Reducing Asymmetric Information in Venture Capital Backed IPOs

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Abstract

Purpose – The purpose of this paper is to model asymmetric information and study the profitability of venture capital (VC) backed initial public offerings (IPOs). Our mixtures approach endogenously separates IPOs into differentiated groups based on their returns' determinants. We also analyze the factors that affect the probability that IPOs belong to a specific group.

Design/methodology/approach – We propose a new method to model asymmetric information between investors and firms in VC backed IPOs. Our approach allows us to identify differentiated companies under incomplete information. We use a sample of 2,404 U.S. firms from 1980 through 2012 to estimate our mixture model via maximum likelihood.

Findings – We find strong evidence that companies can be separated into two groups based on how IPO returns are determined. For companies in the first group the results are similar to previous studies. For companies in the second group we find that profitability is mainly affected by the reputation of the seed VC and capital expenditures. Tangible assets and age help explain group affiliation. We also motivate our findings for a continuum of heterogeneous IPO groups.

Practical implications – The proposed mixture approach helps decrease asymmetric information for investors, regulators, and companies.

Originality/value – Our mixture methods help decrease asymmetric information between investors and firms improving the probability of making profitable investments. Separating between groups of IPOs is crucial because different determinants of an IPO operating performance can potentially have opposite effects for different groups.

Keywords – Venture Capital, Mixture Model, Initial Public Offerings

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1. Introduction

There is a significant amount of interest in newly issued stocks. The underpricing of Initial Public Offerings (IPOs) has been well documented as well as their long run underperformance. For the investor, it would certainly be profitable to obtain as much information as possible on the company that is going public before the IPO date. One category of private companies that have useful information to potential investors is IPOs backed by venture capitalists (VCs). Knowing a company's funding VC can be instrumental in making a profitable investment.

In conjunction with analyzing the firm's information contained in the documents that the U.S. Securities and Exchange Commission (SEC) requires prior to an IPO, such as the S-1, we propose a new methodology to reduce existing asymmetric information between firms and investors. We study the profitability of venture capital backed IPOs where IPOs are endogenously separated into differentiated groups based on how their returns are determined. Moreover we also analyze the determinants of the probability that IPOs belongs to a specific group. Identifying differentiated companies that will go public can help investors determine the usefulness and impact that public information has on profitability. We use variables that have been previously analyzed in the VC literature (Gompers, 1995; Tian, 2011) to categorize VC backed IPOs. The mixture methods we propose allow us to identify differentiated companies even under incomplete information on their characteristics.

Our proposed methods are a good fit to the venture capitalist industry given the existence of asymmetric information between the entrepreneur and the financier. The venture capitalist only has access to a limited number of observable characteristics that will have a marginal impact on the variables that define the profitability of a company. Furthermore, for other investors that want to partake in the IPO, the investment selection becomes easier. After the investor identifies the group affiliation of each IPO, he can then rely on the reputation of the VC to decide in which IPO to invest. If the investor understands that a reputable VC cherry picks the companies and provides managerial and consulting know how, then by relying on the quality of the VC the investor can participate in an IPO with a higher probability of success.

The mixture methods we employ work in the presence of incomplete information and allow separating companies based on the role of their profitability determinants. The separation is based on the VCs capabilities in scrutinizing private information. If a VC is skeptical, then a company will receive more capital rounds than a company that is perceived as promising. Because more capital rounds translate into a less profitable long term performance, it is in the interest of investors to estimate the unobserved characteristics of the company prior to investing in them.

One key benefit of using our proposed mixture specification is that we can model unobserved heterogeneity of VC backed IPOs. Our approach endogenously separates the companies into groups based on limited information about the company. Following the previous literature (Gompers, 1995; Tian, 2011), we compute industry averages based on tangibility of assets, research and development, and market to book value of equity. We find that the ratio of property, plant and equipment to total assets is the main indicator that determines the group affiliation of each company. This separation is crucial because variables that were previously considered as determinants of an IPO operating performance can potentially have opposite effects once heterogeneity across groups is accounted for.

The maximum likelihood estimates of our model find strong evidence supporting the existence of differentiated groups of companies. We find that the results for type-A companies are similar to previous studies, i.e., capital rounds have a negative effect on profitability. Moreover, syndication and market value at IPO also have negative effects on Return on Assets (ROA). The factors that have a positive effect on performance are the length of the financing process prior to the IPO, the reputation of the seed VC, and the ratio of capital expenditures to assets. For type-B companies we find that profitability is mostly affected by the reputation of the seed VC and capital expenditures. The reputation of the VC is positively associated to ROA with a marginal effect on ROA that is about three times the magnitude estimated for type-A companies. Interestingly, the ratio of capital expenditures to assets operates in the opposite direction for different company types and its magnitude is about ten times larger for type-B. This ratio of capital expenditures has been rarely analyzed in previous literature because it was found to be either not statistically significant or with a relatively small marginal effect on ROA. However, our results suggest that capital expenditures have a highly statistically significant effect on returns of the VC backed IPOs. We argue that previous literature that failed to model differentiated groups of companies and pooled all companies into a single group missed the significance of the effect.

For the investor interested in IPOs, there is a high degree of risk given the lack of historical data on these companies. However, our proposed methods give evidence that for VC backed IPOs there is a group of companies that will be strongly and positively influenced by the reputation of the seed VC. For this same group, a high ratio of capital expenditures to total assets on the year of the IPO can decrease the operating performance. The seed VC is information available to all investors through the S-1 form and the reputation of the seed VC can be determined through several measures. Our definition of VC reputation comes from Nahata (2008) that looks at the participation of the VC on the IPO market by computing the ratio of the VC investments to the total amount of VC backed IPOs in a particular year.

The paper is organized as follows. Section 2 provides an overview of venture capital and IPOs. Section 3 describes the data while section 4 explains the empirical approach. Section 5 presents and discusses the results. Section 6 concludes.

