

Synergizing Ventures^{*†}

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Abstract

Venture capital (VC) and growth are examined both empirically and theoretically. Empirically, VC-backed startups have higher early growth rates and initial patent quality than non-VC-backed ones. VC-backing increases a startup's likelihood of reaching the right tails of the firm size and innovation distributions. Furthermore, outcomes are better for startups matched with more experienced venture capitalists. An endogenous growth model, where venture capitalists provide both expertise and financing for business startups, is constructed to match these facts. The presence of venture capital, the degree of assortative matching between startups and financiers, and the taxation of VC-backed startups matter significantly for growth.

Keywords: venture capital, assortative matching, endogenous growth, IPO, management, mergers and acquisitions, patents, research and development, startups, synergies, taxation, technological progress.

JEL Codes: O30, O40, G24

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1 Introduction

Most firms are born small, stay small, and engage in little innovation throughout their lifetimes.¹ Only a few become large, successful businesses that generate breakthrough innovations and contribute significantly to aggregate productivity growth. The fluctuations these large firms experience also matter for aggregate volatility.² Venture capital (VC) is a potential catalyst that can take startups to the right tail of the firm-size and innovation distributions, and turn them into engines of growth. What role does VC play in the making of productive and innovative firms? To what extent do the synergies between entrepreneurs and venture capitalists matter for firm and aggregate outcomes? How critical is VC for the growth of the economy?

Several facts are established empirically and then examined through the lens of a macroeconomic model of innovation and growth where venture capitalists match with and nurture startups. The analysis suggests that the presence of venture capital in an economy, the degree of assortative matching between venture capitalists and startups, and the taxes applicable to VC-backed enterprises, matter significantly for growth.

Certain key events in the early stages of firms are the precursors to subsequent high growth. For instance, having a patent or a trademark early on is strongly predictive of the ultimate success of startups, as measured by rare events such as an IPO or a high-value acquisition—e.g., Fazio et al. (2016). Patenting and research and development (R&D) activity are positively correlated with measures of firm growth—e.g., Foster, Grim, and Zolas (2016). Furthermore, initial firm size is a good indicator of the ultimate success of a firm (Brown et al. (2017)). More generally, ex ante differences among startups appear to be important for understanding ex post firm outcomes at any firm age. Early characteristics of planned businesses predict well the ultimate formation of a business, its initial size (Bayard et al. (2018)), and its subsequent dynamics (Pugsley, Sedlacek, and Sterk (2017)). This paper contributes to the literature by establishing, both empirically and theoretically, that VC backing of startups in early stages is not only a key ingredient of eventual firm success,

¹The median startup in the U.S. barely grows over time (see, e.g., Decker et al. (2016) and Choi (2017)).

²Gabaix (2011) analyzes this “granular hypothesis” and finds that the shocks experienced by the top 100 firms in the “fat” right tail of the firm-size distribution account for a sizable fraction of year-to-year GDP fluctuations.

but also a significant contributor to aggregate innovation and productivity growth.

To motivate the model and its analysis, the empirical analysis combines micro data on firms that receive VC funding, using the VentureXpert database, with data on all employer firms in the U.S., taken from the U.S. Census Bureau’s Longitudinal Business Database (LBD) for the period 1980-2012. The life-cycle dynamics of VC-funded versus non-VC-funded firms are studied to understand their differences in innovativeness, survival, and growth. Several key observations emerge from the empirical inquiry. First, despite the fact that VC-backed startups are subject to higher initial selection, failure rates, and dispersion in growth outcomes, they are much more likely than non-VC-backed ones to eventually land in the right tail of the firm size and innovation distributions. In other words, VC appears to contribute disproportionately to the making of large and productive (“superstar”) firms. The dominance of such firms in the U.S. economy has been increasing.³ Yet, the various mechanisms by which superstar firms emerge are not well understood. The findings here suggest that VC plays a critical role in taking startups to stardom.

Second, the synergies between venture capitalists and entrepreneurs matter for how far a VC-backed startup can go. The empirical analysis provides strong evidence of assortative matching between entrepreneurs and financiers—the latter is composed of venture capitalists and others, such as banks. Startups that have more promising growth and innovation prospects tend to be funded by venture capitalists. Moreover, firms backed by venture capitalists with more experience tend to achieve significantly higher growth.

Third, VC involvement is critical for both firm-level and aggregate innovation. The data on firm-level patenting activity and patent quality reveals that VC disproportionately targets more innovative startups and spurs further innovation, with startups backed by more experienced venture capitalists engaging in better innovation. Innovation by VC-funded firms, especially the highly successful ones, generate large productive externalities on the rest of the economy. This externality is evident in the disproportionately high number of citations to patents filed by successful VC-funded firms, which is one of the key contributions of these firms to growth.

³The consequences include the reallocation of labor to these firms, accompanied by a rising industry concentration of sales and a fall in labor’s share of income—see, e.g., Autor et al. (2017).

Motivated by the empirical findings, a macroeconomic model is developed to match salient features of VC in the U.S. data. In the model, venture capitalists disproportionately nurture talented entrepreneurs by providing the necessary ingredients, advice and money, to bring a startup to the market. The framework stresses the complementarity between an entrepreneur's skill and a venture capitalist's. Not all talented entrepreneurs can find a venture capitalist to back their startup, as the latter are in short supply and there is randomness in the matching process. As a result, they turn to more traditional sources of financing, such as banks. Banks provide a limited amount of expertise for a startup. For a talented entrepreneur, matching with a venture capitalist, as opposed to a bank, will result in a higher probability of success, a greater level of funding for startup R&D, and higher productivity. Entrepreneurs starting more run-of-the-mill enterprises are more likely to use bank financing. The opportunity cost for a venture capitalist is too high to mentor these types of startups.

The calibration strategy allows the model to replicate perfectly a set of stylized facts of interest: the growth rate of U.S. GDP; the success rates of VC- and non-VC-backed firms; the relative employments and patenting of both types of firms; the ratio of firms to workers; and the ratio of the numbers of both types of startups. The calibrated model is used to address three aspects of VC's contribution to growth. First, VC is a form of technological progress in finance and the model suggests that VC-funded startups are important drivers of growth. In fact, the vast majority of non-VC funded startups choose innovation levels that place them behind the technological frontier. If the efficiency of VC financing is lowered to that of bank financing, the economy's growth drops from 1.80 to 1.30 percent, which leads to a welfare loss of 7.58 percent in terms of consumption.

Second, the model is used to assess the importance of assortative matching between entrepreneurs and venture capitalists. The calibrated model imposes the matching structure between entrepreneurs and financiers that is observed in the data. One could ask what would happen if matching was perfectly assortative; i.e., if venture capitalists could magically match just with the most promising startups. The analysis suggests that growth would jump up from 1.80 to 1.96 percent, which has an associated welfare gain of 2.26 percent. If, in addition, the supply of venture capitalists could be expanded to accommodate all gifted

startups, growth would ratchet up to 2.05 percent with a welfare gain of 3.66 percent.

Last, VC-financed startups are taxed at the capital gains tax rate, instead of at either the corporate or personal income tax rates, as with other startups. Raising the rate of taxation on VC-financed startups to the rate faced by other types of startups would lower the growth rate from 1.80 to 1.48 percent, which yields a welfare loss of 4.83 percent.

1.1 Literature Review

The empirical analysis adds to the large literature on the effects of VC funding on firm performance. In early work, Kortum and Lerner (2000) studied the impact of VC funding on firm-level innovation between 1983-1992 and documented a significant positive impact.⁴ Puri and Zarutskie (2012) find that VC-backed firms exhibit higher growth and higher rates of IPO and M&A activity, compared to otherwise similar firms. Some prior evidence suggests that VC monitoring of startups matters. For instance, Bernstein, Giroud, and Townsend (2015) show that venture capitalists' on-site involvement with the firms they fund generates both a higher level of innovation and a higher likelihood of success.⁵ More recently, Wong (2019) finds that a large portion of the variation in the duration of venture capital involvement across startups can be attributed to unobserved venture capitalist and match-specific effects. These findings point to potentially large treatment effects associated with venture capitalists' mentoring and monitoring of startups. The analysis here offers further evidence of such effects.

The empirical work extends the prior literature in a number of dimensions. The selection of startups by venture capitalists based on early innovation potential is explored, as well as the effects of VC treatment on innovation. In addition, a distinguishing aspect of the analysis is its focus on the effects of assortative matching between entrepreneurs and financiers. The presence and extent of synergies between venture capitalists and entrepreneurs is assessed. The analysis also quantifies the disproportionately large innovative externalities generated by VC-backed firms using citations to the patents applied for by these firms. Finally, the

⁴See also the empirical findings in Greenwood, Han, and Sanchez (2022b).

⁵Bernstein, Giroud, and Townsend (2015) exploit an exogenous reduction in VC oversight costs due to the opening of new airline routes that makes it easier for venture capitalists to visit their portfolio companies.

analysis here uses, in addition to the discrete measures of success for firms (such as IPO and M&A), continuous measures of firm growth and innovation to define thresholds for success by the end of a typical VC contract.⁶

This paper contributes to the endogenous growth literature (e.g., Aghion and Howitt (1992) and Romer (1990)) by introducing VC financing into a model with endogenous technological progress. VC can be thought of as technological progress in the financial sector that spurs on the formation of cutting-edge startups. Ates (2014), Greenwood, Sanchez, and Wang (2019), and Opp (2019) are earlier analyses in a similar direction. Ates (2014) and Opp (2019) develop stylized Schumpeterian models of VC. In Ates' (2014) and Opp's (2019) analyses the R&D decisions by new entrepreneurs are limited in the sense that they do not choose how far to launch their productivities ahead of the levels of incumbent firms. Also, the likelihood of success does not depend on the level of development funding. Greenwood, Han, and Sanchez (2022a) model VC from a dynamic contract perspective. Their analysis focuses on the VC funding-round process. They do not explicitly model a banking sector as is done here. Ates (2014), Greenwood, Han, and Sanchez (2022a), and Opp (2019) do not spotlight the initial selection process between different types of entrepreneurs and financiers, and the associated transition from ex ante promise to ex post success. These papers also do not utilize data on firm growth and innovation in the early stages of privately-held startups to assess venture capital selection and treatment effects.

The current analysis also relates to two recent themes in the literature. First, it highlights the importance of financing for innovation and superstar firm creation. Therefore, it connects with research by Autor et al. (2017), that documents the rise of superstar firms and their consequences for inequality. Bloom et al. (2017) and Gordon (2017) have argued that new ideas are harder to find and innovations are more expensive to implement. The current analysis highlights the importance of a good match between financiers and inventors, as well as the taxation of startups, for bringing new ideas to life. Second, at least since

⁶In particular, the analysis estimates the likelihood of a venture capitalist taking a firm to the right tail of the firm-size and innovation distributions (90th percentile) within 10 years. The rationale for doing so is that even though a surviving VC-backed firm may not reach an IPO or M&A stage, it can still achieve substantial growth and innovation on average, compared to non-VC-backed firms. Furthermore, among the firms that are involved in IPO or M&A activity, the heterogeneity in performance can be more finely captured by continuous measures of firm growth. Measuring success in this fashion accounts for the contribution of all VC-backed firms to economic growth and aggregate productivity.

Cameron (1963), economists have been interested in the importance of finance for economic development. The empirical connection between finance and development is exhaustively surveyed by Levine (2005), who concludes that financial development has a causal effect on economic development. Recent quantitative models of the connection between finance and development are Antunes, Cavalcanti, and Villamil (2008), Buera, Kaboski, and Shin (2011), Castro, Clementi, and MacDonald (2004), Cole, Sanchez, and Greenwood (2016), and Erosa (2001). This work has typically focused on developing countries, and does not study whether different forms of finance (such as VC versus bank funding) matter for firm-level and aggregate innovation and growth.

2 Stylized Facts on VC-Funded Firms

To what extent does VC matter for turning startups into engines of economic growth and innovation? Empirical analysis is carried out to offer evidence on both the selection and treatment effects associated with venture capitalist involvement in a firm. This involvement may include, in addition to financial support, providing management advice and mentoring, industry expertise, and business network connections. These factors can lead to potentially different trajectories of growth and innovation for VC-funded firms compared to non-VC-funded ones.

The first goal of the empirical analysis is to explore the nature of selection by venture capitalists, based on key observable startup characteristics such as size, growth, and innovative activity. If venture capitalists tend to pick more promising projects to fund and nurture, there should be a disproportionate presence of VC among larger, faster growing, and more innovative startups.

The second goal is to understand the role that VC plays in catapulting firms to the right tail of the firm size and innovation distributions. How much does VC matter for a startup's survival, growth, and innovation? To investigate such effects, the outcomes of VC-funded firms are compared with those of a control group composed of non-VC-funded firms, which are chosen to match closely the funded firms on a number of key observable characteristics at the time of VC funding.

Finally, the empirical analysis investigates the strength of assortative matching and synergies between venture capitalists and startups. Some venture capitalists may be better than others at identifying and nurturing promising startups. That is, the extent of selection and treatment by venture capitalists may depend on both the type of startup and the type of venture capitalist. Are startups with better growth and innovation prospects disproportionately targeted by more experienced venture capitalists? Do startups funded and supported by more experienced venture capitalists achieve better outcomes? Some evidence on heterogeneous treatment effects is provided by studying the outcomes of startups backed by more-versus less-experienced venture capitalists.

2.1 Data

The empirical work brings together several datasets—see Appendix A for details on the construction of the dataset used for the analysis, as well as supplemental information on all figures and tables. The main dataset that enables the tracking of firms over time is the U.S. Census Bureau’s LBD. The LBD contains longitudinally-linked information for each employer business in the United States starting in 1976, based on administrative data in the Census Bureau’s Business Register (BR). Firms, and their constituent establishments, are observed in the LBD starting from the time of their first appearance as an employer business in administrative records. The LBD includes annual measures of age, employment, and payroll for both firms and establishments, and an annual revenue measure at the firm level for a large fraction of firms.⁷

Firms that receive VC funding are identified using the Thomson Reuters’ VentureXpert database, which contains information on the dates of VC funding, the funding amount, and the identity of the venture capitalists. Firms in VentureXpert are first matched with the BR using name and address matching techniques, and then linked to the LBD using unique firm and establishment identifiers. To include measures of innovation, the U.S. Census Bureau’s patent-firm crosswalk is used to identify firms with patenting activity.⁸ Back and forward

⁷Data on revenue start in 1997.

⁸The patent-firm crosswalk is a result of merging the USPTO’s patent database with the LBD; see Graham et al. (2015).

citations for each patent are also incorporated from the USPTO’s PatentsView. In addition, Standard&Poor’s Compustat database is linked with the LBD to identify publicly-listed firms. The data set tracks all employer firms during the period 1980 to 2012.

An important feature of the assembled dataset is that firms can be tracked over their entire life cycle, starting from their birth to their death.⁹ Other key events in a firm’s life cycle are also observed: the first injection of funds by a venture capitalist, the first patent application, and an IPO or an M&A event. IPO events are identified using the Compustat database. M&A activity is identified based on how the ownership of the firm and its establishments changes from one year to another.¹⁰ The firm outcomes in the analysis are survival, employment, and innovation, as reflected by patenting activity and patent citations.¹¹

2.2 Which Firms do Venture Capitalists Select?

Venture capitalists pick startups to fund and nurture very early during their formation. Figure 1 depicts the age distribution of VC-backed startups at first VC funding. Age is measured by the number of years since a startup first appears in the LBD as an employer business (birth). Negative age values correspond to cases where a startup receives funding even before it is first observed as an employer business.¹² The striking feature of Figure 1 is the spike at age zero. About 42 percent of VC-funded firms receive their first funding in their first year as an employer business. There is also a considerable fraction of startups (about 15 percent) that receive their first funding before they hire their first employee (age

⁹Birth is identified by the first year of an employment record, while death happens if the firm ceases to exist as an employer.

¹⁰For details on identifying IPOs and M&As, see Appendix A.

¹¹The results using revenue are briefly mentioned as an alternative to employment when appropriate. For firm size, employment is the preferred measure in the analysis, since annual revenue data is available starting only in 1997.

¹²Firms outside of the age range in Figure 1 are not included to prevent the disclosure of confidential information—they account for a small fraction of all firms that receive VC funding. In addition, the truncation of age at -5 guards against potential matching errors. Startups that receive VC funding 6 or more years before they hire their first employee are rare, and such cases may be more likely to indicate false positives in the name and address matching procedures. Similarly, startups that receive VC funding after age +5 constitute a small fraction of all firms.

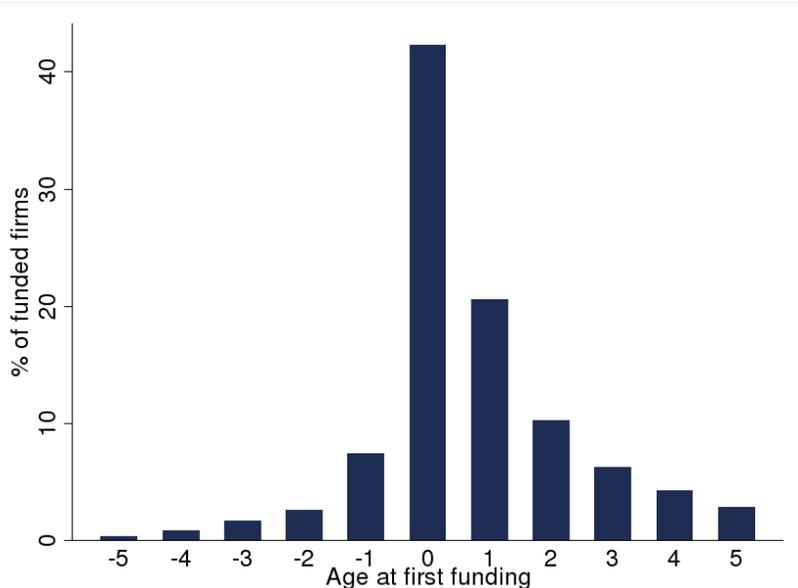


Figure 1: The distribution of firm age in the year of first VC funding. Age 0 corresponds to the first time that a startup is observed as a business with employee(s). Ages -5 to -1 correspond to startups for which the year of first VC funding occurs before the first observation of the startup as an employer.

