HIDDEN IN PLAIN SIGHT:
VENTURE GROWTH WITH OR WITHOUT VENTURE CAPITAL

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ABSTRACT

While the study of high-growth firms focuses predominantly on venture-financed startups, the majority of IPOs and acquisitions are achieved without venture capital. This paper uses a predictive analytics approach to shed light on these "missing" growth firms. To do so, we first estimate a (non-causal) model of the likelihood of receiving venture capital within the population of all business registrants, and then use the predictions from that model to estimate the probability of a successful growth outcome (either an IPO or significant acquisition) among the population of firms that did not raise venture capital. We find striking evidence that observables at birth that predict the ability to attract venture capital are also highly predictive of growth within the non-VC sample. For example, firms that do not receive VC funding but that experience a significant growth outcome are much more likely to have received formal intellectual property protection within a year of founding, are less likely to have named the firm after the founders, and more likely to have registered in Delaware. We then use our estimates of 'VC-likelihood' to perform a fine-grained matching between firms that are born with identical observables, but only differ in whether they will receive venture capital or not. This allows us to study the process of selection into VC and to estimate an upper bound on the returns to venture capital: While a naive comparison of the probability of growth between venture-backed and non-venture-backed firms implies nearly a 500X increase in the probability of an exit, after matching, VC-backed firms are only 5 times more likely to grow than comparable, non-VC-funded firms. Our findings highlight that contrary to a case-based literature emphasizing the differences between firms that grow with and without venture capital, our predictive analytics approach on the full population of firms suggests that firms with growth potential – irrespective of future funding source - are much more similar to each other than they are to the overall population of new businesses.

I. INTRODUCTION

The skewed nature of firm growth outcomes is a striking feature of the process through which entrepreneurship influences broader economic performance. From a financial perspective, only a very small fraction of firms (less than 1 in 2000) reaches a successful financial exit in the form of an IPO or successful acquisition. Most of what we know about these growth firms comes from carefully constructed samples of firms funded by venture capitalists and angel investors (Lerner, 1995; Puri and Hellman, 2000; Chemmanur, Nandy, and Krishnan, 2011; Lerner, Schoar, Sokolinski and Wilson, 2015; Puri and Zarutskie, 2012). By following startups from their earliest funding rounds to an exit, this stream of research surfaced the central role professional investors play in enabling and accelerating startup growth. Although VCs only fund a very small number of startups each year (approximately a thousand in the US), they account for a disproportionate share of growth events: Kaplan and Lerner (2010) estimate that venture-backed companies account for an impressive 30% to 70% of "startup" IPOs (1995-2009)[1], and, more recently, Ritter (2016) traces back 37% of startup IPOs to a VC funding event (1980-2015).

Whereas these shares are a testament to the role VCs play in the selection and nurturing of high potential startups, they also indirectly highlight how little we know about the sizable share of firms that achieve growth without ever being associated with a venture capital firm. Of course, given that VC activity is concentrated within a few regions and sectors, it is possible that firms that grow without VC are simply coming from areas and industries that have not yet developed a thriving venture capital ecosystem. Under this hypothesis, we would anticipate that the firms that ultimately growth without venture capital would be in many respects similar at founding to the firms that growth with venture capital, although their growth trajectories could be somewhat different. For example, it is possible that growth without venture capital would be concentrated among firms that are of even higher quality at founding, since a less favorable funding environment – either within a non-hub region or during a VC downturn – would select out many ventures that could succeed if only venture capital were available. In the absence of VC, growth may also take longer to materialize, as firms have to slowly bootstrap their development through alternative sources of capital such as revenues from sales, loans, government grants etc.

[1] Startup IPOs are all IPOs after excluding financial IPOs, blank check companies, re-listings, reverse LBOs, real estate investment trusts (REIT), and special purpose acquisition companies (SPAC).

An alternative hypothesis is that despite regional, industry and economic cycle differences, multiple routes to equity growth exist, and that the broader availability of data on VC-backed firms has skewed researchers' focus towards just one of the possible paths to growth. Conditional on alternative paths to growth actually existing, this raises the question of how they may differ (if at all) from the venture capital one, and what types of firms are more likely to select into one versus the other. The underlying, key welfare question is one of how society allocates capital to novel, high potential ideas and encourages their development from concept to market.

By design, the study of selection into alternative paths to growth requires first defining the full population of firms at risk of growth, and then following their outcomes *independent* of funding source and path chosen. This has prevented previous studies from systematically examining this process, as most research either: a) starts from a selected sample (e.g. the set of firms that raise venture capital, qualify for a government grant, etc.) and then matches it to controls along idiosyncratically chosen dimensions; or b) directly compares VC-funded firms to the general population of firms, the vast majority of which is never really at risk of growing in the first place. Whereas the first approach typically misses firms with growth potential that do not fit the venture capital 'playbook', the second one overestimates the role of VC on growth because it confounds selection and treatment.

The objective of this paper is to characterize the differences between firms that achieve a significant growth outcome with versus without venture capital. To identify the full set of firms with growth potential – irrespective of future funding source – we extend Guzman and Stern's (2015, 2016) predictive analytics approach, and estimate a *'VC-likelihood'* for all incorporated firms based on information that is available at the time of their founding. We then use this estimate to match VC-funded firms to comparable control firms from the non-VC-funded part of the sample. Our empirical approach follows three steps, which we describe in more detail below.

In the first step, we train a model on a random subsample of all incorporated firms[2] to learn as much as possible, using historical data on VC funding events, from the selection process

[2] A practical requirement for any growth-oriented entrepreneur is business registration (as a corporation, partnership, or limited liability company). These public documents allow us to observe a "population" sample of entrepreneurs observed at a similar (and foundational) stage of the entrepreneurial process. Moving beyond simple counts of business registrants (Klapper, Amit, and Guillen, 2010), we are able to measure characteristics related to entrepreneurial quality at or close to the time of registration. These characteristics include how the firm is organized (e.g., as a corporation, partnership, or LLC, and whether the company is registered in Delaware), how it is named (e.g., whether the owners name the firm eponymously after themselves), and how the idea behind the business is protected (e.g., through an early patent or trademark application). These startup characteristics may reflect choices by founders who perceive

performed by venture capitalists. In this step, our objective is to extract key observable dimensions VCs select on when trying to predict the future growth potential of a firm, and then use the results from this predictive analytics exercise to calculate a *VC-likelihood* for all the firms in our sample (irrespective of them receiving VC funding or not). This measure allows us to replicate elements of the screening process VCs perform on every firm in the economy, including firms VCs may have turned down or never had a chance to evaluate in the first place (e.g. because they do not operate in the region the firm is located, were not aware of the deal, or the company did not look for venture capital funding). Of course, VCs collect substantially more information than us when deciding to invest in a startup or not through face-to-face meetings, due diligence etc. At the same time, as long as some of the dimensions they care about are captured by our data, then our method should be able to replicate at least part of their screening heuristics.

We train our model on venture capitalists because their objective is to maximize the chances of an equity growth event: i.e., by studying the observables that correlate with their decision to invest, we are able to identify firm characteristics that VCs *believe* can predict future growth. Whether or not these observables have any actual predictive power (beyond the self-fulfilling component resulting from the VCs 'treatment effect' on the firms) is an empirical question. It is also not clear, a priori, if the same dimensions VCs select on would be predictive of growth within the sample of non-VC-funded firms. If VCs endogenously match with firms that they know would benefit the most from their approach to scaling startups, then non-VC-funded firms that grow could be fundamentally different than VC-funded ones. If instead there is a single playbook for firm growth, and VCs are able to capture some of the early signals of a firm's future potential, then we would expect non-VC-funded firms that grow to be similar, on at least some of the dimensions VCs care about, to VC-funded firms. The objective of our paper it to test these competing hypotheses.

To do so, in the second step of our approach, we use the estimates resulting from our prediction of the *VC-likelihood* to explore the growth process among firms that *did not receive venture capital*.[3] One can think of our *VC-likelihood* as a proxy – based on firm observables – for

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their venture to have high potential. As a result, though observed startup characteristics are not causal drivers of startup performance, they may nonetheless represent early-stage "digital signatures" of high-quality ventures.

[3] We leverage the fact that, although rare, we observe both the receipt of venture capital (though data on the precise amount and valuation is somewhat noisy) and meaningful growth outcomes for those firms that realize such outcomes (e.g., for equity growth, we can observe firm for example IPO or high-value acquisitions).

the probability that a VC firm would have invested in a focal firm based on what was known about it around the time of its birth. The intuition behind this step is to check if the determinants of venture capital financing are similar to the determinants of growth *outside* of the venture capital sample. If venture growth in the absence of VC is fundamentally different from growth with VC (i.e. if these two paths to growth have little in common), then this analysis would surface the observables that are associated with VC funding, but are not associated with growth within the non-VC sample. If instead the two paths to growth are similar, then we would expect many of the determinants across the two models to be the same, and the *VC-likelihood* would be a good proxy for growth potential also in the absence of venture capital (since it distills some key predictors of growth VCs select on).

In the third step, since the *VC-likelihood* can be calculated for all firms independent of funding source, we explicitly use it to identify a comparable, 'VC-type' firm among the firms that did not receive venture capital for each firm that raised VC. This allows us to perfectly match each VC-funded firm with a control firm from the non-VC sample of the same starting quality (at least from the perspective of a VC). We use this last step to describe both the process of selection into venture capital starting from the full population of new firms, and to estimate an upper bound to the returns from VC.

Applying this three-step approach to a dataset covering all business registrants in 34 US states (comprising more than 80% of US GDP) from 1995-2005, we offer a set of novel findings about the process of venture growth with versus without venture capital. While our estimates of the incidence of venture-backed IPOs are similar to prior estimates in the literature, they nonetheless highlight the important role that non-VC-backed companies play in economic growth: nearly 80% of all firms that achieve an equity growth event do so without venture capital financing. Furthermore, our results show that the process of selection into venture capital, similar to the process of equity growth (Guzman and Stern, 2015, 2016, 2017), is highly skewed, and can be characterized through a small number of firm observables at birth.[4]

When we use our estimates from the predictive analytics approach to understand growth within the non-VC sample, we find that a doubling in the estimated *VC-likelihood* more than

[4] Firms that have short names are more than 500% more likely to receive venture capital, while eponymous firms are more than 80% less likely to receive VC; firms that register in Delaware and receive or apply for a patent within a year of founding are more than 120X more likely to receive venture capital.

doubles the probability of an equity growth outcome, with more than 50% of all non-VC-backed equity growth outcomes estimated to be in the top 5% of the *VC-likelihood* distribution. Similarly, among firms that did not raise venture capital, a firm in the top 1% of our estimated *VC-likelihood* distribution is 768X more likely to achieve an equity growth outcome than a firm in the bottom 10% of the distribution. The results highlight the striking similarity between the determinants of venture capital and the determinants of equity growth in the absence of venture capital. With the exception of trademark, which is more salient among non-venture-backed firms, all other startup characteristics are comparable across the two models. The relationship between our estimated *VC-likelihood* and equity growth within the non-VC-backed sample is also extremely stable across time periods where venture capital was more versus less abundant, and across geographies (startup hubs versus not).

