-1.58921
Mean_Rep_high_others	-0.44902	0.117665	-3.8161
Mean_Rep_mid_others	0.095338	0.094059	1.013606

to a low reputation. Thus, the value of a reputation increase from low to medium comes entirely from the potential to then move into the high reputation bin. Similarly, more high reputation competitors decrease the chance of winning an IPO while more medium reputation competitors relative to low reputation competitors leaves the probability of winning effectively unchanged.

We must also account for the fact that multiple underwriters share the role of IPO manager in all but the smallest IPOs, so we must estimate the number of players involved in each IPO as well. These results appear in Table 3. The estimated coefficients in the eq. (3) can be interpreted as the percentage change of number of lead managers. For instance, an economic expansion increases the number of winning underwriters by 4.86%.[22] When the VC index is high, the number of winning underwriters decreases by 15.01% while medium VC index increases the quantity by 23.34%. This non-monotonicity is difficult to interpret and suggests that the periods of medium and high venture capital funding may proxy for more general conditions in the IPO market. It is also possible that the VC index is picking up a time trend in the number of lead managers for a deal. If the IPO in question is venture capital backed, then the number of lead managers decreases by 1.86% while the high tech IPO dummy reduces the number of winning underwriters by 3.08%. When one more underwriter enters the market, then the number of lead managers is lowered by 0.62%.

Finally, we must estimate the determinants of IPO proceeds, which we estimate via OLS on equation 3. The estimated coefficients should be interpreted as the percentage changes as the

[22]The change of the binary regressor of the economic boom condition yields a change in the independent variable of $\log(y_1) - \log(y_0) = 0.0489$. Then the percentage change of the independent variable ($\frac{y_1 - y_0}{y_0} = exp(0.0474) - 1$.)

Table 3: Number of expected lead managers for an IPO

	Number of Winners		
	Estimate	S.E.	T-stat
Const	0.8484	0.028	30.2958
I_Boom	0.047459	0.01772	2.678305
I_VC_high	-0.16264	0.016162	-10.0635
I_VC_mid	0.209759	0.015439	13.58611
I_VCbacked	-0.0188	0.008779	-2.14197
I_HT	-0.03126	0.008093	-3.86303
Num_Players	-0.00593	0.000183	-32.3747
sigma for normal error term	0.286714	0.000768	373.5615

independent variable is a log quantity. Entering an economic expansion increases the average amount of proceeds by 3.2%. A High VC index more than doubles expected proceeds, with an increase of 110%. If the IPO in question itself is venture capital backed, proceeds increase by 15.4%. The High-Tech IPO variable decreases average proceeds by 19.4%. Increasing the number of incumbents in the market by ten reduces the proceeds by 2.72%. Table 4 presents these results.

Table 4: Determinants of IPO Proceeds

	IPO Proceeds		
	Estimate	S.E.	T-stat
Const	-3.15025	0.122387	-25.7401
I_Boom	0.311615	0.071257	4.373119
I_VC_high	0.74403	0.065614	11.33949
I_VC_mid	0.780166	0.06244	12.49467
I_VCbacked	0.142944	0.039158	3.65046
I_HT	-0.21517	0.031271	-6.88083
Num_Players	-0.00276	0.000776	-3.55782
sigma for normal error term	1.130027	0.013164	85.8406

4.2 IPO Characteristics

To complete the calculation of the flow payoffs, we need to estimate the determinants of the IPO characteristics, specifically venture capital backing and the high tech variable. These results are shown in Tables 5 and 6.

IPO's are less likely to be venture capital backed in an economic expansion. Based on the marginal effect of the probit regression evaluated at the mean value of regressors the condition reduces the probability by 0.03. However, an expansion increases the probability of being a high tech IPO by 0.096, which is likely driven primarily by the tech boom in the 1990s. A high VC index increases the probability of being high tech by 0.4, while this increases the probability of being venture capital backed by 0.26. The medium level of the VC index makes an IPO more likely to be high tech but less likely to be venture capital backed. Having more incumbents in the market has opposite effects on the IPO characteristics. If the number of incumbent underwriters increases from 50 to 60, the probability of an IPO being venture capital backed decreases by 0.0076 while the probability of being a high tech IPO increases by 0.0053.

