Technifying Ventures *†

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Abstract

How do advanced technology adoption and venture capital (VC) shape firm growth and macroeconomic outcomes? Evidence from U.S. Census microdata reveals that while VC is rare and advanced technology adoption is comparatively more widespread, firms that combine both are disproportionately important to the economy. VC-backed firms expand sharply after funding, with employment gains especially pronounced among technology adopters. Technology adoption alone is also followed by modest employment growth. A startup model featuring endogenous technology adoption and financing formalizes this complementarity. Removing either VC or advanced technology produces sizable macroeconomic losses, while tax and subsidy changes trigger substantial reallocation across firms.

Keywords: Advanced technology, technology adoption, firm financing, venture capital, startups, difference-in-differences analysis, reallocation effects, subsidies, taxes

JEL Nos: E13, G24, O30, O40

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1 Introduction

Technological advancement is a crucial driver of economic growth, and innovative startups are often at the forefront of adopting and using new technologies. These firms are vital not only for job creation and economic dynamism, but also for propagating cutting-edge innovations. Understanding the factors that shape a startup's decision to adopt advanced technology, and how that decision influences employment and revenue across a firm's life cycle, is therefore of central importance. The sources of startup funding, particularly venture capital, are likely to be closely linked to technology adoption and firm performance. VC funding and expertise should be especially valuable for promising businesses that leverage advanced technologies, since realizing their exceptional growth potential often requires substantial capital, specialized knowledge, and strategic guidance. More broadly, the interaction between VC and advanced technology may have important macroeconomic implications, especially because taxes and subsidies alter firms' incentives to adopt new technologies and select among financing sources.

This study investigates the startup process with a specific focus on how a firm's employment and revenue outcomes are connected to its adoption of advanced technologies and its source of funding—particularly venture capital.[1] The first part of this study draws on recent U.S. Census Bureau microdata to examine the relationships among VC backing, advanced technology adoption, and firm outcomes. Nationally representative data on firms' use of advanced technologies have historically been scarce. The 2018–2023 Annual Business Survey (ABS) helps fill this gap by providing firm-level information on adoption and use of technologies including AI and robotics; the 2023 edition also captures adoption timing often not measured in surveys of advanced technology. Linking these data to longitudinal employment and revenue records and to VC financing information enables comparisons across firms with different combinations of technology use and funding status. Firms that both adopt advanced technologies and receive VC backing are substantially larger, in employment and revenue, than other firms. Difference-in-differences analyses further indicate that employment rises following both technology adoption and VC funding, with the VC-associated gains especially pronounced among technology adopters.

Guided by this evidence, the second part of the study develops a model in which startups' technology adoption and financing choices are jointly determined. Entrepreneurial ideas differ in both their underlying potential and their suitability for advanced technologies, and these differences influence the gains from adoption. Entrepreneurs seek financing from either banks or venture capitalists. Banks provide loans at fixed interest rates that reflect default risk; venture capitalists receive an equity share and provide expertise and strategic guidance alongside capital. This active

[1] VC is a form of private equity financing that invests in startups assessed by financiers as having a high potential for rapid growth. The venture capitalists take shares in the startup in return for their advice and money. The exit strategy is to sell the startup on the stock market or to another business. This contrasts with traditional private equity, which generally acquires established companies and seeks to improve profitability through restructuring—often using leverage—rather than backing early-stage ventures. VC-backed startups typically do not rely on debt financing of this kind.

support is especially valuable for ambitious projects that adopt advanced technologies, creating a complementarity between VC financing and advanced technology adoption. Venture capitalists are compensated through negotiated profit-sharing arrangements with entrepreneurs. Successful startups typically exit via IPO or merger and acquisition.

The modeling of technology adoption and VC funding is grounded in existing evidence.[2] Founders may choose innovative technologies partly to attract financing: technological signals such as patents often precede and predict VC investment. Consistent with this, the persistence of startups' core business lines suggests that VCs generally select and develop founder-originated technological opportunities rather than determine firms' initial technology choices. VCs nevertheless shape subsequent scaling and strategic direction. Accordingly, the model treats technology as a founder choice made before financing but in anticipation of its effect on the likelihood and value of obtaining VC.

The model is calibrated to match key U.S. empirical patterns in technology adoption and startup financing—particularly the rarity of, and substantially larger size of, firms that combine VC backing with advanced technology. Counterfactual experiments then quantify the macroeconomic roles of technology and financing. Removing either VC or advanced technology generates sizable losses in output, employment, and welfare. Eliminating the additional benefit of VC for technology adopters isolates the complementarity between the two and shows that it accounts for a significant share of VC's macroeconomic contribution. Finally, changes in corporate income and capital gains tax rates, as well as the provision of startup subsidies, induce substantial reallocation across firms with different technology and financing profiles.

This study makes three contributions. First, it provides systematic evidence on the relationship between advanced technology adoption and firm performance using recent nationally representative U.S. data that include adoption timing—an element rarely available in empirical work. Second, it bridges literatures on technology adoption and VC finance by showing that post-VC employment gains are especially strong among technology adopters. Third, it develops a unified quantitative framework in which technology adoption and financing choices are jointly determined, quantifying the separate and complementary macroeconomic roles of advanced technology and VC and demonstrating how taxes and subsidies reallocate activity across firms.

2 Literature Review

A growing empirical literature uses Census Bureau microdata to study firms' adoption of advanced technologies. Using the technology module in the 2018 Annual Business Survey (ABS), Zolas et al. (2020) provide comprehensive estimates of AI and robotics adoption, and McElheran et al. (2024) examine how early firm characteristics relate to AI adoption and how AI use is associated with startup growth. Bonney et al. (2024, 2026) use the Business Trends and Outlook Survey

[2]See, e.g., Hellmann and Puri (2000), Kaplan, Sensoy, and Stromberg (2009), and Haeussler, Harhoff, and Mueller (2014).

to provide frequent estimates of current and expected near-term AI use. Dinlersoz, Dogan, and Zolas (2024) identify business applications focused on developing or using AI and compare their formation and subsequent performance with those of other applications. Dinlersoz and Wolf (2024) use the earlier Survey of Manufacturing Technology to study the relationships among automation, productivity, and labor share at the plant level. Complementary survey evidence from Baslandze et al. (2026) documents considerable variation across firms in reported AI use and its expected effects on productivity and employment.

Several stylized facts have emerged from this empirical literature. The adoption rates of advanced technologies, such as AI and robotics, are still relatively low. Adoption is concentrated among large firms and, conditional on size, among young firms. Advanced technology users also tend to have higher employment, revenue, and labor productivity. Many firms report no employment change attributable to technology use, and among those reporting a change, increases appear more common than decreases. Whether firms grow after adopting technology, or whether firms with greater growth potential are more likely to adopt it, is not well established.

Evidence that follows firms through adoption is still limited, partly because most U.S. surveys lack firm-specific adoption dates. Studies using European data illustrate the value of observing this transition. Koch et al. (2021) find that firms expand following robot adoption, while Acemoglu, Lelarge, and Restrepo (2020) show that adopting firms grow relative to competitors, highlighting the possibility of reallocation across firms. For the United States, Acemoglu et al. (2023) compare adopters and non-adopters, without matching firms, based on broad historical adoption windows for AI and robotics, but the 2019 ABS data they use do not identify when individual firms adopted the technologies. The present study uses firm-level adoption timing from the 2023 ABS and matched control groups in a difference-in-differences framework. The estimates show higher employment following adoption, although selection on unobserved factors may still remain. Linking PitchBook to Census Bureau data also permits an examination of whether the association between VC backing and firm performance differs by technology adoption status.

Macroeconomic models of VC financing remain relatively rare. Akcigit et al. (2022) use U.S. Census Bureau data to show that VC-backed startups outperform other startups and develop a quantitative model emphasizing synergies between entrepreneurs and venture capitalists. The present study complements their framework by endogenizing both technology adoption and the choice of funding source. Heterogeneity in venture potential, together with productivity shocks, generates a nondegenerate firm-size distribution that evolves over the firm life cycle and permits analysis of reallocation across firms with different financing and technology profiles under counterfactual tax and subsidy policies. Ando (2026) introduces angel investors and finds that VC-backed firms outperform angel-financed firms, which in turn outperform bank-financed firms. Ates (2018) develops a Schumpeterian growth model in which venture capitalists provide operational knowledge alongside financing. Greenwood, Han, and Sanchez (2022) embed a dynamic contracting model of VC financing in an endogenous growth framework and discipline it using data on VC funding rounds.

None of these studies jointly endogenizes technology adoption and financing or examines whether the contribution of VC differs between technology adopters and non-adopters.