2. Discussion of the Interaction between Venture Capital and IPOs

A key element for venture capitalists is the IPO and one of the most studied elements in IPOs has been its underpricing. Ibbotson (1975), Ritter (1987), and Loughran and Ritter (2004) have documented IPO underpricing in the United States. After the initial euphoria that results from the underpricing discount, these investments have long run average returns (Boyer, 2004; Loughran and Ritter, 1995). Long term stockholders should also be concerned with the post-issue operating performance. Jain and Kini (1994) document a decline in operating return on assets despite an increase in sales and capital expenditures. Jain and Kini (1995) compare the operating performance of VC backed IPOs to non VC IPOs. They find that VC backed IPOs perform better than the remaining IPOs in terms of operating returns on assets. They argue that these results are due to better monitoring by the VC before and after the IPO.

The behavior of the VC is designed not only to reduce the adverse selection problem but it is also motivated to improve its reputation on the market. Nahata (2008) shows that VCs with a strong reputation have a positive effect on a company's asset productivity at their IPOs. Krishnan, Ivanov, Masulis, and Singh (2011) find similar effects on the long term performance.

Sørensen (2007) states that experienced VCs are better at sorting promising entrepreneurs and their advising further enhances the profitability of the entrepreneur. If more experienced VCs can select the most promising companies, then the performance of these companies strengthens the reputation of the VC regardless of the advising. Endogeneity arises because an experienced VC can judge a company better than a young VC and this is reflected in the company's future profitability. This phenomenon can be observed in our results where one of the two main characteristics that affect a company's performance is the reputation of the seed VC. Other relevant participant in the IPO process is the underwriter. Yip, Su, and Ang (2009) find that the underwriter's reputation has a strong influence in the performance of an IPO. If a VC backed IPO is underwritten by a leading investment bank, investors earn above market returns in the long run. Jones and Swaleheen (2010) find that underwriter's reputation is positively related to short term returns.

VCs allocate capital based on their estimation of an entrepreneur's future profitability. These capital allocation decisions are made under uncertainty and with limited information on the characteristics of the company. When looking at the VCs decisions to invest we have that, for example, based on a survey by

Kaplan and Strömberg (2004), management quality is cited by 60% of the respondents, good performance by 27%, large and growing markets by 69%, and competitiveness and likelihood of customer adoption by 30%. This information is not observed and it is still largely uncertain during the first year after the IPO. We expect our mixtures approach to capture part of this information.

Our approach to analyze VC backed IPOs is new as we exploit recent developments in mixture models (see, e.g., Gan and Hernandez, 2013). Simpler mixture structures were used in Lee and Porter (1984) to separate firms into cooperating and non-cooperating with a railroad cartel during the 1880s. Gan and Mosquera (2008) study credit card consumers and estimate the probability that consumers belong to a group that is more credit worthy. In the insurance industry companies are concerned with the pricing of policies based on individuals' heterogeneous risk preferences. Interestingly, individuals have private information with regards to their own risk that creates a problem of adverse selection to insurance companies. Gan, Huang, and Mayer (2011) use mixtures and divide individuals into two types. One group prefers insurance and is less likely to suffer an accident whereas the other group dislikes insurance and is more likely to experience an accident.

3. Data

Our main source of data comes from the Securities Data Company (SDC) Global New Issues database. We use IPOs backed by venture capital firms that became public between January 1, 1980 and August 1, 2012. We exclude foreign issues, IPOs with an offer price less than $5, utilities (SIC code between 4900 and 4999), finance (SIC code between 6000 and 6999), and spin-offs. We also remove firms with missing venture capital information or round information. Accounting information such as assets, book value of equity, research and development, net income, capital expenditures, and property, plant and equipment is from Compustat. Market value information on the IPO date is from CRSP and the founding date is from Jay Ritter's database (http://bear.cba.ufl.edu/ritter/ipodata.htm). The final sample has 2,404 IPOs.

We are concerned with understanding what variables affect the profitability of firms. The main dependent variable is Return on Assets (ROA) measured as net income including extraordinary items divided by total assets on the year of the IPO. For robustness, we also compute Returns on Equity (ROE) which equals net income including extraordinary items divided by total book value of equity. Additional variables in the model include the number of capital rounds ($Rounds$) that the entrepreneur receives before going public and the number of venture capitalists (VCs) that participate in the IPO process. Moreover, $Incubation$ indicates the number of years between the year when the company receives the first capital round until the year of the IPO. The ratio $Capex/Assets$ equals the company's capital expenditures divided by its total assets on the year of the IPO. Following Nahata (2008)'s measure for VC reputation ($VC\ Cap$), we construct a measure of the rating of the VC. That is, we compute the capitalization share of the VC as the market value of all companies taken public by the seed VC from 1980 until the year of the first round and then divide this by the aggregate market value of all VC backed IPOs for the same period. If the VC had no IPOs on the year of the first capital round, we use the closest aggregate IPO value within a 3 year window. If there are still no IPOs backed by the VC in this window, we use the average VC capitalization share during the year of the first round. Finally, if there is more than one seed VC, we keep the highest capitalization share. We also use Market Value (MV) defined as the closing price times the number of shares outstanding on the day of the IPO.

Additional variables include the number of years between the founding year and the year of the first venture capital round ($Year1Round$) and the amount of money given in the first round ($First\ Money$). We also include annual industry average ratios for three variables. The average industry market-to-book ratio ($Industry\ MTB$) measured as the market value of equity divided by book value of equity, the average industry research and development to total assets ($Industry\ R\&D$), and the average ratio of property, plant and equipment to total assets ($Industry\ PPE$). We follow Gompers (1995)'s methodology to obtain the industry ratios. That is, we compute the mean average industry ratio across all years when venture capital rounds take place. For each ratio we compute the average of all companies in Compustat for that particular year with the same four digit SIC. If there are not at least 4 companies with the same 4 digit code we look at companies with the same 3 digit and even 2 digit SIC.