The stability of these estimates supports the view that our predictive analytics approach is able to capture fundamental firm characteristics that are predictive of growth irrespective of funding source and VC presence in a region or sector. The same estimates also allow us to revisit the question of the role of venture capital in the process of equity growth, as they can be used to perfectly match each venture-backed firm with a control firm with similar growth potential from birth. The method provides us with a lower-bound estimate of the returns to venture capital investment on equity growth, as VCs also select firms based on characteristics that are unobservable to us. Relative to a "naïve" estimate where venture capital is associated with a 500X increase in the probability of equity growth, our matching results suggest up to a 5X boost to equity growth from venture capital. Interestingly, in our data, the returns to venture capital are lower in the upper tail of the estimated *VC-likelihood* distribution (e.g., firms in the top 0.05% of the distribution receive only a 140% increase in their probability of growth), where firm quality is extremely high to start with, within startup hub, and when follow on capital is more likely to be scarce (returns are highest during the earliest stages of the Internet boom).

Taken together, our findings support the idea that whereas funding source may differ, it is possible to identify a standard 'playbook' growth firms follow from the very beginning. Firms that achieve growth without venture capital are similar in characteristics to those that receive VC funding, suggesting that not only multiple paths to growth exist, but that there are strong similarities between firms that grow through either of these routes. Furthermore, once the estimated *VC-likelihood* – a proxy for firm quality from the perspective of a VC – is accounted for, the gap between VC-funded and other firms of comparable potential is much smaller than previously documented.

The paper proceeds as follows. Section 2 discusses the process of selection into venture capital and equity growth. Section 3 develops our predictive analytics approach. Section 4 introduces the data and descriptive statistics, before turning to the main empirical findings in Sections 5 and 6. Section 7 concludes.

II. VENTURE QUALITY, SELECTION INTO VENTURE CAPITAL, AND GROWTH

Over the past decade, there has been increasing appreciation for the skewed nature of entrepreneurial outcomes, and for the disproportionate impact high quality new ventures have on innovation, employment and productivity growth. Starting from founding, firms exhibit substantial heterogeneity in quality, and only a very small fraction of successful startups is responsible for the economy-wide benefits from entrepreneurship (Kerr, Nanda, and Rhodes-Kropf, 2014). While there is increasing understanding of the importance of accounting for such heterogeneity in the measurement and impact of entrepreneurship on the economy (Schoar, 2010; also see Hurst and Pugsley, 2010, Lerner, 2009, and Decker, Haltiwanger, Jarmin, and Miranda, 2014), systematic measurement of new venture quality has been challenging. In the area of entrepreneurial finance, researchers often rely on samples of firms that have reached rare milestones such as raising venture capital. While this facilitates the examination of the dynamics of high-potential firms, it also creates a disconnect between these small, selected samples of firms and the overall population of new ventures.[5]

As emphasized by Hathaway and Litan, the challenge in directly incorporating heterogeneity is fundamentally a measurement problem: *"The problem is that it is very difficult, if not impossible, to know at the time of founding whether or not firms are likely to survive and/or grow. This is true even with venture-capital backed firms…"* (Hathaway and Litan, 2014). Though it is certainly the case that entrepreneurship is a highly uncertain activity, it is nonetheless also the case that entrepreneurs and investors make (somewhat) informed decisions at a relatively early stage of the life of a firm, based on their best assessment of the growth potential of that firm. For

[5] One notable and insightful exception is the positive relationship between organizing your firm as a corporation and entrepreneurial income highlighted by Levine and Rubinstein (2017).

example, given the objective of predicting and enabling startup growth, venture capital firms explicitly seek to identify new ventures that have a higher likelihood of achieving an equity growth outcome over a relatively bounded period of time (i.e., typically the lifetime of the fund). After selecting a firm, they also do not rely on a passive investment strategy, but actively support the ventures they add to their portfolio in order to accelerate their path to growth. At the same time, as shown by multiple studies in this area, their search and investment activities are concentrated not only in specific industries and geographies, but also disproportionately focus on specific types of firms, founding teams and technology trends. VCs are more likely to fund ventures that have secured (or are in the process of securing) formal intellectual property, and do not currently have a sizable stream of revenues (Hellman and Puri, 2000). Furthermore, their investments tend to be focused on a narrow range of industries (Gans and Stern, 2002), on firms located in close proximity to their offices (Lerner, 1995) and startup hubs (Chen et al., 2014), on sectors where they have previous investment experience (Sorenson and Stuart, 2001), and where they expect follow-on capital to be available (Nanda and Rhodes-Kropf, 2014). They also prefer to invest in teams with a strong track-record (Gompers et al., 2016) and in serial entrepreneurs (Gompers, Lerner, and Sharfstein, 2005; Gompers et al, 2010). Interestingly, in a recent paper, whereas Nanda, Samila and Sorenson (2017) find evidence of VCs being able to select good investments, they do not find evidence of them being able to correctly identify, ex-ante, the very top right tail outcomes. This speaks to both VCs' ability to identify key predictors of future firm growth, but also to the presence of residual uncertainty about the prospects of the high potential candidates that enter their portfolios.

While it is possible that venture capitalists do identify many of the firms with growth potential, the full population of growth firms may be quite different (as emphasized, among others, by Bhide (1998)). Differences between the process of selection into venture capital and the overall process of firm growth might be driven both by supply and by demand-side factors. On the supply side, it is possible that differences in regional and industry composition may result in a relatively lower rate of entrepreneurial activity for certain types of businesses. Furthermore, if VCs face higher search costs outside of regional startup hubs or specific industries they have experience in, then some firms with high growth potential might be excluded from venture capital investment because they do not fall within the traditional VC 'search space'. On the demand side, firms that can bootstrap through other means and generate enough cash flow to sustain their growth may have little demand for venture capital to begin with, and may want to avoid the loss of equity and control that is associated with raising external funding.

Understanding the process of selection into venture capital and how it relates to the broader process of firm growth – even in the absence of VC funding – matters for estimating how efficiently society allocates resources to new ventures, and for regional policies targeted at sustaining entrepreneurship and economic growth outside of startup hubs. If VC-backed firms and non-VC-backed firms are similar, but VC funding drastically increases the odds of firm growth, then from a policy perspective it is useful to examine the barriers to venture financing in regions or industries where it is lacking, and what can be done to remove them. It would also suggest that the prior literature's focus on venture capital has not overlooked an alternative, critical path to firm growth, but that instead venture capital is a critical accelerant of growth within a single growth 'playbook'. If instead VC-funded and non-VC-funded firms that achieve growth are fundamentally different (and need different types of resources, investors and policies), then efforts targeted at expanding venture capital to these different types of firms, sectors and regions may be completely ineffective at accelerating them, and different types of interventions may be needed to support their alternative path to an equity growth outcome. Empirically, to adjudicate between these competing hypotheses, we need to develop a methodology which allows us to identify the growth potential of firms at founding – irrespective of future funding source – and systematically compare firm characteristics and growth outcomes between these possibly different paths to growth. Our next section explores in detail how our predictive analytics approach, by leveraging the information contained in VCs funding decisions, helps us make progress in this direction.

III. A PREDICTIVE ANALYTICS APPROACH FOR STUDYING THE PATHS TO FIRM GROWTH

To break through this impasse, we develop a predictive analytics approach that allows us to take advantage of the process of selection into venture capital to identify firm characteristics that are predictive of future growth. We then use the resulting 'VC-likelihood' estimate to study growth within the sample of firms that *do not* receive venture capital. Our goal is to estimate the relationship between an informed signal of growth potential (i.e., receiving venture capital), early firm characteristics and founder choices, and the resulting probability of growth for all firms in the economy.

Building on Guzman and Stern (2015, 2016, 2017), our approach takes advantage of three interrelated insights. First, a practical requirement for any entrepreneur trying to achieve a growth outcome is business registration (as a corporation, partnership, or limited liability company). This practical requirement allows us to form a population sample of entrepreneurs "at risk" of growth at a similar (and foundational) stage of the entrepreneurial process. Second, we are able to distinguish among different types of business registrants through the measurement of characteristics related to entrepreneurial quality observable *at or close to the time of registration.* For example, we can capture firm characteristics such as whether the founders name the firm after themselves (eponymy), whether the firm is organized in order to receive equity financing (e.g., registering as a corporation or in Delaware), or whether the firm seeks intellectual property protection (e.g., a patent or trademark). Third, we leverage the fact that, though rare, we observe both a signal of an informed investor's willingness to invest in a firm with growth potential (receipt of venture capital) as well as equity growth outcomes such as IPOs or acquisitions for all firms in our sample.

We combine these insights to develop a predictive analytics model that leverages the fact that venture capital is an informed (although imperfect) signal of growth potential to characterize the potential of firms that *do not* receive venture capital. In particular, we begin by estimating a predictive analytics model of the process of selection into venture capital. Specifically, for a firm *i* at time *t*, with startup characteristics $H_{i,t}$, we observe the receipt of venture capital $VC_{i,t+s}$ *s* years after founding and estimate:

$$\phi_{\ i,t} = P\left(VC_{i,t+s} \middle| H_{i,t}\right) = f\left(\alpha + \beta H_{i,t}\right) \qquad (1)$$

This model allows us to *predict* quality as the probability of receiving venture capital given the focal startup characteristics at founding, and estimate a 'VC-likelihood' (a proxy for quality and potential as assessed by venture capitalists) as $\widehat{\phi}_{i,t}$. We use these estimates to characterize whether the same startup characteristics of firms that *do not* receive venture capital are similarly informative for achieving an equity growth exit within the non-VC-backed sample. Specifically, from (1), we are able to form an estimate of the 'VC-likelihood', $\widehat{\phi}_{i,t}$, and then consider how informative this estimate is within a regression where we estimate the probability of growth among firms *that do not receive venture capital:*

$$g_{i,t+s} = \alpha + \beta\hat{\phi}_{i,t} + \epsilon_{i,t} \text{ if } VC_{i,t+s} = 0 \quad (2)$$