A related macroeconomic literature shows why uneven technology adoption and differences among entrants can matter in the aggregate. Baslandze and Vardishvili (2026) study innovative spinouts and show how technological differences at entry contribute to firm growth and aggregate productivity. Hubmer and Restrepo (2026) model fixed costs of automation and show how adoption concentrated among large firms can generate aggregate outcomes that differ from those of the typical firm. Firooz, Liu, and Wang (2025) link automation to the rise of superstar firms in a model of heterogeneous firms and technology choice. More recently, Firooz, Leduc, and Liu (2026) model AI adoption and show that its diffusion can have different implications for industry concentration as smaller firms begin to adopt. These studies highlight the aggregate importance of adoption and reallocation but leave open how startup financing shapes technology choices. The present framework jointly models adoption and the choice between bank and VC financing, allowing VC's capital and guidance to be especially valuable to technology adopters. It then quantifies the interaction's aggregate contribution and how tax and subsidy policies reallocate activity across firms with different technology and financing choices.

Finally, King and Levine (1993) provide early evidence linking financial development to economic growth. A substantial subsequent literature—including Quadrini (2000), Greenwood, Han, and Sanchez (2022), and Cavalcanti et al. (2023)—seeks to explain this relationship. Work on technology policy also emphasizes that the adoption decision is a distinct margin: Donald (2022) studies how targeting automation adoption changes the case for taxing capital. In the VC setting, separating the value of capital from venture capitalists' expertise and other inputs remains empirically difficult. Akcigit et al. (2022) provide some evidence of synergy after controlling for initial funding amounts. The framework developed here focuses on selection into VC financing, joint technology and financing choices, and how their interaction shapes aggregate outcomes and responses to tax and subsidy policies.

3 Data

The empirical analysis combines three main data sources.

Annual Business Survey (ABS). Conducted annually from 2018 through 2023 and jointly designed by the U.S. Census Bureau and the National Center for Science and Engineering Statistics, the ABS provides information on advanced technology use among nonfarm employer businesses in the United States. Each survey covers the calendar year preceding the survey year; for example, the 2018 ABS collects information for 2017. The 2018 and 2023 surveys each sampled approximately 850,000 businesses and correspond to the 2017 and 2022 Economic Census years, respectively. Approximately 300,000 businesses were sampled annually from 2019 through 2022. The ABS records whether a firm used each advanced technology during the reference period. The 2023 ABS also

reports the timing of advanced technology adoption in five-year intervals.[3] In addition, the ABS provides information on the initial characteristics of startups and their owners.

The technologies chosen for the analysis are listed in Appendix A and include a wide range of advanced and emerging technologies; a few examples are additive manufacturing, artificial intelligence (AI), distributed ledgers, radio-frequency identification (RFID), and robotics.[4] Their selection reflects several criteria. First, the analysis is limited to technologies covered by Census Bureau surveys, which focus on technologies deemed both advanced and economically important by the Census Bureau and the National Center for Science and Engineering Statistics. Second, the selected technologies were measured relatively consistently across the ABS instruments fielded between 2018 and 2023, providing adequate sample sizes and supporting comparisons across survey years. Third, because adoption timing is available only in the 2023 ABS—and only for five technology categories—the timing analysis centers on AI and robotics, consistent with the study's focus on advanced technologies. Nevertheless, using all five technologies does not change the main findings qualitatively.[5]

VC Financing Data. The 2018 ABS records whether a business received VC financing at founding. This information is supplemented with data from PitchBook and information on initial public offerings (IPOs).[6] Together, these sources identify VC funding for firms appearing in the ABS from 2018 through 2023. PitchBook also provides information on deal size and the equity stakes acquired by investors; further details appear in Appendix A. The VC records are matched by firm name and address to the Census Bureau's Business Register/Standard Statistical Establishment List and then linked to the ABS using firm identifiers in Census Bureau datasets.

Longitudinal Business Database (LBD). Firm outcomes and characteristics—including employment, revenue, age, industry, and location—are drawn from the LBD, a longitudinally linked dataset covering nearly all nonfarm employer businesses in the United States from 1976 through 2022, the latest year available at the time of the analysis. Linking the ABS, VC financing, and LBD data enables the tracing of firm size and other outcomes over time, with comparisons across firms defined by technology use and VC status.

[3]See the ABS website (https://www.census.gov/programs-surveys/abs.html) for additional information.

[4]The history of these five technologies is described in Appendix B.

[5]The three additional technologies are cloud, specialized equipment, and specialized software. All three were much more diffused than AI and robotics, making them more conventional technologies at this point compared to AI and robotics. Moreover, cloud and AI adoption are very highly correlated, as AI use typically requires a digital infrastructure often supported by cloud technologies – see also Acemoglu et al. (2023).

[6]The SDC Platinum New Issues and Jay Ritter's IPO dataset are used.

Table 1: Descriptive Statistics

	Fraction (%)	Employment Share (%)	Revenue Share (%)
High-tech Firms	11.63%	38.76%	44.11%
VC-backed Firms	0.64%	13.26%	14.98%

Notes: The sample consists of firms in the ABS (2018–2022). High-tech firms are defined as firms that have adopted advanced technologies. VC-backed firms are firms that have raised VC financing, according to the ABS (2018) or PitchBook. Employment share is the share of employment contributed by tech firms or VC-backed firms out of total employment in the economy. Employment and revenue are obtained from the LBD (2017-2021). For firms whose revenue is missing in the LBD, sales in the ABS are used instead. All statistics are computed using the sample weights constructed from the Longitudinal Business Database (LBD).

4 Empirical Evidence

4.1 Baseline Statistical Analysis

Stylized facts are presented now on advanced technology adoption, VC backing, and firm outcomes. VC-backed firms adopt advanced technologies at substantially higher rates than firms without VC backing. Moreover, firms that combine advanced technology adoption with VC backing tend to have higher employment and revenue than firms with other combinations of technology adoption and VC status.

Descriptive Statistics. Table 1 reports descriptive statistics for the main analysis sample, drawn from the 2018–2022 ABS, using population weights to produce nationally representative estimates.[7] Advanced technologies were adopted by 11.63% of firms in the sample period. Despite their relatively small share of the firm population, these tech firms account for 38.76% of total employment and 44.11% of total revenue, consistent with earlier ABS-based evidence [e.g., Acemoglu et al. (2023)]. VC-backed firms are considerably rarer, representing only 0.64% of firms, yet account for 13.26% of employment and 14.98% of revenue. These disproportionate shares reflect the substantially larger average size of VC-backed firms and their economically significant contribution to macroeconomic activity [see also Akcigit et al. (2022)].

Regression Analysis. Table 2 documents the firm-level relationships among VC presence, technology adoption, employment, and revenue. OLS regressions are estimated on a pooled cross-section for the years 2017-2021, with year-by-4-digit-NAICS industry fixed effects, state fixed effects, and firm age fixed effects included.[8]

Column (1) shows that VC-backed firms have a significantly higher technology adoption rate: 38.61%, roughly 27 percentage points above the overall sample rate of 11.63%. Columns (2) and (3) compare employment and revenue across four mutually exclusive groups defined by VC presence and technology adoption status. Each group is defined by a pair of indicators that identify a

[7] This was the broadest sample available at the time of the initial analysis. Adoption-timing information from the 2023 ABS is used later in the analysis.

[8] The year × 4-digit NAICS fixed effects absorb industry-level price differences across years, which are relevant in the regression with revenue. For multi-unit firms, the industry and state refer to the industry and state with the largest employment share.

Table 2: Baseline Regression

	(1) **adoption**	(2) ln(**emp**)	(3) ln(**rev**)
VC-financed	0.170***		
	(0.00677)		
VC high-tech		1.660***	1.479***
		(0.0358)	(0.0553)
VC non-high-tech		1.051***	1.048***
		(0.0298)	(0.0404)
Non-VC high-tech		0.483***	0.626***
		(0.00562)	(0.00706)
+ Fixed effects			
R-squared	0.0734	0.2403	0.2151
N (rounded)	1,050,000	1,050,000	1,050,000
Adoption rate (all firms)	11.63%		
Adoption rate (VC firms)	38.61%		

Notes: The fixed effects are: year×NAICS (4 digits), state, and firm age. The dependent variable in column (1) is firms that have adopted advanced technologies. The dependent variables in columns (2) and (3) are firm-level ln(employment) and ln(revenue), respectively. The independent variables are binary variables that are equal to one if firms belong to the category. The regressions use LBD weights. Standard errors are shown in parentheses and are clustered by firmid. * p<0.05 ** p<0.01 *** p<0.001. N is rounded to protect confidentiality.

distinct combination of VC presence and technology adoption status. VC high-tech firms (i.e., firms that have VC backing and that have adopted advanced technologies) have significantly higher employment and revenue than the omitted group of firms that have no VC backing and no advanced technology. The size gap is approximately 425% [$= 100 \times (\exp(1.660) - 1)$] and 338% [$= 100 \times (\exp(1.479) - 1)$], respectively, for employment and revenue, based on the estimated coefficients. VC-backed, non-high-tech firms also exhibit significantly higher employment and revenue than the omitted group, but less so than VC high-tech firms. Non-VC-backed, high-tech firms rank third in outcomes relative to the omitted group. All pairwise comparisons between the four groups of firms are statistically significant. Table 11 in Appendix C shows that these relationships are broadly robust to controlling for a large set of detailed owner characteristics and business strategies and motivations related to innovation and growth.[9] Furthermore, exploiting the panel dimension of the data and the adoption-timing information in the 2023 ABS, descriptive regressions in Table 12 in Appendix C show, for the case of AI, that firm size increases after AI adoption and after VC financing. These relationships are examined more formally below using matched controls based on alternative difference-in-differences estimation approaches.