Table 1 presents the summary statistics. The mean ROA and ROE tell a similar story of VC backed IPOs that have a negative profitability on the first year. However, for both profitability measures the standard deviation is approximately three times the mean. The range of observations is even wider for ROA where the minimum value is -7.658 and the maximum value is 0.584. For ROE, the range is only 1.911 going from a minimum of -1.552 to a maximum of 0.359. The number of venture capital rounds before an IPO is 4.879, going from 1 round to 24 rounds. The number of venture capitalists that participate on an IPO is 6.34. The difference between the number of rounds and the number of venture capitalists that participate in an IPO show that the process can be very different for some firms. The incubation process takes an average of 4.46 years and its standard deviation is 3.53. Our sample also shows that there are 10 companies that spent more than 20 years in the process. The measure of VC reputation suggested by Nahata (2008) is the VC capitalization ratio and its standard deviation is almost twice the average. The minimum and the maximum indicate a wide variety of venture capitalist firms trying to take companies public. The market value of firms also shows a wide spectrum of firms going public. The mean market value of an IPO is more than $400 million and its standard deviation is almost three times larger. Capital expenditures show the amount invested in improving or acquiring tangible assets which serves to ameliorate the asymmetry of information between the entrepreneur and the financier. This is because the financier can keep the physical assets in the case of liquidation. The average capital expenditures over assets is .074 with a standard deviation barely above this level.

[Table 1, here]

The mean of $Year1Round$ indicates that there is an average of 4.86 years between founding and the first round of VC capital. The range is 113 years, which tells us that some companies have acquired significant reputation (as measured in years) to decrease the information asymmetry but some VCs may invest in premature companies where the asymmetry can be very large. $First\ Money$ equals the amount of money received at the first round. There is also a very wide range of values for these companies. $Industry\ MTB$ is the average market to book value of equity. Some companies have a relatively low book value which creates a relatively wide range for this variable. We also observe in the sample that for 70 companies the market value is ten times larger than its book value of equity. The average industry research and development expense has an impact on the number of capital rounds as shown by Gompers (1995). The more research and development expense in a given industry, the greater the number of rounds. The standard deviation shows the wide range between ratios. The last indicator variable is the industry property, plant and equipment. This ratio also measures the tangibility of assets, Gompers (1995) and Tian (2011) have previously shown that tangibility decreases the number of capital rounds prior to an IPO. The average ratio is 0.295 and the standard deviation is 0.115. The range is far narrower than the range of the previous two industry measures.

4. Empirical Model

The empirical approach is initially aimed at understanding the variables that affect profitability of firms. Our approach is new in the sense that it allows for differentiated effects of firms' profitability determinants depending on the type of firm. Moreover, firm type is unobserved and filtered from the data. Our dependent variable that captures profitability will be either ROA or ROE. For the set of independent variables X we have the number of capital rounds ($Round$), number of venture capitalists (VCs), the years between first round and IPO ($Incubation$), market value (MV), $VC\ Cap$ and

$Capex/Assets$ as described in detail in the data section. To model unobserved firm types in the determination of profitability we jointly estimate the following equations:

$$ROA_i = \begin{cases} X\beta_A + \varepsilon_{i,A} & \text{if } \delta = A \\ X\beta_B + \varepsilon_{i,B} & \text{if } \delta = B \end{cases} \tag{1}$$

where i denotes the firm, X is the matrix of regressors and $\varepsilon_{i,\delta}$ for $\delta = A, B$ is the error term. Notice that equations (1) capture differentiated marginal effects β_A or β_B of each of the elements of X on ROA_i depending on whether firms are of type-A or type-B.

We estimate equations (1) via maximum likelihood under the assumptions that the each of the error terms follow a normal distribution, i.e., $\varepsilon_{i,\delta} \sim N(0, \sigma^2_{\varepsilon,\delta})$. Then we can write the log-likelihood for the ith firm as:

$$\ln l_i = \ln\left[\frac{q_i}{\sigma_{\varepsilon,A}\sqrt{2\pi}}\exp\left(-\frac{\varepsilon^2_{i,A}}{2\sigma^2_{\varepsilon,A}}\right) + \frac{(1-q_i)}{\sigma_{\varepsilon,B}\sqrt{2\pi}}\exp\left(-\frac{\varepsilon^2_{i,B}}{2\sigma^2_{\varepsilon,B}}\right)\right] \tag{2}$$

where the mixing parameter q_i can be interpreted as the probability that firm i is in a regime dominated by type-A firms.

We can additionally model this probability to be a function of observable factors:

$$q_i = \text{Prob}(\delta = A) = F(Z\alpha) \tag{3}$$

where Z is the matrix of observable factors that includes the years between founding and the first round of VC capital ($Year1Round$), the amount of money received in the first round ($First\ Money$), and industry averages of the market-to-book ratio ($Industry\ MTB$), research and development ($Industry\ R\&D$), and the ratio of property, plant and equipment to total assets ($Industry\ PPE$). We expect the different variables in Z to help us identify the firm type. α is the vector of coefficients to be estimated and $F(\cdot)$ is a function that we approximate using the logistic cumulative distribution function.