To the extent that the estimate in (2) is informative (i.e. to the extent that determinants of growth within VC-backed firms are similar to the determinants of growth within the non-VC sample), we can also use our 'VC-likelihood' estimates to construct matched sample control groups to evaluate the returns to venture capital on equity growth itself, and separate the role of selection into venture capital (based on observables), from treatment:

$$g_{\,i,t} = h\left(VC_{i,t+s} \middle| \hat{\phi}_{i,t}\right) \quad (3)$$

IV. DATA AND DESCRIPTIVE STATISTICS

Our analysis uses business registration records, which are public records created when an individual registers a new business as a corporation, LLC or partnership (Guzman and Stern, 2015; 2017a; 2017b)[6]. We rely on all registrations from 1995 to 2005 in 34 US states,[7] representing 95% of the United States venture capital market in 2014 (SSTI, 2015, see Figure A1). While it is possible to found a new business without appearing in these data (e.g., a sole proprietorship), the benefits of registration are substantial, and include limited liability, various tax benefits, the ability to issue and trade ownership shares, and credibility with customers. Furthermore, all corporations, partnerships, and limited liability companies must register with a Secretary of State[8] in order to take advantage of these benefits, as the act of *registering* the firm triggers the legal creation of the company. As such, these records reflect the population of businesses that take a form that is a practical prerequisite for growth. Our analysis draws on the complete population of firms satisfying one of the following conditions: (a) a for-profit firm in the local jurisdiction or (b) a for-

[6] This section draws heavily from this prior work, where we introduce business registration records and many of the measures used in this paper.
[7] Arizona, California, Colorado, Florida, Iowa, Idaho, Illinois, Kentucky, Massachusetts, Maine, Michigan, Minnesota, North Carolina, North Dakota, New Jersey, New Mexico, New York, Ohio, Oklahoma, Oregon, Rhode Island, South Carolina, Tennessee, Texas, Utah, Virginia, Washington
[8] Or Secretary of the Commonwealth.

profit firm whose jurisdiction is Delaware but whose principal office address is in the local state. In other words, our analysis excludes non-profit organizations as well as companies whose primary location is not in the state. The resulting dataset contains 10,451,896 observations.[9] For each observation we construct variables related to: (a) growth outcomes (IPO or significant acquisition); (b) venture capital financing events; (c) firm characteristics based on business registration observables; and (d) firm characteristics based on external data that can be directly linked to the firm (e.g. patents, trademarks). We briefly review each one in turn.

Growth Outcomes. The growth outcome used in this paper, *Growth*, is a dummy variable equal to 1 if the firm has an initial public offering (IPO) or is acquired at a meaningful positive valuation within 10 years of registration as reported in the Thomson Reuters SDC database[10]. Between 1995 and 2005, we identify 6,353 firms that achieve growth, representing 0.06% of the total sample of firms.

Venture Capital Financing. We collect information on Series-A venture capital financing events from multiple databases: AngelList, CapitalIQ, Preqin, and Thompson Reuters VentureXpert. Our main variable, *Gets Venture Capital*, is a dummy equal to 1 if a firm receives financing and 0 otherwise.

Firm Characteristics. We develop two types of firm characteristics: (a) those based on business registration data, and (b) those based on external indicators of quality that are observable at or near the time of business registration.

a. *Measures based on business registration data.* In the first category, we first create two binary measures that relate to how the firm is registered: *Corporation*, which captures whether the firm is a corporation rather than an LLC or partnership, and *Delaware*,

[9] The number of firms founded in our sample is substantially higher than the US Census Longitudinal Business Database (LBD), done from tax records. For example, for Massachusetts in the period 2003-2012, the LBD records an average of 9,450 new firms per year and we record an average of 24,066 firm registrations. We have yet to explore the reasons for this difference. However, we expect that it may be explained, in part by: (i) partnerships and LLCs that do not have income during the year do not file a tax returns and are thus not included in the LBD, and (ii) firms that have zero employees and thus are not included in the LBD. Gonzalez-Uribe and Paravisini (2017) find comparable rates of business registrations in the UK.

[10] Although the coverage of IPOs is likely to be nearly comprehensive, the SDC data set excludes some acquisitions. SDC captures their list of acquisitions by using over 200 news sources, SEC filings, trade publications, wires, and proprietary sources of investment banks, law firms, and other advisors (Churchwell, 2016). Barnes, Harp, and Oler (2014) compare the quality of the SDC data to acquisitions by public firms and find a 95% accuracy (Nette, Stegemoller, and Wintoki (2011), also perform a similar review). While we know this data not to be perfect, we believe it to have relatively good coverage of 'high value' acquisitions. We also note that none of the cited studies found significant false positives, suggesting that the only effect of the acquisitions we do not track will be an attenuation of our estimated coefficients.

equal to one if the firm is registered in Delaware. We then create five additional measures based directly on the name of the firm. *Eponymous* is equal to 1 if the first, middle, or last name of the top managers is part of the name of the firm itself.[11] Our last measure relates to the structure of the firm name. Based on our review of naming patterns of growth-oriented startups versus the full business registration database, a striking feature of growth-oriented firms is that the vast majority of their names are at most two words (plus perhaps one additional word to capture the organizational form, e.g. "Inc."). We define *Short Name* to be equal to one if the entire firm name has three or less words, and zero otherwise.[12] We then create several measures based on how the firm name reflects the industry or sector within which the firm is operating, taking advantage of the industry categorization of the US Cluster Mapping Project ("US CMP") (Delgado, Porter, and Stern, 2016) and a text analysis approach. We develop seven such measures. The first three are associated with broad industry sectors and include whether a firm can be identified as local (*Local*), traded (*Traded*) or resource intensive (*Resource Intensive*). The other five industry groups are narrowly defined high technology sectors that are typically associated with high growth firms, including whether the firm is within the biotech (*Biotech Sector*), e-commerce (*E-Commerce*), other information technology (*IT*), medical devices (*Medical Devices*) or semiconductors (*Semiconductor*) space.

b. *Measures based on External Observables.* We also construct two measures related to quality based on data from the U.S. Patent and Trademark Office. *Patent* is equal to 1 if a firm holds a patent application within the first year and 0 otherwise. We include patents that are filed by the firm within the first year of registration and patents that are assigned to the firm within the first year from another entity (e.g., an inventor or another firm). Our second measure, *Trademark*, is equal to 1 if a firm applies for trademark protection within a year from registration.

[11] Belenzon, Chatterji, and Daley (2017a, 2017b) perform a more detailed analysis of the interaction between eponymy and firm performance finding an important negative relationship between an intent to use equity financing and eponymy.
[12] Companies such as Akamai or Biogen have sharp and distinctive names, whereas more traditional businesses often have long and descriptive names (e.g., "New England Commercial Realty Advisors, Inc.").

Descriptive Statistics. Table 1 reports summary statistics. There are 10,451,896 firms in our data: 0.05% of these firms achieve an equity growth outcome within ten years from incorporation, and 0.08% receive venture capital (0.05% within 2 years)[13]. 0.2% of firms have a patent (within 1 year from birth), and 0.09% have a trademark. 59% of firms are corporations, 47% have a short name, 7.9% are eponymous and 3.6% are registered in Delaware.

In Table 2, we directly compare the share of firms in our sample that grow with versus without VC: although only 0.05% of non-VC-funded firms achieve growth, this share is 16.7% for VC-funded firms (Panel A). If we only focus on IPOs, whereas 1 out of 28 VC-funded firms achieves this milestone, among the remaining firms it is only 1 every 10,000 firms. Similarly, while approximately 1 out of 8 VC-funded firms is successfully acquired, only 1 out of 2,500 non-VC-funded firms does so.

V. WHAT THE PROCESS OF SELECTION INTO VENTURE CAPITAL REVEALS ABOUT THE PROCESS OF GROWTH IN THE ABSENCE OF VENTURE CAPITAL

In this section, we use a predictive analytics approach to characterize the process of selection into venture capital, and then estimate the likelihood of receiving venture capital financing for all business registrants (including firms that never received VC funding). Following the approach outlined in Section III, in Table 3 we estimate a predictive model that relates observables at founding to ex-post VC financing. The observables we use in the logit regressions are the same as Guzman and Stern (2015, 2016, 2017), although the dependent variable (*Gets Venture Capital)* in this case is equal to 1 if the firm receives VC funding, and 0 otherwise. To avoid overfitting and ensure the robustness of our estimates of 'VC-likelihood', in this first step we use a random, 50% subsample of the data. This allow us to calculate an 'out of sample' VC-

[13] This number of investments is not comparable with the number of investments in these states within those years for at least three reasons. First, we only include firms registered after 1995, but investments occurring in the early part of our sample could be on firms registered earlier than 1995, which we do not observe. Second, we only include *local* firms, but some regions such as Silicon Valley or Boston, have a history of firms that are not local but instead move to these locations after receiving venture capital financing, and might receive follow-on financing in these regions. For example, many Israeli firms move to the United States after receiving their first round of financing. Our dataset is designed to exclude these firms. Finally, naturally, our matching cannot be perfect. While we have applied to matching improvements developed by Balasubramanian and Sivadasan (2008) and Kerr and Fu (2008), our focus has intently been on avoiding as many false-positives as possible. We have high confidence that the investments we observe reflect the true investment as stated in Thompson Reuters VentureXpert. Through manual checks, we do not believe the number of false-positives to be many.

likelihood for the excluded, 50% of firms (including those that do not receive VC-funding), which we will base the rest of our analysis on. For ease of interpretation, coefficients are presented as incidence rate ratios.

Table 3 explores the correlation between business registration observables and selection into venture capital financing within a random, 50% sample of all firms (our 'training set' for studying the determinants of venture capital). Column 1 does not control for intellectual property variables nor industry characteristics, which are respectively introduced in Columns 2 and 3. In Column 1, firms registered as corporations are 6.8 times more likely to receive VC funding, firms with a short name are 7 times more likely to reach the same milestone, eponymous firms are 87% less likely to be VC-backed, and Delaware registered firms are 20 times more likely to get VC capital. Column 2 relates only intellectual property measures to venture capital: Consistent with VCs selecting ventures of high quality and that have secured (or are in the process of securing) intellectual property protection, firms with a trademark are 3 times more likely to attract VC, and firms with a patent are 79 times more likely to do so.

Column 3 represents our main predictive model, which brings all of our observables together. While we could use a more flexible and complex functional form (and improve our predictive performance), we opt for a simple one to allow for easy interpretation of our next sets of results, and a higher degree of transparency on what the predictive model is based on. In Column 3, corporate form observables are quite informative of whether a firm will receive VC or not: Corporations are 5.5 times more likely to raise venture capital than non-corporations[14], and Delaware firms are 16 times more likely to raise VC. The naming choices of the firms are also predictive of future funding source. Firms with a short name are 6 times more likely to raise VC, and eponymous firms are 84% *less* likely to raise VC[15]. Firms with intellectual property are also more likely to raise VC. Firms with a trademark are 88% more likely to raise VC, and firms with a patent are 38 times more likely to receive VC financing. Firms that hold both a patent and are Delaware incorporated are significantly more likely to receive venture capital - 121 times more than other firms. The name-based industry coefficients are also significant, and sectors typically

[14] Though it might seem counter-intuitive that *any* venture-backed firm is not a corporation, the data during the late 1990's does include several LLCs that received venture capital financing.