Differences in Firm-Size Distributions. Table 3 applies Kolmogorov-Smirnov tests to compare firm-size distributions across VC status and technology status. The VC-backed firm-size distribution stochastically dominates that of non-VC-backed firms (0 vs 1), because the cumulative

[9]Some coefficient estimates naturally attenuate as a large number of variables correlated with VC funding are added. Nevertheless, point estimates remain statistically significant.

Table 3: Kolmogorov-Smirnov test

Variable	Context	D(0 vs 1)	D(1 vs 0)	p(0 vs 1)	p(1 vs 0)
ln(emp)	VC	0.3331	0.0000	0.0000	1.0000
ln(emp)	High-tech	0.2217	0.0000	0.0000	1.0000
ln(rev)	VC	0.3159	-0.0087	0.0000	0.1141
ln(rev)	High-tech	0.2316	0.0000	0.0000	1.0000

Notes: Depending on the context, 0 and 1 refer to the empirical cumulative distribution functions for either non-VC and VC funded, respectively, or non-high-tech and high-tech. D(0 vs 1) is the test statistic that measures the distance between the cumulative distribution functions 0 and 1. D(1 vs 0) is the test statistic that measures the distance between the cumulative distribution functions 1 and 0. p(0 vs 1) and p(1 vs 0) give the significance level (probability) of the tests. The sample consists of firms in the ABS (2018–2022).

distribution function of the latter lies above the former statistically, while the opposite does not hold (1 vs 0). Likewise, the high-tech firm-size distribution stochastically dominates that of non-high-tech firms, but again no dominance in the opposite direction is detected. This evidence further motivates and informs the quantitative model, which is designed to capture these distributional differences.

4.2 Difference-in-Differences Analysis

A natural question to ask is whether firms expand after VC backing and technology adoption, or alternatively whether firms that receive VC backing and adopt advanced technologies are intrinsically different and perform better than other firms even in the absence of VC backing and advanced technologies. Towards addressing this question, difference-in-differences (DiD) analyses are used to estimate the treatment effects of VC presence and technology adoption. Furthermore, potential heterogeneity in the treatment effect of VC presence for high-tech and non-high-tech firms is examined. DiD analyses are conducted using matched control samples to estimate the average treatment effect on firm employment. The matched sample is constructed to improve similarity between treated and control firms, particularly with respect to pre-treatment trends and estimated probabilities of treatment. While matching enhances the credibility of the DiD design, the results cannot be interpreted as causal effects, as unobserved factors that simultaneously influence selection into VC backing or technology adoption and firm outcomes cannot be fully ruled out.

The sample used for estimating VC treatment effects covers firms that appear in the ABS for the years 2018 to 2023—the broadest sample where both technology adoption *and* VC presence are observed. The first VC funding dates are obtained from PitchBook. Firm employment is drawn from the LBD (1978–2022). The matched sample used for estimating the treatment effects of advanced technology contains treated firms and their controls that appear in ABS for 2023, since the timing of technology adoption is available only for 2023. For each treated firm, the pool of potential controls is restricted to untreated firms with the same firm age, three-digit NAICS industry, and employment-size bin in the year preceding treatment. From this pool, the control firm closest to the treated firm in its estimated probability of treatment and employment trajectory during the five preceding

years is selected.[10] The probability of treatment takes into account, among other observables, the technology adoption status (in the case of VC treatment probability) and VC status (in the case of technology treatment probability). Including the other treatment's pre-treatment status in the propensity model allows observable selection along this dimension to enter the matching criterion. It does not, however, eliminate selection on unobserved characteristics.

The ABS (2023) coarsely measures the timing of advanced technology adoption using 5-year intervals (e.g., whether adoption occurs in the windows 2001-2005, 2006-2010, etc.). The first year in a given 5-year interval is regarded as the year of technology adoption in the DiD analysis.[11] This yields a conservative estimate of treatment effects, as some firms assumed to be treated under this definition may actually be treated after the first year of the interval. Figure 1 documents the fraction of firms with advanced technologies that adopt the technologies within a given firm age range (shown on the x-axis). Nearly half of the firms in the process of adopting advanced technologies are between 0 and 4 years old (and nearly 70% are less than 10 years old). While some firms adopt technology later in their life cycle, the high fraction of young firms (0-4 years of age) among technology adopters suggests that the technology adoption decision is often made at the beginning of a firm's life.[12]

The treatment effect on firm employment is estimated using three complementary methodologies. The first approach is a DiD analysis using two-way fixed effects (TWFE) regression:

$$Y_{it} = \alpha_i + \phi_t + \sum_{j=-3, j\neq 0}^{10} \gamma^j \times D_i \times \mathbf{1}\{\tau_{it} = j\} + \epsilon_{it},$$

where the subscript i refers to a firm and t to the time period. The variable $\tau_{it} \in \{-3, -2, -1, 0, \cdots, 10\}$ is time relative to (potential) treatment, where $\tau_{it} = 1$ indicates the first treated period.[13] Firm fixed effects, α_i, and calendar year fixed effects, ϕ_t, are included. This specification is used to estimate the dynamic treatment effects γ^j in each post-treatment period ($j = 1, ..., 10$) relative to

[10] For each treated firm, potential controls are assigned the treated firm's treatment year to align their employment histories. The selected control is the firm with the smallest combined discrepancy in the estimated probability of treatment and log employment during the five years preceding treatment. Treatment probabilities are estimated separately for VC funding and technology adoption using probit models. The covariates in the models include the detailed control variables from the ABS used in the regression analysis (Table 11), NAICS 4-digit industry code, ABS vintage, year, and the tech-adoption status in the case of estimating the probability of receiving VC (or VC status in the case of estimating the probability of tech adoption). A similar approach to constructing a matched sample is adopted by Dinlersoz et al. (2023). See Ham and Miratrix (2024) for an analysis of the benefits and costs associated with matching on pre-treatment outcomes.

[11] The ABS (2023) reports the adoption of five technologies, specifically artificial intelligence, robotics, cloud-based computing systems, specialized software, and specialized equipment. AI and robotics are the advanced technologies used here. If a firm has both technologies, then the earliest year for the adoption of one of the technologies is used for the treatment time.

[12] As will be clear in the theoretical analysis, the exact timing of adoption in the model may not be critical, as the nature of the business idea formed in the early stages of a firm may dictate the compatibility of advanced technology with the business, even if actual adoption occurs at a later stage.

[13] Denote the treatment period for treated firms by t_i^*. Then, $\tau_{it} = t - t_i^* + 1$. The treatment period for control group firms is defined by that of their matched treated firms [i.e., $t_i^* = t_{i'}^*$ for a treated-control pair (i, i')].

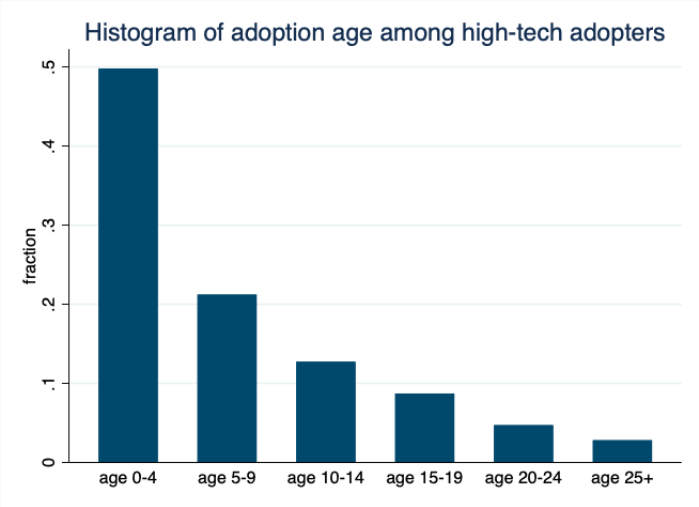


Figure 1: The timing of advanced technology adoption.
Notes: The ABS (2023) reports the timing of technology adoption in 5-year intervals. The age of a firm reporting the adoption of high technology within one of these intervals is known. Thus, firms may appear in more than one age bin. The sample consists of firms born in or after 1991 that have adopted advanced technologies. Observations are weighted by the LBD weights.