< 0).^{13,14}

Figure 2 plots the probability of ever receiving VC funding by employment growth quintiles, where the quintiles are based on growth during a startup’s first three years as an employer business.¹⁵ The probability of funding jumps nearly two hundred-fold as one moves from the lowest quintile to the highest, suggesting that venture capitalists tend to select firms that exhibit relatively high growth in their early phases.¹⁶

The relationship between a startup’s probability of receiving its first VC funding within five years of its first patent application and the quality of its early patents is plotted in Figure 3. The quality of early patenting is measured by the total number of citations for all patents

¹³Most likely, these firms receive VC funding at a stage when they are still non-employers; i.e., businesses with no payroll/employees. Recent work by Bento and Restuccia (2019) highlights the contribution of non-employer businesses to business dynamism in the United States.

¹⁴For the rest of the analysis, startups that receive VC funding before age zero are treated as having received funding at age zero. This approach is necessary because several key variables (e.g., employment and patenting) for the subsequent analysis are available only for employer firms starting at age zero.

¹⁵The employment growth rate for the first three years of a firm’s life-cycle is measured as $g = 2 \times (emp_{t+2} - emp_t) / (emp_{t+2} + emp_t)$, where t is the year a startup is first observed as an employer business.

¹⁶A similar conclusion emerges when growth is measured in terms of revenue instead of employment.

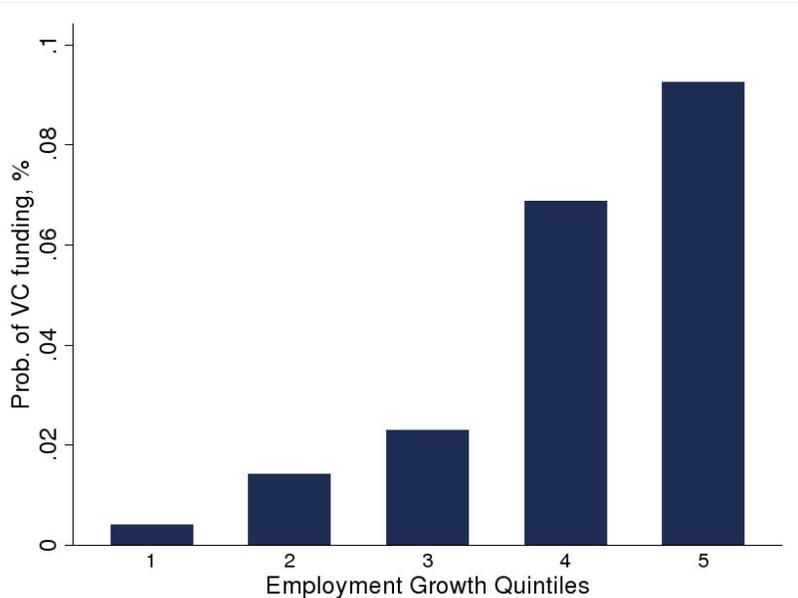


Figure 2: Firm employment growth and the probability of VC funding at any point in the firm life-cycle. Employment growth is the 3-year growth rate for a startup, starting from the first year of observation as an employer.

up to three years after the first patent (and before any VC funding). Figure 3 suggests that VC funding is concentrated in startups with relatively high quality early innovation. The probability of receiving VC funding for startups in the bottom quintile of the patent quality distribution is only about 1 percent, but rises to nearly 6 percent in the top quintile. Further, the probability of VC-funding is overall much higher for startups that have a patent (Figure 3), compared with all startups considered in Figure 2. The sample containing startups with early patent activity is much smaller and represents a highly selective group of innovating firms, resulting in much higher rates of VC funding overall.

Table 1 presents statistics on startups in their year of first VC funding. The average employment at funding is normalized to one for VC-funded startups that are in the top decile (≥ 90 th percentile) of the firm employment distribution in the first year of funding. For non-VC-funded startups, the hypothetical age at first funding is set to the average age at which a VC-funded firm receives funding.¹⁷ The numbers in Table 1 imply that at the time of funding the average employment of VC-funded firms is about 3 times that of non-

¹⁷The average age at VC funding is calculated using the age distribution of VC-funded firms in the year of first VC funding, assuming a VC-funding age of zero for firms that receive VC funding before age zero.

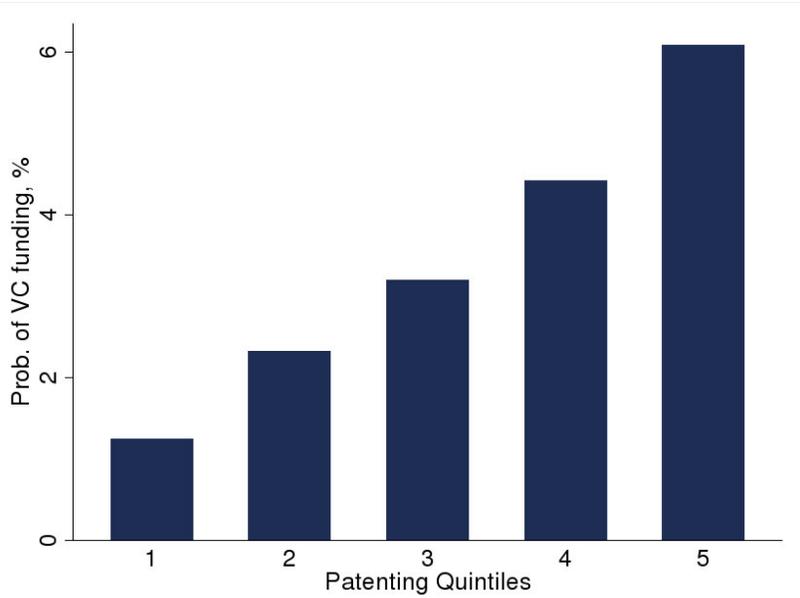


Figure 3: The quality of a firm’s early patenting and the probability of VC funding. The figure is conditional on having a patent. Patenting quintiles pertain to the quality distribution for startups’ early patenting activity, measured within (up to) three years of a startup’s first patent and before any VC funding. Patent quality is the number of citations received, demeaned by average citations in patent class, excluding self-citations. The probability of VC funding is measured within 5 years of the first year of patenting.

VC-funded firms.¹⁸ VC-funded startups in the top decile of the employment distribution are about 43 percent larger than the non-funded firms that are also in the top decile. However, there is not a big difference in the average employment of VC-funded versus non-VC-funded firms in the bottom 90 percent.¹⁹

There is strong evidence that the initial match between a financier and a startup is highly assortative in nature—better startups tend to match disproportionately with venture capitalists. One way to see this is to look at the fraction of VC-funded firms in the top

¹⁸The ratio of the average sizes is given by $r = (E_{VC}/N_{VC})/(E_{Non-VC}/N_{Non-VC})$, which can be written as

$$\frac{(E_{VC}/E)/(N_{VC}/N)}{(E_{Non-VC}/E)/(N_{Non-VC}/N)},$$

where E is the total employment and N is the total number of firms. From Table 1, $E_{VC}/E = 0.25\% + 0.04\% = 0.3\%$, $N_{VC}/N = 0.03\% + 0.07\% = 0.1\%$, $E_{Non-VC}/E = 57.8\% + 41.9\% = 99.7\%$, and $N_{Non-VC}/N = 10.7\% + 89.2\% = 99.9\%$. Therefore, the ratio r is given by $(0.3/0.1)/(99.7/99.9) = 3.0$.

¹⁹A caveat to these comparisons of startup sizes at the time of VC funding is that most startups at this stage are very small, and there is not a very large variation in size across firms within the top 10 percent or within the bottom 90 percent. Firm sizes diverge as startups grow and selection takes place, as discussed below.

decile, and compare it with the corresponding fraction among non-VC-funded ones. As shown in Table 1, these fractions are $p_{VC} = 0.326$ and $p_{Non-VC} = 0.107$, respectively. The observed odds ratio is therefore $(0.326/0.674)/(0.107/0.894) \simeq 4$. Random matching would imply $p_{VC} = p_{Non-VC} = 0.10$, or an odds ratio of 1. To assess formally the difference between the two groups, a two-sample test of proportions is implemented. Specifically, the null $H_0 : p_{VC} - p_{Non-VC} = 0$ is tested versus the alternative $H_A : p_{VC} - p_{Non-VC} > 0$, where standard errors are adjusted for clustering within each venture capitalist, because in many cases a venture capitalist matches with many firms, and among these matches the assumption of independence is unlikely to hold. The two-sample test rejects the null hypothesis in favor of the alternative at a significance level much higher than 1%, suggesting the presence of strong assortative matching between startups and financiers.²⁰

Overall, the patterns in Figures 2 and 3 and Table 1 suggest the presence of a high degree of selection in VC funding. Among startups in the economy, venture capitalists choose those that are on average larger, and exhibit higher early-stage employment growth and innovation. Furthermore, venture capitalists select these startups very early in their life cycles, as indicated by the firm age distribution at the time of first VC funding (Figure 1). This timing is consistent with venture capitalists’ reliance on their experience and expertise in assessing the promise of a business idea almost immediately upon its inception.²¹

2.3 How Much do Venture Capitalists Matter?

Next, consider the effects of venture capitalist involvement on the post-funding evolution of a startup. To assess the magnitude of these effects, the selection of startups by venture capitalists must be taken into account. To control for selection based on observables, a group of non-VC-funded firms that closely match VC-funded firms on a number of key

²⁰In addition, both of the individual hypotheses, $p_{VC} = 0.10$ and $p_{Non-VC} = 0.10$, are rejected in favor of the alternatives $p_{VC} > 0.10$ and $p_{Non-VC} > 0.10$.

²¹Anecdotal evidence suggests that venture capitalists may even target early stage projects with no business plan at all. For example, the 8/29/2018 interview “Venture capitalism: Investing today in the companies of tomorrow” by Ryssdall and Hollenhorst in NPR’s Marketplace, features venture capitalist Ann Miuro-Ko’s investment of \$1M in an early project that consists of merely a few math papers written by a Stanford professor.

STARTUPS—YEAR OF FIRST VC FUNDING

Type	Share of (%)						Average	
	<i>Firms</i>		<i>Empl</i>		<i>Firms by funding type</i>		<i>Empl (Rel)</i>	
	≥ 90 th	≤ 90 th	≥ 90 th	≤ 90 th	≥ 90 th	≤ 90 th	≥ 90 th	≤ 90 th
VC funded	0.03	0.07	0.25	0.04	32.6	67.4	1.00	0.05
Non-VC funded	10.7	89.2	57.8	41.9	10.7	89.4	0.70	0.06

Table 1: Stylized facts about startups. A firm’s type refers to whether or not it is in the top decile (90th percentile) for employment at the time of first VC funding. Average employment is measured with respect to the VC-funded firms in the top decile. Non-VC-funded firms are assigned a hypothetical age of funding equal to the average age at first funding for VC-funded firms.

characteristics are identified. A coarsened exact matching is implemented to form a control group for VC-funded firms. Because there is a large number of potential matches in the constructed dataset, it is possible to find exact matches for any VC-funded firm based on many key characteristics. Each firm that received first VC funding in a given year is matched with non-VC-funded firms in the same year that are of the same age, in the same narrowly defined employment bin, operate in the same 4-digit NAICS industry, have the same multi-unit/single-unit firm designation, and are located in the same state.²² The treated and control groups are then used to perform an event study that considers employment and the quality-adjusted patent stock as the key outcome variables—see Appendix A.3.4 for further details on the construction of event study samples.

Figure 4 plots the evolution of (ln) average employment for VC-funded firms and their matched counterparts. The data points in Figure 4 are relative to the (ln) average employment of VC-funded firms at the time of first VC funding ($t = 0$), which is normalized to 1. The two types of firms are followed up to 10 years after they receive VC funding, and up to 3 years before that point—that is, only the firms that receive VC at ages 1, 2 or 3 are included.²³ The horizon of 10 years is chosen to approximate the duration of VC contracts,

²²The main firm size measure, employment, cannot always be matched exactly conditional on other match criteria, especially for relatively large VC-funded firms. Instead, a coarser matching based on employment bins is considered.

²³After first funding, firms are followed until the point where they fail, get involved in an M&A or IPO, or the 10th year after VC—whichever occurs the earliest. That is, the samples are not balanced panels; the evolution of average employment is influenced by selection due to firm failure, M&A, or IPO. In addition, firms that receive VC funding at age zero are excluded, since these firms have no observations for the pre-VC period for a proper event study. Last, all firms that report zero employment are excluded from the analysis for both groups.

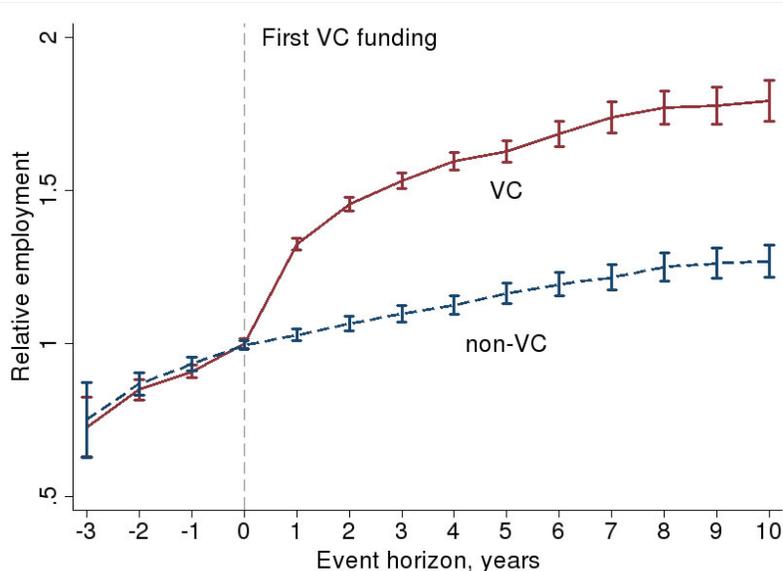


Figure 4: The evolution of average employment before and after first VC funding date: VC-funded firms versus non-VC-funded controls. The observations are relative to average employment (normalized to 1) for VC-funded startups in the year of first VC funding, $t = 0$.

which is about a decade.

The two groups exhibit virtually identical trajectories of average employment before VC funding, indicating that the matching does a decent job of accounting for the pre-VC-funding trends. The VC-funded firms grow, on average, much more following first funding. Average employment increases by approximately 475 percent by the end of the horizon for VC-funded firms, whereas growth is much more modest for the matched non-VC-funded control group (about 230 percent). Based on these differential growth rates, the treatment by venture capitalists accounts for up to nearly half of the growth experienced by VC-funded startups.²⁴

The kernel density estimates for the growth rates of employment conditional on survival 10 years after VC funding are plotted in Figure 5 for VC-funded and *all* non-VC-funded firms. The growth rates of VC-funded firms, conditional on survival, exhibit considerable dispersion. These rates are also very different from those of non-VC-funded startups. The growth-rate distribution for VC-funded firms is negatively skewed, with a large mass of

²⁴Although not reported, the patterns are similar if revenue is considered as a measure of firm size. Revenue is not used as a variable in selecting the control group.

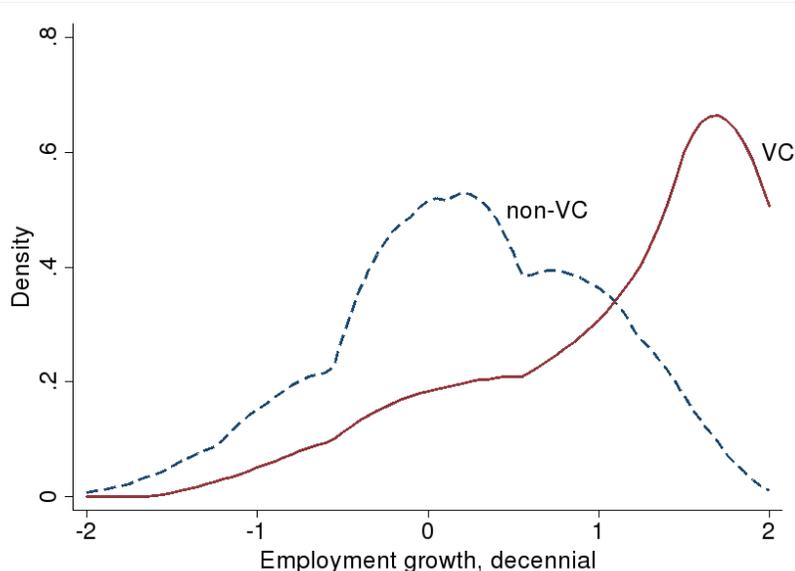


Figure 5: The distribution of the Davis-Haltiwanger-Schuh (DHS) employment growth rate, measured 10 years after first VC-funding, for both VC-funded and all non-VC-funded firms (not just the ones that are matched with VC-funded firms). The figure is conditional on survival.

firms beyond the growth rate of 100 percent, and a peak density around the growth rate of 200 percent. In contrast, non-VC-funded firms have a much more symmetric growth-rate distribution that is centered slightly above zero.²⁵ The dispersion of growth rates is also higher for VC-funded firms. VC involvement is associated with more dispersed, but on average much higher, employment growth rates, conditional on survival.²⁶

The evolution of innovative activity, as measured by the (ln) quality-adjusted patent stock, is shown in Figure 6.²⁷ The treatment and control groups underlying this figure are restricted to firms with patents, but the two groups are not matched based on patent quality similarity.²⁸ As in Figure 4, the observations are relative to the (ln) average quality-adjusted

²⁵The relatively low median 10-year growth rate for non-VC-funded firms is consistent with earlier findings that indicate a very low average growth rate for startups in the U.S. economy—see, for example, Decker et al. (2016) and Choi (2018).