[15] The negative effect of eponymy in the financing dynamics of firms is explored more systematically by Belenzon, Chatterji, and Daley (2017).

associated with the VC 'search space', such as IT, biotechnology, e-commerce, medical devices, and semiconductors are all more likely to receive venture capital financing.

We define *VC Likelihood* as the predicted probability resulting from this regression. This estimate is a useful summary statistic for how similar a specific firm is to other 'VC-type' firms. It is also a proxy of firm quality from a venture capitalist's perspective. Since we have the observables it is based on for the full set of incorporated firms, we can calculate the *VC Likelihood* also for firms that never received VC (either because they were rejected by professional investors, or because they never tried to raise from a VC firm in the first place). Furthermore, the measure is independent from the relative availability of VC in the region or time period the firm is created in.

Of course, VCs observe substantially more information than us when screening candidates for investment, as our approach only captures quality on dimensions that are public around the time of incorporation. If VCs predominantly select firms on measures of quality that are unobservable to us, then our *VC Likelihood* estimate would not be able to perfectly separate, at birth, VC-backed firms from other firms, as our observables would be too noisy of a predictor for future VC investment. We would still expect to see more VC-funded firms for higher levels of observable *VC Likelihood*, but the relationship could be possibly very noisy. Notwithstanding these limitations, the measure, is highly informative: In Figure 1, we plot the share of venture-backed firms in each of twenty, 5 percent bins in the distribution of predicted *VC Likelihood*. To avoid overfitting, we estimate this through a 10-fold cross validation approach: we separate our sample into 10 random groups, and calculate this summary statistic ten times, each time with one of these 10 groups as the out of sample group and the other 9 as the ones with which the model is built. This is the preferred testing approach in machine learning applications, since it also allows all data-points to be included in the test only once. The maximum, minimum, and mean of this statistic across the quality distribution are reported inside each bar. The distribution is highly skewed and the predictive capacity of our estimate is significant: 72% of all venture-backed firms are in the top 5% of the *VC Likelihood* distribution, and 53% are clustered in the top 1%.

Together, these results highlight three key findings. First, when looking at population-level data, VC activity is disproportionately concentrated on the right tail of the observable quality distribution that can be built, from the perspective of a venture capitalists, using firm characteristics at the time of founding. Whereas it is known that VCs invest in high quality firms, from a policy perspective it is interesting to benchmark these firms to the broader population in their respective regions and sectors. Second, our simple model based only on observables around birth is clearly able to effectively separate firms with some possibility of raising VC from the vast majority of incorporated firms. Third, *some* VC investment takes place all the way down to the 50th percentile of the quality distribution, suggesting that professional investors may be screening on dimensions that are sometimes not visible to the econometrician.

The *VC Likelihood* – a measure of firm quality and potential from the VC perspective – can also be used to identify how likely it would have been for a firm to raise VC, independent of the funding actually taking place. To begin testing the relationship between growth within the non-VC-backed firm sample and the *VC Likelihood*, we repeat the out of sample cross validation procedure but use non-VC-backed growth outcomes as our dependent variable. The resulting estimates, reported in Figure 2, tell us where in the distribution of *VC Likelihood* are the non-VC-funded firms that ended up achieving an IPO or significant acquisition. Similar to the findings illustrated in Figure 1, the relationship between *VC Likelihood* and growth outcomes is substantial: 54% of non-VC growth firms are in the top 5% of VC likelihood, and 66% in the top 10%.

We further explore this relationship within a regression framework in Table 4, where we compare the role of the *VC Likelihood* in predicting non-VC-funded growth in the 50% test sample that was not used to build the original *VC Likelihood* model (Table 3). The regression uses *Growth* as the dependent variable and includes state and year fixed effects. All VC-backed firms are excluded from the sample. Standard errors are clustered at the level of state-year pairs. In Column 1, we introduce the *VC Likelihood* in its log-odds form to account for its highly skewed nature.[16] The IRR of this coefficient is 2.26 and significant, with small standard errors. This indicates that for a *non*-VC-backed firm, a doubling of the odds of *VC Likelihood* increases its chances of growth by 126% percent. In other words, firms that are on observables more likely to fit the VC playbook, are substantially more likely to grow, independent of raising VC. Column 2 repeats this estimation with the *VC Likelihood* variable standardized to a standard deviation of 1. The resulting IRR indicates that increasing a firm's *VC Likelihood* by one standard deviation is associated with an increase of 11% in the likelihood of growth. The R^2 drops by half, reflecting the more precise fit of the log-odds estimate (due to the highly skewed nature of the probability of VC).

[16] The log odds of a variable X is $Ln\left(\frac{X}{1-X}\right)$

Figure 3 reports a different estimate of the relationship between the *VC Likelihood* and the ultimate performance of non-VC-backed firms. We report the IRRs of a logit model regressing the probability of growth on indicator variables for different ranges of *VC Likelihood*. Estimates indicate the change in odds of an equity growth outcome relative to firms in the bottom 0-10% of the *VC Likelihood* distribution (the excluded category). The figure highlights a monotonically increasing relationship, with a significant increase in the returns to a higher *VC Likelihood* towards the top of the distribution. Firms between the 80th to 90th percentile of the *VC Likelihood* distribution are 20 times more likely to achieve growth, firms between the 90th to 99th percentile are 65 times more likely to achieve growth, and, most striking, non-VC-backed firms in the top 1% of the *VC Likelihood* are 767 times more likely to achieve growth than the bottom 10%.

To further unpack the relationship between the *VC Likelihood* and growth in the non-VC sample, in Table 5 we compare the role the different observables that constitute it play in predicting growth (Columns 2 to 4) relative to the role they play in predicting venture capital financing (Column 1). The main comparison of interest is between Columns 1 and 4: The coefficients for corporate form, intellectual property, and industry dummies in the regression explaining growth within the non-VC sample (Column 4) have all the same sign and significance than the coefficients for the same variables within the VC financing models (Column 1). We also observe a few differences. The importance of being a corporation is significantly lower for explaining non-VC growth, suggesting that, though firms may benefit from the stronger corporate governance tools offered by this incorporation form, a large portion of the benefit might be related to the ability to sell shares to investors. We also see a much higher importance of having an early trademark (an indicator that the firm is planning to commercialize a product or service) for growth without venture capital, an effect consistent with these firms bootstrapping through sales. The role of naming appears to be different, with short names predicting VC financing much more closely than equity growth, though it is unclear if this reflects differences in VC preferences or in the underlying types of firms and industries represented by each group. More interestingly, the role of Delaware jurisdiction and patenting — the two indicators with the most predictive power in both regressions — is surprisingly similar across specifications. Firms with ideas that can be protected through intellectual property rights, and firms that seek the more flexible (but also more expensive) protection of Delaware incorporation are substantially more likely to both receive venture capital financing, and achieve equity growth even in the absence of VC funding, reflecting large similarities in the at-birth observables of firms across these two groups.

Last, in Table 6 repeats our estimate of the association between the log-odds of *VC Likelihood* and equity growth outcomes for non-VC-backed firms across different geographies and time-periods. The coefficient is stable and similar across all columns, suggesting that the relationship we have identified between observables at the time of incorporation, how VCs interpret them, and ultimately firm growth within a sample of firms that never raised VC holds across very different types of regions and time periods.

VI. THE RETURNS TO VENTURE CAPITAL FINANCING

We now turn to studying the full population of firms and the role venture capital financing plays in their ability to reach a growth outcome (IPO or acquisition). In Table 7, our objective is to partially separate VC selection (on observables) from treatment using the estimates from our predictive analytics approach. Raising venture capital is an informative signal of quality: as we have seen in Section V, VCs select startups that are on the extreme right tail of the observable *VC Likelihood* distribution. They also contribute to the success of the firms they invest in by providing capital, offering mentorship, performing monitoring, helping or replacing founding teams, connecting firms to possible customers and suppliers etc. Hence, in the absence of exogenous variation, any estimate of the correlation between VC funding and growth will always be a composition of the VCs' role in the selection of higher quality firms as well as in increasing their chances of success. Both effects will also vary with the underlying quality of the investors involved, as high quality VCs will not only see better deals, but may also provide better support to their portfolio companies (e.g. through their networks, etc.).

To account for selection on observables, we rely on our predictive analytics approach to deliver us a proxy for a firm's quality and potential — from the perspective of VCs — around the time of birth. As we are unable to fully control for firm differences (since VCs also select firms based on variables that are unobservable to us), accounting for such a measure when estimating the association between VC and growth should return an upper bound on the VC treatment effect (as we are likely underestimating selection). Before introducing the summary measure directly, in Table 7 we progressively add the controls we used so far in Columns 1 to 4. In each column, we perform logit regressions with *Gets VC in 2 Years* (a binary measure indicating whether a firm receives VC financing within the first two years)[17] as the main independent variable, and our binary outcome measure *Growth* — achieving an equity growth outcome in 10 years— as the dependent variable. Results are reported as incidence rate ratios, and standard errors are clustered at the state-year pair level. All the remaining tables in the paper only use the 50% random subsample we did not use to develop our predictive approach.

Column 1 of Table 7 compares VC-funded firms to non-VC-funded firms within the subsample. The probability of growth for firms that raise venture capital is over 500 times higher than that of a random firm in the sample. Selection is obviously a major concern here, as the vast majority of firms in the sample have an extremely low probability of achieving an IPO or acquisition in the first place, and therefore are not a credible control group for VC funded firms. Adding state and year fixed effects, and controlling for traditional proxies for quality such as the presence of patents and trademarks reduces this estimate by an order of magnitude in Column 2. Nonetheless, VC-funded firms are still 64 times more likely to grow than non-VC-funded firms. Interestingly, the introduction of our basic firm observables revealed at incorporation in Column 3 leads to a sizable reduction in the coefficient, bringing VC firms fairly close to firms of comparable characteristics in terms of outcomes. Once all our measures are accounted for in Column 4, VC-funded firms are only 15 times more likely to grow than other firms, a result that is robust to using our summary *VC Likelihood* measure in Column 5.

Column 6 is our preferred estimate. In this column we extend approach for separating selection on observables from treatment by performing an exact matching procedure. For each VC-backed firm, we randomly select a non-VC-backed firm founded in the same year and geographic region, with the same exact value of observable *VC Likelihood*. The matching is at the same zip code level for 86% of firms, with remaining firms matched at the MSA and state level. After matching, we estimate the differences in the odds of achieving an equity growth outcome between our 'treated' firms (i.e. the firms that received VC funding) and our 'control' firms (i.e. firms that did not raise VC funding, but that have exactly the same *VC Likelihood* of doing so at

[17] As documented in Appendix Figure A2, the majority of firms that eventually raise VC do so within 2 years (about 25% receives financing within 3 months, 56% within a year, 75% within 2 years). The short time-frame between firm birth and VC financing motivates our choice to focus the rest of our analyses on receiving a series A investment within two years, which has the additional benefit of allowing us to evaluate firms across time without running into truncation issues.

birth). The incidence rate ratio drops from 15 to 6.1. This estimate is significant: conditional on the *VC Likelihood*, firms that raise VC are still 5 times more likely to achieve an equity growth outcome than non-VC-funded firms. However, while significant, the coefficient is also two orders of magnitude lower than the original, naïve estimate from Column 1. While the implied role of venture capital on firm performance is meaningful, 99% of the difference in outcomes between VC-backed and non-VC-backed firms is accounted for by characteristics that are observable at founding. Interestingly, our estimate is comparable to those of Chemmanur et al. (2011) and Puri and Zarutskie (2002), even though there are important differences in the specifications and samples we use since we start from the full population of incorporated firms.