$\tau_{it} = 0$. The estimated coefficients γ^j for pre-treatment periods ($j = -3, ..., -1$) are used to examine the absence of pre-treatment trends. In addition, a static TWFE model with only one dummy variable $\mathbf{1}\{\tau_{it} \geq 1\}$ is used to estimate the average effect from $\tau = 1$ to $\tau = 10$. Finally, a dynamic TWFE regression with interaction terms between τ_{it} for VC treatment and technology adoption status, $\sum_{j \neq 0} \gamma^{j,\text{het}} \times D_i \times \mathbf{1}\{\tau_{it} = j\} \times \mathbf{1}\{\text{tech}_i = 1\}$, is also used to estimate the heterogeneous treatment effect of VC backing between tech and non-tech firms.

While commonly used and easy to implement, the TWFE approach has shortcomings.[14] Therefore, two other methods are used that are designed to remedy these shortcomings. The first alternative method is a DiD estimation developed by de Chaisemartin and d'Haultfoeuille (2024), referred to as the "CD method" hereafter.[15] In the second alternative approach, the treatment effect is estimated using the "DiD by hand" method, following the approach of Callaway and Sant'Anna (2021).[16]

[14]The TWFE methodology does not correctly aggregate treatment effects across cohorts, since treatment timing varies across firms. Instead, it produces a weighted average of different treatment effects, which can be biased due to negative weighting, particularly if treatment effects evolve over time. In addition, if treatment effects are heterogeneous across cohorts, the TWFE estimate may not represent a meaningful average treatment effect on treated (ATT) firms.

[15]The CD method is robust to potential bias when the treatment effect is heterogeneous across groups or periods, and provides a DiD estimator that corrects for negative weighting issues. It also offers a robust estimator that recovers a weighted average of correct ATT values across cohorts. The CD method is implemented by using the *did_multiplegt_dyn* Stata package. The outcome variable is ln(employment), the group variable is firm ID, the time period variable is τ, and the treatment variable is equal to 1 if $\tau_{it} \geq 1$ for treated firms (and 0 otherwise). Only never-switchers are used as control units. Observations are weighted by the LBD weights.

[16]The advantage of this method is that it explicitly compares firms within each treated-control pair and properly accounts for treatment effect heterogeneity, while being robust to staggered treatment.

Table 4: Difference-in-Differences Analyses (Average Effect from $\tau = 1$ to $\tau = 10$)

	Methodologies			
	TWFE	**CD**	**DiD by hand**	**Observations**
1. VC Treatment Effect	0.355	0.403	0.360	35,000
	(0.036)	(0.037)	(0.029)	
2. VC Heterogeneity (tech – non-tech)	0.183	0.156	0.123	
	(0.054)	(0.071)	(0.057)	
3. High-Tech Treatment Effect	0.044	0.065	0.038	214,000
	(0.007)	(0.009)	(0.007)	

Notes: The outcome variable is ln(employment). Standard errors are in parentheses. The DiD analysis is conducted three ways: namely, with (i) two-way fixed effects (TWFE) regressions, (ii) estimators developed by de Chaisemartin and d'Haultfoeuille (CD), and (iii) DiD by hand based on the sample average of the difference-in-differences between treated-control pairs. The sample used for estimating the VC treatment effects contains treated firms and their controls that appear in ABS (2018–2023)—the broadest sample where both advanced technology adoption *and* VC presence in firms are observed. The sample used for estimating the treatment effects of advanced technology contains only the treated firms and their controls in ABS (2023), since the timing of technology adoption is available only for 2023. The latter sample is larger than the former since a small number of firms receive VC backing. Observations are weighted by LBD weights. The number of observations is rounded to protect confidentiality.

In this method, the DiD is computed for each treated-control pair (i, i') and then aggregated by taking the sample average.[17]

Results. Table 4 reports treatment average effects over the post-treatment periods $\tau = 1$ to $\tau = 10$. Following VC backing, employment increases by 0.35–0.40 log points (42–49%) on average over 10 years relative to matched controls—see row 1. The VC treatment effect is larger for technology adopters by 0.12–0.18 log points (13–20%) compared with non-adopters—row 2.[18] The employment of high-tech treated firms increases on average by 0.038–0.065 log points (or by 4–7%) following technology adoption, relative to the control firms without high-tech adoption—row 3. While the magnitude of the estimated treatment effects varies to some extent across estimation methods, overall the findings consistently show that firm employment expands after both VC backing and technology adoption.[19] Moreover, the VC treatment effect is larger for firms that adopt advanced technology than for those that do not.

Figures 2 and 3 illustrate the dynamic treatment effects from $\tau = -3$ to $\tau = 10$. In both figures,

[17]The DiD for each pair is defined by $\text{DiD}_{i\tau} = (Y_{i,t_i^*-1+\tau} - Y_{i,t_i^*-1}) - (Y_{i',t_i^*-1+\tau} - Y_{i',t_i^*-1})$, where again t_i^* is the treatment period for treated firms. The treatment effect is estimated by the sample average of $\text{DiD}_{i\tau}$, where observations are weighted by the LBD weights to render results representative of all U.S. employer firms. Standard errors are clustered by firms in the average treatment effect from $\tau = 1$ to $\tau = 10$.

[18]With a TWFE regression, the heterogeneity of the VC treatment effect is estimated by γ^{het} in the following specification:

$$Y_{it} = \alpha_i + \phi_t + \gamma \cdot D_i \cdot \mathbf{1}\{\tau_{it} \geq 1\} + \gamma^{\text{het}} \cdot D_i \cdot \mathbf{1}\{\tau_{it} \geq 1\} \cdot \mathbf{1}\{\text{tech}_i = 1\} + \epsilon_{it}.$$

With CD estimation and DiD by hand, the treatment effect is separately estimated in the sample of tech firms and in the sample of non-tech firms. The difference between the two estimators is then taken. The standard errors are defined as $\text{se}^{\text{het}} = \sqrt{(\text{se}^{\text{tech}})^2 + (\text{se}^{\text{non-tech}})^2}$, as in the standard two sample unequal variance t-test.

[19]Table 13 in Appendix C shows that the treatment effect in the 10th year after the treatment event is larger than the average effect over the post-treatment periods from $\tau = 1$ to $\tau = 10$.

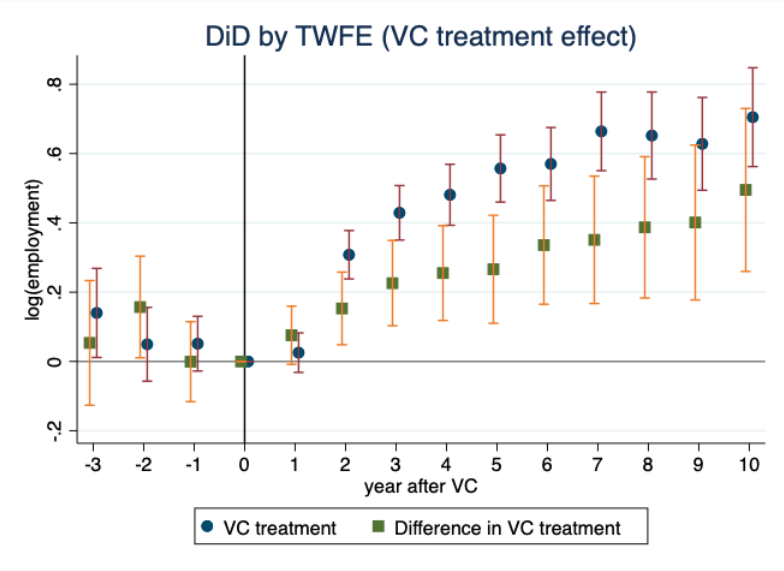


Figure 2: Dynamic Treatment Effect (TWFE) of VC backing.
Notes: Difference in VC treatment refers to the difference in the impact of VC treatment on high-tech adopters versus non-high-tech ones. 95% confidence intervals are based on standard errors clustered by firm.

the pre-treatment differences between treated and control firms are mostly statistically insignificant. The VC treatment effect in Figure 2 increases over time, whereas the high-tech treatment effect peaks around $\tau = 7$. These plots present the results of TWFE analyses, while the dynamic effects estimated using the CD method and DiD by hand are provided in Appendix C. All methods yield qualitatively similar results.