Table 5: Probability of Venture Backing

Venture Capital Backing			
	Estimate	S.E.	T-stat
Constant	-0.12508	0.151481	-0.82575
I_Boom	-0.0757	0.104663	-0.72329
I_VC_high	0.669732	0.068288	9.807399
I_VC_mid	-0.15514	0.073956	-2.09777
Num_Players	-0.00196	0.000904	-2.16999

Table 6: Probability of a High Tech IPO

High Tech IPO			
	Estimate	S.E.	T-stat
Constant	-0.79688	0.148746	-5.35727
I_Boom	0.25039	0.10453	2.395388
I_VC_high	1.099753	0.07178	15.32106
I_VC_mid	0.304017	0.071189	4.270574
Num_Players	0.001366	0.000879	1.55346

4.3 Macroeconomic Transitions

Macroeconomic transitions are exogenous in the model. The estimated Markov transition matrix for the economic state turns out to be symmetric as there are an equal number of expansion and recession periods. The transition intensity is estimated as 4.74×10^{-4}. The transition intensities for venture capital are given in Table 7. Reported coefficients are intensities for transition from the row state into the column state. Time unit is days and coefficients are reported $\times 10^{-}5$. Index thresholds were selected to create approximately equal bins, which leads to similar coefficients for transitions.

Table 7: Transition rates for the venture capital index

	Low VC	Mid VC	High VC
Low VC	–	18.9	0
Mid VC	9.44	–	18.9
High VC	0	18.9	–

4.4 Reputation transitions

Each incumbent underwriter has a reputation level, as measured by the Carter-Manaster reputation ranking, collected from Jay Ritter's IPO data website. This rank is based on the frequency with which a given underwriter appears in the most prominent position on the IPO tombstone (the initial advertising document for the offering). Thus, this reputation measure should capture the extent to which a firm would like to advertise its association with different underwriters. Our results show, consistent with prior literature, that higher reputation underwriters tend to obtain more IPOs than lower reputation underwriters. This variable then plays an important role in entry and exit decisions. We face a challenge in using this variable as the measure is by definition not continuous, and therefore we cannot identify the specific instant in time when an underwriter's reputation changes. Instead, reputation is computed over an interval of several years. We proceed by assuming that the reputation ranking given to a particular underwriter is a measure of its reputation at the midpoint of the interval used for calculation; the time intervals used for these calculations range from two years to five years. We use these discrete observations to estimate a transition intensity matrix, assuming the underlying reputation changes following a continuous time Markov process. Table 8 presents the annual transition matrix implied by our estimated Markov process. The probability of transitioning directly from low to high reputation is exceedingly small, which is driven by the fact that only one firm ever makes this transition. Firms do have some chance of "climbing the ladder" into the highest reputation level by transitioning first to a medium reputation and then to a high reputation.

Table 8 reports the estimated reputation transitions. Reported coefficients are intensities for transition from the row state into the column state. Time unit is days and coefficients are reported $\times 10^{-}5$.

Table 8: Transition rates for Reputation

	Low Reputation	Mid Reputation	High reputation
Low Reputation	–	5.63	.187
Mid Reputation	.631	–	2.01
High Reputation	0	1.63	–

We assume that new entrants do not observe their own reputation before entering the IPO market. This assumption vastly simplifies the estimation as we can simply assume that the distribution of realized reputation upon entry is a consistent estimate of the expected reputation upon entry. This assumption must be treated with caution, however, as entrants include both large commercial banks such as Wells Fargo and much smaller and potentially less reputable operations like Stratton Oakmont. Table 9 compares the distribution of reputation of incumbent firms over the entire sample to the distribution of the reputation of firms that are new entrants. Clearly, new entrants have a lower reputation than incumbents on average. Much of the benefit of entry likely comes from the expectation of an eventual increase in reputation, which can lead to large payoffs in the future. Note that we treat the evolution of reputation as an exogenous process; a natural extension of the model would be to allow for investment to increase the probability of a increase in this quality, as in the model of Pakes and McGuire [1994].