Table 8 extends the previous table by introducing a series of additional fixed effects to control for regional and microgeographic heterogeneity in our matching estimator. Consistent with the idea that unobservables may be less of a concern after we perform our matching on *VC Likelihood*, adding state-year pair fixed effects, MSA fixed effects, or controls for the average quality of the zip code level neighbors of the focal firm does not change our estimates: VC-funded firms continue to be approximately 5 times more likely to grow than their counterparts, irrespective of which controls we introduce.

It is important to stress that the estimate based on matching is still likely to be an upper bound on the true effect of VCs on firm growth, as the firms in our sample are still likely to differ on unobservable quality. Nevertheless, given the informational imbalance between the VC partners actually making the investment decisions and our regressions, it is surprising to see how much of the variance in outcomes we are able to explain. Furthermore, our *VC Likelihood* measures are defined many years before the actual acquisition or IPO takes place, i.e. when the uncertainty surrounding a startup is still extremely high.

Taken together, results from Tables 7 and 8 highlight just how much of the initial difference in the probability of growth between VC-funded-firms and other firms is driven by selection. Whereas in the most naïve estimation VC-funded firms are 518 times more likely to grow than other firms, this premium is reduced to only 6 times using our matching approach. This is consistent with our descriptive results on selection presented in Figures 1 and 2, and confirms that

VCs select firms that are already of very high quality based on observables.[18] Our exercise places an upper bound on how much value, on average, VCs may be adding to the firms they invest in.

In Table 9, we re-estimate our model for firms on the right tail of the observable *VC Likelihood* distribution (firms in the top 5%, 1%, 0.1% and 0.05%). As we move up our quality distribution, the marginal contribution of VCs to growth is drastically reduced, possibly because for these right tail firms we do have a better measure of actual growth potential (i.e. our information gap relative to the VCs is smaller). For firms that exhibit extremely high, observable quality at incorporation (Column 4 and 5), VC-funded firms are only 2.4 times more likely to grow than similar firms that do not receive VC funding. It is important to stress that this represents a sizable share of all VC funded firms (34%).

Last, in Table 10 we divide the sample by startup hubs versus not (Columns 2 to 4), and over economic cycles (Columns 5 to 7). Estimates for the role of VC are higher outside of hubs, where VC-funded firms are 9 times more likely to grow than their counterparts, and when follow-on capital is more likely to be available (as in the .com boom period). The first effect suggests that the marginal VC-funded company in a non-hub region may be of higher quality than the marginal VC-funded firm in a hub, and is consistent with the results Catalini and Hui (2017) find when looking at US equity crowdfunding investments.

VII. CONCLUSION

Taken together, our results support both the presence of multiple, alternative paths to startup growth, but also of a common profile for high potential firms which is independent of funding source. Though a large portion of firms grow without venture capital, the characteristics of these startups are strikingly similar to the characteristics of startups that are typically selected by VCs. Almost 50% of the firms that never raise VC are in the top 5% of our estimated *VC Likelihood* distribution, and non-VC-backed firms in the top 1% of the same estimate are over 700 times more likely to achieve an equity growth outcome (compared to the bottom 10%).

[18] In terms of the type of growth outcomes we observe, VCs are associated with a larger increase in the probability of an acquisition than in the probability of an IPO, which is consistent with them supporting their portfolio firms in the search for potential buyers through their professional network.

Our estimates of the 'VC-effect', while inherently imperfect because of our inability to capture many of the firm and founder characteristics VCs observe through their due diligence and screening process, place an upper bound on the contribution of VCs to growth. In our matched sample estimates, VC funded firms are 6 times more likely to grow than non-VC-funded firms of comparable quality. Furthermore, when we focus on the right tail of the observable, *VC Likelihood* distribution, the 'VC-effect' is substantially reduced: firms in the top 0.1% of our quality measure at birth, are only 2.5 times more likely to grow with VC funding than without it.

Overall, our findings highlight just how much selection accounts for the perceived contribution of venture capital to startup growth. Given how simple the observables from our prediction model are, their public nature, and the fact that they are collected many years before an exit event, it is striking to see how much they explain of the process of selection into VC and startup growth both for VC-backed and non-VC-backed firms.

The data also surfaces the presence of a single type of high-potential firm that has a substantially higher probability of growth than the vast majority of other firms in the economy from birth, independent of funding source. Whereas the existing literature on high-growth firms has mostly focused on VC-funded startups, our findings uncover a set of firms that have not only similar observable characteristics to VC-funded firms, but also similar potential from the start. Further exploring how these alternative paths to growth differ, should be a fruitful research area for scholars interested in how society allocates capital to novel, high potential ideas and converts them from ideas to massively scalable businesses.

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TABLE 1

Summary Statistics

Measure	Source	Description	Mean	Std. Dev.
Firm Outcomes				
Gets Venture Capital	Multiple	Whether the firm receives any financing.	0.0008	0.028
Gets Venture Capital in 2 years	Multiple	Whether the firm receives any financing within 2 years of founding.	0.0005	0.023
Equity Growth (IPO or Acquisition)	SDC Platinum IPO and M&A.	Whether the firm has an equity growth event in the first 10 years.	0.0005	0.024
Business Registration Observables				
Corporation	Business Reg.	1 if a firm is a corporation (not an LLC or partnership)	0.589	0.492
Delaware	Business Reg.	If the firm's jurisdiction is Delaware	0.036	0.186
Short Name	Business Reg.	If the firm's name length is 3 words or less (including firm type (e.g. "inc."))	0.468	0.499
Eponymous	Business Reg.	Business Reg. If the president or CEO share the name of the firm.	0.079	0.270
Intellectual Property Observables				
Trademark	USPTO	If the firm acquires for a trademark within 1 year of founding.	0.0009	0.031
Patent	USPTO	If the firm acquires for a patent application within 1 year of founding.	0.0020	0.045
USCMP Name Based Industry Measures				
Industry Dummies	Business Reg.	If firm name is associated to an industry group (see Appendix for details).		
Observations			10,451,896	

This table represents our full dataset, comprised of all registered firms registered within the years 1995 and 2005 in 34 US states. These states account for 83% of US GDP and 95% of US venture capital investments in 2015. All measures defined in detail in Section III of this paper. Venture capital outcomes are taken for all firms reported in Thompson Reuters VentureXpert, Prequin, Capital IQ, and AngelsList. Business registration records are public records created endogenously when a firm registers as a corporation, LLC, or partnership. IP observables include both patents and trademarks filed by the firm within a year of founding, as well as previously filed patents assigned to the firm close to founding. All business registration observables, IP observables, and industry measures are estimated at or close to the time of firm founding. Further information on all measures can also be found in Guzman and Stern (2015), Guzman and Stern (2016), and Guzman and Stern (2017). Growth IPOs include only 'true' startup IPOs, we exclude all financial IPOs, REITs, SPACs, reverse LBOs, re-listings, and blank check corporations.

TABLE 2

Distribution of Equity Outcomes with and without VC

Panel A. Growth with and without VC

	Firms with VC	Firms without VC
Firms without Growth	6,885	10,438,652
(Share)	(83.4%)	(99.95%)
Firms with Growth	1,379	4,980
(Share)	(16.7%)	(0.05%)
Growth Split by IPO and Acquisition		
Share that IPO	3.5%	0.01%
Share that are Acquired	13.2%	0.04%

We perform an analysis of all firms that achieve IPO or acquisition (at any point) vs those that do not. IPOs are taken from SDC Capital and exclude all re-listings, reverse LBOs, SPACs, REITs, blank check companies, and financial IPOs.

TABLE 3

Determinants of Venture Capital Financing
Training Sample (50% Random Sub-Sample)
Logit model. Incidence Rate Ratios Reported

	Gets Venture Capital		
	(1)	(2)	(3)
Business Registration Observables			
Corporation	6.789***		5.523***
	(0.823)		(0.649)
Short Name	7.461***		6.039***
	(0.587)		(0.517)
Eponymous	0.128***		0.157***
	(0.0229)		(0.0282)
Delaware	20.39***		
	(3.071)		
Intellectual Property			
Trademark		3.192***	1.888**
		(0.724)	(0.388)
Patent		79.12***	
		(7.773)	
Patent Delaware Interactions			
Delaware Only			15.62***
			(2.191)
Patent Only			37.56***
			(3.625)
Patent and Delaware			121.4***
			(20.43)
USCMP Industry Dummies			
Local Industry			0.323***
			(0.0435)
Traded Industry			0.764***
			(0.0342)
Resource Intensive Industry			0.650***
			(0.0452)
IT			3.213***
			(0.181)
Biotechnology			2.503***
			(0.308)
E-Commerce			1.648***
			(0.126)
Medical Devices			1.231**
			(0.0922)
Semiconductor			2.358***
			(0.392)
State F. E.	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	5225947	5225947	5225947
pseudo R-sq	0.270	0.180	0.330

This table reports a logit model estimating the determinants of firm growth for all firms without venture capital in a 50% random subsample of our data. Using firms without VC allows us to measure the possibility of growth independent of this input. We use this as a training sample for our predictive analytics model of entrepreneurial quality. Incidence rate ratios reported. Robust standard errors in parenthesis. ** p < .01 , *** p < .001

TABLE 4

Relationship of VC Likelihood to Equity Growth Outcomes
Dependent Variable: Equity Growth (IPO or Acquisition)
50% Test Sample. Firms with VC excluded.

	(1)	(2)
Log-Odds of VC Likelihood	2.263***	
	(0.0286)	
VC Likelihood (Standardized)		1.105***
		(0.00663)
State F. E	Yes	Yes
Year F E	Yes	Yes
N	5221901	5221901
pseudo R-sq	0.186	0.095

Robust standard errors in parenthesis clustered at the state-cohort level. VC likelihood is the estimated likelihood of raising venture capital given the at-birth characteristics of a company, it is estimated in a separate training sample, showing in Table 4.