Three central findings emerge. Advanced technologies are generally adopted early in a firm's life cycle. Employment rises following both technology adoption and VC funding. And the employment gains associated with VC are larger among technology adopters, pointing to a complementarity between VC and technology. The last result fills an important gap: existing studies estimate average VC effects on firm employment [e.g., Puri and Zarutskie (2012) and Akcigit et al. (2022)] but do not quantify heterogeneity by advanced-technology status. Newly available adoption timing also permits some of the first U.S. firm-level estimates of employment changes following advanced technology adoption. The model developed next provides a general equilibrium framework for interpreting these patterns and quantifying their macroeconomic implications.

5 The Model

A new framework is presented for analyzing startups' joint decisions on technology adoption and financing. The model focuses on the startup process and has three phases of a firm's life cycle.

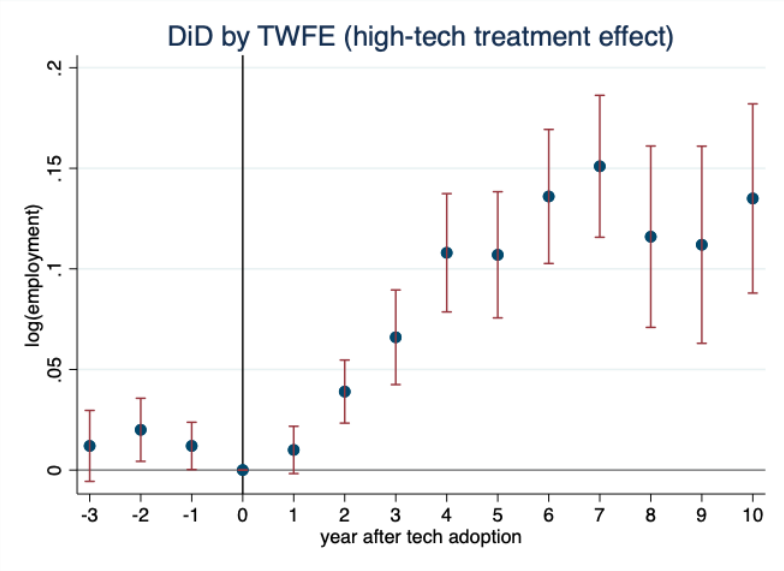


Figure 3: Dynamic Treatment Effect (TWFE) of high-tech adoption.
Notes: 95% confidence intervals are based on standard errors clustered by firm.

- ***Phase 1 (Newborn)***. Entrepreneurs conceive an idea and choose a production technology. At this time they have no funding. At the end of this phase they secure funding from either a bank or VC.
- ***Phase 2 (Adolescent)***. Startups have obtained financing from a bank or venture capitalist and begin production. At the end of this phase the enterprise is sold. Financiers are repaid in this stage.
- ***Phase 3 (Adult)***. The sold firms hire capital and labor on frictionless spot markets.

The setup for the model is described first. The model is then developed by working backwards from Phase 3 adult production to the newborn technology choice in Phase 1. This section ends with a specification of equilibrium. Going forward, the model is calibrated in Section 6 using moments from U.S. Census data and then applied to a series of thought experiments in Section 7.

5.1 Setting the Stage

In Phase 1 a unit mass of entrepreneurs are blessed with ideas. Each entrepreneur chooses between two production technologies: an advanced production technology (dubbed high tech) and a conventional one (dubbed non-high tech). A startup's production technology has two attributes: its current level of productivity and its potential for the future. A startup may have low current productivity—and consequently low output—while possessing strong future potential. The joint distributions over initial productivities and potentials differ across the advanced and conventional

production technologies. The analysis does not impose an ex ante ranking of high-tech and conventional technologies. Instead, their relative performance is determined by the data. Some ideas are better suited for using the advanced technology than others—military drones versus restaurants, for example. Entrepreneurs choose their production technology to maximize expected profits, which depend on the odds of receiving bank or VC financing and the anticipated value of the technology that will be adopted. Because most technology-adopting firms in the data are very young (Figure 1), modeling this decision at an early phase is a natural choice.[20]

Entrepreneurs then seek financing from banks or venture capitalists to fund Phase 2 production. Under bank financing an entrepreneur enters into a debt agreement with the bank; under VC financing, the entrepreneur and venture capitalist enter into an equity partnership.[21] Financing is used to acquire the capital needed for production in Phase 2. With bank financing, the entrepreneur borrows funds from the bank in Phase 1 at a fixed interest rate. The loan is paid back in Phase 2. The bank takes into account the likelihood of default. Projects are funded by VC based on their potential. While the potential observed in Phase 1 is positively correlated with future output, it is an imperfect signal of that output. At the time of funding in Phase 1, the entrepreneur and the venture capitalist decide on a sharing rule for Phase-2 profits. The sharing rule is determined by Nash bargaining. Funding by a venture capitalist increases the likelihood that a startup will be successful in Phase 2 due to a synergy effect. That is, unlike a bank, a venture capitalist plays an instrumental role in starting up a venture. This requires effort by the venture capitalist. The contract between an entrepreneur and a venture capitalist rewards the latter for their value added to the project as well as for the effort they expend. The possibility of VC funding affects the technology adoption decision in Phase 1, due to the synergy effect.

Adolescent startups are sold at the end of Phase 2, with their value reflecting the success of the venture. Firms then enter Phase 3 where they produce using capital hired on a spot market. Behind the scenes, banks and venture capitalists borrow funds from a representative consumer/worker at a fixed interest rate. The representative consumer/worker supplies labor, l, on a spot market at the wage rate, w. Figure 4 summarizes the timing of events in a startup's life cycle.

5.2 Production by Adult Firms

By Phase 3 adult firms have been sold off by the founders at the end of Phase 2 either through a merger and acquisition or through an initial public offering. There are four generic types of adult firms operating in this period. Some adult firms became high-tech in the startup phase and were

[20] The empirical evidence discussed in the introduction also supports this choice.

[21] The data do not allow a precise determination of whether technology adoption or VC financing occurs first, as both events take place very early in the firm's life cycle, while the 2023 ABS reports the timing of technology adoption only at five-year intervals. From a theoretical perspective, even if a firm adopts an advanced technology after receiving VC funding, the business model that makes such adoption possible may have been determined beforehand.

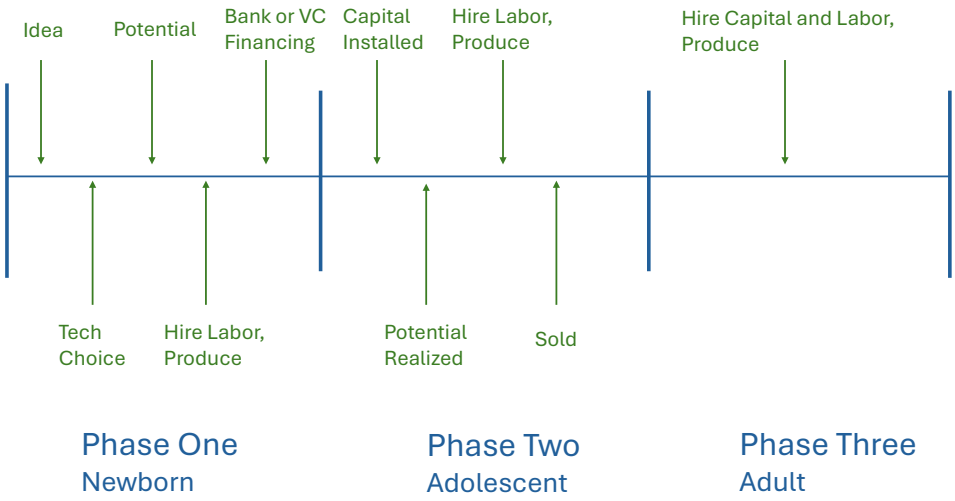


Figure 4: Timing of Events.

financed by either a bank or venture capitalists. Others chose non-high-tech production and utilized one of the two sources of financing. In Phase 3 adult firms hire capital, $k^3_{\tau f}$, and labor, $l^3_{\tau f}$, on spot markets and produce output, $o^3_{\tau f}$, according to

$$o^3_{\tau f} = (z^3_{\tau f})^{\zeta}(k^3_{\tau f})^{\kappa}(l^3_{\tau f})^{\lambda}, \text{ with } \zeta + \kappa + \lambda = 1,$$

where the subscript $\tau = h, n$ denotes the high-tech, h, and the non-high-tech, n, production and the subscript $f = b, v$ represents the (initial) source of finance, either a bank, b, or a venture capitalist, v. Total factor productivity in Phase 3, $z^3_{\tau f}$, is a function of the level of total factor productivity realized in Phase 2, $z^2_{\tau f}$. Specifically,

$$z^3_{\tau f} = \chi_{\tau f} z^2_{\tau f},$$

where the growth factor, $\chi_{\tau f}$, depends both on the type of technology and the source of finance. Labor is hired in Phase 3 at the wage rate w and capital can be raised at cost r.