Table 9: Reputation Distribution

	Entrants	All
Low Reputation	0.59	0.31
Mid Reputation	0.26	0.31
High Reputation	0.15	0.38

5 Entry and exit hazards

To estimate the structural parameters, the key pre-estimation step is to recover empirical entry and exit hazards, which replace value function differences in the final estimation step. Our data has significant advantages and disadvantages for estimation of entry and exit hazards. As an advantage, we have effectively continuous data as IPOs can occur on any weekday and we have the date of each IPO. The disadvantage of our data is that we observe only the winner (or winners) of a particular IPO, not the players who unsuccessfully sought an IPO. Thus, we have effectively continuous but imperfect data about the the entry and exit date for each underwriter. In the interest of keeping things simple, we assume that an underwriter enters the market for providing IPOs on the date of its first IPO and exits on the date of its last IPO.[23] If the first IPO is sufficiently close to the beginning of our data or the last IPO is sufficiently close to the end of the data, we treat the underwriter as an initial incumbent or as an underwriter who does not exit, respectively.

Since potential entrants are assumed to observe only economy wide variables, we model entry as a function of macroeconomic conditions, venture capital activity, the number of players in the market, and the average reputation of the incumbent players. The strongest determinant of entry is, unsurprisingly, economic conditions; more firms start up their IPO business when there are many IPOs taking place. Some caution is needed in interpreting this result as we define a firm as an entrant when it has an IPO. Thus, for example, our procedure could never detect entry during a period where there are no IPOs taking place, even though a new firm could, in principal, set up

[23] The approach to defining entry and exit here is not completely innocuous. In particular, we are likely to systematically assign exit dates that are too early for firms that exit during periods of infrequent IPO as a firm may remain in the market but be unsuccessful in obtaining an IPO for some time before deciding to fully exit the market, particularly when there are few IPOs taking place. We have, in effect, a species sampling problem.

an IPO underwriting business during such a lull. Absent independent data on the timing of such corporate decisions, there is little that can be done about this issue.

Notably, the reputation index for other IPO underwriters plays a significant role in determining entry behavior; when the current set of incumbents has a relatively high reputation, fewer new firms enter. More surprisingly, we detect an insignificant but positive effect of the number of players on the entry decisions of firms. This result is not as counterintuitive as it might appear. First, while a larger number of firms in the market will lead to a lower probability of winning a particular IPO, there is a countervailing effect where additional firms can increase the total number of IPOs. Further, the estimates show that entry decisions are strongly driven by the characteristics of the incumbents, which play a large role in determining the probability that a new entrant will obtain a sufficient fraction of the IPO business to justify entry. Still, the positive relationship between the number of firms in the market and the new entry decisions does suggest that an unobserved variable may be influencing the entry variable; thus, if possible, our model should be extended to allow for persistent unobserved heterogeneity as in Arcidiacono and Miller [2011].

Exit hazards depend on the same variables as entry hazards but can also be influenced by the reputation of the firm itself, as this variable is now observable to the firm. Exits occur more frequently when the number of players is higher, when the economy is in a recession, and, perhaps surprisingly, when there is greater venture capital activity. Higher reputation firms are less likely to exit, while the effect of other players reputation has a surprising negative, though insignificant, effect when there are more high reputation underwriters. More mid-reputation underwriters relative to low reputation underwriters does increase the exit hazard.

6 Structural Estimates – A – HIGHLY PRELIMINARY AND SUBJECT TO CHANGE

We seek to identify entry costs and scrap values, along with the variance parameter on the choice specific error term. Our primary question is whether the entry and exit behavior of IPO underwriters during our sample period can be rationalized with reasonable parameter values for these quantities. Our answer is effectively no. Specifically, we find that parameter estimates that best explain entry and exit behavior are associated with a speculative entry model; the magnitude of the cost and scrap value parameters, along with the variance of the choice specific error term, are such that the anticipated flow payoff from engaging in IPOs is effectively irrelevant to entry and exit decisions. Table 10 presents the estimates. For these estimates, entry opportunities are assumed to arrive on $\frac{1}{4}$ of IPOs, and each incumbent underwriter has, on average, one opportunity to exit per quarter. The discount rate is set to %20; the level of the discount rate does not appreciably affect the qualitative analysis.