TABLE 5

Determinants of Growth without Venture Capital
Training Sample (50% Random Sub-Sample)
Logit model. Incidence Rate Ratios Reported

	Gets Venture Capital	Equity Growth without Venture Capital Financing (VC-Backed firms Excluded)		
	(1)	(2)	(3)	(4)
Business Registration Observables				
Corporation				
	5.523***	2.378***		1.988***
	(0.649)	(0.176)		(0.144)
Short Name				
	6.039***	2.975***		2.793***
	(0.517)	(0.213)		(0.203)
Eponymous				
	0.157***	0.180***		0.210***
	(0.0282)	(0.0285)		(0.0344)
Delaware				
		19.95***		
		(1.906)		
Intellectual Property				
Trademark				
	1.888**		12.17***	6.434***
	(0.388)		(2.272)	(1.005)
Patent				
			50.09***	
			(4.475)	
Patent Delaware Interactions				
Delaware Only				
	15.62***			15.42***
	(2.191)			(1.596)
Patent Only				
	37.56***			31.08***
	(3.625)			(4.276)
Patent and Delaware				
	121.4***			118.7***
	(20.43)			(15.23)
USCMP Industry Dummies				
Local Industry				
	0.323***			0.582***
	(0.0435)			(0.0901)
Traded Industry				
	0.764***			1.268***
	(0.0342)			(0.0669)
Resource Intensive Industry				
	0.650***			1.243*
	(0.0452)			(0.115)
IT				
	3.213***			1.555***
	(0.181)			(0.173)
Biotechnology				
	2.503***			2.495***
	(0.308)			(0.402)
E-Commerce				
	1.648***			1.295**
	(0.126)			(0.112)
Medical Devices				
	1.231**			1.167
	(0.0922)			(0.104)
Semiconductor				
	2.358***			1.358
	(0.392)			(0.310)
State F. E.	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	5225947	5221731	5221731	5221731
pseudo R-sq	0.330	0.166	0.116	0.210

This table reports a logit model estimating the determinants of firm growth for all firms without venture capital in a 50% random subsample of our data. Using firms without VC allows us to measure the possibility of growth independent of this input. We use this as a training sample for our predictive analytics model of entrepreneurial quality. Incidence rate ratios reported. Robust standard errors in parenthesis. ** $p < .01$, *** $p < .001$

TABLE 6

Growth without Venture Capital
Logit Regression.
50% Test Random Sample

		Place Heterogeneity			Time Heterogeneity		
	All Firms	Silicon Valley	Startup Hubs	Non Startup Hubs	.com Boom 1995-Sept, 1999	.com Crash Sept, 1999-2001	Recovery 2001-2005
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log-Odds of VC Likelihood	2.263***	2.261***	2.315***	2.215***	2.140***	2.336***	2.392***
	(0.0286)	(0.0611)	(0.0584)	(0.0513)	(0.0452)	(0.113)	(0.0723)
State F. E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Incorporation F. E.	Yes	Yes	Yes	Yes			
N	5221901	129280	857638	4364199	1357982	825380	2994715
pseudo R-sq	0.186	0.252	0.259	0.155	0.160	0.216	0.194

TABLE 7

Venture Capital and Growth Outcomes Controlling for Observables and VC Likelihood

DV: Equity Growth: 1 if Firm Achieves IPO or Acquisition

	All Firms					Exactly Matched Sub-sample
	(1)	(2)	(3)	(4)	(5)	(6)
Gets VC in 2 Years	518.2***	63.69***	28.44***	15.01**	14.16***	6.059***
	(28.48)	(7.093)	(2.244)	(1.397)	(1.269)	(0.776)
Business Registration						
Corporation			2.351***	2.004**		
			(0.125)	(0.108)		
Short Name			16.03***	11.73**		
			(0.826)	(0.641)		
Eponymous			0.246***	0.275**		
			(0.0380)	(0.0427)		
Delaware			2.691***	2.536**		
			(0.128)	(0.126)		
Intellectual Property						
Patent		20.36***		6.959**		
		(2.151)		(0.600)		
Trademark		13.29***		5.520**		
		(1.784)		(0.712)		
USCMP Industry Dummies						
Local Industry				15.01**		
				(1.397)		
Traded Industry				0.572**		
				(0.0531)		
Resource Intensive Industry				1.137**		
				(0.0557)		
IT				1.259**		
				(0.0774)		
Biotechnology				1.717**		
				(0.144)		
E-Commerce				2.049**		
				(0.334)		
Medical Devices				1.256**		
				(0.0978)		
Semiconductor				1.042		
				(0.101)		
Entrepreneurial Quality Controls						
Log-Odds of VC Likelihood				1.464	1.016	
				(0.497)	(0.119)	
Log-Odds of VC Likelihood^2					0.831***	
					(0.0284)	
Log-Odds of VC Likelihood^3					0.985***	
					(0.00392)	
Log-Odds of VC Likelihood^4					1.000	
					(0.000154)	
State F. E.	No	Yes	Yes	Yes	Yes	Yes
Incorporation Year F.E.	No	Yes	Yes	Yes	Yes	Yes
N	5225949	5225949	5225949	5225949	5225949	4815
pseudo R-sq	0.106	0.192	0.241	0.269	0.262	0.124

We estimate the relationship between entrepreneurial quality indicators and firm equity growth. All regressions are run on a 50% test sample drawn separately from the 50% training sample used to estimate quality in Table 3.

TABLE 8

VC Financing and Equity Growth Outcomes

Logit Regression on Matched Sample.

DV: Equity Growth Outcome: 1 if firm achieves IPO or Acquisition				
	Baseline Model		Extra Controls	
	(1)	(2)	(3)	(4)
Gets VC in 2 Years	6.059***	6.143***	6.250***	6.106***
	(0.776)	(0.804)	(0.819)	(0.795)
Year F. E.	Yes		Yes	Yes
State F. E.	Yes			
State X Year F. E.		Yes		
MSA F. E.			Yes	
Control for Average Neighbor Quality				Yes
N	4815	4359	4272	4811
Pseudo R-sq	0.124	0.131	0.131	0.143

Robust standard errors in parenthesis. Matching approach uses exact quality values to match firms. All regressions run only on the 50% test sample not included in training the entrepreneurial quality model in Table 3. Some observations dropped when including State X Year Fixed Effects, MSA Fixed Effects, and average neighbor quality. Control for neighbor quality is natural log of the average quality of the ZIP Code excluding the focal firm. Matching algorithm matches each company that gets VC finance to another company with the same quality, born in the same year and ZIP Code. In about 20% of the sample, we do not find a match in the same ZIP Code and use a match in the same MSA instead. Incidence rate ratios reported. Robust standard errors in parenthesis. *** p < .001

TABLE 9

Logit Regression, Matched Firms.

DV: Equity Growth Outcome. 1 if firm achieves IPO or Acquisition.

	All Firms	Within the Quality Distribution			
		Top 5%	Top 1%	Top 0.1%	Top 0.05%
	(1)	(2)	(3)	(4)	(5)
Gets VC in 2 Years	6.059***	5.779***	4.287***	2.436***	2.425***
	(0.776)	(0.765)	(0.595)	(0.427)	(0.515)
N	4815	3802	2835	1083	694
Pseudo R-sq	0.124	0.120	0.093	0.064	0.076

Robust standard errors in parenthesis. State fixed effects and year fixed effects included in all regressions. Matching algorithm matches each company that gets VC finance to another company with the same quality, born in the same year and ZIP Code. In about 20% of the sample, we do not find a match in the same ZIP Code and use a match in the same MSA instead. Incidence rate ratios reported. Robust standard errors in parenthesis. *** p < .001

TABLE 10

VC Financing and Equity Growth Outcomes.
Logit Regression, Odds Ratios Reported.
Matched Sample. Heterogeneous Effects.
DV: Equity Growth. 1 if firm achieves IPO or acquisition

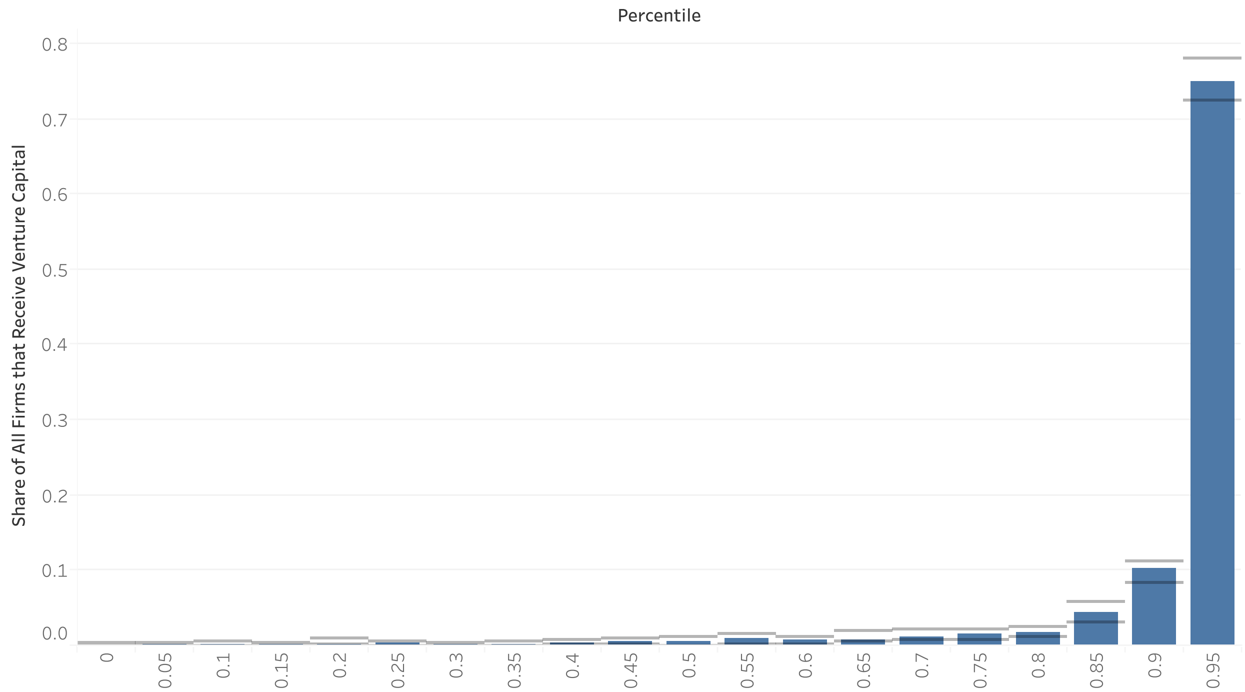
		Place Heterogeneity			Time Heterogeneity		
	All Firms	Silicon Valley	Startup Hubs	Non Startup Hubs	.com Boom Born: 1995-Sept, 1999	.com Crash Born: Sept, 1999-2001	Recovery Born: 2001-2005
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gets VC in 2 Years	6.059***	4.893***	5.403***	9.100***	9.330***	5.362***	3.472***
	(0.776)	(0.915)	(0.806)	(2.288)	(2.047)	(1.121)	(0.809)
State F.E.	Yes				Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes			
N	4921	1777	2957	1996	1338	2104	1293
Pseudo R-sq	0.124	0.124	0.124	0.121	0.155	0.081	0.068

Robust standard errors in parenthesis. State fixed effects excluded from regressions that vary location, year fixed effects excluded from regressions that vary time, to allow differences in each dimension to show in the coefficient Matching algorithm matches each company that gets VC finance to another company with the same quality, born in the same year and ZIP Code. In about 20% of the sample, we do not find a match in the same ZIP Code and use a match in the same MSA instead. VC Quality only observed for California, Massachusetts, New York state, Texas, and Washington state. Incidence rate ratios reported. Robust standard errors in parenthesis. *** p < .001

FIGURE 1

VC Prediction vs Realized VC Financing Outcomes
Out of Sample Performance of Predictive Model

72% of all VC-backed firms in top 5% of predicted VC distribution.
53% of all VC-backed firms in top 1% of predicted VC distribution.