²⁶The growth patterns are similar if revenue is used instead of employment as the outcome measure.

²⁷This figure only includes firms that receive VC funding at ages 1 and 2 only, compared to Figure 4, which also includes firms that receive funding at age 3. The reason is that the control group for firms that receive VC funding at age 3 is much smaller and only contains a small number of firms that have patents, leading to a very large confidence interval for the average patent stock.

²⁸Matching based on this criterion turns out to yield no close matches for many treated firms.

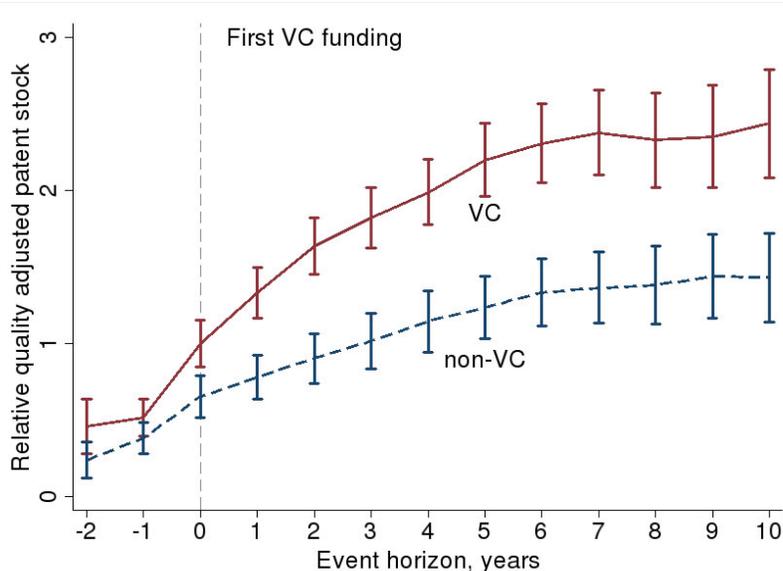


Figure 6: The evolution of the average quality-adjusted patent stock before and after first VC funding date: VC-funded firms versus non-VC-funded controls. The observations are relative to the average patent stock (normalized to 1) for VC-funded firms in the year of VC funding, $t = 0$.

patent stock of VC-funded firms at the time of funding ($t = 0$), which is normalized to 1. Pre-VC trends for the two groups do not differ substantially, again indicating a close match based on the same criteria used in the employment case. The post-VC trends indicate that VC-funded firms experience, on average, a much higher growth in their patent stock. On average, the patent stock of VC funded firms grows by 1,100 percent, as compared to about 440 percent for the control group. These rates suggest that up to 60 percent of the growth in the patent stock can be attributed to treatment by venture capitalists.

The results indicate strong post-funding effects associated with VC involvement. VC-backed firms achieve (on average) better outcomes in terms of employment and innovation, after controlling for selection based on observables. Consequently, VC-backed startups are much more likely to make it into the right tail of the firm employment and innovation distributions, compared with non-VC-funded ones.

2.4 Does Venture Capitalist Experience Matter?

Are the effects of VC involvement larger when firms are matched with more experienced venture capitalists? While the experience of venture capitalists is not explicitly considered in the model, the estimated magnitude of synergies between an entrepreneur and a venture capitalist reflects the latter’s average experience. To highlight the dependence of firm outcomes on experience, venture capitalists in the sample are first divided into two groups: low versus high experience. A venture capitalist is labelled “high experience” if the number of deals it is involved in over the entire sample period is in the 90th percentile of the distribution over the total number of VC deals, and “low-experience” otherwise. VC-funded firms are then divided into two mutually exclusive groups: those funded by high-experience venture capitalists and those funded by low-experience ones. A startup is in the high-experience group if 50 percent or more of the venture capitalists that fund the startup in its first year of funding are high experience. If instead, more than 50 percent of its funders are of low experience, it is considered to be a firm funded by low-experience venture capitalists. This rule is adopted because it is common for startups to be funded by multiple venture capitalists, but the data does not provide details on the lead venture capitalist, or the one with the highest funding contribution.²⁹

Figure 7 plots the evolution of (ln) average employment of firms by venture capitalist experience. In the pre-funding periods ($t < 0$), the trajectories for the two groups are similar, but at $t = 0$ the average employment is higher for startups funded by high-experience venture capitalists. In the years following VC funding ($t > 0$), firms funded by high-experience venture capitalists also grow significantly more on average. Following a notable jump at $t = 1$, the gap between the trajectories continues to open up. By the end of the horizon, average employment grows by about 400 percent in the high-experience group, and by about 320 percent in the low-experience group.

A similar picture emerges when the event study is repeated for the (ln) average quality-

²⁹In the following analysis, the sample of VC-funded firms is larger than the one used to generate Figures 4 and 6, because the latter consider only the VC-funded firms for which close matches within the set of non-funded firms are available. In addition, some VC-funded firms have missing funding information, which generates additional differences from the samples used in Figures 4 and 6.

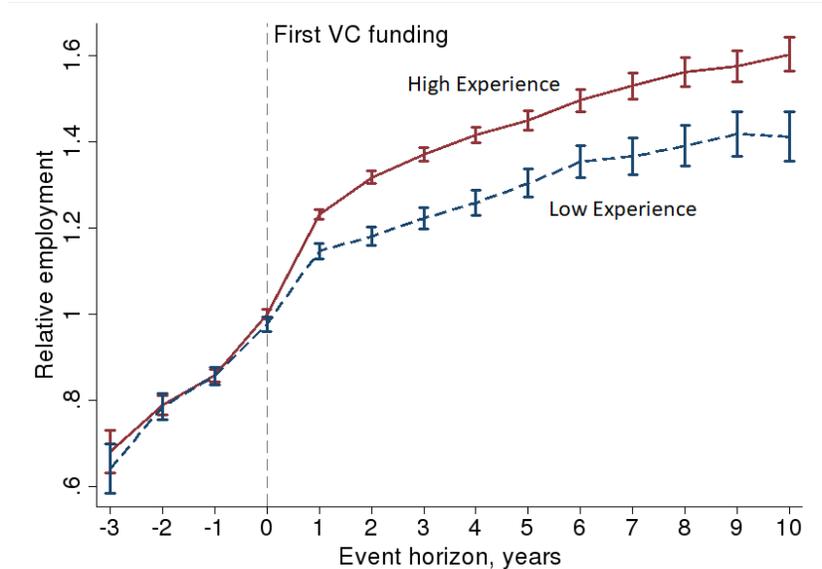


Figure 7: The evolution of average employment before and after first VC funding, by the experience of venture capitalists. The observations are relative to the average employment (normalized to 1) for startups funded by high-experience venture capitalists in the year of first VC funding, $t = 0$.

adjusted patent stock, as shown in Figure 8.³⁰ While the difference between the firms funded by high-experience versus low-experience venture capitalists is small for the periods before funding ($t < 0$), a gap appears at $t = 0$, which grows over time after funding. By the end of the horizon, the average patent stock grows by nearly 50-fold for the high-experience group, and by only about 19-fold for the low-experience group.³¹

There is also some evidence that the experience of a venture capitalist matters beyond just the amount of initial funding provided. To assess the benefits of VC experience, such as better mentoring and monitoring, employment 10 years after birth (or in the year of failure or M&A activity, if any of these events occur before the 10 year window ends) is projected on the initial amount of VC funding and a dummy variable that indicates backing by a high-experience venture capitalist. Employment and age at the time of funding are also included

³⁰Note that the pre-VC period extends to 3 periods in this figure, compared to only 2 periods in the analysis associated with Figure 6. The reason is that in the latter analysis the control group is very small and does not include a large enough number of patenting firms for $t < -2$.

³¹The findings in Figures 7 and 8 are qualitatively similar when revenue is considered as an alternative outcome. Many of the results are also similar when alternative measures of experience for venture capitalists are considered—for instance, when experience is measured by total all-time funding by a venture capitalist, by average funding per year, or by the average number of deals per year.

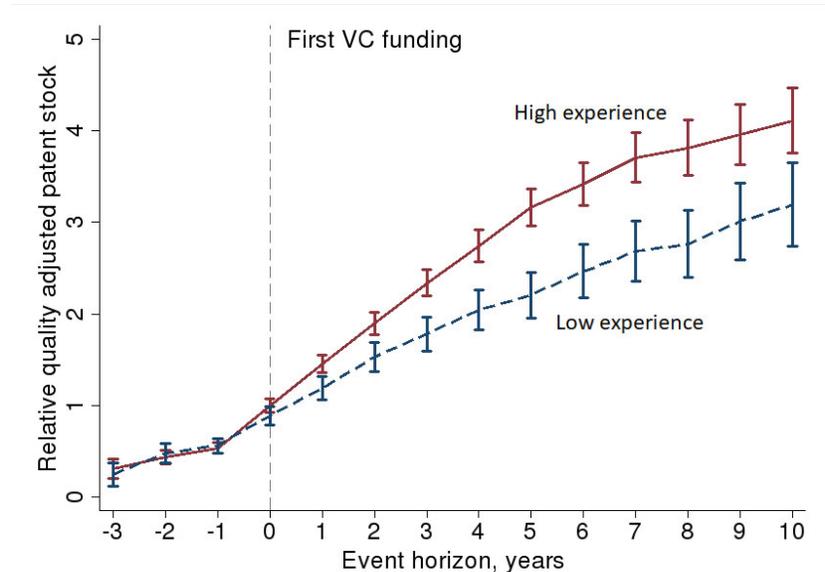


Figure 8: The evolution of the average patent stock before and after first VC funding, by the experience of venture capitalists. The observations are relative to the average patent stock (normalized to 1) for startups funded by high-experience venture capitalists in the year of first VC funding, $t = 0$.

to control for the initial characteristics/conditions of startups that may reflect selection, as well as entrepreneurial ability. Because some startups fail or get involved in M&A before the end of the 10-year horizon, the number of years from first funding is also added to proxy for the duration of venture capitalist involvement. Finally, industry and year fixed effects (associated with the year of failure or M&A, or with the 10th year after first funding) are included to control for variation across sectors, and economy-wide factors at the time of measurement that can influence firm outcomes.

Results from alternative specifications are shown in Table 2. In all specifications, the initial funding level has positive and highly significant coefficients, which imply that a 1 percent increase in initial funding is associated with about a 0.35 to 0.41 percent increase in ultimate employment. The key coefficient estimates, associated with the dummy for high-experience venture capitalists, all indicate a positive association between high experience and ultimate employment. In particular, controlling for the funding level and other observables (specification 4), startups backed by a high-experience venture capitalist are estimated to

EMPLOYMENT OUTCOMES AND THE EXPERIENCE OF VENTURE CAPITALISTS

Independent Variables	Employment at 10 years from funding (ln)			
	1	2	3	4
High-experience funder (dummy)	0.253*** (0.030)	0.260*** (0.029)	0.292*** (0.028)	0.274*** (0.028)
Equity at first funding (ln)	0.414*** (0.013)	0.368*** (0.012)	0.352*** (0.012)	0.347*** (0.012)
Employment at first funding (ln)		0.267*** (0.008)	0.278*** (0.008)	0.249*** (0.008)
Age at first funding			0.074*** (0.006)	0.082*** (0.006)
Years since first funding				0.146*** (0.004)
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	14,000	14,000	14,000	14,000
R^2	0.17	0.23	0.24	0.30

Table 2: Effect of VC experience on employment. Standard errors clustered by industry are in parentheses. The high-experience funder dummy equals 1 if the funder is in the top decile of the distribution of the total number of deals made by venture capitalists. The omitted category is the low-experience funder. The regressions include a constant, and industry and year fixed effects.

end up with approximately 32 percent larger employment.³² This finding suggests that firms matched with high-experience venture capitalists have better outcomes, even conditional on the amount of initial funding.³³

Overall, the empirical findings indicate both strong selection and treatment effects associated with venture capitalist involvement. VC funding is concentrated in firms that are younger, larger, and that have better growth and innovation prospects. Outcomes of VC-funded firms in terms of firm size and innovation are much better than those of non-VC-funded firms that are otherwise observationally similar to VC-funded firms at the time of first funding. Moreover, it is not just the funding level that matters—startups that are backed by high-experience venture capitalists achieve better outcomes even after controlling

³²The estimated effect is given by $e^{0.274} - 1 \simeq 0.32$.

³³The conclusions from Table 2 also apply to alternative measures of experience for a venture capitalist.

for initial funding infusion. In other words, there appears to be considerable heterogeneity in the effects associated with venture capital.³⁴

While venture capitalist experience matters for startup outcomes, the effects of VC experience differ across types of ventures. For instance, Gompers et al. (2010) find that venture capitalist experience matters most for first time entrepreneurs, but not for more seasoned entrepreneurs with past success. The subsequent ventures of successful first-time entrepreneurs tend to perform well regardless of the venture capitalist experience. First, seasoned entrepreneurs may need less nurturing by venture capitalists as they have learnt how to start a successful venture. Second, initial success may reveal information to investors about an entrepreneur’s ability, implying that there is less need for an experienced venture capitalist with expertise in identifying promising ventures. Luck may also play a large role in this initial success. Subsequent ventures of first time lucky entrepreneurs may still benefit from the experience and reputation gained during the first success. The analysis of Catalini, Guzman, and Stern (2019) further suggests that there are also entrepreneurs who succeed without venture capital at all. They find similarity between the determinants of equity growth with and without venture capital. New firms with growth potential, regardless of future funding source, tend to be similar in early characteristics.

The next section proposes a model that can account for many of the stylized facts presented so far. First, luck is an element of success, and ventures may fail given any amount of funding and nurturing provided by a financier (venture capitalist or bank)—consistent with high failure rates for both types of ventures, as discussed below. Second, success without venture capital is possible: some ventures are successfully launched and perform well without any venture capital involvement. Third, while the model does not directly feature heterogeneity in venture capital experience, the synergies between venture capitalists and entrepreneurs in the model are disciplined to reflect the underlying effects of venture capitalist involvement and experience relevant for both low- and high-performance ventures.³⁵

³⁴This view is further supported by recent studies that directly aim to estimate the unobserved venture capitalist and match quality effects using funding duration data. For instance, Wong (2019) finds that about two-thirds of the variation in venture capital funding duration is attributable to venture capital and match-specific unobserved effects.

³⁵Likewise, the estimated synergies reflect the average performance of ventures launched by first time versus and more seasoned serial entrepreneurs, since these two types of ventures are not distinguishable in the data used in the empirical analysis. The latter group is a much smaller fraction of ventures as documented

3 The Model

Every period s new entrepreneurs approach financiers to acquire funding for startups, where s is exogenous. Entrepreneurs come in two *ex ante* types, $i \in \{h, l\}$, namely high or low. High-type entrepreneurs are more *likely* to develop a successful project, have a higher level of synergy with a financier, and attain a higher level of productivity than low-type entrepreneurs, other things equal. There are 2 types of financiers, $f \in \{v, n\}$; venture capitalists, v , and non-venture capitalists, n , the latter corresponding to traditional financial institutions, such as banks. Out of the s new startups, s^n are financed by banks and s^v by venture capitalists. A venture capitalist nurtures startups by providing both expertise and funding. A traditional financial institution offers a much more limited amount of expertise. In the equilibrium being modeled, $s^v < s$ so that not all new entrepreneurs can be financed by venture capitalists, some must go to traditional financial institutions. The analysis will focus on balanced growth paths. Specifically, aggregate productivity, \mathbf{x} , will grow at some endogenous gross rate, $g_{\mathbf{x}} > 1$, which in turn results in wages, w , growing at another constant endogenous rate, $g_w > 1$.

A successful venture is one that starts producing. Success depends on *luck*, which is contingent on any funding and nurturing the startup receives. Funded startups face two sources of uncertainty regarding success. First, a startup may fail. Second, even if it succeeds, the startup can enter either a high or low *ex post* state for production, represented by $j \in \{h, l\}$. An entrepreneur who begins in *ex ante* state i and then who transits to *ex post* state j will be referred to as type (i, j) .

There are synergies between an entrepreneur and a financier that raise a venture's output. The synergy between a type- f financier and a type- (i, j) entrepreneur is represented by z_{ij}^f , for $f = v, n$ and $i, j = h, l$. A reasonable conjecture might be that venture capitalists provide more nurturing for startups. Hence, it should transpire that $z_{ij}^v > z_{ij}^n$ for $i, j = h, l$. Additionally, because the high states are better than the low ones, it might be sensible to presume that $z_{hj}^f > z_{lj}^f$ and $z_{ih}^f > z_{il}^f$, for $f = v, n$. The z 's will be estimated in Section 6, so the validity of these suppositions can be examined.

in Table 1 in Gompers et al. (2010).

EX ANTE MATCHING

Financing	Entrepreneurs, fraction	
	High	Low
VC Funded	μ_h^v	$\mu_l^v = 1 - \mu_h^v$
Non-VC Funded	μ_h^n	$\mu_l^n = 1 - \mu_h^n$

Table 3: The ex ante matching process between entrepreneurs and financiers. By construction the numbers in a row sum to one. The number of VC-funded startups in the ex ante high and low states are $s^v \mu_h^v$ and $s^v \mu_l^v$, while the corresponding numbers for non-VC-funded startups read $s^n \mu_h^n$ and $s^n \mu_l^n$.

The matching process between entrepreneurs and financiers is random, and potentially assortative in nature. The fraction μ_h^v of the projects financed by venture capitalists are with ex ante high-type entrepreneurs, while the remaining fraction, $\mu_l^v = 1 - \mu_h^v$, are with low-type ones. The corresponding fractions for non-VC funding are given by μ_h^n and $\mu_l^n = 1 - \mu_h^n$. The matching process is summarized in Table 3. There is positive assortative matching when $\mu_h^v > \mu_h^n$, which turns out to be the case in the U.S. data—based on the statistical tests done in Section 2.2.