The maximization problem for an adult firm is entirely standard and given by

$$\tilde{\pi}^3_{\tau f} = \max_{l^3_{\tau f}, k^3_{\tau f}} \{(z^3_{\tau f})^{\zeta}(k^3_{\tau f})^{\kappa}(l^3_{\tau f})^{\lambda} - w l^3_{\tau f} - r k^3_{\tau f}\}, \text{ for } \tau = h, n \text{ and } f = b, v, \tag{1}$$

where $\tilde{\pi}^3_{\tau f}$ is the per period profits for an adult firm. This problem yields the familiar first-order conditions

$$\lambda(z^3_{\tau f})^{\zeta}(k^3_{\tau f})^{\kappa}(l^3_{\tau f})^{\lambda-1} = w \tag{2}$$

and

$$\kappa(z^3_{\tau f})^{\zeta}(k^3_{\tau f})^{\kappa-1}(l^3_{\tau f})^{\lambda} = r. \tag{3}$$

The discounted stream of profits from an adult firm at the beginning of phase 3 is

$$\pi^3_{\tau f} = \frac{1}{1-\delta^3}\tilde{\pi}^3_{\tau f} = \frac{1}{1-\delta^3} z^3_{\tau f}(1-\kappa-\lambda)[(\frac{\kappa}{r})^{\kappa}(\frac{\lambda}{w})^{\lambda}]^{1/\zeta},$$

where δ^3 is the phase-3 survival-adjusted discount factor.

5.3 Production by Adolescent Startups

The profitability of a startup is realized in Phase 2. Output in Phase 2 is governed by

$$o^2_{\tau f} = (z^2_{\tau f})^{\zeta}(k^2_{\tau f})^{\kappa}(l^2_{\tau f})^{\lambda}, \text{ for } \tau = h, n \text{ and } f = b, v.$$

As can be seen, there are four generic types of adolescent firms. Total factor productivity, $z^2_{\tau f}$, is drawn in Phase 2 according to

$$\ln z^2_{\tau f} = \ln p_{\tau} + \ln \varepsilon_{\tau f},$$

and depends on two factors p_{τ} and $\varepsilon_{\tau f}$. The first factor is the project's potential, p_{τ}, which is known in Phase 1. This depends on the technology adopted, τ. The second factor is a random shock, $\varepsilon_{\tau f}$, which is drawn in Phase 2. The distribution function for this shock depends both on the source of finance, either a bank, b, or a venture capitalist, v, and on the technology used, τ. In particular,

$$\ln \varepsilon_{\tau f} \sim N(\gamma_{\tau f}, \sigma^2_{\epsilon_{\tau}}), \text{ for } \tau = h, n \text{ and } f = b, v, \tag{4}$$

where $\gamma_{\tau v} > \gamma_{\tau b} = 0$. Therefore, a high-tech project funded by a venture capitalist draws the phase-two shock from a distribution function with a higher mean than a similar bank-funded venture. This captures the synergy effect from VC, which differs by technology status, τ, in line with the evidence in the data. The input of capital is decided in Phase 1 before $\varepsilon_{\tau f}$ is known. Labor is hired in Phase 2 after the shock $\varepsilon_{\tau f}$ is realized.

5.4 Venture Capital Financing

Banks and venture capitalists are risk neutral; there is no aggregate uncertainty so by lending to a large number of startups risk can be diversified. The profits from firms are distributed to a representative consumer/worker so they too are diversified. Consequently, entrepreneurs are also assumed to be risk neutral. The classical economist Frank Hyneman Knight felt entrepreneurs had high levels of risk tolerance and, indeed, there is empirical evidence suggesting that this may be the case—see Kerr, Kerr, and Xu (2018). In the analysis all venture capitalists are identical. They have deep pockets and can obtain funds at the risk-free rate. Entrepreneurs are free to negotiate with

any VC, but just one. Since the VC industry is competitive the same deal will be offered by all VC funds. Alternatively, entrepreneurs can borrow from banks. This is their outside option when negotiating with a VC. Entrepreneurs will choose what is best for them.

The partnership agreement between a newborn entrepreneur and a venture capitalist takes place in Phase 1 before the phase-two technology shock is known. At this time the technology employed for the project, either h or n, and their associated potentials, p_h and p_n, are known. For a given technology, $\tau = h, n$, some ideas are better than others. Differences in potential could also reflect differences in entrepreneurial ability. The two parties agree on three things that are contingent on the technology employed: the initial investment in capital, $k^2_{\tau v}$, the amount of labor to be hired in Phase 2 contingent on the shock, $l^2_{\tau v}(z^2_{\tau v})$, and the venture capitalist's share of realized profits, s_τ. The venture capitalist must expend effort, e_τ, overseeing the project according to

$$e_\tau = \alpha_\tau + \xi p_\tau, \text{ for } \tau = h, n,$$

which is increasing in a venture's potential, p_τ.

The Nash bargaining problem appears as

$$\max_{k^2_{\tau v}, l^2_{\tau v}(z^2_{\tau v}), s_\tau} \Big\{ E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - r k^2_{\tau v} - w l^2_{\tau v}(z^2_{\tau v}) + \delta^2 \pi^3_{\tau v}] - \mathfrak{b}_\tau | p_\tau \Big]^\eta$$
$$\times E\Big[s_\tau[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - r k^2_{\tau v} - w l^2_{\tau v}(z^2_{\tau v}) + \delta^2 \pi^3_{\tau v}] - \alpha_\tau - \xi p_\tau | p_\tau \Big]^{1-\eta} \Big\}, \text{ for } \tau = h, n, \quad (5)$$

where $\mathfrak{b}_\tau$ is the threat point of the entrepreneur or what they could receive from bank funding. The term on the first line is the entrepreneur's expected share of profits (net of their threat point). This includes the expected payoff from selling the startup just before phase-3 production starts, which is discounted at rate δ^2. This term is weighted by the entrepreneur's bargaining power, η. The term on the second line is the venture capitalist's expected share of profits net of their exertion of effort. Expected profits are conditioned both on an enterprise's potential, p_τ, and its source of finance, v.

Lemma 1. *(Nash Bargaining) The upshot of the Nash bargaining problem (5) is the following set of efficiency conditions (for $\tau = h, n$):*

$$\kappa E[(z^2_{\tau v})^\zeta (k^2_{\tau v})^{\kappa-1} l^2_{\tau v}(z^2_{\tau v})^\lambda | p_\tau] = r, \quad (6)$$

$$\lambda (z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^{\lambda-1} = w, \quad (7)$$

and the sharing rule

$$s_\tau = 1 - \eta + \frac{\eta(\alpha_\tau + \xi p_\tau) - (1-\eta)\mathfrak{b}_\tau}{E[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - r k^2_{\tau v} - w l^2_{\tau v}(z^2_{\tau v}) + \delta^2 \pi^3_{\tau v} | p_\tau]}. \quad (8)$$

Proof. See Appendix D. □

The first condition sets the expected marginal product of capital equal to the rental rate. Labor is hired to the point where the realized marginal product of labor equals the wage rate, as the second condition specifies. Thus, capital and labor are hired in an efficient manner. The last condition gives the venture capitalist's share of profits. It states that the venture capitalist is entitled to the fraction $1-\eta$ of profits, plus the fraction η of the venture capitalist's effort and less the fraction $1-\eta$ of the entrepreneur's value elsewhere, both expressed as shares of profits. Denote the entrepreneur's expected profits from the Nash bargaining problem by

$$E[\pi^2_{\tau v}|p_\tau] = E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}]|p_\tau\Big], \tag{9}$$

which includes the discounted expected profits from selling off a successful startup at the end of phase 2.