Our mixture model of equations (1) and (3) is similar in flexibility to Gan and Hernandez (2013) who use mixtures to study hotels' spatial competition where collusive regimes are unobserved. Their model jointly estimates the price and occupancy rates, while in our setting we estimate a single profitability equation. Asymmetric information occurs in both models as hotels in Gan and Hernandez (2013) know more than consumers about when collusion takes place. Likewise in our setting investors have less information than firms during an IPO.[1]

5. Results

5.1 Pooled Results

As a first approach in the estimation of equation (1) we pool across all observations and assume $\beta_A = \beta_B$. The maximum likelihood estimates are reported in Table 2. Columns 1 through 3 have ROA as the dependent variable, while profitability is captured by ROE in columns 4 through 6. Moreover, different columns provide different specifications for the matrix of controls X. Across all columns the effect of $Rounds$ on profitability is negative and highly statistically significant. This is consistent with previous work on IPOs. In particular, Jain and Kini (1995) also find a negative effects for VC backed IPOs. Moreover, Tian (2011) shows that the number of rounds has a negative effect on ROA.[2] This result provides some evidence that rationing capital is hampering the profitability of companies. Even though VCs need to monitor companies in order to minimize any potential pursuance of private benefits by the entrepreneurs, the costs of rationing capital are larger than the benefits of monitoring. Therefore, entrepreneurs are either focusing mostly on short term goals to guarantee the next round of capital or simply they do not have enough resources to focus on long term projects that will increase the profitability of the company.

Consistent across all specifications that include the number of venture capitalists that participate in an IPO, we have that VCs also has a negative and statistically significant effect on profitability. While the effect is smaller in magnitude and marginally significant in columns 2 and 5, once we include our full set of regressors in X it is significant at the 1 percent level. This negative effect of syndication can be a signal that the seed capitalists only allow the participation of other VCs when there is a high degree of uncertainty about the company. Also, when several VCs fund a company they may be more interested in future growth rather than near profitability. This is consistent with Tian (2011) who finds a negative effect of syndication on the first year's ROA. However, Tian (2012) also finds that the effect of syndication on the average ROA after four years of an IPO is positive.

From columns 3 and 6 we find that $Incubation$ has a positive and highly significant effect on ROA and ROE, which is in line with the findings of Tian (2011). He finds that the age of the firm also has a positive effect on ROA. Our $Incubation$ estimates shows that the longer the time a company spends

[1] While our methods are applied to VC, they can easily be extended to any IPO.

[2] In addition, Jain and Kini (1994) indicate that the profitability of an IPO is negative in the short-term, which is consistent with the mean values of ROA and ROE in Table 1.

maturing, the more profitable it will become. We can explain this positive effect as a result from decreasing asymmetric information. It is reasonable to believe that as time passes by, information asymmetry between the venture capitalist and the company decreases. These companies were financed by seed VC firms that had little pressure to go public prematurely in order to raise capital from their partners for future projects. Through this patient financing process, companies were taken public after achieving a certain level of success. Therefore, we should expect higher ROA from a longer incubation period because these companies were probably already profitable prior to the IPO date.

[Table 2, here]

Turning to $VC\ cap$ we find that a positive and highly statistically significant coefficient. When comparing the point estimates from columns 3 and 6 we see that the magnitude of the effect of $VC\ cap$ is larger when ROE is the dependent variable. In line with our results Nahata (2008) also finds that the reputation of the lead VC has a positive effect on the sales to book asset of the VC backed firm one year prior to the IPO and an even stronger effect on the year of the IPO.

5. 2 Allowing for Differentiated Effects

We now turn to the estimation of equations (1) when allowing for a differentiated effect from the variables in X on profitability. The maximum likelihood estimates using equation 2 are reported in Table 3. We initially need to assess whether the two-type model represents an improvement from the pooled model. To do this we use the likelihood ratio test under the null that the pooled model represents a better fit. We find that the likelihood ratio statistic for ROA is 1792.02 while it is 1469.6 for ROE. Both have an associated p-value of zero showing strong evidence against the null. Hence, we conclude that the two-type model represents an improvement in terms of model fit. Moreover, we also test if there are additional types using the null that the two-type model has a better fit when compared to a model with three-types. The likelihood ratio statistics for ROA and ROE are 8.984 and 6.976 respectively with the corresponding p-values being 0.254 and 0.431. We interpret this as strong evidence supporting the two-type model.

Table 3 reports two separate columns for each model because the estimation endogenously separates each of the observations into one of two different groups. We have that 88.7% of the firms in the sample can be considered type-A firms as the predicted probability of being type-A is greater than 0.5 (i.e., q_i > 0.5). In terms of sign and magnitude the point estimates on $Rounds$, VCs, $Incubation$, $VC\ Cap$, and MV

for type-A firms are consistent and very close to the pooled model. On the other hand the estimates show that group B firms are heavily influenced by the seed VC capitalization ($VC\ Cap$) with the magnitude of the estimates on $VC\ Cap$ being about three times larger for type-B firms. This difference shows that the reputation of the VC can have a huge impact on the profitability of an IPO. This could be because the seed VC can provide expertise to improve the operations of a company or that a VC with a strong reputation cherry-picks which company to finance amongst the several entrepreneurs looking for venture capital funds.

[Table 3, here]

Similar differentiated effects hold for $Capex/Assets$. Interestingly for group A firms, the sign is positive and consistent with the pooled model. However while statistically significant, for group B firms the effect is negative. The negative effect of $Capex/Assets$ on profitability for type-B firms (with a point estimate of -0.881 for model 1) in the presence of a reputable VC can be interpreted as a long term investment that decreases profitability on the year of the IPO. For this group it would helpful to investors if they know the fixed assets required to operate in the industry and the seed VC. These two variables have a strong effect on the profitability of the company. A feasible explanation is that group B companies have not made enough capital expenditures prior to the IPO but after the IPO, they have the necessary capital to make these investments but short term profitability decreases. This is consistent with post IPO monitoring by VCs that are concerned with the growth prospects of the company. The ratio of capital expenditures to assets for group A operates in the opposite direction. This suggests that when the seed VC is not as relevant, then other variables will have a greater effect. If the VC is not as strong as in group B, then capital rounds, syndication, and market value have a negative effect. Incubation and capital expenditures have positive and significant coefficients, which can help overcome a weak VC.