3.1 Successful Ventures

There is no production before success occurs. The output, o_{ij}^f , of a successful ex post type- (f, i, j) startup is

$$o_{ij}^f = (x_{ij}^f z_{ij}^f)^\zeta (k_{ij}^f)^\kappa (l_{ij}^f)^\lambda, \text{ with } \zeta + \kappa + \lambda = 1, \text{ for } f = v, n \text{ and } i, j = h, l. \quad (1)$$

where k_{ij}^f and l_{ij}^f are the amounts of capital and labor used in production, x_{ij}^f is the firm's level of productivity, and z_{ij}^f is the synergy level between the entrepreneur and financier. In the analysis x_{ij}^f is an endogenous variable that will be a function of the amount of research the startup does. This variable will be disciplined in Section 6 using the observed patenting activity of the various types of startups. The synergy levels will be estimated using facts about employment for startups.

A producing firm can freely rent capital at the rate r and hire labor at the wage rate w .

It does so to maximize profits. The rental price for capital incorporates a depreciation rate of $1 - \delta$. The profit function associated with this maximization problem is

$$x_{ij}^f z_{ij}^f (1 - \kappa - \lambda) \left[\left(\frac{\kappa}{r} \right)^\kappa \left(\frac{\lambda}{w} \right)^\lambda \right]^{1/\zeta} = \max_{k_{ij}^f, l_{ij}^f} \{ o_{ij}^f - r k_{ij}^f - w l_{ij}^f : \text{s.t. (1)} \}, \quad (2)$$

for $f = v, n$ and $i, j = h, l$. Along a balanced growth path, wages will grow at some (endogenous gross) rate, g_w . As can be seen from the profit function, rising wages operate to reduce the profits of an enterprise as it ages. The present value of the profits from a successful venture in the *current* period is

$$\begin{aligned} & x_{ij}^f z_{ij}^f \sum_{t=0}^{\infty} \left(\frac{\delta \mathbf{s}}{g_w^{\lambda/\zeta}} \right)^t (1 - \kappa - \lambda) \left[\left(\frac{\kappa}{r} \right)^\kappa \left(\frac{\lambda}{w} \right)^\lambda \right]^{1/\zeta} \\ & \equiv x_{ij}^f z_{ij}^f I(\cdot), \text{ for } f = v, n \text{ and } i, j = h, l, \end{aligned} \quad (3)$$

where \mathbf{s} is the survival rate for a venture and $I(\cdot) \equiv \sum_{t=0}^{\infty} (\delta \mathbf{s} / g_w^{\lambda/\zeta})^t (1 - \kappa - \lambda) [(\kappa/r)^\kappa (\lambda/w)^\lambda]^{1/\zeta}$. The value from a successful venture turns out to be linear in $x_{ij}^f z_{ij}^f$.

3.2 Startups

The productivity level of a type- (f, i, j) startup, x_{ij}^f , is endogenous. The more ambitious a new enterprise is at the time of inception, or the higher productivity, x_{ij}^f , is relative to the current level of aggregate productivity, denoted by \mathbf{x} , the greater is the initial research cost. The state-specific research cost for a startup is specified by the function

$$R\left(\frac{x_{ij}^f}{\mathbf{x}}\right) = w \left(\frac{x_{ij}^f}{\mathbf{x}}\right)^\iota / (\iota \chi_{ij}^f), \text{ with } \iota > 1, \text{ and for } f = v, n \text{ and } i, j = h, l.$$

The higher χ_{ij}^f is, the lower the cost of research. This parameter will be estimated for the various types of startups in Section 6.

The likelihood that a startup will be successful depends upon the amount of development funding it receives. Let σ_{ij}^f denote the odds that a type- (f, i, j) venture will be successful.

These odds can be secured with a funding level of $D(\sigma_{ij}^f)$, where

$$D(\sigma_{ij}^f) = w\left(\frac{1}{1 - \sigma_{ij}^f} - 1\right)\sigma_{ij}^f/\psi_{ij}^f, \text{ for } f = v, n \text{ and } i, j = h, l.$$

The cost of developing a project drops with ψ_{ij}^f . This parameter will also be estimated for a type- (f, i, j) startup in Section 6.

R&D is done separately for each ex post state, $j = h, l$, before the realization of the state is known. A type (f, i) startup will only enter the ex post high state, h , with the productivity/synergy combination x_{ih}^f and z_{ih}^f , with probability $\sigma_{ih}^f < 1$. Consequently, a contingency plan for the low state, l , is also developed. Of course, an all or nothing strategy for the high state could be pursued, which would involve setting $x_{il}^f = \sigma_{il}^f = 0$, but this will never be done. The entrepreneur must seek outside funding to cover these R&D startup costs, $R(x_{ih}^f/\mathbf{x}) + D(\sigma_{ih}^f) + R(x_{il}^f/\mathbf{x}) + D(\sigma_{il}^f)$, where $f = v, n$.

4 Decision Problems

4.1 VC-Financed Startups

Suppose that an ex ante type- i entrepreneur receives funding and mentoring from a venture capitalist. The entrepreneur and the venture capitalist sign a contract, which stipulates that the entrepreneur must pay the venture capitalist p_{ih}^v if the project is successful in the high state and p_{il}^v if it lands in the low state. The probabilities of success in the high and low states, σ_{ih}^f and σ_{il}^f , are also specified by the contract, as are the productivities, x_{ih}^v and x_{il}^v . The terms of the agreement are prescribed by the following Nash Bargaining problem

$$\begin{aligned} \max_{\sigma_{ih}^v, \sigma_{il}^v, x_{ih}^v, x_{il}^v, p_{ih}^v, p_{il}^v} & [\sigma_{ih}^v \delta x_{ih}^v z_{ih}^v I(\cdot) + \sigma_{il}^v \delta x_{il}^v z_{il}^v I(\cdot) - \sigma_{ih}^v \delta p_{ih}^v - \sigma_{il}^v \delta p_{il}^v - E_i] \\ & \times [\sigma_{ih}^v \delta p_{ih}^v + \sigma_{il}^v \delta p_{il}^v - R\left(\frac{x_{ih}^v}{\mathbf{x}}\right) - R\left(\frac{x_{il}^v}{\mathbf{x}}\right) - D(\sigma_{ih}^v) - D(\sigma_{il}^v) - V], \end{aligned} \tag{P1}$$

where E_i and V are the threat points of the ex ante type- i entrepreneur and the venture capitalist, respectively.^{36,37} Here δ is the market discount factor, or the reciprocal of the risk-free gross interest rate on saving and lending by consumers. This is used to discount the payoffs to both parties for each ex post state $j = h, l$. The term in brackets on the first line presents the expected reward to the entrepreneur, net of his threat point, while the term on the second line gives the same object for the venture capitalist.

The upshot of the above Nash Bargaining problem is the following three first-order conditions:

$$\delta x_{ij}^v z_{ij}^v I(\cdot') = D_1(\sigma_{ij}^v), \text{ for } j = h, l, \quad (4)$$

$$\delta \sigma_{ij}^v z_{ij}^v I(\cdot') = R_1\left(\frac{x_{ij}^v}{\mathbf{x}}\right)/\mathbf{x}, \text{ for } j = h, l, \quad (5)$$

and

$$\begin{aligned} \sigma_{ih}^v \delta p_{ih}^v + \sigma_{il}^v \delta p_{il}^v &= R\left(\frac{x_{ih}^v}{\mathbf{x}}\right) + R\left(\frac{x_{il}^v}{\mathbf{x}}\right) + D(\sigma_{ih}^v) + D(\sigma_{il}^v) \\ &\quad + \frac{1}{2}[\sigma_{ih}^v \delta x_{ih}^v z_{ih}^v I(\cdot') + \sigma_{il}^v \delta x_{il}^v z_{il}^v I(\cdot') \\ &\quad - R\left(\frac{x_{ih}^v}{\mathbf{x}}\right) - R\left(\frac{x_{il}^v}{\mathbf{x}}\right) - D(\sigma_{ih}^v) - D(\sigma_{il}^v) + V - E_i]. \end{aligned}$$

The first condition implies that the probability of success for each ex post state j is chosen in the first-best manner. A marginal increase in the state- j success probability, σ_{ij}^v , raises the discounted value of a successful venture by $\delta x_{ij}^v z_{ij}^v I(\cdot')$, which is the marginal benefit. Development costs move up by $D_1(\sigma_{ij}^v)$, which represents the marginal cost. Therefore, the marginal benefit from increasing σ_{ij}^v equals its marginal cost. The next condition sets, for each ex post state j , the discounted expected marginal benefit from an increment in productivity, $\delta \sigma_{ij}^v z_{ij}^v I(\cdot')$, equal to the marginal cost of research, $R_1(x_{ij}^v/\mathbf{x})/\mathbf{x}$. Thus, x_{ij}^v is also set in a first-best manner. The third condition specifies the venture capitalist's expected discounted payment, $\sigma_{ih}^v \delta p_{ih}^v + \sigma_{il}^v \delta p_{il}^v$. It is equal to his R&D startup costs, $R(x_{ih}^v/\mathbf{x}) +$

³⁶The notation $I(\cdot')$ signifies that the arguments of I should be evaluated at their values in the next period.

³⁷Silveira and Wright (2016) build a canonical search model of the process where entrepreneurs are matched with venture capitalists. Upon meeting, the parties bargain in Nash fashion over each one's investment and how to split the proceeds. Their analysis is entirely theoretical in nature and does not focus on the process of innovation and growth.

$R(x_{il}^v/\mathbf{x}) + D(\sigma_{ih}^v) + D(\sigma_{il}^v)$, plus one half of the expected surplus, net of the difference in threat points, or $[\sigma_{ih}^v \delta x_{ih}^v z_{ih}^v I(\cdot) + \sigma_{il}^v \delta x_{il}^v z_{il}^v I(\cdot) - R(x_{ih}^v/\mathbf{x}) - R(x_{il}^v/\mathbf{x}) - D(\sigma_{ih}^v) - D(\sigma_{il}^v) + V - E_i]/2$.³⁸

The upshot of the first two conditions is summarized by Lemma 1.

Lemma 1 (*The Impact of Synergy*) *The higher the ex post state- j synergy, z_{ij}^v , between an ex ante type- i entrepreneur and the venture capitalist, the more ambitious a project will be as reflected by:*

1. a higher level of productivity, x_{ij}^v ;
2. a higher likelihood of success, σ_{ij}^v ; and
3. a higher level of funding, $R(x_{ij}^v/\mathbf{x}) + D(\sigma_{ij}^v)$,

for $j = h, l$.

Proof. See Appendix B. ■

An ex ante type- i entrepreneur can always go to a bank for funding. So, his threat point, E_i , is given by maximized value of the bank startup problem (P2) presented below. Now, suppose that a venture capitalist has only one draw in the matching scenario. Then, he will have no outside option. Thus, his threat point is given by $V = 0$. Therefore, the venture capitalist's expected profits from a contract with ex ante type- i entrepreneur, V_i , are

$$V_i = [\sigma_{ih}^v \delta x_{ih}^v z_{ih}^v I(\cdot) + \sigma_{il}^v \delta x_{il}^v z_{il}^v I(\cdot) - R(x_{ih}^v/\mathbf{x}) - R(x_{il}^v/\mathbf{x}) - D(\sigma_{ih}^v) - D(\sigma_{il}^v) - E_i]/2, \quad (6)$$

which represents half of the surplus from the enterprise net of the entrepreneur's threat point.³⁹

³⁸Jovanovic and Szentes (2013) build a model of venture capital that focuses on characterizing and measuring the excess returns earned by venture capitalists, due to the latter's scarcity. Their analysis abstracts from innovation and growth.

³⁹The division of profits between the entrepreneur and venture capitalist plays no role in the analysis. As can be seen from the first-order conditions (4) and (5), the division of profits doesn't affect the choices for σ_{ij}^v and x_{ij}^v .

4.2 Non-VC-Financed Startups

A banker lends to an ex ante type- i entrepreneur at the market discount factor i_i , which is the reciprocal of the gross interest rate for startup borrowing. This discount factor differs by a startup's ex ante type, i , and takes into account that the startup might fail. When a startup fails, the entrepreneur defaults on the loan's interest and principal, $[D(\sigma_{ih}^n) + R(x_{ih}^n/\mathbf{x}) + D(\sigma_{il}^n) + R(x_{il}^n/\mathbf{x})]/i_i$. The gross interest rate charged by banks, $1/i_i$, will be determined by a zero-profit constraint for bankers. If bankers can raise funds from consumers at the risk-free rate $1/\delta$, then

$$\frac{\sigma_{ih}^n + \sigma_{il}^n}{i_i} = \frac{1}{\delta} \text{ or } \frac{1}{i_i} = \frac{1}{\delta(\sigma_{ih}^n + \sigma_{il}^n)}. \quad (7)$$

Therefore, the gross interest rate charged by banks, $1/i_i$, is decreasing in the success probability, $\sigma_{ih}^n + \sigma_{il}^n$. Clearly, $1/i_i > 1/\delta$ or $i_i < \delta$.

Now, the entrepreneur's maximization problem is

$$\begin{aligned} E_i = & \max_{\sigma_{ih}^n, \sigma_{il}^n, x_{ih}^n, x_{il}^n} \delta \{ \sigma_{ih}^n x_{ih}^n z_{ih}^n I(\cdot) + \sigma_{il}^n x_{il}^n z_{il}^n I(\cdot) \\ & - (\sigma_{ih}^n + \sigma_{il}^n) [R(\frac{x_{ih}^n}{\mathbf{x}}) + R(\frac{x_{il}^n}{\mathbf{x}}) + D(\sigma_{ih}^n) + D(\sigma_{il}^n)] / i_i \}, \end{aligned} \quad (P2)$$

subject to (7). Here, the entrepreneur takes into account how his business plan for the startup influences the gross interest rate that he pays. The two sets of first-order conditions associated with the above maximization problem are:

$$\delta x_{ij}^n z_{ij}^n I(\cdot) = D_1(\sigma_{ij}^n), \text{ for } j = h, l, \quad (8)$$

and

$$\delta \sigma_{ij}^n z_{ij}^n I(\cdot) = R_1(\frac{x_{ij}^n}{\mathbf{x}}) / \mathbf{x}, \text{ for } j = h, l. \quad (9)$$

These two efficiency conditions for σ_{ij}^n and x_{ij}^n have the same generic form as (4) and (5). The values for σ_{ij}^n and x_{ij}^n will differ from σ_{ij}^v and x_{ij}^v for two reasons. First, $z_{ij}^n \neq z_{ij}^v$. Second, the cost functions for research and development differ; i.e., within the R and D functions, $\chi_{ij}^n \neq \chi_{ij}^v$ and $\psi_{ij}^n \neq \psi_{ij}^v$. This will be discussed further in Section 6. Last, E_i is the threat point for the ex ante type- i entrepreneur in the Nash Bargaining problem (P1).

5 Balanced Growth

A key step in characterizing a balanced growth path is to determine the growth in aggregate productivity, \mathbf{x} . This will be a function of the endogenous innovation levels and success rates of the various types of startups. The pattern of ex ante matching between entrepreneurs and venture capitalists will also matter.

Denote the gross growth rate for aggregate productivity, or \mathbf{x} , by $g_{\mathbf{x}} \equiv \mathbf{x}'/\mathbf{x}$. Define the average level of productivity for a type- f financed venture in the ex post high state, $j = h$, by

$$x_h^f = (\mu_h^f \sigma_{hh}^f x_{hh}^f + \mu_l^f \sigma_{lh}^f x_{lh}^f) / (\mu_h^f \sigma_{hh}^f + \mu_l^f \sigma_{lh}^f), \text{ for } f = n, v.$$

The fractions of all successful startups in the high state that have type- f funding are

$$\nu_h^f = \frac{s^f (\mu_h^f \sigma_{hh}^f + \mu_l^f \sigma_{lh}^f)}{s^v (\mu_h^v \sigma_{hh}^v + \mu_l^v \sigma_{lh}^v) + s^n (\mu_h^n \sigma_{hh}^n + \mu_l^n \sigma_{lh}^n)}, \text{ for } f = n, v. \quad (10)$$

In a similar vein, the average level of productivity over *all* startups in the ex post low state, $j = l$, is given by⁴⁰

$$x_l = \frac{s^v (\mu_h^v \sigma_{hl}^v x_{hl}^v + \mu_l^v \sigma_{ll}^v x_{ll}^v) + s^n (\mu_h^n \sigma_{hl}^n x_{hl}^n + \mu_l^n \sigma_{ll}^n x_{ll}^n)}{s^v (\mu_h^v \sigma_{hl}^v + \mu_l^v \sigma_{ll}^v) + s^n (\mu_h^n \sigma_{hl}^n + \mu_l^n \sigma_{ll}^n)}. \quad (11)$$

Next, define the following growth factors for the above three ex post classes of enterprises

$$g_h^f \equiv \frac{x_h^f}{\mathbf{x}}, \text{ for } f = v, n, \text{ and } g_l \equiv \frac{x_l}{\mathbf{x}}.$$

The g 's are determined by the choice problems (P1) and (P2), and must be constant along a balanced growth path. For this to be the case, the x_{ij}^f 's have to grow over time at the same rate as \mathbf{x} . Additionally, the σ_{ij}^f 's must be constant. Note that ex ante matching odds, or the μ_i^f 's, are exogenously fixed.