5.5 Bank Financing

Entrepreneurs can also approach banks for financing. Once again capital is installed in place before the technology shock is realized in Phase 2. Labor is hired after the shock is known. Banking is a competitive industry. The banker and entrepreneur sign a loan contract. The contract specifies that for a loan of size $k^2_{\tau b}$ the entrepreneur will have to pay back the amount $\hat{r}_\tau(k^2_{\tau b}; z^2_{\tau b}, p_\tau)$. The loan payment, $\hat{r}_\tau(k^2_{\tau b}; z^2_{\tau b}, p_\tau)$, has two mutually exclusive parts: a fixed interest part, $\tilde{r}_\tau(k^2_{\tau b}; p_\tau)$, when the venture can cover its loan payment, and a default payment, $i_\tau(z^2_{\tau b}, k^2_{\tau b})$, when it can't. To understand the default payment, note that in some states the entrepreneur will not be able currently to repay all of the fixed loan payment, $\tilde{r}_\tau(k^2_{\tau b}; p_\tau)$, because

$$(z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^\lambda - wl^2_{\tau b}(z^2_{\tau b}) + \delta^2\pi^3_{\tau b} < \tilde{r}_\tau(k^2_{\tau b}; p_\tau).$$

If this is the case, the bank seizes the startup, takes the current profits, $(z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^\lambda - wl^2_{\tau b}(z^2_{\tau b})$, and subsequently sells the enterprise for $\delta^2\pi^3_{\tau b}$. Thus, upon a default the bank receives

$$i_\tau(z^2_{\tau b}, k^2_{\tau b}) = (z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^\lambda - wl^2_{\tau b}(z^2_{\tau b}) + \delta^2\pi^3_{\tau b}. \tag{10}$$

Define z^{2*}_τ to be the value of $z^2_{\tau b}$ at which the entrepreneur can just make his fixed interest payment. Thus, z^{2*}_τ solves

$$i_\tau(z^{2*}_\tau, k^2_{\tau b}) = (z^{2*}_\tau)^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^{2*}_\tau)^\lambda - wl^2_{\tau b}(z^{2*}_\tau) + \delta^2\pi^3_{\tau b} = \tilde{r}_\tau(k^2_{\tau b}; p_\tau). \tag{11}$$

This threshold is a function of $k^2_{\tau b}$, which in turn is a function of the enterprise's potential, p_τ. It also is a function of the fixed interest payment $\tilde{r}_\tau(k^2_{\tau b}; p_\tau)$. Therefore the loan payment takes the

following form:

$$\hat{r}_\tau(k^2_{\tau b}; z^2_{\tau b}, p_\tau) = \begin{cases} i_\tau(z^2_{\tau b}, k^2_{\tau b}), & \text{if } z^2_{\tau b} < z^{2*}_\tau; \\ \tilde{r}_\tau(k^2_{\tau b}; p_\tau), & \text{if } z^2_{\tau b} \geq z^{2*}_\tau. \end{cases}$$

The bank's zero-profit condition reads

$$rk^2_{\tau b} = \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)\tilde{r}_\tau(k^2_{\tau b}; p_\tau) + [1 - \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)]E[i_\tau(z^2_{\tau b}, k^2_{\tau b}) | z^2_{\tau b} < z^{2*}_\tau, p_\tau],$$

where r is the rental rate on capital. The first term on the righthand side is the fixed interest payment, $\tilde{r}_\tau(k^2_{\tau b}; p_\tau)$, that is received with probability $\Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)$. The second term is the expected value of the default payment, $E[i_\tau(z^2_{\tau b}, k^2_{\tau b}) | z^2_{\tau b} < z^{2*}_\tau, p_\tau]$, an event that occurs with the odds $1 - \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)$. This zero-profit condition implies that the fixed interest component, $\tilde{r}_\tau(k^2_{\tau b}; p_\tau)$, can be expressed as

$$\tilde{r}_\tau(k^2_{\tau b}; p_\tau) = \frac{rk^2_{\tau b} - [1 - \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)]E[i_\tau(z^2_{\tau b}, k^2_{\tau b}) | z^2_{\tau b} < z^{2*}_\tau, p_\tau]}{\Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)}. \tag{12}$$

The entrepreneur's choice of capital and labor (for $\tau = h, n$) is given by

$$E[\pi^2_{\tau b} | p_\tau] = \max_{k^2_{\tau b}, l^2_{\tau b}(z^2_{\tau b})} \left\{ \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau) E[(z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^\lambda - \tilde{r}_\tau(k^2_{\tau b}; p_\tau) - w l^2_{\tau b}(z^2_{\tau b}) + \delta^2 \pi^3_{\tau b} | z^2_{\tau b} \geq z^{2*}_\tau, p_\tau] \right\}. \tag{13}$$

The entrepreneur's expected profits, $E[\pi^2_{\tau b} | p_\tau]$, incorporate the discounted expectation of selling off the startup just before phase-3 production starts. Note that $\pi^2_{\tau b}$ is the entrepreneur's threat point in the Nash Bargaining problem (5) so that $E[\mathfrak{b}_\tau] = E[\pi^2_{\tau b} | p_\tau]$.

Lemma 2. *(Bank Financing) The solution to the bank financing problem (13) is the following set of efficiency conditions for capital and labor:*

$$\kappa E[(z^2_{\tau b})^\zeta (k^2_{\tau b})^{\kappa - 1} l^2_{\tau b}(z^2_{\tau b})^\lambda | p_\tau] = r \tag{14}$$

and

$$\lambda (z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^{\lambda - 1} = w. \tag{15}$$

Proof. Once again see Appendix D, where equation (28) gives the entrepreneur's expected profits, $E[\pi^2_{\tau b} | p_\tau]$. □

The lemma implies that capital accumulation and the hiring of labor are done efficiently. This transpires because: (i) banking is a competitive industry, (ii) both bankers and entrepreneurs are risk neutral, and (iii) upon a default bankers can seize the full value of a startup. The entrepreneur's expected profits are the same as if they could finance the capital themselves, at an opportunity cost of r per unit of lost savings—this can be seen from the form of the objective function (28) in

Appendix D. The benefit from using VC is the synergy effect. The form of the contract resembles the costly state verification models of Townsend (1979) and Williamson (1986), but here there is no private information problem.

5.6 Determination of Financing

The entrepreneur selects the type of financing that yields the highest expected payoff. The payoff depends on the type of technology used and the idea's potential. The financing decision is given by (for $\tau = h, n$)

$$\begin{array}{rl} \texttt{VC}, & \text{if } E[\pi^2_{\tau v}|p_\tau] \geq E[\pi^2_{\tau b}|p_\tau]; \\ \texttt{Bank}, & \text{if } E[\pi^2_{\tau v}|p_\tau] < E[\pi^2_{\tau b}|p_\tau]. \end{array} \tag{16}$$

This can be rewritten in terms of a threshold rule. Specifically,

$$\begin{array}{rl} \texttt{VC}, & \text{if } p_\tau \geq p^*_\tau; \\ \texttt{Bank}, & \text{if } p_\tau < p^*_\tau, \end{array}$$

where the threshold p^*_τ solves the indifference condition

$$E[\pi^2_{\tau v}|p^*_\tau] = E[\pi^2_{\tau b}|p^*_\tau]. \tag{17}$$

The fraction of type-τ projects funded by venture capitalists is given by $\Pr[p_\tau \geq p^*_\tau]$, while the fraction receiving loans from banks is $1 - \Pr[p_\tau \geq p^*_\tau]$. The determination of financing is portrayed by Figure 5. Therefore, the model has both VC synergy and selection effects at work, as specified by equations (4) and (17). Since venture capitalists must be compensated for their effort expended advising and monitoring the startup [as specified by the sharing rule (8)], not all startups will choose this funding source.

5.7 Production by Newborn Startups

Output in Phase 1 is produced before the newly born entrepreneur approaches a bank or venture capitalists for funding but after the entrepreneur has made a technology choice. Phase-one output is governed by the production function (for $\tau = h, n$)

$$o^1_\tau = (z^1_\tau)^\zeta m^\kappa (l^1_\tau)^\lambda,$$

where m is a fixed amount of intangible entrepreneurial capital in the startup. So, there are two generic types of newborn startups. The technology shock z^1_τ is uncorrelated with the potential p_τ.

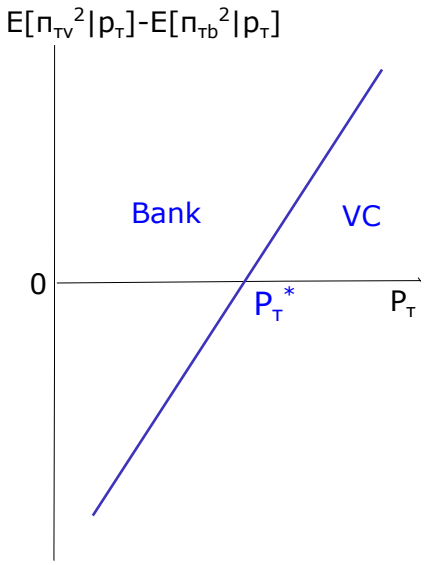


Figure 5: The determination of financing.
Notes: At low levels of potential, $p_\tau < p_\tau^*$, the entrepreneur prefers using a bank. This transpires because of the fixed cost, α_τ, associated with a venture capitalist's effort. As the firm's potential rises the benefit of VC financing in terms of a *likely* higher level of productivity, $z_{\tau v}^2 > z_{\tau b}^2$, overcomes the presence of the fixed cost.