On the estimates for $Rounds$ and VCs have a differentiated effect on profitability for different VC backed IPOs. We argue that for group B, rounds do not have costs on profitability because a reputable VC has more experience in monitoring a company while limiting the costs of capital rationing. In terms of syndication, a VC with more experience may invite other VCs to participate in the IPO to improve the operations of the company but the negative effects on profitability disappear. Since our measure of VC reputation is based on long term market capitalization, it would be detrimental for the seed VC to invite other VCs only when the profitability of the company is uncertain. If the seed VC only invited other VCs to invest if it is unsure about the company, it would be a signal of the weakness of the company. The differentiated effect we find on $Rounds$ and VCs when comparing groups A and B from both models 1 and 2 provide evidence that type-B companies depend more on a reputable VC. This type of VCs do not need to grandstand and have less incentive to damage their reputation by inviting other VCs to invest only when there is a low probability of success.

5. 3 Explaining the Differentiated Effects

The estimates in Table 3 assume that the probability that a firm belongs to a particular group is fixed. We now relax this assumption and following equation 3 we allow the probability to depend on a particular set of observables Z. As an initial approach the set of variables in Z include the amount of money the VC received in the first year ($First\ Money$) and the number of year prior to the first round of money ($Year1Round$). Previous literature on VC does not consider these variables as right-hand-side regressors in equation 1, but rather as variables that affect the number of capital rounds (Tian, 2011). As such we expect these variables in Z to be correlated with information about the company that is available to investors and that is correlated with unobservables that determine the type of VC. The maximum likelihood estimates are presented in Table 4.

[Table 4, here]

Consistent across both models in Table 4, the marginal effect of the variables in X on profitability are very close to the results in Table 3. For the estimates of α in equation 3 we observe that both specifications find that $First\ Money$ is not statistically significant. Moreover, $Year1Round$ is statistically significant at at least 1% level. This positive estimate indicates that the longer the firm waits for the first round of funding by a VC, the more likely it is to be a type-A firm. For example, firms that wait very little for the first round of funding are more likely to be type-B, hence the number of rounds ($Rounds$) is more likely to have no statistically significant effect on profitability.

[Table 5, here]

Table 5 models Z by additionally including three industry averages calculated previously in Gompers (1995) and Tian (2011). Consistent across both of the models in the table, the average market value to book value of equity has no statistically significant effect. Moreover research and development also is not statistically significant. Only the industry average ratio of property, plant and equipment to assets is statistically significant and has a positive effect on the probability of being type-A. This positive effect means that if the company belongs to an industry with particularly large values for property, plant and equipment (relative to assets) this company is more likely to be in group A. Likewise, $Rounds$ and VCs are more likely to have no effect on profitability for companies that come from industries with lower levels of expenditures on property, plant and equipment. A firm from group B may suffer short term profitability in the IPO year from an increase in capital expenditures. However, since it belongs to an industry with low tangible assets it might not be necessary to spend in property, plant, and equipment. Also supporting the statistical significance of $Industry\ PPE$ on the probability equation, we have that the tangibility of assets decreases the information asymmetries because the venture capitalists can keep the fixed assets in case of liquidation. The amount of fixed assets decrease the number of venture capital rounds (Gompers, 1995; Tian, 2011). In addition, an increase in capital rounds can decrease the profitability of a company by limiting the amount of capital available. If information asymmetries are too high, rounds can help monitor the entrepreneur and limit him from pursuing private benefits. Therefore, if there is a high amount of tangibility of assets, then rounds have more costs than benefits because there are less deleterious effects from information asymmetry. Finally, $Year1Round$ and $FirstMoney$ have qualitatively the same effects as in Table 4. For the differentiated marginal effect of X on profitability across groups, the estimates in Table 5 appear very close to the estimates in Tables 3 and 4.

5.4 Continuous Types

The estimation of equations 1 and 3 along with the interpretation of the results has focused on the existence of two types of companies. This interpretation is based on an implicit threshold of 0.5 in the probability of being of a particular type (e.g., being type-A). Notice that the probability q_i of being of a particular type is a continuum that goes from zero to one. An alternative interpretation of the results in Tables 3 through 5 is that there exists a continuum of types that fall in between group A and group B. That is, for each company in the sample the profitability determinants X will be a linear combination of the marginal effects of groups A and B. More formally, the marginal effects of X on profitability for firm i are given by $\beta_i = q_i\beta_A + (1 - q_i)\beta_B$. The probability q_i is specific to the company and it is determined by the fitted values from equation 3 for each firm given its firm characteristics as captured in Z. Because different firms are expected to have different values for q_i, hence our alternative interpretation of a continuum of types.

Figure 1 shows the histogram of the fitted values $\hat{q}_i$ for the companies in the sample using the specification of model 1 in Table 5. As before, these fitted values are interpreted as the probability that firm i is in group A. If we set a threshold of 0.5 (i.e., $\hat{q}_i$ > 0.5), we have that 77.7% of the firms belong to group A. Figure 1 illustrates how most of the firms are closer to group A, meaning that the marginal effects on profitability put a relatively heavier weight on the estimates of group A. If investors are not aware of the observables in Z and given that it is more likely that a firm will belong to group A, then consistent with the estimates of the pooled model investors will expect a positive effect on profitability from $Capex/Assets$ and to a lower extent the reputation of the seed VC. The length of the incubation should also have a positive effect on profitability. $Rounds$, VCs, and MV will most likely decrease the profitability of the IPO.

[Figure 1, here]

However, if an investor proceeds to use the observables in Z and infers on the type of firm (A or B or a linear combination of A and B) then the investor can have a more accurate assessment of the IPOs and the determinants of its profitability. If the investor can identify the firms that belong to group B, then he will know that the reputation of the seed VC will have a high positive effect on profitability and that the ratio of capital expenditures to assets will have the opposite effect on ROA. On the other hand, if an investor fails to use the information in Z and uses the pooled model for investment decisions, the investor may not be able to accurately identify a group B company. Hence investment decisions based on $Rounds$ or VCs will be suboptimal.