Suppose that the aggregate level of productivity in the current period, \mathbf{x} , reflects the average productivities of each of the above three classes of enterprises as well as their mass

⁴⁰Amalgamating the low-state productivities into a single measure did not materially affect the results.

in the set of producing startups. Specifically, let \mathbf{x}' be given by

$$\mathbf{x}' = c(\nu_h^v x_h^v)^{\gamma_h^v} (\nu_h^n x_h^n)^{\gamma_h^n} (x_l)^{1-\gamma_h^v-\gamma_h^n}, \quad (12)$$

where c is a constant term and $0 < \gamma_h^v, \gamma_h^n, \gamma_h^v + \gamma_h^n < 1$.⁴¹ The exponents γ_h^v and γ_h^n govern the size of the spillover effects that innovators in the high state have on aggregate productivity. Data on patent citations by VC-funded and non-VC-funded enterprises will be used to pin down these parameters. This law of motion depends upon both the extensive (the ν 's) and intensive (the x 's) margins of the three ex post categories of startups. The aggregate level of productivity's gross growth rate, $g_{\mathbf{x}}$, will be

$$\begin{aligned} g_{\mathbf{x}} &\equiv \frac{\mathbf{x}'}{\mathbf{x}} = \frac{c(\nu_h^v x_h^v)^{\gamma_h^v} (\nu_h^n x_h^n)^{\gamma_h^n} (x_l)^{1-\gamma_h^v-\gamma_h^n}}{\mathbf{x}} \\ &= c(\nu_h^v g_h^v)^{\gamma_h^v} (\nu_h^n g_h^n)^{\gamma_h^n} (g_l)^{1-\gamma_h^v-\gamma_h^n}. \end{aligned} \quad (13)$$

because $g_h^v \equiv x_h^v/\mathbf{x}$, $g_h^n \equiv x_h^n/\mathbf{x}$, and $g_l \equiv x_l/\mathbf{x}$. Therefore, the gross growth rate in the aggregate level of productivity, or $g_{\mathbf{x}}$, is just a geometric average of the average rates of innovation by each type of enterprise, or the g 's, weighted by their respective masses, the ν 's. The extent to which high-type VC-funded enterprises propel the economy forward is governed by g_h^f , γ_h^f , and ν_h^f , for $f = \nu, n$.

Next, the market discount factor, δ , is given by

$$\delta = \beta/g_{\mathbf{x}}^{\zeta/(\zeta+\lambda)}, \quad (14)$$

where β is the representative agent's subjective discount factor.⁴² If the depreciation factor

⁴¹Note that one could write $\mathbf{x}' = c(\nu_h^v x_h^v)^{\gamma_h^v} (\nu_h^n x_h^n)^{\gamma_h^n} (\nu_l x_l)^{1-\gamma_h^v-\gamma_h^n}$. But, the fraction of successful firms in the low state receiving either non-VC or VC-funding is one, implying $\nu_l = 1$.

⁴²That is, in the background there is a representative consumer/worker who inelastically supplies one unit of labor and has a lifetime utility function (in period 1) of the form

$$\sum_{t=1}^{\infty} \beta^{t-1} \ln c_t,$$

where c_t is his consumption in period t .

on capital is \mathfrak{d} , then the rental rate, r , is

$$r = 1/\delta - \mathfrak{d}. \quad (15)$$

The rest of the characterization of a balanced growth path is fairly standard. The details are relegated to Appendix B. Along a balanced growth path, wages and output will grow at the constant gross rate

$$g_w = \left(\frac{\mathbf{x}'}{\mathbf{x}}\right)^{\zeta/(\zeta+\lambda)} = g_{\mathbf{x}}^{\zeta/(\zeta+\lambda)},$$

which is a function of the growth rate in aggregate productivity, $g_{\mathbf{x}}$. The rest of the variables, the ν_j^f 's, x_{ij}^f 's, z_{ij}^f 's, δ , and $g_{\mathbf{x}}$, are all constant.

6 Matching the Model with U.S. Census Data

The model is now calibrated with stylized facts computed using data from the LBD, PatentsView, and VentureXpert. The length of a period is 10 years. The baseline level of aggregate productivity, \mathbf{x} , is normalized to one; hence, $\mathbf{x} = 1$. Some parameters are standard in macroeconomics. These are assigned common values. The spillover parameters in equation (12) are taken directly from the data. The rest of the parameters are calibrated in the recursive fashion discussed below. The calibration procedure uses the following facts: the average growth rate of the U.S. economy; the employment levels of non-VC-funded and VC-funded startups; the ex ante matching probabilities between entrepreneurs and venture capitalists; the number of firms per worker in the economy; the patenting rates for non-VC-funded and VC-funded firms; the ratio of non-VC-funded to VC-funded startups; and the success rates for non-VC-funded and VC-funded firms. Given the saturated structure of the model, the parameter values unique to this study are exactly identified. In fact, all but one of the parameters can be pinned down using analytical expressions that connect data to parameter values. The last parameter requires simulating the model to match a desired data target. The following is a summary of the calibration procedure; the details are presented in Appendix C.

1. *The Number of Startups, s^n and s^v .* The number of non-VC-funded and VC-funded

EX ANTE MATCHING PROBABILITIES (%)		
Type	$\geq 90\text{th}$	$\leq 90\text{th}$
VC Funded	32.55	67.45
Non-VC Funded	10.64	89.36

Table 4: The ex ante matching probabilities between entrepreneurs and financiers. The data sources are discussed in Section 2.1. A firm’s type refers to whether or not it is in the top decile for employment at the time of initial VC funding. These are the μ_i^f ’s used in the benchmark calibration for the pattern of assortative matching.

startups can be recovered using data on the ex ante matching probabilities, the success rates of both types of startups, the number of entrepreneurs per worker, and the ratio of non-VC-funded to VC-funded startups. This step is mechanical in nature, involving accounting identities. Given the ex ante matching probabilities and the success rates, it is straightforward to calculate the fractions of startups by funding source that end up in each ex post state. Then, using the number of employees per firm and the ratio of non-VC- to VC-funded startups, it is possible to deduce number of non-VC- and VC-funded startups. The ex ante matching probabilities in the U.S. data are reported in Table 4. Venture capitalists fund a higher percentage of high-type firms than do other financiers—assortative matching was discussed in Section 2.2.

2. *Growth in Startup Productivities, the g_j^f ’s.* The patenting activity of a successful startup is used as a proxy for its innovation. The innovation rates of startups are computed using facts about patenting by each type of startup and the average rate of GDP growth. Only stylized facts for the average patenting activity of type- (f, j) firms are available; i.e., the numbers cannot be broken down by the initial type, i , of the enterprise.⁴³ Therefore, the calibration procedure imposes the restriction that $x_{hj}^f = x_{lj}^f \equiv x_j^f$, for $f = v, n$ and $j = h, l$. The growth rate of GDP depends on the growth rate of aggregate productivity, which is a geometric average of the innovation levels of the various types of startups—recall equation (12). The spillover parameters, or the γ_j^f ’s, are computed from the shares of type- (f, j) firms in total patent citations. The levels of patenting activity are scaled so that the model matches the U.S. growth rate. The distribution of patent citations by firm type in the

⁴³This is due to disclosure restrictions imposed by the U.S. Census Bureau for reasons of confidentiality.

PATENT CITATIONS (%)		
Type	$\geq 90\text{th}$	$\leq 90\text{th}$
VC Funded	26.22	2.67
Non-VC Funded	39.17	31.93

Table 5: The distribution of patent citations across successful startups. Again, the data sources are discussed in Section 2.1. A firm’s type refers to whether or not it is in the top decile for employment 10 years after VC funding. The first column of numbers gives the figures used for the spillover parameters, γ_h^v and γ_h^n .

United States is displayed in Table 5. On this account, $\gamma_h^v = 0.2622$ and $\gamma_h^n = 0.3917$. This calibration step depends on the number of non-VC-funded and VC-funded startups found in Step 1, since these speak to the aggregate level of innovation in the economy.

3. *Synergies, the z_{ij}^f ’s.* The relative employments of firms are used to identify the synergy parameters or the z_{ij}^f ’s. This step depends on the innovation levels found in Step 2. Given an innovation level, a firm’s employment will be bigger the higher is its synergy factor. So, by observing employment one can back out what the synergy factor must be. Facts are at hand only for the average employment of type- (f, j) firms; that is, for the four observations $l_j^f = (\mu_h^f \sigma_{hj}^f l_{hj}^f + \mu_l^f \sigma_{lj}^f l_{lj}^f) / (\mu_h^f \sigma_{hj}^f + \mu_l^f \sigma_{lj}^f)$, for $f = v, n$ and $j = h, l$.⁴⁴ (In other words, data cannot also be categorized by the ex ante type i of enterprise.) This imposes some limitations on the structure that can be calibrated. After this stage in the calibration, the model’s wage rate can be computed.

4. *Efficiencies of research and development, the ψ_{ij}^f ’s, χ_{ij}^f ’s, and ι .* The desired values for the startups’ productivities and success rates, x_{ij}^f and σ_{ij}^f , can be recovered by reverse engineering the constant parameters for the research and development functions, the χ_{ij}^f ’s and ψ_{ij}^f ’s, so that the model hits these data targets. This involves using the first-order conditions for the success rates and innovation levels. These first-order conditions depend on the wage rate found in Step 3. In a nutshell, the idea is to select the efficiency levels of R&D that will support the firms in the model optimally choosing the observed productivities and success rates. The first-order condition for success involves the elasticity term ι . Henrekson and Sanandaji (2018) report that Canada had a tax rate on VC-funded startups of 32 percent

⁴⁴Again, this is due to disclosure restrictions imposed by the U.S. Census Bureau.

CALIBRATED PARAMETER VALUES

<i>Parameter Values</i>	<i>Description</i>	<i>Identification</i>
Consumers		
$\beta = 0.95$	Discount factor—annualized	7% risk-free rate
Firms		
$\kappa = 1/3 \times 0.85 = 0.283$	Capital's share	Standard
$\lambda = 2/3 \times 0.85 = 0.567$	Labor's share	Standard
$1 - \delta = 0.10$	Depreciation rate—annualized	Standard
$s = 0.96$	Firm survival rate—annualized	Expected life of Compustat firms
Research		
$\chi_{hh}^v = 41.270, \chi_{hl}^v = 37.540$	VC research efficiency, x_{ij}^v	VC patenting/success rates
$\chi_{lh}^v = 57.486, \chi_{ll}^v = 23.610$		
$\chi_{hh}^n = 1.616, \chi_{hl}^n = 0.341$	Non-VC research efficiency, x_{ij}^n	Non-VC patenting/success rates
$\chi_{lh}^n = 18.780, \chi_{ll}^n = 0.193$		
$\iota = 3.5$	Research cost elasticity, x_{ij}^v and x_{ij}^n	Canada/U.S. tax elasticity
Development		
$\psi_{hh}^v = 0.002, \psi_{hl}^v = 0.042$	VC development efficiency, σ_{ij}^v	VC patenting/success rates
$\psi_{lh}^v = 0.001, \psi_{ll}^v = 0.071$		
$\psi_{hh}^n = 0.006, \psi_{hl}^n = 0.249$	Non-VC development efficiency, σ_{ij}^n	Non-VC patenting/success rates
$\psi_{lh}^n = 0.0004, \psi_{ll}^n = 0.597$		
Synergies		
$z_h^v = 1.00, z_l^v = 0.042$	VC	Employment ratios
$z_h^n = 0.801, z_l^n = 0.083$	Non-VC	
Ex ante Matching Odds		Firm counts
$\mu_h^v = 0.326, \mu_l^v = 0.675$		
$\mu_h^n = 0.106, \mu_l^n = 0.894$		
Growth Externality		
$\gamma_h^v = 0.262, \gamma_h^n = 0.392$	Exponents on high-state innovation	Citation distribution
Model Period	10 years	VC contract durations

Table 6: Parameter values used to replicate the data targets in Table 7.

and a VC-investment-to-GDP ratio of 0.04 percent. Their numbers for the United States are 15 and 20 percent. This implies a tax elasticity of $-\ln(0.20/0.04)/\ln(0.15/0.32) = 2.12$. The parameter ι is fit to match this elasticity.

6.1 The Model's Fit

The parameter values resulting from the calibration procedure are presented in Table 6, while the calibration targets for the United States and the model's fit for these targets are shown in Table 7. Over the time period in question, GDP grew at 1.80 percent a year.

The model matches this number. A VC-funded startup is much more likely to be highly successful than a non-VC-funded one. A VC-funded venture that starts out in the top decile of employment has a 33.11 percent chance of making it into the top employment decile 10 years later, as Table 7 shows. This compares with 19.53 percent of non-VC-funded firms. A VC-funded startup that begins in the bottom 90 percent of the employment distribution still has a 23.77 percent chance of making it to the top, compared with only 1.68 percent for a non-VC-funded firms. Recall from Table 4, though, that a VC-funded firm is much more likely to start out in the top decile than a non-VC-funded one; 32.55 versus 10.64 percent. This is due to selection. The unconditional probabilities for VC-funded and non-VC-funded firms ending up in the high and low states are presented in Table 8. VC-funded firms have 26.81 and 9.06 percent chances of ending up in the high and low states, while for non-VC-funded startups the numbers are 3.58 and 31.71 percent. Conditional on success, VC-funded firms have a much higher likelihood of winding up in the high state (74.75 percent), relative to non-funded ones (10.15 percent). The failure rates for both VC- and non-VC-funded startups are very high, 64.1 and 64.7 percent respectively.

A VC-funded startup that makes it into the top 10 percent of firms has a much higher employment than a non-VC-funded firm in the same group. The latter's employment is only 16 percent of the former's. The employment levels of both types of startups, should they end up in the bottom 90 percent, are much smaller. Still, a VC-funded firm has 1.6 times the employment of a non-VC-funded firm. Unconditionally speaking, a VC-funded firm has 38.60 times $[\cong (0.75 \times 100 + 0.25 \times 0.59)/(0.10 \times 16.23 + 0.90 \times 0.36)]$ the employment of a non-VC-funded one. Only a small number of startups are funded by venture capitalists. Specifically, there are 1,035.34 non-VC-funded startups for every VC-funded one. Yet, while VC-funded firms account for only 0.1 percent of all startups, 10 years after first funding these firms account for 3.64 percent of total employment $[\cong 0.36 \times 38.02/(0.36 \times 38.02 + 1035.34 \times 0.35)]$. Hence, their punch far exceeds their weight.

Likewise, the patent stock of a VC-funded startup in the top 10 percent of firms is much greater than that for a non-VC-funded firm. Non-VC-funded startups have only 20.27

CALIBRATION TARGETS

<i>Target</i>	<i>U.S. Data</i>		<i>Model</i>	
Economic growth—annualized	1.80		1.80	
Success Rates, %—the σ_{ij}^f 's	Top 10%	Bottom 90%	Top 10%	Bottom 90%
VC funded				
ex ante top 10%	33.11	6.48	33.11	6.48
ex ante bottom 90%	23.77	10.30	23.77	10.30
Non-VC funded				
ex ante top 10%	19.53	18.83	19.53	18.83
ex ante bottom 90%	1.68	33.24	1.68	33.24
Employment, Relative %—the \tilde{e}_j^f 's	Top 10%	Bottom 90%	Top 10%	Bottom 90%
VC funded	100.00	0.59	100.00	0.59
Non-VC funded	16.23	0.36	16.23	0.36
Patenting, Relative %—the $\tilde{\phi}_j^f$'s	Top 10%	Bottom 90%	Top 10%	Bottom 90%
VC funded	100.00	14.09	100.00	14.09
Non-VC funded	20.27	4.33	20.27	4.33
Firms per Worker, %	4.30		4.30	
Ratio non-VC to VC Startups	1,035.34		1,035.34	
Tax Elasticity	2.12		2.05	

Table 7: U.S. data versus model. See Section 2.1 for the data sources. Average employment and patent stocks are measured with respect to VC-funded firms in the top 10 percent. Patenting is measured using a quality-adjusted patent stock. Transition probabilities (the success rates) give the likelihood that an ex ante type- i firm ends up as an ex post type- j firm 10 years after funding, for $i, j =$ top 10 percent, bottom 90 percent.

UNCONDITIONAL SUCCESS PROBABILITIES %						
Type	<i>By state</i>		<i>By state</i> \sim failing		<i>Overall</i>	<i>Failure</i>
	≥ 90 th	≤ 90 th	≥ 90 th	≤ 90 th	$\pi_h^f + \pi_l^f$	$1 - \pi_h^f + \pi_l^f$
VC Funded	26.81	9.06	74.75	25.25	35.87	64.13
Non-VC Funded	3.58	31.71	10.15	89.85	35.29	64.71

Table 8: Unconditional success probabilities for VC-funded and non-VC-funded firms. Success probabilities are not conditioning on the initial type of startup. The calibration procedure ensures that numbers are the same for both the U.S. data and model. The figures are computed by using equation (19) in Appendix C and the information in Tables 4 and 7.

percent of the patents that VC-funded startups have, even when they resolve into the top decile of firms. VC-funded firms in the bottom 90th percentile of firms still have 3 times the patent stocks of non-VC-funded firms. As with employment, VC-funded firms have an outsized share of innovation. Though they account for 0.10 percent of startups, they account for 1.2 percent of patenting activity ten years post funding. Last, in the United States there are 23 workers (1/0.043) for every firm, which the model matches in addition to the above statistics.

6.2 Interpretation of Backed-Out Parameter Values

The backed-out parameter values are reasonable, albeit there are anomalies. As can be seen from Table 6, the synergy level between an entrepreneur and the financier is highest for VC-funded firms in the ex post high state; i.e., $z_h^v > z_j^f$, for all $(f, j) \neq (v, h)$. Also, synergy levels are always higher in the high state than the low state, $z_h^f > z_l^f$, for all f . The synergy between entrepreneurs and financiers is very low in the ex post low state. Somewhat surprisingly, it is lowest for VC-funded firms; i.e., $z_l^v < z_l^n$. The reason is that non-VC-funded firms in the low state do almost no innovation; i.e., their productivity level, or x_l^n , is very small. Therefore, to match employment for these firms, the synergy level must be raised a little to compensate.⁴⁵ Of course, VC-funded firms in the ex post low state are still better than non-VC-funded ones because $z_l^v x_l^v > z_l^n x_l^n$.