Table 10: Structural Parameters

Structural Parameter Estimates			
	α=0.25$	α=0.5$	α=0.75$
κ_{exit} (scrap value)	\$216 million		
κ_{entry} (entry cost)	\$4.09 million		
σ_{exit} (exit error term)	\$675 million		
σ_{entry} (entry error term)	\$717 million		

These parameters should be interpreted with care. In the region represented by the parameters presented, the payoff from IPOs is almost irrelevant, and as such the variance of the choice specific error terms and the scrap and entry cost values are not separately identified. Scaling up, say, κ_{exit} and σ_{exit} by the same rate yields almost identical objective function values. This lack of identification is not a result of the selection of the initial values for the optimization routine; starting values were selected in the region where the two quantities are separately identified, and where the probabilities implied by the starting values match approximately the empirical probabilities of entry and exit

At best, the ratio of κ and σ is identified. These parameters should be interpreted as indicating that entry and exit behavior is not closely related to the expected profitability of the IPO underwriting process. This conclusion follows from the fact that the variance of the choice specific error terms are high, and the magnitude of the scrap value is sufficiently large to make the contribution

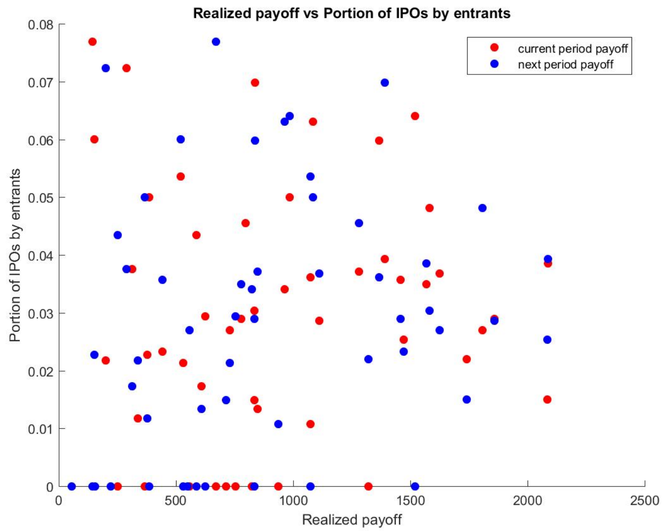

Figure 1: Payoffs vs. Entry

to profits of the IPOs small.

Figure 1 provides some evidence to support this interpretation of the estimates. This scatterplot has on the x-axis the fee revenue raised in each 6 month period in our data, while the y-axis gives the fraction of IPOs in that 6 month period that are completed by a new entrant (with blue dots representing lagged entry). There is a best a weak relationship between these quantities, suggesting that entry decisions are not strongly influenced by the current or expected state of the IPO market. Instead, greater entry during periods with high IPO activity is driven by the greater number of opportunities to enter the market.

7 Conclusion

Our analysis of the industrial organization of the IPO underwriting business can illuminate some of the more puzzling aspects of this important market. Our structural estimates do not immediately suggest that barriers to entry in the IPO market are high. Underwriters, however, do not appear to respond strongly to the profitability of the market, and as such Markov perfect equilibrium dynamics appear to do a poor job of explaining behavior in the industry. Entry and exit may instead arise from firms exploiting idiosyncratic opportunities that arise to take particular firms public. This conclusion is somewhat supported by the short stay of many entrants into the IPO market, despite the apparent profitability of being in the market. On a related point, our reduced form pre-estimates show that it is difficult for new firms to climb the IPO underwriting market hierarchy in a way that would allow a new firm to obtain a significant market share. Our analysis is hopefully a small step toward better understanding the state of competition in the market for the important service of taking firms public.

These results and this interpretation highlight the importance of careful structural modeling of the IPO underwriting industry. Conventional reduced form measures of competition, such as entry frequency and the Herfindahl index do not necessarily reflect the true nature of competition in the market. In particular, the heterogeneity in market share and behavior of entrants versus long established incumbent firms likely plays an important role in the extent to which underwriting firms can exert market power. Work to extend the analysis to more directly model and address this heterogeneity is clearly warranted.

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