5.5 Implications

Our empirical results have implications at various levels. Using data from the Securities and Exchange Commission investors can use the estimates of equations (1) to predict first year profitability of VC backed IPOs to guide their investment decisions. Given the high demand for IPOs by institutional investors, it is quite useful to distinguish indicators of a firm's future profitability. Furthermore if other investors are hesitant about investing on IPOs, our mixture approach should be helpful in reducing existing asymmetric information. Therefore, a wider and more diverse pool of investors should decrease the cost of capital for newly public companies. Other avenue for acquiring IPOs is through Exchange Traded Funds (ETF) such as the Renaissance Capital IPO. If the average investor can estimate with more certainty the profitability of a company, then there should be more investors willing to acquire ETFs.

The same estimates can also be used by investment banks to guide IPO initial pricing decisions and by firms themselves to decrease underpricing. If investment banks purposely underprice an IPO to decrease the probability of litigation after the IPO, they will be more comfortable providing a more accurate price if they can better determine the profitability of a stock after the IPO. If an established VC can limit the underpricing problem and enhance the profitability of the firm, then investors will benefit from a lower volatility in the price of the stock after the IPO. The new company will have a lower litigation risk if the investor does not experience a sharp wealth decline. The litigation procedures after Facebook's IPO are a good example of the information asymmetry between the firm and investors. Shareholders argue that Facebook and Morgan Stanley hid information about future growth prospects. If investors have better indicators of a firm's future profitability, then there will be less information asymmetries and lower litigation risk not only for the company but also for the underwriter. Additional cases where shareholders believe that the company tried to influence investors are Google and Salesforce.com in 2004. In both IPOs managers violated the going public process and provided information that was not included in the S-1. Because our methodology identifies the factors that enhance the performance of the IPO, the firm will be less susceptible to frivolous lawsuits if shareholders identify these factors and invest accordingly. If the SEC wants to avoid litigation after the IPO, it can include more information in the S-1 that can help investors determine what factors will have a greater effect on a VC backed firm.

If a reputable VC continues to monitor the performance of the firm after the IPO, then there will be lower probability of a decline in shareholders wealth due to mismanagement. To decrease litigation risk, the SEC can encourage investing in firms backed by reputable VCs or encourage new VCs to continue monitoring the firm even after the IPO. If investors identify the firms that increase their profitability due to having the financial support of a reputable VC, then the demand for reputable VC backed IPOs should increase. Less reputable VCs will then have more pressure to do IPOs with mature firms and to continue monitoring them after the IPO.

In addition to the typical prediction of profitability, the benefit in the estimation of the system of equations (1) and (3) is that profitability determinants change by the type of firm and that firm type can also be predicted. The implications regarding reducing asymmetric information can be generalized to other markets as the use of mixture methods can serve to help identify different market equilibria that correspond to differentiated types of market participants.[3] Reducing asymmetric information in markets can also help mitigate problems associated with asymmetric information (i.e., adverse selection and moral hazard).

[3] The mixture methods employed are very flexible and contingent on obtaining appropriate data they can also be applied to other markets where asymmetric information exists.

6. Conclusions

This paper proposes new methods to model multiple equilibria and heterogeneous VC backed companies to assess the determinants of profitability (i.e., ROA and ROE) and reduce asymmetric information. In addition, our methods account for potential unobservable factors that separate IPOs into differentiated groups. Differentiation of firms is determined endogenously by the data with different groups having differentiated effects of the factors that affect first year profitability. After separating the VC backed IPOs into groups, we observe that the reputation of the seed venture capitalist is an important factor affecting the profitability of a small group of firms (group B). For this same group, an increase in capital expenditures decreases the return on assets. On the other hand for a larger group of firms (group A), profitability is also influenced by the reputation of the seed venture capitalist but its effect is much smaller. Interestingly, for group B companies capital expenditures operate in the opposite direction. For both groups of companies a longer period between the first round of VC capital and the IPO has a positive impact on profitability (as captured by ROA).

Our approach also models the probability of a firm belonging to a particular group. Our maximum likelihood estimates show that the average tangibility of assets in the industry where the company operates is one key separating factor explaining the differentiated effects on profitability. We also extend the interpretation to a continuum of types that allows us to more accurately capture the heterogeneity across VC backed companies.

The benefit of our proposed methods is that investors have more information to assess the profitability of a company in its IPO year. Tian (2011) is mostly concerned with the effects of the interaction between capital rounds and distance on a firm's profitability. However, because his approach involves a pooled regression model, the particular source of unobserved heterogeneity and asymmetric information that we modeled in the IPOs is not taken into account. By incorporating factors that are observable prior to the IPO, the investor can differentiate across otherwise unobserved heterogeneous companies. This should increase the investor's information set and help him evaluate more accurately what variables are key determinants of the profitability of an IPO.

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Table 1. Summary Statistics

	(1)	(2)	(3)	(4)	(5)
Variables	obs	mean	sd	min	max
ROA	2,404	-0.122	0.361	-7.658	0.584
ROE	2,397	-0.171	0.459	-1.552	0.359
$Rounds$	2,404	4.879	3.132	1	24
VCs	2,404	6.340	5.008	1	37
$Incubation$	2,404	4.467	3.536	0	37
$VC\ Cap$	2,404	0.0582	0.100	3.25e-05	0.814
MV	2,404	4.168e+08	1.102e+09	2.058e+06	2.422e+10
$Capex/Assets$	2,387	0.0740	0.0901	-0.00280	0.945
$Year1Round$	2,396	4.862	10.97	0	113
$First\ Money$	2,338	7.949e+09	8.050e+10	1,000,000	3.760e+12
$Industry\ MTB$	2,402	2,868	57,803	0.713	2.161e+06
$Industry\ R\&D$	2,378	24.15	341.6	5.05e-10	14,401
$Industry\ PPE$	2,403	0.295	0.115	0.0433	0.750