The development parameters also reveal reasonable rankings. First, it is more costly to achieve success in the ex post high state than the low one. This is reflected by the fact that $\psi_{ih}^f < \psi_{il}^f$, for all f and i , where a higher value for ψ represents a lower cost. Second, if a firm starts out in the ex ante low state, as opposed to the high state, it is harder to end up in the ex post high state; i.e., $\psi_{ih}^f < \psi_{hh}^f$, for all f . Still, it is more expensive for a firm starting out as a high type to achieve success in the low state as opposed to one starting out as a low-type one; that is, $\psi_{hl}^f < \psi_{ul}^f$. This occurs because the observed odds of winding up in the low state are smaller for ex ante high-type firms. Hence, the calibration procedure places a high cost on this transition that is achieved by lowering ψ_{hl}^f relative to ψ_{ul}^f .⁴⁶

⁴⁵In line with calibration equation (22) in Appendix C.

⁴⁶See equation (23) in Appendix C.

RATES OF INNOVATION, ANNUALIZED %		
<i>Rate of Innovation</i>	<i>Top 10%</i>	<i>Bottom 90%</i>
VC funded	29.23	6.23
Non-VC funded	10.17	-5.59

Table 9: Annualized rates of innovation for each type of firm as measured by their percentage distance from the frontier at the time of startup, $100 \times [(x_{ij}^f/\mathbf{x})^{1/10} - 1]$.

Last, the research parameters look reasonable, but again with some exceptions. First, the cost of doing research is lower for a VC-funded firm than for a non-VC-funded one; that is, $\chi_{ij}^v \geq \chi_{ij}^n$ for all i, j . Thus, it is easier to do research when backed by a venture capitalist, perhaps because they lend expertise. Second, for a VC-backed firm the cost of researching an ex post high idea starting out from the ex ante low state is lower than for the ex ante high state; i.e., $\chi_{lh}^v > \chi_{hh}^v$. This is an artifact of the Census data disclosure restriction on reporting patenting activity that imposed the constraint $x_{lh}^v = x_{hh}^v$, when almost certainly $x_{lh}^v < x_{hh}^v$. Now, note that $z_{lh}^v = z_{hh}^v$ and that $\sigma_{lh}^v < \sigma_{hh}^v$. Given the low success rate when starting out from the ex ante low state it must transpire that, to get the same level of patenting as the ex ante high state, the research costs in the ex ante low state must be lower.⁴⁷

7 VC and Growth

How important is the presence of venture capital for the economy? As a prelude to answering this question, Table 9 shows that in the calibrated equilibrium most innovation in the economy, relative to the aggregate level of productivity, is driven by VC-funded firms that make it into the top 10 percent. In fact, non-VC-funded startups that don't make it into the top decile drag down the average level of productivity in the economy. This occurs because even after these firms innovate, they lag behind the aggregate level of productivity in the economy at the time of their inception. Additionally, they make up 89.77 percent of the firms in the economy, whereas VC-funded firms in the top decile comprise only 0.07 percent.

⁴⁷As equation (24) in Appendix C dictates.

To gauge the importance of venture capital for the economy, VC is shut down. This is done by setting the synergy parameters for VC-backed enterprises equal to the ones for non-VC-backed ones, implying $z_j^v = z_j^n$. Likewise, the values for the R&D cost parameters for VC-funded firms are fixed to those for non-VC-funded firms; i.e., $\chi_{ij}^v = \chi_{ij}^n$ and $\psi_{ij}^v = \psi_{ij}^n$. This renders VC-backed firms the same as non-VC-backed ones. Last, since both types of firms are the same now, in the law of motion for aggregate productivity, or equation (13), the spillover parameter for VC-funded startups in the ex post high state is set equal to that of non-VC funded ones in this state, so that $\gamma_h^v = \gamma_h^n$ and $\nu_h^v = \nu_h^n$.⁴⁸ This experiment is equivalent to requiring all firms to use bank financing, and shuts down all VC treatment effects in the economy.

The results of this experiment are reported in Table 10. Growth falls from 1.80 percent annually to 1.30. The drop in the growth rate derives from two key features of the baseline calibration. First, the success rates of entering into the ex post high state for non-VC-backed startups are lower than for VC-backed ones. Second, the level of patenting activity in the high state for non-VC-backed startups is much lower than for VC-backed ones. Requiring all firms to use bank financing leads to a large welfare loss of 7.58 percent in terms of consumption, as measured by a compensating variation.⁴⁹

8 Assortative Matching between Entrepreneurs and Financiers

How much does the observed ex ante match between entrepreneurs and venture capitalists matter for growth? To address this question, two extreme cases will be examined: perfect assortative matching and random matching. For the first experiment, consider the case where there is perfect assortative matching between entrepreneurs and venture capitalists, which is illustrated by the second panel of Table 11. Recall out of s startups, s^n are funded

⁴⁸In similar fashion, the constant term c given by equation (21) in Appendix C needs to be renormalized by fixing $\nu_h^v = \nu_h^n$.

⁴⁹The initial level of baseline consumption in both regimes is assumed to be the same and the utility function is logarithmic.

NO VENTURE CAPITAL THOUGHT EXPERIMENT

	<i>Baseline</i>	<i>No Venture Capital</i>
Variable		
Growth	1.80	1.30
Compensating variation	0	-7.58
VC firms, high		
percentage, $\nu_h^v\%$	0.73	0
patenting, x_{hh}^v and x_{lh}^v	12.99, 12.99	2.58*, 2.57*
success, $\sigma_{hh}^v\%$ and $\sigma_{lh}^v\%$	33.11, 23.77	19.00*, 1.61*
VC share of all patenting	1.28	0
Non-VC firms, high		
fraction, $\nu_h^n\%$	99.28	100
patenting, x_{hh}^n and x_{lh}^n	2.63, 2.63	2.58, 2.57
success, $\sigma_{hh}^n\%$ and $\sigma_{lh}^n\%$	19.53, 1.68	19.00, 1.61
Non-VC share of all patenting	98.72	100.00

Table 10: Results for the no venture capital thought experiment. The table reports what happens when venture capital is shut down. The entries with the asterisks show what VC-backed startups look like when they are degraded to resemble non-VC-backed ones. These startups are now counted as non-VC-backed ones.

by banks and s^v by venture capitalists; i.e., $s = s^n + s^v$. There are $0.10 \times s$ entrepreneurs in the top decile of projects. The maximum number of matches between startups in the top decile and venture capitalists is $\mathfrak{v} \equiv \min\{s^v, 0.10 \times s\}$. Therefore, the probability of a venture capitalist funding a startup in the top decile is \mathfrak{v}/s^v . When venture capitalists are in short supply, as in data, $\mathfrak{v} = s^v$ (so that the odds of a VC funding a startup in the top decile are 100 percent). The short supply of venture capitalists also means that there are no startups below the top decile that receive VC. Moreover, because of the short supply of venture capitalists, a fraction of entrepreneurs in the top decile ($0.10 \times s - \mathfrak{v}$) will have to seek financing from an alternate source, such as a bank. The resulting probability of a match between a high-type entrepreneur and a bank is $(0.10 \times s - \mathfrak{v})/s^n$. Finally, the remaining entrepreneurs below the top decile will also be funded by bank. Therefore, the probability of a bank funding a low-type entrepreneur is $(s^n - 0.10 \times s + \mathfrak{v})/s^n$.

The movement to perfect assortative matching increases growth from 1.80 to 1.96 percent—see the second column of Table 12. Virtually all of the uptick in growth derives from a movement along the extensive margin. That is, from an increase in the fraction of VC-funded

EX ANTE MATCHING PROBABILITIES

	(1)		(2)		(3)		(4)	
	<i>Data</i>		<i>Perfect Assortative</i>		<i>Perfect Assort. with More VC</i>		<i>Random</i>	
Type	$\geq 90\text{th}$	$\leq 90\text{th}$	$\geq 90\text{th}$	$\leq 90\text{th}$	$\geq 90\text{th}$	$\leq 90\text{th}$	$\geq 90\text{th}$	$\leq 90\text{th}$
VC Funded	32.55	67.45	100.00	0	100.00	0	10.00	90.00
Non-VC Funded	10.64	89.36	9.91	90.09	0	100.00	10.00	90.00

Table 11: Ex ante matching probabilities, U.S. data and experiments. The ex ante matching probabilities observed in the data (first panel), when matching is perfectly assortative (second panel), perfectly assortative matching with an increased supply of venture capitalists (third panel), and completely random (last panel). The numbers used are reported as percentages.

firms that are operating in the ex post high state. This fraction moves up from 0.73 to 0.91 percent. This is partially offset by a decline in the fraction of non-VC-funded firms producing in this state. The percentage increase in VC-funded firms is however much larger. Effectively, the number of non-VC-funded firms barely moves from its baseline. Observe that the success and patenting rates increase a little. This occurs because the equilibrium wage rate drops slightly. So, the increase in growth comes from an increase in the fraction of firms in the high state that are funded by venture capitalists. The contribution of VC firms to patenting activity also rises from 1.28 to 1.55 percent. This increase has a noticeable impact on growth due to the sizeable spillover coefficient, γ_h^v , on VC-funded firm patenting activity in the high state. While the increase in growth might seem modest, it leads to a significant welfare gain as measured by the compensating variation for a move from the baseline economy to the one with perfect assortative matching. A person would be willing to give up 2.26 percent of his consumption in each and every period along a balanced growth path in the new regime in order to effect the move.

Recall that venture capitalists are in short supply in the baseline equilibrium. Now, suppose that one could increase the supply of venture capitalists so that all firms in the top decile could be funded by VC. The third panel of Table 11 shows the resulting matching probabilities. Growth would now pick up from 1.80 to 2.05 percent, which would be worth 3.66 percent in terms of consumption—the third panel of Table 12. One might have expected an even larger welfare gain, but the impact is dampened due to a rise in wages in general equilibrium. This is reflected in the lower levels of patenting and success rates for both VC-

and non-VC-financed firms. So, all of the uptick in growth comes from the fact that more firms are financed by venture capitalists. VC-funded firms have higher levels of patenting and success rates than non-VC-funded firms, which allows growth to rise.

The relatively large gains in growth when matching becomes perfectly assortative suggests that policies that increase the degree of assortative matching can enhance growth. An example of such a policy is early-stage R&D subsidies to startups. Recent evidence on the effectiveness of Small Business Innovation and Research (SBIR) grants by the federal government suggests that an important function of these grants is to allow startups to develop a “prototype” and demonstrate the feasibility of their technology or product. This demonstration can reduce uncertainty about the viability of a startup, and make it more attractive to private investment. For instance, Howell (2017) finds that a Phase I SBIR grant nearly doubles the likelihood of VC investment in a startup. In other words, such grants can act like a “match-maker” and allow startups that may otherwise be unnoticed by venture capitalists to be selected and funded by them. Making such grants available to a broader set of startups or raising the grant amount can therefore increase the degree of assortative matching, leading to higher growth.

For the final experiment, suppose that matching is random—that is, selection by venture capitalists is eliminated. The counterfactual is given by the last column of Table 12. There are s^v venture capitalists in total. With random matching, $0.1 \times s^v$ venture capitalists will be matched with firms in the top 10 percent, the rest with firms in the bottom 90 percent. Growth and welfare now drop, but ever so slightly—see Table 12. This occurs primarily from a fall in the number of VC-funded firms operating in the high state from 0.73 to 0.68 percent. The movement from the matching structure observed in the data to the random matching structure is much smaller than moving to perfect assortative matching, as can be seen in Table 11.⁵⁰ So, the impact on growth and welfare from random matching is more

⁵⁰The magnitude of these movements can be assessed using a matrix distance metric. For instance, based on the Frobenius norm, the distance between two matrices A and B is given by $\sqrt{\sum_{(i,j)} (a_{ij} - b_{ij})^2}$, where a_{ij} and b_{ij} are the (i, j) elements of A and B , respectively. Using this measure, the movement from the baseline to random matching represents a distance of 31.9, whereas the movement from the baseline to perfectly assortative matching amounts to a much larger distance of 95.4.

MATCHING THOUGHT EXPERIMENTS

	(1)	(2)	(3)	(4)
	<i>Baseline</i>	<i>Perfect</i>	<i>Perfect Assort.</i>	<i>Random</i>
Variable		<i>Assortative</i>	<i>with More VC</i>	
Growth	1.80	1.96	2.05	1.78
Compensating variation	0	2.26	3.66	-0.22
VC firms, high				
fraction, $\nu_h^v\%$	0.73	0.91	78.43	0.68
patenting, x_{hh}^v and x_{lh}^v	12.99, 12.99	13.13, 13.15	8.35, 7.89	13.06, 13.07
success, $\sigma_{hh}^v\%$ and $\sigma_{lh}^v\%$	33.11, 23.77	33.56, 24.18	17.94, 11.18	33.12, 23.78
VC share of all patenting	1.28	1.55	69.87	1.20
Non-VC firms, high				
fraction, $\nu_h^n\%$	99.28	99.09	21.57	99.32
patenting, x_{hh}^n and x_{lh}^n	2.63, 2.63	2.67, 2.68	1.56, 1.38	2.55, 2.57
success, $\sigma_{hh}^n\%$ and $\sigma_{lh}^n\%$	19.53, 1.68	19.91, 1.73	8.59, 0.55	19.72, 1.71
Non-VC share of all patenting	98.72	98.45	30.13	98.8

Table 12: Results for the matching thought experiments. The table reports what happens when the initial matching between entrepreneurs and financiers is perfect assortative, perfect assortative with an increased supply of venture capitalists, and random. All rates are reported as percentages.

muted than the impact on growth from perfect assortative matching.

9 Taxation of Startups

The model can be used to assess the role of the differential taxation of VC-funded startups compared to other startups. In the United States, VC-funded startups are taxed when they are floated or sold at the capital gains rate, currently 17 percent. This happens because the key officers of the companies are remunerated in the form of stock options or preferred shares that only attain value when the firm goes public or is bought by another company. Other types of startups are taxed at either the corporate or personal income tax rates, which are much higher. Until recently the corporate income tax rate was 35 percent.

From the analysis of the balanced growth path, it can be deduced that a uniform tax on all forms of startups will have no impact on economic growth. This transpires because it acts as an equiproportional reduction in all synergies, or on the z_{ij}^f 's. A uniform tax operates in the same manner as a once-and-for-all reduction in aggregate productivity.

Lemma 2 (*Neutrality of a Uniform Startup Tax on Long-Run Growth*) *Suppose the government levies an income tax at rate τ on all producing enterprises, with all revenue rebated back to consumers/workers in the form of lump-sum transfers. There is no effect on long-run growth; i.e., on g_x and g_w .*

Proof. See Appendix B. ■

While Lemma 2 states that the taxation of all startups at a uniform rate would have no impact on an economy’s balanced growth path, differential taxation across VC-funded and non-VC funded startups will. As an experiment, consider what happens if both VC- and non-VC-funded startups are taxed at a uniform rate of 35 percent; that is, if the tax rate on VC-funded ventures is raised to the rate on non-VC-funded ones. Note that the historical tax rates on VC- and non-VC-funded startups are built into the calibrated synergies (the z ’s). So, the experiment amounts to degrading the synergy factor on VC-funded startups by a factor of $(1.0 - 0.35)/(1.0 - 0.17)$.⁵¹

When VC-funded startups are taxed at a higher rate, economic growth drops from 1.80 to 1.48 percent per year, as Table 13 shows. The level of patenting activity by VC-funded firms in the ex post high state drops. This is not made up for by an increase in patenting activity by non-VC-funded firms. Additionally, VC-funded firms’ success rate in the high state drops off sharply. The success rates for non-VC-funded firms do not rise to offset this fall. The share of VC-funded firms in patenting activity drops fairly dramatically. Since VC-funded firms are the prime drivers of innovation in the economy, all of this results in a decline in the growth rate. Raising taxes on VC-funded startups results in a large welfare loss of 4.83 percent in terms of consumption. In other words, the lower tax rates currently applicable to VC-backed startups contribute significantly to growth.

10 Conclusion

An endogenous growth model is developed to study the implications of venture capital backing on aggregate productivity and innovation. In the model, entrepreneurs take ideas for

⁵¹This can be gleaned by examining the proof for Lemma 2 in Appendix B.

UNIFORM TAXATION EXPERIMENT

	<i>Baseline</i>	<i>Uniform Taxation</i>
Variable		
Growth	1.80	1.48
Compensating variation	0	-4.83
VC firms, high		
fraction, $\nu_h^v\%$	0.73	0.53
patenting, x_{hh}^v and x_{lh}^v	12.99, 12.99	10.44, 10.14
success, $\sigma_{hh}^v\%$ and $\sigma_{lh}^v\%$	33.11, 23.77	24.79, 16.52
VC share of all patenting	1.28	0.74
Non-VC firms, high		
fraction, $\nu_h^n\%$	99.28	99.47
patenting, x_{hh}^v and x_{lh}^v	2.63, 2.63	2.60, 2.59
success, $\sigma_{hh}^n\%$ and $\sigma_{lh}^n\%$	19.53, 1.68	19.18, 1.64
Non-VC share of all patenting	98.72	99.26

Table 13: Results for the uniform taxation experiment. The table reports what happens when the tax rate on VC-funded startups is raised from 17 percent to the 35 percent rate on non-VC-funded startups. All rates are reported as percentages.

projects to either banks or venture capitalists for financing. In the U.S. data, startups backed by venture capitalists have more promising growth and innovation prospects than other startups. The initial selection process observed in the data is imposed on the model. Additionally, in the U.S. data, startups that are financed by venture capitalists, as opposed to banks, have a much higher likelihood of making it into the top decile of firms in terms of employment ten years later. They also have much higher rates of growth and patent quality, conditional on surviving. The model's saturated structure allows the framework to be calibrated so that it matches exactly the observed transitions from ex ante promise to ex post success for both bank- and VC-financed firms. It also matches the small ratio of VC-financed to bank-financed startups, the small average firm size in the U.S. economy, and GDP growth per capita.