Note: We perform a 10 fold out of sample cross validation procedure to study the predictive capacity of our VC likelihood estimate. Bars indicate the average share of all out of sample VC-backed firms in different points of the predicted VC distribution, by 5 percent bins. Lines indicate the minimum and maximum estimate in this test.

FIGURE 2

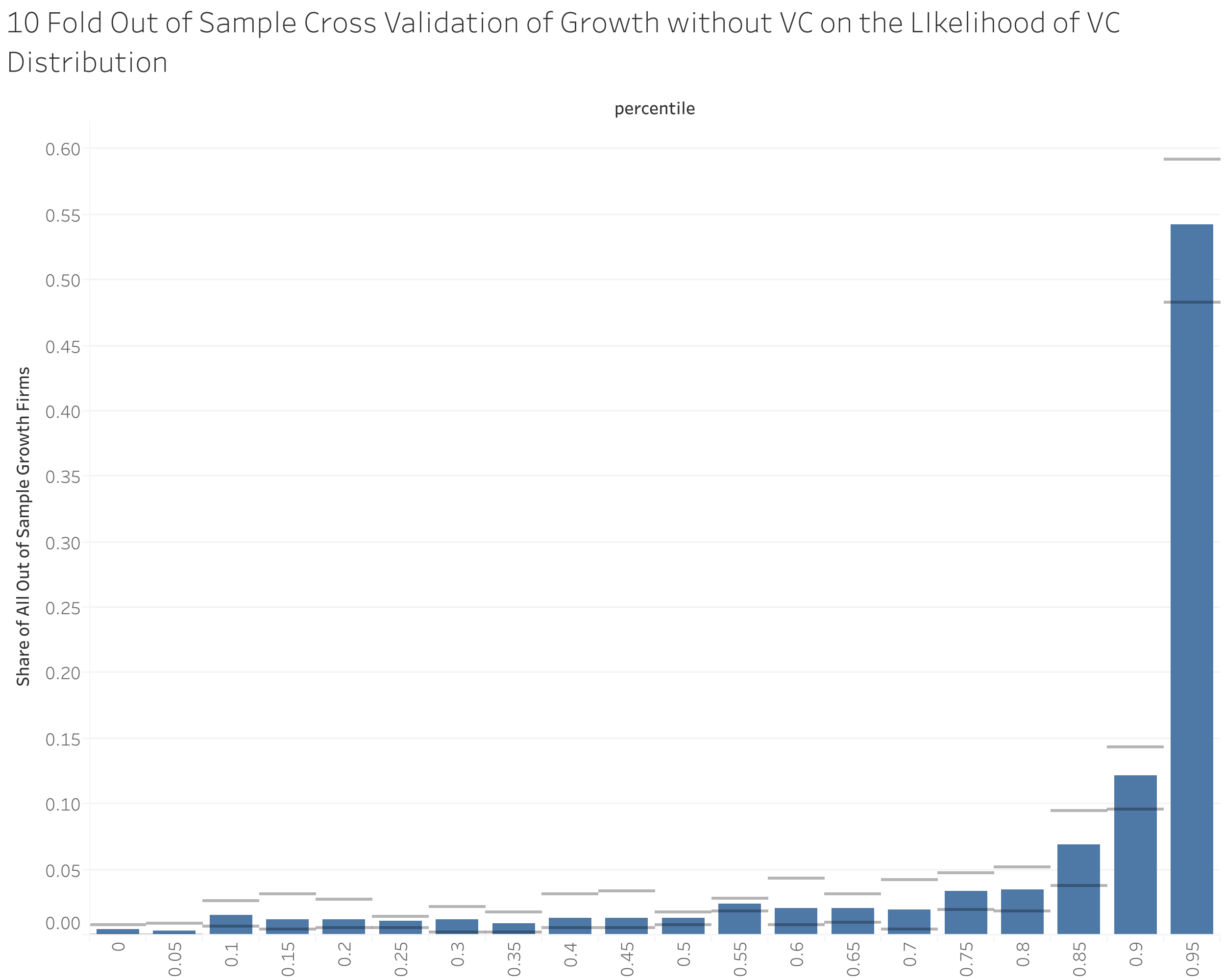
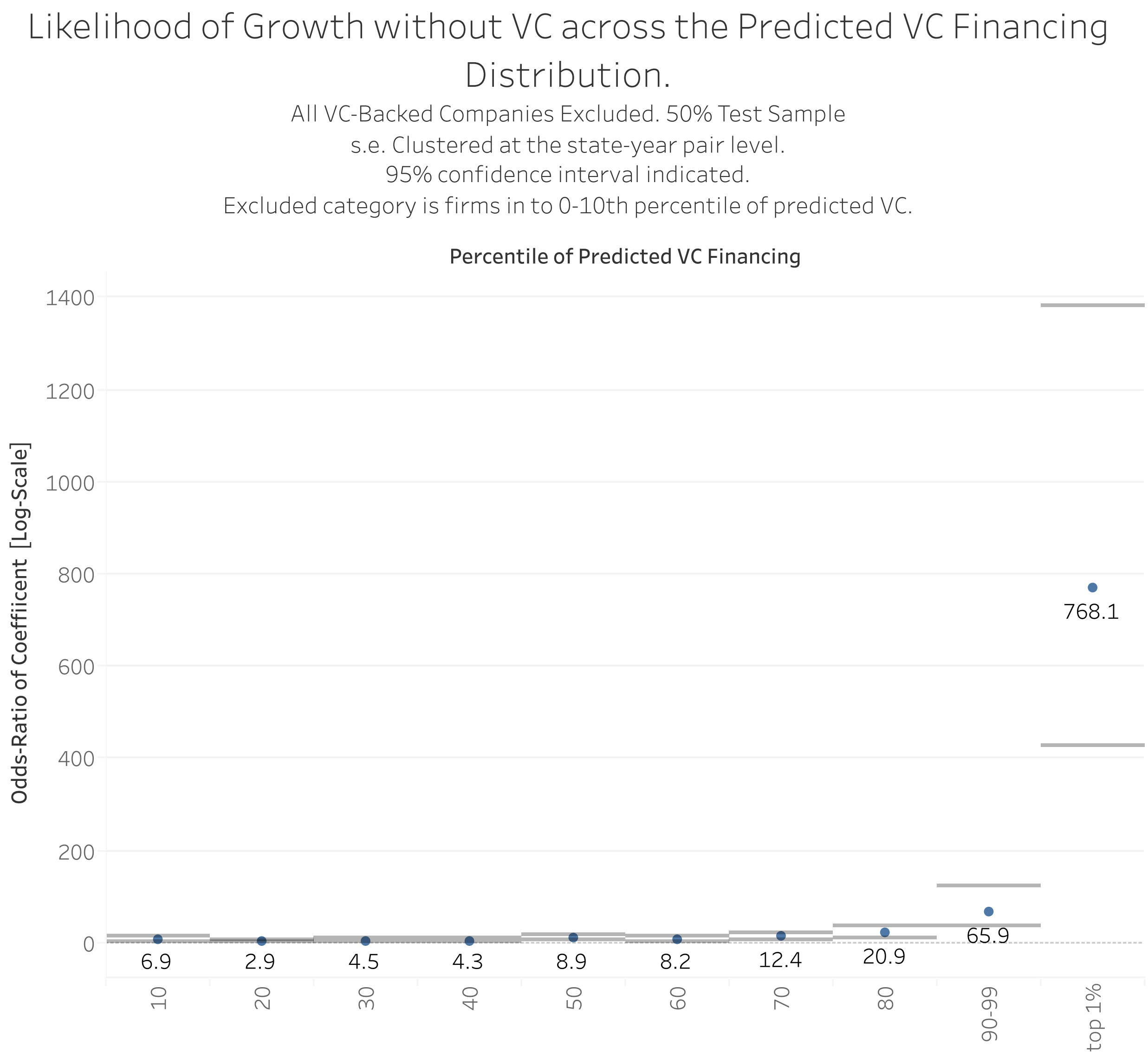

10 Fold Out of Sample Cross Validation of Growth without VC on the LIkelihood of VC Distribution
percentile
Share of All Out of Sample Growth Firms
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
0.55
0.6
0.65
0.7
0.75
0.8
0.85
0.9
0.95

FIGURE 3


Likelihood of Growth without VC across the Predicted VC Financing Distribution.
All VC-Backed Companies Excluded. 50% Test Sample
s.e. Clustered at the state-year pair level.
95% confidence interval indicated.
Excluded category is firms in to 0-10th percentile of predicted VC.
Percentile of Predicted VC Financing
Odds-Ratio of Coefficient [Log-Scale]
1400
1200
1000
800
600
400
200
0
6.9
2.9
4.5
4.3
8.9
8.2
12.4
20.9
65.9
768.1
10
20
30
40
50
60
70
80
90-99
top 1%

APPENDIX

Appendix A – Business Registration Requirements and Data

Business registration is the act of forming a firm as a corporation, limited liability company (LLCs), or partnership. In the process of providing financing, venture capitalists invest in registered businesses[19] by providing capital in exchange for ownership in the company[20]. The rights and obligations between the firm and the VC firm are then governed by the entity type, the jurisdiction, and the by-laws of each company. Being a shareholder in a corporation provides several benefits to venture capitalists relative to partnerships. In particular, minority shareholders have stronger rights in the corporation, which can be further augmented through provisions in the by-laws of the company, its operating agreements, or other contracts with the VCs. It also allows stricter governance. Finally, only corporations can be publicly traded companies, hence only corporations can exercise an initial public offering (IPO)—one of the main exit strategies for VCs. In the United States, the ability to exercise specific rules governing the VC contract depends on the state jurisdiction under which the firm operates. Due to a historical accident, there is a precedent of strong predictability of corporate law in the state of Delaware, and venture capitalist (as well as over half of all public companies) have a strong preference for firms registered under Delaware corporate law, even when this comes at an extra cost to the firm.