Notes: This table provides descriptive statistics of venture capital backed IPOs between 1980 and 2012. ROA is measured as net income including extraordinary items divided by total assets on the year of the IPO, ROE is net income including extraordinary items divided by total book value of equity on the year of the IPO, $Rounds$ is the number of venture capital rounds that the company receives, VCs are the number of venture capitalists that finance a company, $Incubation$ is the number of years between the first capital round and the IPO date, $VC\ Cap$ is the aggregate market value of all firms taken public by the seed VC from 1980 to the year of the first round divided by the aggregate market value of all VC backed IPOs during the same period, MV is the market value at the IPO date, $Capex/Assets$ equals the company's capital expenditures divided by its total assets on the year of the IPO, $Year1Round$ is the number of years between the funding and the year when the first round of VC money was received, $First\ Money$ is the dollar amount received during the first capital round, $Industry\ MTB$ is the average industry market-to-book ratio measured as the market value of equity divided by book value of equity, $Industry\ R\&D$ is the average industry research and development to total assets, and $Industry\ PPE$ is the average ratio of property, plant, and equipment to total assets.

Table 2. Maximum Likelihood Estimates of the Pooled Model

Dependent variable:	ROA			ROE		
Variables in X:	(1)	(2)	(3)	(4)	(5)	(6)
$Rounds$	-0.0119***	-0.00841***	-0.0125***	-0.0179***	-0.0126***	-0.0183***
	(0.00234)	(0.00301)	(0.00314)	(0.00297)	(0.00383)	(0.00396)
VCs		-0.00343*	-0.00653***		-0.00518**	-0.00967***
		(0.00188)	(0.00194)		(0.00240)	(0.00244)
$Incubation$			0.0129***			0.0175***
			(0.00224)			(0.00282)
$VC\ Cap$			0.472***			0.702***
			(0.0753)			(0.0948)
MV			-2.00e-11***			-2.72e-11***
			(6.68e-12)			(8.42e-12)
$Capex/Assets$			-0.156*			-0.341***
			(0.0811)			(0.102)
Constant	-0.0642***	-0.0594***	-0.0855***	-0.0842***	-0.0769***	-0.103***
	(0.0135)	(0.0138)	(0.0167)	(0.0172)	(0.0175)	(0.0210)
σ	-1.025***	-1.026***	-1.043***	-0.787***	-0.788***	-0.813***
	(0.0144)	(0.0144)	(0.0145)	(0.0144)	(0.0144)	(0.0145)
Observations	2,404	2,404	2,387	2,397	2,397	2,380
Log Likelihood	-946.1	-944.4	-897.3	-1515	-1512	-1443

Notes: This table shows MLE estimates of the pooled model. The dependent variable is ROA in columns 1 through 3 and ROE in columns 4 through 6. Figures in parentheses are standard errors. ***, **, * significant at 1%, 5%, and 10% respectively. Our sample includes venture capital backed IPOs between 1980 and 2012. Definitions of all variables are explained in the notes of Table 1.

Table 3. Maximum Likelihood Estimates of the Mixture Model

Dependent variable:	ROA		ROE	
Model:	(1)		(2)	
Variables in X:	Group A	Group B	Group A	Group B
$Rounds$	-0.00968***	-0.00409	-0.0126***	0.00358
	(0.00174)	(0.0163)	(0.00222)	(0.0133)
VCs	-0.00662***	0.00380	-0.00811***	0.00623
	(0.00103)	(0.00961)	(0.00135)	(0.00746)
$Incubation$	0.0108***	-0.00111	0.0136***	0.00167
	(0.00119)	(0.0111)	(0.00157)	(0.0100)
$VC\ Cap$	0.306***	0.926**	0.386***	1.165***
	(0.0379)	(0.416)	(0.0516)	(0.299)
MV	-1.50e-11***	-8.06e-11	-3.59e-11***	1.33e-11
	(3.25e-12)	(5.44e-11)	(6.45e-12)	(1.69e-11)
$Capex/Assets$	0.140***	-0.881**	0.247***	-1.206***
	(0.0423)	(0.378)	(0.0551)	(0.286)
Constant	-0.0153*	-0.530***	0.0264**	-0.866***
	(0.00879)	(0.104)	(0.0117)	(0.101)
σ	-1.877***	-0.478***	-1.652***	-0.693***
	(0.0277)	(0.0419)	(0.0265)	(0.0436)
Observations	2,387		2,380	
Log Likelihood	-1.288		-708.2	

Notes: This table shows MLE estimates of the mixture model. The dependent variable is ROA (model 1) and ROE (model 2). Figures in parentheses are standard errors. ***, **, * significant at 1%, 5%, and 10% respectively. Our sample includes venture capital backed IPOs between 1980 and 2012. Definitions of all variables are explained in the notes of Table 1.

Table 4. Maximum Likelihood Estimates of the Mixture Model

Dependent variable:	ROA		ROE	
Model:	(1)		(2)	
Variables in X:	Group A	Group B	Group A	Group B
$Rounds$	-0.00944***	-0.00146	-0.0123***	-0.00628
	(0.00180)	(0.0132)	(0.00222)	(0.0122)
VCs	-0.00579***	0.00359	-0.00689***	0.00439
	(0.00104)	(0.00782)	(0.00137)	(0.00673)
$Incubation$	0.00981***	0.0132	0.0127***	0.0167*
	(0.00122)	(0.0110)	(0.00157)	(0.00957)
$VC\ Cap$	0.273***	0.912***	0.335***	1.186***
	(0.0380)	(0.345)	(0.0513)	(0.268)
MV	-3.32e-11***	5.65e-12	-7.39e-11***	2.67e-11**
	(6.93e-12)	(1.65e-11)	(1.37e-11)	(1.21e-11)
$Capex/Assets$	0.150***	-0.817**	0.258***	-1.371***
	(0.0423)	(0.330)	(0.0552)	(0.272)
Constant	0.00173	-0.576***	0.0490***	-0.757***
	(0.00941)	(0.0849)	(0.0123)	(0.0842)
σ	-1.964***	-0.546***	-1.723***	-0.678***
	(0.0380)	(0.0421)	(0.0286)	(0.0338)
Variables in Z:				
$Year1Round$	0.105***		0.0887***	
	(0.0205)		(0.0154)	
$First\ Money$	-5.97e-13		-1.66e-12	
	(3.50e-12)		(1.51e-12)	
Constant	1.060***		0.792***	
	(0.134)		(0.107)	
Observations	2,315		2,308	
Log Likelihood	31.01		-640.3	