Simulations of the model establish that the presence of venture capital is crucial for growth. Shutting down venture capital in the economy reduces growth. In addition, the degree of ex ante assortative matching between startups and financiers matters. Improving the degree of assortative matching from its existing level in the U.S. economy enhances growth, while moving to random matching impedes it. Last, the differential taxation of

VC-financed startups is important for growth. If the prevailing tax rates, which imply lower taxation of VC-funded startups, are raised so that tax rates are uniform across all startups, then the growth rate of the economy would decline significantly.

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A Appendix: Data

This Data Appendix describes the assembling of the main dataset and the analysis sample. It also provides further detail about how the tables and figures are constructed.

A.1 Data merging procedure

To construct the analysis data, the Thomson-Reuter's VentureXpert data on firms receiving VC funding is combined with the U.S. Census Bureau's Business Register (BR) using probabilistic name and address matching. The resulting data is then linked with the U.S. Census Bureau's Longitudinal Business Database (LBD).

The procedure to combine VentureXpert and BR involves several steps. The first step is to clean the two datasets to facilitate matching. For VC-backed firms between 1970 and 2015,

VentureXpert provides the following information: firm identifier, firm name, street address, city, state, zip code, and the year in which VC funding is received. The analysis uses only firms located in the United States and identifies the first and last years of funding for all such firms. The BR is the main sampling frame for U.S. Census Bureau’s surveys and it is the main source data for the LBD. Establishment and firm identifiers, years of operation, and employment from the LBD are integrated with the information on firm name, street address, city, state, and zip code from the BR for the period 1976 through 2013. The firm name, street address, city, and zip code variables in both the BR and VentureXpert are standardized using the same protocol.

The second step involves merging VentureXpert with the BR-LBD in a sequential manner using nine passes. Each pass uses a less stringent screening than the previous one, to prevent some valid potential matches from being eliminated. The quality of the matches obtained at the end of the procedure are then assessed, as discussed below. In each pass, firms are linked based on certain firm name and address criteria, and removed from the set of linked firms before proceeding to the next pass. In the first pass, the merge is based on firm name, street address, city, and state. In the second pass, the merge is performed using firm name, city, state, and zip code. In the third through fifth passes, the merge is done on firm name and two additional address criteria. In the sixth through eight passes, the merge utilizes firm name and one additional address criterion. Finally, in the ninth pass, only firm name is used for matching. The implementation of the procedure described above results in multiple BR-LBD links for each VC-funded firm.

In the third step, the best BR-LBD match is identified for each VC-funded firm using a composite match quality score, which is constructed based on the quality of the name, city, state, and zip code match. To determine the quality of a match, the Jaro-Winkler string comparator is utilized. For each VC-funded firm, only the highest quality BR-LBD links are kept based on the composite score. In the process, low-quality links are also dropped—these are the links based only on name with a low Jaro-Winkler score, and only based on name and one address variable with a low Jaro-Winkler score. After implementing the above three steps, there still remain multiple BR-LBD links for each VC-funded firm.

The fourth step involves validating these links using information on the years in which

firms were funded. A link is considered valid if a firm is determined to be active within a five year window of the first and last year of VC funding. In particular, it is required that the funded firm appears in the LBD at least within the first five years of receiving its first VC funding, and that the funded firm does not disappear (exit) from the LBD more than five years before receiving its last VC funding. Applying this window also helps account for some potential lags in reporting or recording errors. In cases where multiple links remain, firms whose first year of operation is closest to the founded year recorded by VentureXpert are kept. Remaining cases with multiple links are dropped to reduce false positives. Overall, the entire procedure results in a BR-LBD match rate of 70 percent for the VC-funded firms in VentureXpert.

It is important to note that each VC-funded firm is effectively matched to an establishment in the LBD, since the majority of firms in the United States are single-unit (single-establishment) firms, particularly when they are in the age range when most firms receive VC funding (i.e., when they are very young). The identifier for an establishment is time invariant in the LBD across all the firms an establishment is associated with throughout its life. Hence, an establishment's expansion can be tracked, including the opening of additional establishments under the same firm and M&A (the funded establishment being subsumed into an existing firm).⁵²

A.2 Analysis sample construction

The empirical analysis focuses on VC-funded firms that receive funding between 1980 and 2012. This is the period with the best overlapping coverage across all three data sets—LBD, patenting data, and VentureXpert. The last year of the analysis is set to 2012 to take into account lags in the patenting data.

The empirical analysis compares the performance of VC-funded firms with all non-VC-funded firms in the economy. For this purpose, a sample of non-VC-funded firms is assembled using a procedure similar to the construction of the VC-funded firms sample. In particular,

⁵²In cases when the establishment identifier disappears, but the firm identifier associated with the establishment in the last year of the establishment's existence continues, the latest firm the establishment belongs to is followed.

between 1980 and 2012 the analysis considers all non-VC-funded firms that are born as single-units and follows the associated establishment identifier across all the firms it is part of throughout its life. Firms that are born as multi-units (a very small fraction of new-born firms) are excluded, as well as those single-unit firms that have an initial age different than zero—these firms are parts of existing businesses.

For both the VC-funded and non-VC-funded firms in the sample, there is information on firm-level industry, age, location (state), multi-unit status, employment, and payroll. Years associated with significant events in the firm’s life are also identified. These events are firm failure, M&A, and IPO. Firm failure is identified when all of the establishments of a firm cease to report employment and stop appearing in the LBD. M&A are identified when one or more of the establishments belonging to a particular firm appear in subsequent years to be part of a different firm that: (i) existed in the two years prior to the acquisition, (ii) continues to exist for at least two years after the acquisition, and (iii) is a multi-unit firm, which means that it operates more than one establishment. IPOs are identified by the first year in which a firm meets two criteria: (i) it appears in the Compustat-BR bridge constructed at the U.S. Census Bureau and (ii) records a positive stock price in Compustat.

For each VC-funded firm, the first year in which it received funding is also identified. In addition, firm-level patenting information is brought in using the LBD-PatentsView link file. The links identify which firms in the sample engage in patenting activity and allow tracking of a number of innovation outcomes: the number of new patents, the stock of patents, the number of citations received by new patents, and the stock of citations based on patent application year. Two adjustments are made to the citation data. Self-citations are dropped and all citations are scaled by the average citations received by other patents applied for in the same year and same broad NBER technology class.

In the data when VC-backed startups are acquired by existing firms, the firm identifier they are associated with changes. This change often leads to jumps in employment and patenting arising from the fact that the acquiring firm usually operates at a larger scale than the acquired firm. These abrupt changes in firm outcome measures can confound the analysis. Therefore, in cases where mergers or acquisitions are identified, the employment and patenting of the acquired firm are no longer tracked, and the last observed values are

used.

A.3 Construction of figures and tables

A.3.1 Tables 1 and 7

In Tables 1 and 7, the outcomes of VC-funded and non-VC-funded firms are compared at the time of VC funding, as well as 10 years after VC funding. First, using the sample of VC-funded firms, average firm age at the first funding event is calculated. This average age (rounded to the nearest integer) is used as the synthetic date to impute a first funding year for all non-VC-funded firms. Second, the analysis is restricted to firms for which the first actual or synthetic funding occurs in 2002 or earlier to ensure that survivors (firms that do not fail or get involved in an M&A) are observed for a minimum of 10 years. For Table 1, employment at the time of first VC funding is used to separate firms into those in the top 10 percent versus the bottom 90 percent of firm employment at the time of first VC funding. These two groups are further divided into those firms that were funded by venture capitalists versus those that were not. For each group, their shares in the number of firms and employment are calculated for the time of first VC funding. Their shares in VC-funded versus non-VC-funded firms are also computed, as well as their average employment relative to VC-funded firms in the top decile.

In Table 7, the focus is on the subsample of firms that survive 10 years either after first actual or synthetic VC funding. If a firm is involved in an M&A activity before the 10 year mark, it is also included in the subsample, with the M&A year being the last observation year for the firm. Firms are separated into two groups based on the distribution of employment 10 years after VC funding—those that fall into the top 10 percent of the distribution versus the bottom 90 percent. The two groups are then further divided into those that were funded by venture capitalists versus those that were not. As in Table 1, for each group statistics on their share of the number of firms and employment 10 years after first VC funding are calculated, as well as average employment and the patent stock relative to VC-funded firms in the top 10 percent.

Transition probabilities between groups in Table 1 and Table 7 are also computed. These

are the conditional probabilities with which a firm ends up in each of the four groups 10 years post first funding (Table 7), contingent upon which of the four groups it started in at the time of first funding (Table 1)—provided that such a transition is feasible.

A.3.2 Figure 1

To generate Figure 1, firm age at first VC funding is calculated as the difference between the first year in which the firm is observed as an employer business in the LBD and the first year of VC funding. The figure is restricted to those firms that receive funding between the ages of -5 and +5, where negative numbers indicate that funding was received prior to the first year when the firm hired employees. Firms outside of this age range are not included to prevent the disclosure of confidential information—they account for a small fraction of all firms that receive VC funding.

A.3.3 Figures 2 and 3

To generate Figure 2, the DHS average annual employment growth rate in the firm’s first three years of life is calculated.⁵³ The firms in the analysis sample are then grouped into quintiles based on the distribution of DHS average employment growth rate, with the top quintile representing the highest average growth rates. For each quintile, the number of firms that subsequently receive VC funding is then divided by the total number of firms in that quintile to obtain the percentage probability plotted in the y-axis.

To generate Figure 3, the sample is restricted only to patenting firms, and the total quality-adjusted patenting of each firm is calculated over a period of three years starting with the first year of patenting.⁵⁴ This calculation is done before VC funding. Most firms only patent in the first year of the three year period, so effectively this procedure mainly captures the first patenting activity. Firms are then grouped into quintiles based on the quality-adjusted patenting measure, with the highest quintile corresponding to the largest amount of patenting. The y-axis is the ratio of the number of firms that subsequently receive

⁵³The DHS growth rate is given by $g_t = 2 \times (\text{EMP}_t - \text{EMP}_{t-1}) / (\text{EMP}_t + \text{EMP}_{t-1})$. Firm births are associated with an annual growth rate of +2 in the first year of their lives. Firm failures are associated with a DHS growth rate of -2 in the year of failure.

⁵⁴For example, if the first patent of a startup is in 1995, the first three years are 1995, 1996, and 1997.

VC funding to the total number of firms in that quintile (expressed as a percentage). The VC funding probability is based on VC funding observation within the 5 years *following* the first patent by a firm.

A.3.4 Figures 4, 5, and 6

In Figures 4, 5, and 6, the outcomes of funded firms are compared with those of the non-VC-funded firms. The employment, age, industry, and location distributions of VC-funded and non-VC-funded firms are quite different, which may lead to an overstatement of the differences between the two groups. To address these differences, for each VC-funded firm in the sample, matching non-VC-funded firms are found that are observationally similar to the VC-funded firm in the year first VC funding is received. Specifically, for each year in the time frame from 1980 to 2012 a firm that received first VC funding in a year is matched with a non-VC-funded firm in the same year that is of the same age, is in the same narrowly defined employment bin, has the same multi-unit status, is located in the same state, and operates in the same 4-digit NAICS industry.

Ultimately, the matching procedure assigns multiple matches to each VC-funded firm, each of which is given an equal weight in the analysis. Of the nearly 19,000 VC-funded firms in the full sample, approximately 13,000 are matched with non-VC-funded firms that form the control group. The control group consists of a total of about 649,000 firms. For each VC-funded firm, this procedure sometimes generates multiple matches from the non-VC-funded firm sample, owing to the large set of potential matches available. For the cases with multiple matches, only those matches are kept where the percentage differences in initial employment (at age zero) between the VC-funded and non-VC-funded firms do not exceed 50 percent. After this elimination of multiple matches, there are still cases where multiple non-VC-funded firms match to a single VC-funded firm. In these cases, equal weights are assigned to each matching firm. In certain cases, one non-VC-funded firm also matches to multiple VC-funded firms. To ensure that a single trajectory is followed for the non-VC-funded firm, its earliest match is kept.

For the analysis of firm innovation, a separate set of matched VC-funded and non-VC-funded samples are created following the same procedure described above, but with the

additional restriction that treated and control firms have to be patenting firms—a restriction fulfilled by a relatively small number of firms.⁵⁵ The subsample of VC-funded firms that have patents consists of nearly 6,500 firms. Of these about 2,500 are successfully matched based on the criteria described above to about 5,000 non-VC-funded firms that also have patents.

In Figure 4 the evolution of average employment for VC-funded and non-VC-funded firms is plotted. To construct the figure, the sample is restricted to those VC-funded firms (and their non-VC-funded matches) that received funding at ages 1, 2, or 3 and have non-zero employment. These restrictions ensure that the focus is on a sample where firm employment is observed in at least one year prior to the first year of funding. In Figure 6 the sample is also restricted to those VC-funded firms (and their non-VC-funded counterparts) that receive their first funding at age 1, 2, or 3, but no additional restrictions are placed based on employment.

Using the matched sample, in Figure 5 the focus is on those firms that survive for at least 10 years post VC funding. For each firm, the DHS employment growth rate is calculated between the year in which funding is received and 10 years later. For both the VC-funded and non-VC-funded groups, the kernel density estimate of the resulting growth rate is plotted. The extreme tails of the distributions were trimmed to comply with the disclosure requirements and protect confidentiality.

A.3.5 Figures 7 and 8, and Table 2

In Figures 7 and 8, and in Table 2, the focus is on high- versus low-experience venture capitalists. There are several steps involved in assigning VC-funded firms a VC funder experience measure. The VentureXpert data predominately consist of one observation per VC-funded firm per year. Each row of data has a list of funders and the average equity invested per funder. First, a separate indicator is created for each funder, which is used to generate a full list of VC funders in the data. Since the underlying VentureXpert data are obtained from regulatory disclosures, slight variations are observed in the spelling of funder names across deals and over time. In order to take these variations into account, alternate

⁵⁵No matching is done based on patent quality similarity, because many treated firms do not have matched controls that are also close in terms of patent quality similarity.

spellings of funder names in the data are taken into account to group these slight variations in spelling under the same identifier. These identifiers are then used to create a measure of total number of deals in which the funder was involved in over the years. A funder is defined to be of high experience if it is in the top 10 percent of the total number of deals distribution, and of low experience if it is in the bottom 90 percent.

It is common for a VC-funded firm to receive funding from multiple venture capitalists within the first year of funding. If 50 percent or more of the firms' funders (in counts) are high experience, it is considered to be a firm funded by high-experience venture capitalists. If, instead, more than 50 percent of its funders are low experience, it is considered to be a firm funded by low-experience venture capitalists. As a result, each VC-funded firm is unambiguously classified to be financed by either a high-experience or a low-experience funder for the first year it received VC funding.

In Figures 7 and 8 the sample is restricted to those VC-funded firms that receive their first funding at age 1, 2, or 3. The evolution of employment (Figure 7) and patenting (Figure 8) are separately plotted for those firms identified as being funded by high- versus low-experience venture capitalists. In Table 2, the outcomes of firms funded by high- and low-experience funders are compared more formally by using regression analysis. A VC-funded firm's employment in the year of failure, M&A, or at 10 years out after first VC funding (whichever comes first) is used as the dependent variable. The independent variables are an indicator of whether funding was provided by a high- or low-experience funder (omitted category is the low experience), age at which first funding is received, years since the first funding event, initial firm size (employment) at funding, the amount of equity received at time of first funding, 4-digit NAICS fixed effects, and year effects, where the year is defined as the year in which the outcome variable is measured.