Entrepreneurs (and their lawyers) take these trade-offs into account as they convert their intentions for the firm into a legal structure. For example, they might prefer to register in Delaware if they expect to grow or seek VC financing. They also need to choose a name for the firm, whether to file for intellectual property protection through trademarks and patents, whether to be a corporation, partnership or LLC, etc. These choices are of strategic importance, and self-reveal part of the entrepreneur's ambition and own signal about the potential of the firm.

The timing of registration, while flexible, is influenced by similar considerations. While the cost of registration itself is low ($100 in California) and the process can usually be completed online in less than two hours, founders might struggle to register if they are not ready to choose a governance structure. As such, registration represents a moment in time when the core idea of the firm is developed enough to make these choices. Last, business registration is extremely useful in building a population-level dataset, as it is comprehensive and a necessary condition for equity

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[19] This is an empirical fact rather than a theoretical requirement.

[20] In the case of LLCs and partnerships, purchasing ownership effectively make venture capital firms partners of the target firm. In the case of corporations, they become shareholders. While most venture capital investment occurs through the purchase of corporation shares, there are a few LLC companies invested on during the 1980s as well as the dot-com boom that where not corporations.

financing. This allows us to build a complete population of firms at risk of venture capital without selecting firms along idiosyncratic dimensions.

TABLE A1

Summary Statistics of industry measures

Measure	Source	Description	Mean	Std. Dev.
USCMP Name Based Industry Measures				
Local Industry	Business Reg.	If firm name is associated to a local industry.	0.194	0.396
Traded Industry	Business Reg.	If firm name is associated to a traded industry.	0.535	0.499
Resource Intensive Industry	Business Reg.	If firm name is associated to a resource intensive industry.	0.130	0.337
IT	Business Reg.	If firm name is associated to the IT industry cluster.	0.025	0.156
Biotechnology	Business Reg.	If firm name is associated to the Biotechnology industry cluster.	0.002	0.044
E-Commerce	Business Reg.	If firm name is associated to the E-Commerce industry cluster.	0.052	0.222
Medical Devices	Business Reg.	If firm name is associated to the Medical Devices industry cluster.	0.030	0.172
Semiconductor	Business Reg.	If firm name is associated to the Semiconductor industry cluster.	0.0005	0.023
Observations			10,451,896	

This table represents our full dataset, comprised of all registered firms registered within the years 1995 and 2005 in 34 US states. These states account for 83% of US GDP and 95% of US venture capital investments in 2015. All measures defined in detail in Section III of this paper. Venture capital outcomes are taken for all firms reported in Thompson Reuters VentureXpert, Prequin, Capital IQ, and AngelsList. Business registration records are public records created endogenously when a firm registers as a corporation, LLC, or partnership. IP observables include both patents and trademarks filed by the firm within a year of founding, as well as previously filed patents assigned to the firm close to founding. All business registration observables, IP observables, and industry measures are estimated at or close to the time of firm founding. Further information on all measures can also be found in Guzman and Stern (2015), Guzman and Stern (2016), and Guzman and Stern (2017). Growth IPOs include only 'true' startup IPOs, we exclude all financial IPOs, REITs, SPACs, reverse LBOs, re-listings, and blank check corporations.

TABLE A2

Comparison of Means Between Growth, No Growth, VC Backed and Non VC Backed firms.

	No Equity Growth	Equity Growth	All		No Equity Growth	Equity Growth	All
Corporation				*Eponymous*			
No VC Financing	0.589	0.788	0.589	No VC Financing	0.079	0.017	0.079
VC Financing	0.901	0.954	0.909	VC Financing	0.009	0.005	0.009
All	0.589	0.824		All	0.079	0.015	
Delaware				*Patent*			
No VC Financing	0.035	0.478	0.036	No VC Financing	0.002	0.163	0.002
VC Financing	0.518	0.629	0.533	VC Financing	0.207	0.341	0.225
All	0.036	0.510		All	0.002	0.201	
Short Name				*Trademark*			
No VC Financing	0.468	0.742	0.468	No VC Financing	0.001	0.065	0.001
VC Financing	0.886	0.920	0.890	VC Financing	0.034	0.046	0.036
All	0.468	0.780		All	0.001	0.061	

TABLE A3

Share of firm in IPO and Acquisition Samples
that Raise Venture Capital

	IPO	Acquisition
Firms with VC Financing	288	1,091
(Share)	(33%)	(20%)
Firms without VC Financing	590	4,390
(Share)	(67%)	(80%)

Our estimates are based on firms *founded* between 1995 and 2005 in our sample of states that eventually IPO. Reitter (2015) estimates that the average VC incidence for firms that IPO between 1990 and 2015 as 37%. Kaplan and Lerner (2010) show this highly fluctuates through time.

TABLE A4

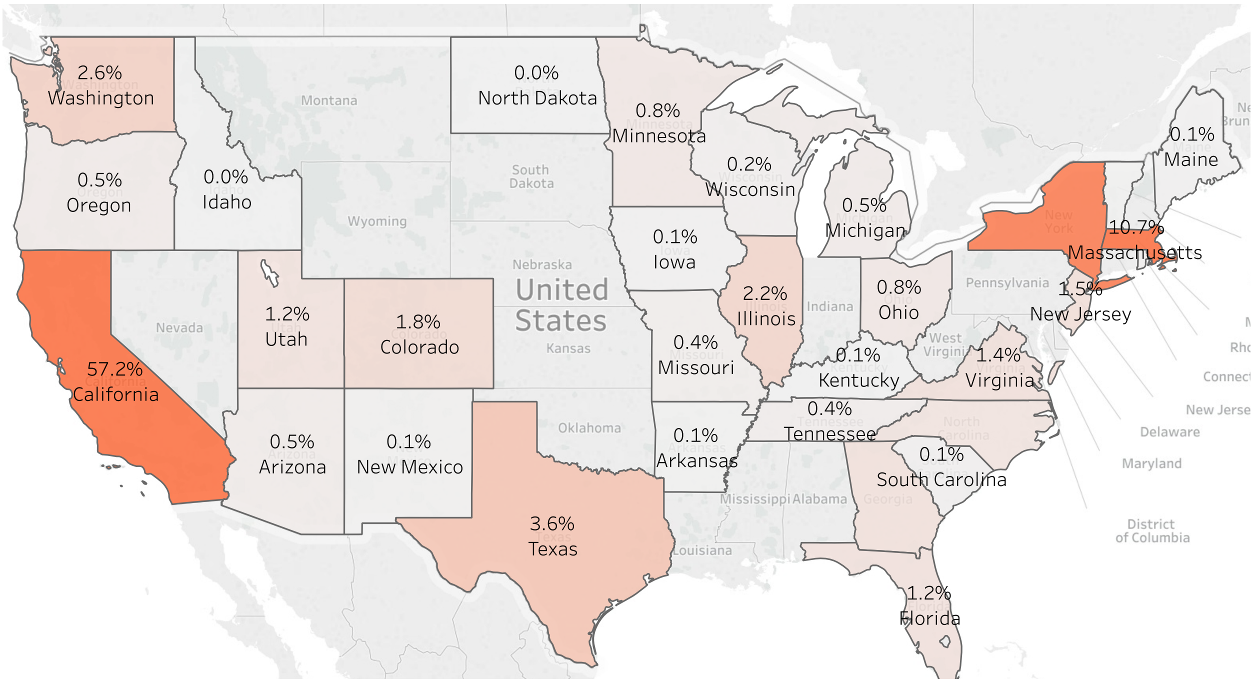
Relationship of VC Likelihood to Equity Growth Outcomes for all firms
Dependent Variable: Equity Growth (IPO or Acquisition)
50% Test Sample.

	All Firms that Achieve Growth	
	(1)	(2)
Log-Odds of VC Likelihood	2.391***	
	(0.0251)	
VC Likelihood (Standardized)		1.110***
		(0.00256)
State F. E	Yes	Yes
Year F E	Yes	Yes
N	5225949	5225949
pseudo R-sq	0.232	0.122

Robust standard errors in parenthesis clustered at the state-cohort level. VC likelihood is the estimated likelihood of raising venture capital given the at-birth characteristics of a company, it is estimated in a separate training sample, showing in Table 4.

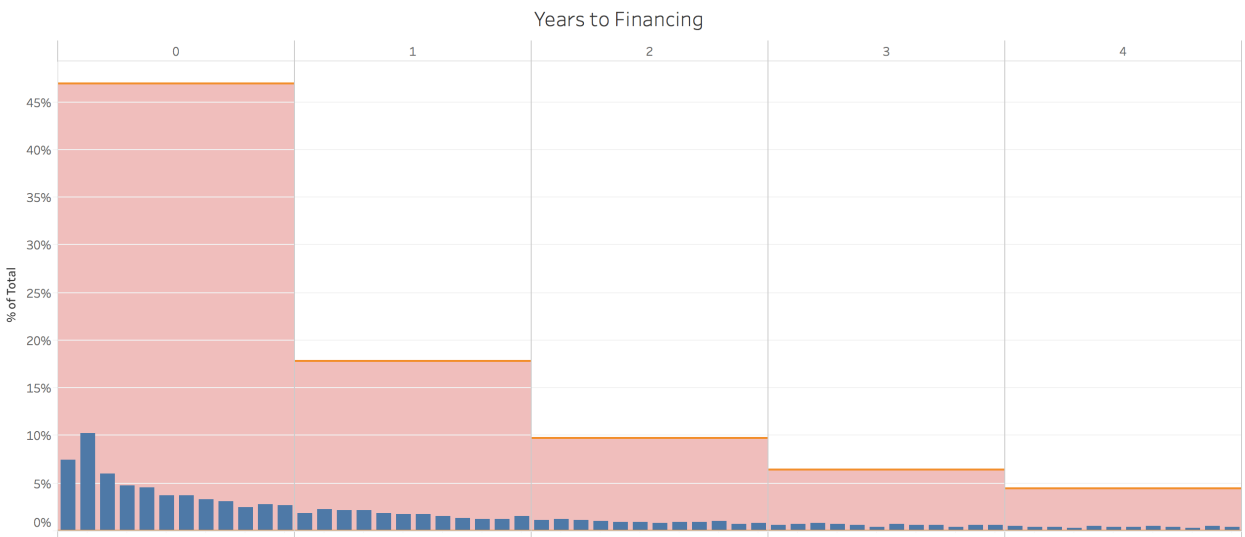
FIGURE A1

DATA COVERAGE AND VC MARKET SHARE



Notes: This map represents all states for which we have data and the amount of VC financing in each of those states as reported by NVCA in 2014.

FIGURE A2
Time to VC Financing



Notes: This graph shows the time to financing by years (in pink) and months (in blue) for all firms that receive VC, estimated as the number of months between incorporation date and date of first VC investment.