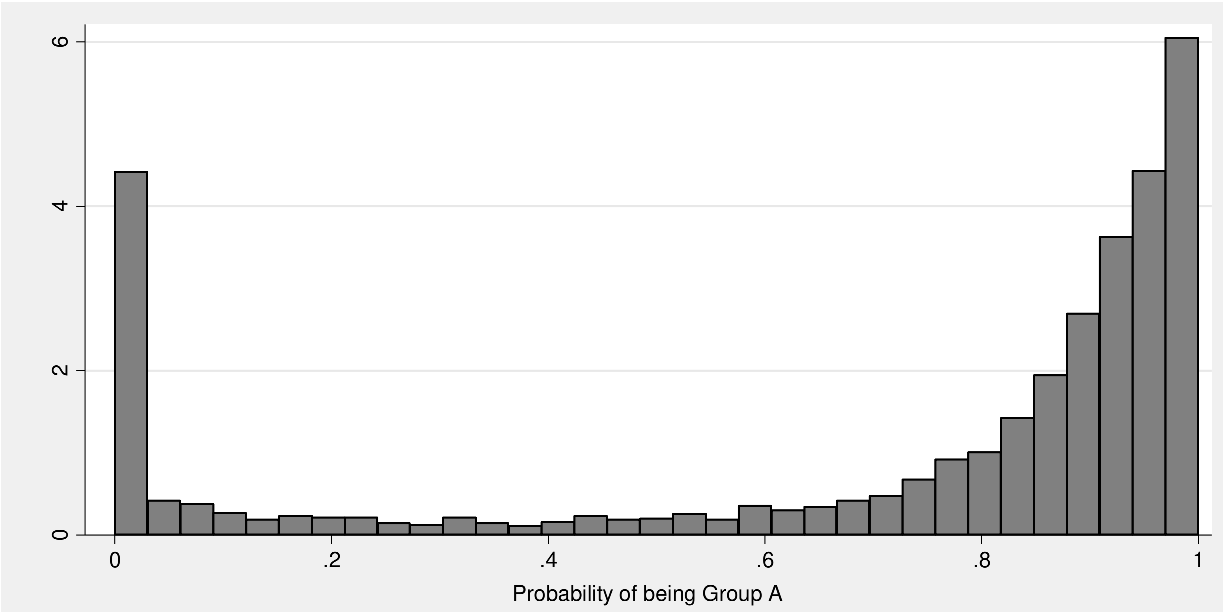
Notes: This table shows MLE estimates of the mixture model. The indicator factors are Year 1 Round and First Money. The dependent variable is ROA in model 1 and ROE in model 2. Figures in parentheses are standard errors. ***, **, * significant at 1%, 5%, and 10% respectively. Our sample includes venture capital backed IPOs between 1980 and 2012. Definitions of all variables are explained in the notes of Table 1.

Table 5. Maximum Likelihood Estimates of the Mixture Model

Dependent variable:	ROA		ROE	
Model:	(1)		(2)	
Variables in X:	Group A	Group B	Group A	Group B
$Rounds$	-0.00705***	-0.00754	-0.0118***	-0.0105
	(0.00166)	(0.00956)	(0.00219)	(0.0111)
VCs	-0.00380***	0.000372	-0.00600***	0.00266
	(0.00102)	(0.00564)	(0.00134)	(0.00616)
$Incubation$	0.00749***	0.0148*	0.0120***	0.0152*
	(0.00117)	(0.00810)	(0.00155)	(0.00881)
$VC\ Cap$	0.193***	0.758***	0.301***	1.123***
	(0.0356)	(0.274)	(0.0494)	(0.265)
MV	-6.32e-11***	1.35e-11	-8.99e-11***	2.84e-11**
	(7.41e-12)	(1.13e-11)	(1.25e-11)	(1.15e-11)
$Capex/Assets$	0.118***	-1.104***	0.227***	-1.693***
	(0.0377)	(0.266)	(0.0546)	(0.263)
Constant	0.0273***	-0.414***	0.0626***	-0.637***
	(0.00887)	(0.0629)	(0.0116)	(0.0738)
σ	-2.152***	-0.674***	-1.769***	-0.689***
	(0.0546)	(0.0377)	(0.0281)	(0.0307)
Variables in Z:				
$Year1Round$	0.118***		0.0942***	
	(0.0185)		(0.0157)	
$First\ Money$	-1.19e-12		-2.04e-12	
	(4.23e-12)		(1.30e-12)	
$Industry\ MTB$	3.24e-06		3.23e-06	
	(3.02e-06)		(3.12e-06)	
$Industry\ R\&D$	-0.000367		-0.000601	
	(0.000472)		(0.000452)	
$Industry\ PPE$	6.978***		5.226***	
	(0.823)		(0.707)	
Constant	-1.391***		-0.829***	
	(0.273)		(0.230)	
Observations	2,315		2,308	
Log Likelihood	31.01		-640.3	

Notes: This table shows MLE estimates of the mixture model. The dependent variable is ROA in model 1 and ROE in model 2. Figures in parentheses are standard errors. ***, **, * significant at 1%, 5%, and 10% respectively. Our sample includes venture capital backed IPOs between 1980 and 2012. Definitions of all variables are explained in the notes of Table 1.

Figure 1. Probability of being in Group A



Notes: Estimated based on Model 1, Table 5.