B Appendix: Theory

B.1 The Impact of Synergy—Proof of Lemma 1

Proof. (The Impact of Synergy) The six first-order conditions connected with the Nash Bargaining problem (P1) are

$$\begin{aligned} & [\delta x_{ij}^v z_{ij}^v I(\cdot) - \delta p_{ij}^v] \times \{ \sigma_{ih}^v \delta p_{ih} + \sigma_{il}^v \delta p_{il} - R(\frac{x_{ih}^v}{\mathbf{x}}) - R(\frac{x_{il}^v}{\mathbf{x}}) - D(\sigma_{ih}^v) - D(\sigma_{il}^v) - V \} \\ & + \{ \sigma_{ih}^v \delta x_{ih}^v z_{ih}^v I(\cdot) + \sigma_{il}^v \delta x_{il}^v z_{il}^v I(\cdot) - \sigma_{ih}^v \delta p_{ih}^v - \sigma_{il}^v \delta p_{il}^v - E_i \} \times [\delta p_{ij}^v - D_1(\sigma_{ij}^v)] = 0, \end{aligned}$$

$$\begin{aligned} & \sigma_{ij}^v \delta z_{ij}^v I(\cdot) \times \{ \sigma_{ih}^v \delta p_{ih} + \sigma_{il}^v \delta p_{il} - R(\frac{x_{ih}^v}{\mathbf{x}}) - R(\frac{x_{il}^v}{\mathbf{x}}) - D(\sigma_{ih}^v) - D(\sigma_{il}^v) - V \} \\ & - \{ \sigma_{ih}^v \delta x_{ih}^v z_{ih}^v I(\cdot) + \sigma_{il}^v \delta x_{il}^v z_{il}^v I(\cdot) - \sigma_{ih}^v \delta p_{ih}^v - \sigma_{il}^v \delta p_{il}^v - E_i \} \times R_1(\frac{x_{ij}^v}{\mathbf{x}})/\mathbf{x} = 0, \end{aligned}$$

and

$$\begin{aligned} & - \sigma_{ij}^v \delta \times [\sigma_{ih}^v \delta p_{ih} + \sigma_{il}^v \delta p_{il} - R(\frac{x_{ih}^v}{\mathbf{x}}) - R(\frac{x_{il}^v}{\mathbf{x}}) - D(\sigma_{ih}^v) - D(\sigma_{il}^v) - V] \\ & + [\sigma_{ih}^v \delta x_{ih}^v z_{ih}^v I(\cdot) + \sigma_{il}^v \delta x_{il}^v z_{il}^v I(\cdot) - \sigma_{ih}^v \delta p_{ih}^v - \sigma_{il}^v \delta p_{il}^v - E_i] \times \sigma_{ij}^v \delta = 0, \end{aligned}$$

for $j = l, h$. Using the last first-order condition to cancel out the terms in braces in the first two statements leads to the two efficiency conditions (4) and (5). Displacing (4) and (5) with respect to z_{ij}^v yields

$$\begin{bmatrix} \delta z_{ij}^v I(\cdot) & -D_{11} \\ -R_{11}/\mathbf{x}^2 & \delta z_{ij}^v I(\cdot) \end{bmatrix} \begin{bmatrix} dx_{ij}^v \\ d\sigma_{ij}^v \end{bmatrix} = - \begin{bmatrix} \delta x_{ij}^v I(\cdot) \\ \delta \sigma_{ij}^v I(\cdot) \end{bmatrix} dz_{ij}^v,$$

so that

$$\frac{dx_{ij}^v}{dz_{ij}^v} = \frac{-[\delta I(\cdot)]^2 x_{ij}^v z_{ij}^v - \delta \sigma_{ij}^v I(\cdot) D_{11}}{\Delta} > 0,$$

and

$$\frac{d\sigma_{ij}^v}{dz_{ij}^v} = \frac{-[\delta I(\cdot)]^2 z_{ij}^v \sigma_{ij}^v - (R_{11}/\mathbf{x}^2) \delta x_{ij}^v I(\cdot)}{\Delta} > 0,$$

with

$$\Delta \equiv [\delta z_{ij}^v I(\cdot)]^2 - D_{11} R_{11} / \mathbf{x}^2 < 0,$$

where the sign of Δ follows from the second-order condition for a maximum.⁵⁶ ■

B.2 Characterization of the Balanced Growth Path

How is the wage rate determined in general equilibrium and at what gross rate will it grow along a balanced growth path? This is a key step in characterizing a balanced growth path. To address this question, first note that there are eight types of enterprises producing: ex ante high- and low-type startups that evolve into ex post high- and low-type firms, which were initially financed by venture capitalists and non-venture capitalists. Recall that each period there are s^v firms funded by VC and s^n by non-VC sources. Let $\#_{ij}^f$ refer to the number of current startups that will turn into type- (f, i, j) enterprises in the subsequent period. It can be deduced that

$$\#_{ij}^f = \sigma_{ij}^f s^f \mu_i^f, \text{ for } f = v, n \text{ and } i, j = h, l.$$

Now, the survival rate for an operating firm is \mathbf{s} . Thus, the numbers of t -period-old type- (f, i, j) enterprises that will still be around are

$$\#_{ij,t}^f = \mathbf{s}^t \#_{ij}^f, \text{ for } f = v, n; i, j = h, l; \text{ and } t = 0, 1, \dots$$

Here, an age-0 enterprise is one that just starts producing in the current period.

Next, the generic demand for labor by a type- (f, i, j) enterprise, arising from the first-

⁵⁶The maximization problem linked to the above two efficiency conditions is

$$\max_{\sigma_{ij}^v, x_{ij}^v} \{ \sigma_{ij}^v \delta x_{ij}^v z_{ij}^v I(\cdot) - D(\sigma_{ij}^v) - R(x_{ij}^v / \mathbf{x}) \}.$$

For the second-order condition for a maximum to hold, it must transpire that

$$\begin{vmatrix} -D_{11} & \delta z_{ij}^v I(\cdot) \\ \delta z_{ij}^v I(\cdot) & -R_{11} / \mathbf{x}^2 \end{vmatrix} > 0,$$

or that

$$D_{11} R_{11} / \mathbf{x}^2 - (\delta z_{ij}^v I(\cdot))^2 > 0.$$

order condition for labor, is

$$l_{ij}^f = \left(\frac{\kappa}{r}\right)^{\kappa/\zeta} \left(\frac{\lambda}{w}\right)^{(\zeta+\lambda)/\zeta} x_{ij}^f z_{ij}^f, \text{ for } f = v, n \text{ and } i, j = h, l.$$

Hence, the labor demanded by an enterprise that came on line t periods ago is

$$l_{ij,t}^f = \left(\frac{\kappa}{r}\right)^{\kappa/\zeta} \left(\frac{\lambda}{w}\right)^{(\zeta+\lambda)/\zeta} \frac{x_{ij}^f}{g_{\mathbf{x}}^{t+1}} z_{ij}^f = \frac{l_{ij}^f}{g_{\mathbf{x}}^{t+1}}, \quad (16)$$

since $x_{ij,t}^f = x_{ij}^f / g_{\mathbf{x}}^{t+1}$. Thus, the total demand for labor by type- (f, i, j) enterprises reads

$$\sum_{t=0}^{\infty} \#_{ij,t}^f l_{ij,t}^f = \sum_{t=0}^{\infty} \mathbf{s}^t \#_{ij}^f \frac{l_{ij}^f}{g_{\mathbf{x}}^{t+1}} = \frac{\#_{ij}^f l_{ij}^f}{g_{\mathbf{x}}(1 - \mathbf{s}/g_{\mathbf{x}})}.$$

The labor-market clearing condition appears as

$$\sum_{f=v,n} \sum_{i=h,l} \sum_{j=h,l} \frac{\#_{ij}^f l_{ij}^f}{g_{\mathbf{x}}(1 - \mathbf{s}/g_{\mathbf{x}})} = 1,$$

Therefore, the solution for wages is given by

$$w = \lambda \left(\frac{\kappa}{r}\right)^{\kappa/(\zeta+\lambda)} \left[\frac{\sum_{f=v,n} \sum_{j=h,l} \sum_{i=h,l} \#_{ij}^f z_{ij}^f x_{ij}^f}{g_{\mathbf{x}}(1 - \mathbf{s}/g_{\mathbf{x}})} \right]^{\zeta/(\zeta+\lambda)} \mathbf{x}^{\zeta/(\zeta+\lambda)}. \quad (17)$$

Focus on the right-hand side of the above equation. Along a balanced growth path, the $\#_{ij}^f$'s, x_{ij}^f 's, z_{ij}^f 's, and $g_{\mathbf{x}}$ will all be constant. The only variable growing is \mathbf{x} . Therefore, wages grow at the gross rate

$$g_w = \left(\frac{\mathbf{x}'}{\mathbf{x}}\right)^{\zeta/(\zeta+\lambda)} = g_{\mathbf{x}}^{\zeta/(\zeta+\lambda)}. \quad (18)$$

The formalization of the model's balanced growth path is summarized by the definition below.

Definition 1 (*Balanced Growth*) *The following characterizes a balanced growth path:*

1. *R&D by VC-backed startups, or σ_{ij}^f and x_{ij}^f for $i, j = h, l$, is determined by the Nash*

Bargaining problem (P1), taking as given δ , E_i , r , w , g_w , V , and \mathbf{x} .

2. *R&D by non-VC-backed startups, or σ_{ij}^n and x_{ij}^n for $i, j = h, l$, and the threat point for entrepreneurs, E_i , solve the bank finance problem (P2), taking as given δ , i , r , w , g_w , and \mathbf{x} .*
3. *The wage rate, w , clears the labor market in accordance with (17), taking as given σ_{ij}^f , μ_i^f , x_{ij}^f , and s_f , for $f = v, n$ and $i, j = h, l$, and $g_{\mathbf{x}}$. The gross growth rate in wages, g_w , is pinned by (18) given $g_{\mathbf{x}}$.*
4. *The market discount factor, δ , and the rental rate on capital, r , are specified by (14) and (15), assuming a value for $g_{\mathbf{x}}$. The gross interest rate on bank loans, $1/i_i$, is determined by (7), conditional on values for δ , σ_{ih}^n , and σ_{il}^n .*
5. *The threat point for a venture capitalist is $V = 0$.*
6. *Aggregate productivity, \mathbf{x} , and its gross growth rate, $g_{\mathbf{x}}$, are specified by (12) and (13).*

B.3 Neutrality of a Uniform Startup Tax on Long-Run Growth— Proof of Lemma 2

Proof. The profits for an ex ante type- (f, i, j) enterprise are now $(1 - \tau)x_{ij}^f z_{ij}^f (1 - \kappa - \lambda)[(\frac{\kappa}{r})^\kappa (\frac{\Delta}{w})^\lambda]^{1/\zeta}$. Rewrite this as $x_{ij}^f \tilde{z}_{ij}^f (1 - \kappa - \lambda)[(\frac{\kappa}{r})^\kappa (\frac{\Delta}{w})^\lambda]^{1/\zeta}$, where $\tilde{z}_{ij}^f \equiv (1 - \tau)z_{ij}^f$. Hence, the introduction of a uniform startup tax amounts to an equiproportional renormalization of all of the synergies. From equation (17), it can be seen that wages will fall by a factor of $(1 - \tau)^{\zeta/(\zeta + \lambda)}$. This fact, in conjunction with (3), implies that the value of a successful venture will drop by this factor too. Last, as can be seen from the first-order conditions for σ_{ij}^f and x_{ij}^f , or (4), (5), (8), and (9), the marginal benefits and costs of research and development fall in lock step by same factor $(1 - \tau)^{\zeta/(\zeta + \lambda)}$. Therefore, the solutions for σ_{ij}^f and x_{ij}^f are unchanged. ■

C Appendix: Calibration

The recursive procedure used to calibrate the model is detailed here. The procedure follows the steps below in the order presented. The intuition underlying the calibration procedure is outlined in the main text. A \sim over a variable denotes that its value for calibration purposes can be assigned directly from the U.S. data.

C.1 Number of Startups, s^n and s^v

From the U.S. data, the success rates for the eight types of startups are known. That is, σ_{ij}^f can be assigned the value $\tilde{\sigma}_{ij}^f$, for $f = v, n$ and $i, j = h, l$. Let π_j^f represent the fraction of all initial startups that were funded by source f and ended up in ex post state j . It can be shown that

$$\pi_j^f = \tilde{\mu}_h^f \tilde{\sigma}_{hj}^f + \tilde{\mu}_l^f \tilde{\sigma}_{lj}^f < 1, \text{ for } f = v, n \text{ and } j = h, l. \quad (19)$$

The π_j^f 's are known since the $\tilde{\mu}_i^f$'s and $\tilde{\sigma}_{ij}^f$'s are. They lie below one because most startups fail. The ex ante matching probabilities in the U.S. data are reported in Table 4.

In the United States, the number of entrepreneurs (employer businesses) per worker is 4.3 percent. Therefore,

$$\frac{s^v(\pi_h^v + \pi_l^v) + s^n(\pi_h^n + \pi_l^n)}{(1 - \mathbf{s})} = 0.043,$$

where \mathbf{s} is the survival rate for a producing firm. Additionally, the ratio of non-VC to VC-funded startups can be calculated from the U.S. data, so that a value for $\widetilde{s^n/s^v}$ is pinned down. Hence, using the above equation

$$s^v = 0.043 \times (1 - \mathbf{s}) / [(\pi_h^v + \tilde{\sigma}_l^v) + (\widetilde{s^n/s^v})(\pi_h^n + \pi_l^n)],$$

This equation can be used to back out values for s^v and $s^n = (\widetilde{s^n/s^v})s^v$.

C.2 Growth in Startup Productivities, the g_j^f 's

The model is calibrated so that the benchmark economy grows at 1.8 percent a year. This implies a target growth rate for aggregate productivity, $g_{\mathbf{x}}$, given by

$$g_{\mathbf{x}} = 1.018^{10 \times (\zeta + \lambda) / \zeta}.$$

Data on patent stocks is used to identify the innovation rates of firms. As discussed, stylized facts for patenting activity can only be reported at the level of type- (f, j) firms; i.e., it cannot be broken down by the initial type, i , of the enterprise. So, the calibration procedure will impose the restriction that $x_{hj}^f = x_{ij}^f \equiv x_j^f$, for $f = v, n$ and $j = h, l$. The observed innovation rates for a type- (f, j) enterprise relative to a type- (v, h) firm are represented by $\tilde{\phi}_j^f$. Then,

$$x_j^f = \tilde{\phi}_j^f x_h^v, \text{ for } (f, j) \neq (v, h).$$

Recall that the spillover parameters, or the γ_j^f 's, are computed from the shares of type- (f, j) firms in total patent citations, as displayed in Table 5. On this account, $\tilde{\gamma}_h^v = 0.2622$ and $\tilde{\gamma}_h^n = 0.3917$. From equation (13) it then follows that

$$g_{\mathbf{x}} = c x_h^v (\nu_h^v)^{\tilde{\gamma}_h^v} (\nu_h^n \tilde{\phi}_h^n)^{\tilde{\gamma}_h^n} (\tilde{\phi}_l)^{1 - \tilde{\gamma}_h^v - \tilde{\gamma}_h^n}, \quad (20)$$

where equation (10) defines ν_h^f and by using (11) it is easy to deduce that

$$\phi_l \equiv \frac{s^v (\tilde{\mu}_h^v \tilde{\sigma}_{hl}^v + \tilde{\mu}_l^v \tilde{\sigma}_{ll}^v) \tilde{\phi}_l^v + s^n (\tilde{\mu}_h^n \tilde{\sigma}_{hl}^n + \tilde{\mu}_l^n \tilde{\sigma}_{ll}^n) \tilde{\phi}_l^n}{s^v (\tilde{\mu}_h^v \tilde{\sigma}_{hl}^v + \tilde{\mu}_l^v \tilde{\sigma}_{ll}^v) + s^n (\tilde{\mu}_h^n \tilde{\sigma}_{hl}^n + \tilde{\mu}_l^n \tilde{\sigma}_{ll}^n)}.$$

Now, choose

$$c = 1 / [(\nu_h^v)^{\tilde{\gamma}_h^v} (\nu_h^n)^{\tilde{\gamma}_h^n}], \quad (21)$$

an innocuous normalization. So, at the *calibration point* the impact of the ν_h^f 's will wash out. This will not be true for the experiments. Then, from (20)

$$g_h^v = x_h^v = \frac{g_{\mathbf{x}}}{(\tilde{\phi}_h^n)^{\tilde{\gamma}_h^n} (\tilde{\phi}_l)^{1 - \tilde{\gamma}_h^v - \tilde{\gamma}_h^n}} \quad (\text{recall } \mathbf{x} = 1).$$

Therefore,

$$g_j^f = \tilde{\phi}_j^f g_h^v, \text{ for } (f, j) \neq (v, h).$$

C.3 Synergies, the z_{ij}^f 's

The relative employments of firms are used to identify the synergy parameters or the z_{ij}^f 's. Let \tilde{e}_j^f denote the observed employment of a type- (f, j) firm relative to a type- (v, h) one. There are four of these. As was discussed earlier, unfortunately employment cannot be categorized by the ex ante type i of an enterprise. Given this only four unique synergy parameters can be backed out using U.S. Census data from the calibration procedure. So, set $z_{hj}^f = z_{lj}^f \equiv z_j^f$ in the calibration procedure. The four synergy parameters, $z_h^v, z_l^v, z_h^n,$ and z_l^n , are pinned down as follows. First, set $z_h^v = 1$. Then, using the labor demand functions (16) and the data on relative employments, \tilde{e}_j^f , the following holds

$$\frac{x_h^v z_h^v}{x_j^f z_j^f} = \left(\frac{x_h^v}{x_j^f}\right) \frac{1}{z_j^f} = \tilde{e}_j^f,$$

so that

$$z_j^f = \left(\frac{x_h^v}{x_j^f}\right) / \tilde{e}_j^f, \text{ for } (f, j) \neq (v, h). \quad (22)$$

Note that x_h^v/x_j^f was determined in the previous step. The wage rate, w , can be now determined at the calibration point using (17).

C.4 The Efficiencies of Research and Development, the ψ_{ij}^f 's, χ_{ij}^f 's, and ι

The desired values for the startups' productivities and success rates, x_{ij}^f and σ_{ij}^f , can be obtained by backing out the constant parameters for the research and development functions, χ_{ij}^f 's and ψ_{ij}^f 's, so that the model hits these targets. In particular, the first-order condition for σ_{ij}^f states that

$$\delta x_{ij}^f z_{ij}^f I(\cdot) = w \left[\frac{\tilde{\sigma}_{ij}^f}{(1 - \tilde{\sigma}_{ij}^f)^2} - \left(\frac{1}{1 - \tilde{\sigma}_{ij}^f} - 1 \right) \right] / \psi_{ij}^f,$$

so that

$$\psi_{ij}^f = \left\{ w \left[\frac{\tilde{\sigma}_{ij}^f}{(1 - \tilde{\sigma}_{ij}^f)^2} - \left(\frac{1}{1 - \tilde{\sigma}_{ij}^f} - 1 \right) \right] \right\} / [\delta x_{ij}^f z_{ij}^f I(\cdot)]. \quad (23)$$

Following a similar procedure for x_{ij}^f 's gives

$$\chi_{ij}^f = w \left(\frac{x_{ij}^f}{\mathbf{x}} \right)^{\iota-1} / [\mathbf{x} \delta \tilde{\sigma}_{ij}^f z_{ij}^f \times I(\cdot)]. \quad (24)$$

Since there are eight values for the $\tilde{\sigma}_{ij}^f$'s, there will be eight unique value for the χ_{ij}^f 's and ψ_{ij}^f 's (even though there are only four unique values for the x_{ij}^f 's). The backed-out parameter values for ψ_{ij}^f and χ_{ij}^f depend upon the elasticity parameter ι in the research cost function. The parameter ι is fit to match a tax elasticity of 2.12.