Specifically, the two follow independent normal distributions

$$\ln z_\tau^1, \ln p_\tau \sim N(\mu_{z_\tau^1}, \mu_{p_\tau}, \sigma_{z_\tau^1}^2, \sigma_{p_\tau}^2, \sigma_{z_\tau^1, p_\tau} = 0).$$

A startup's potential depends upon which technology is used with some ideas being better than others. The draw for potential can also be thought of as reflecting an entrepreneur's talent. The bivariate normal distribution implies that the initial employment and output of a very young firm will not perfectly predict whether a startup will get VC funding. An infant startup using technology $\tau = h, n$ chooses labor to maximize its profits in line with

$$\pi_\tau^1 = \max_{l_\tau^1} \{(z_\tau^1)^\zeta m^\kappa (l_\tau^1)^\lambda - w l_\tau^1\}, \tag{18}$$

which yields the standard looking first-order condition

$$\lambda (z_\tau^1)^\zeta m^\kappa (l_\tau^1)^{\lambda - 1} = w. \tag{19}$$

The entrepreneur lives off of all of the return from his entrepreneurial capital and the profits generated by the newborn startup.

Choice of Technology

At the beginning of phase one a newly born entrepreneur is endowed with an idea. They can implement the idea using either the high-tech or non-high-tech technology. They make this choice before knowing the potential of the respective technologies. Furthermore, they only know the probability of the type of finance that they will procure, which is contingent on the type of technology that is chosen. Implementing the advanced technology involves an idiosyncratic fixed implementation cost, ϕ, which is distributed according to a Gumbel distribution:

$$\phi \sim G(\mathfrak{g}, \mathfrak{l} = 1),$$

where $\mathfrak{g}$ and $\mathfrak{l}$ are the scale and location parameters. This feature captures the notion that some ideas are better suited for high tech (e.g., military drones) than others (e.g., restaurants). The entrepreneur picks the technology that yields the highest discounted expected profits, after factoring in its implementation cost. The presence of VC in the economy affects this choice. The unconditional expected payoffs from using the advanced and conventional technologies, $E[\pi^1|h]$ and $E[\pi^1|n]$, can be written as

$$E[\pi^1|h] = E[\pi^1_h] + \Pr[p_h \geq p^*_h]\delta^1 E[\pi^2_{hv}|p_h \geq p^*_h] + \{1 - \Pr[p_h \geq p^*_h]\}\delta^1 E[\pi^2_{hb}|p_h < p^*_h]$$

and

$$E[\pi^1|n] = E[\pi^1_n] + \Pr[p_n \geq p^*_n]\delta^1 E[\pi^2_{nv}|p_n \geq p^*_n] + \{1 - \Pr[p_n \geq p^*_n]\}\delta^1 E[\pi^2_{nb}|p_n < p^*_n].$$

To understand these formulas take the first one. The probability of obtaining VC funding using the high-tech technology is $\Pr[p_h \geq p^*_h]$ while the expected discounted phase-2 payoff with VC funding is $\delta^1 E[\pi^2_{hv}|p_h \geq p^*_h]$, where δ^1 is the discount factor applied to phase two profits. With the complementary probability $1 - \Pr[p_h \geq p^*_h]$ the entrepreneur obtains a bank loan from which phase-2 discounted profits are expected to be $\delta^1 E[\pi^2_{hb}|p_h < p^*_h]$.

The choice of technology is then summarized by

$$\begin{array}{rl} \texttt{High-Tech}, & \text{if } E[\pi^1|h] - \phi \geq E[\pi^1|n]; \\ \texttt{Non-High-Tech}, & \text{if } E[\pi^1|h] - \phi < E[\pi^1|n]. \end{array} \tag{20}$$

Condition (20) makes clear that the implementation cost can be equivalently interpreted as indicating that some ideas are more profitable to pursue using high-tech methods than others. That is, alternatively ϕ could be encapsulated into the $E[\pi^1|h]$ term. For example, $\ln p_\tau$ could be drawn from the independent normal distribution $N(\mu_{z^1_\tau}, \mu_{p_\tau} - \ln\phi, \sigma^2_{z^1_\tau}, \sigma^2_{p_\tau}, \sigma_{z^1_\tau, p_\tau} = 0)$, where ϕ is drawn from $G(\mathfrak{g}, \mathfrak{l} = 1)$ and is known at the time of the technology adoption decision. The fraction of

high-tech startups reads

$$\Pr\Big[E[\pi^1|h] - \phi \geq E[\pi^1|n]\Big].$$

If the VC synergy effect is stronger for high-tech startups, this will tilt the adoption decision toward using advanced technologies.

5.8 Equilibrium

In the background, there is a representative consumer/worker living in a stationary equilibrium—for more detail see Appendix F. Endow this person with a momentary utility function of the following form:

$$u = \ln(c - \upsilon \frac{l^{1+\theta}}{1+\theta}),$$

where c is consumption and l is labor effort. This utility function has the simple solution for labor supply

$$l = (w/\upsilon)^{1/\theta}. \tag{21}$$

This consumer/worker supplies their labor to firms and their savings to banks and venture capitalists. The person earns income from their labor and savings and reaps the profits from firms and VC operation. Banks and venture capitalists can borrow funds at the fixed interest rate, ι, which represents the consumer/worker's rate of time preference. If the depreciation rate of physical capital is $\mathfrak{d}$, then the rental rate for capital, r, is

$$r = \iota + \mathfrak{d}. \tag{22}$$

Each period a unit mass of newborn startups flows into the economy. Newborn startups either survive to become adolescent startups with probability $\mathfrak{s}_n$ or suffer an infant death. Likewise, adolescent startups become adult ones with survival odds $\mathfrak{s}_a$. Similarly, adult firms survive a period with probability $\mathfrak{s}_e$. So, there will be 1 unit of newborn startups, $\mathfrak{s}_n$ units of adolescent startups, and $\mathfrak{s}_n\mathfrak{s}_a/(1-\mathfrak{s}_e)$ units of adult firms. The survival-adjusted discount factors, δ^1, δ^2, and δ^3, are accordingly given by

$$\delta^1 = \frac{\mathfrak{s}_n}{1+\iota},\ \delta^2 = \frac{\mathfrak{s}_a}{1+\iota},\ \text{and}\ \delta^3 = \frac{\mathfrak{s}_e}{1+\iota}. \tag{23}$$

For an equilibrium to obtain, the labor market must clear. There are 10 types of generic firms: newborn startups using either high-tech or non-high-tech production technology, adolescent high-tech and non-high-tech adopting startups that are financed by either banks or venture capitalists, and adult high-tech and non-high-tech firms that are initially financed by one of the two sources. Thus, labor-market-clearing condition reads

$$
\begin{aligned}
&\Pr\Big[E[\pi^1|h]-\phi\geq E[\pi^1|n]\Big]E[l_h^1(z_h^1)]+\Pr\Big[E[\pi^1|h]-\phi< E[\pi^1|n]\Big]E[l_n^1(z_n^1)]\\
&+\mathfrak{s}_n\Big\{\Pr\Big[E[\pi^1|h]-\phi\geq E[\pi^1|n]\Big]\{\Pr[p_h\geq p_h^*]E[l_{hv}^2(z_{hv}^2)|p_h\geq p_h^*]+\Pr[p_h< p_h^*]E[l_{hb}^2(z_{hb}^2)|p_h< p_h^*]\}\Big\}\\
&+\mathfrak{s}_n\Big\{\Pr\Big[E[\pi^1|h]-\phi< E[\pi^1|n]\Big]\{\Pr[p_n\geq p_n^*]E[l_{nv}^2(z_{nv}^2)|p_n\geq p_n^*]+\Pr[p_n< p_n^*]E[l_{nb}^2(z_{nb}^2)|p_n< p_n^*]\}\Big\}\\
&+\frac{\mathfrak{s}_n\mathfrak{s}_a}{1-\mathfrak{s}_e}\Big\{\Pr\Big[E[\pi^1|h]-\phi\geq E[\pi^1|n]\Big]\{\Pr[p_h\geq p_h^*]E[l_{hv}^3(z_{hv}^3)|p_h\geq p_h^*]+\Pr[p_h< p_h^*]E[l_{hb}^3(z_{hb}^3)|p_h< p_h^*]\}\Big\}\\
&+\frac{\mathfrak{s}_n\mathfrak{s}_a}{1-\mathfrak{s}_e}\Big\{\Pr\Big[E[\pi^1|h]-\phi< E[\pi^1|n]\Big]\{\Pr[p_n\geq p_n^*]E[l_{nv}^3(z_{nv}^3)|p_n\geq p_n^*]+\Pr[p_n< p_n^*]E[l_{nb}^3(z_{nb}^3)|p_n< p_n^*]\}\Big\}\\
&\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad=l. \quad (24)
\end{aligned}
$$

The first line gives labor demand from newborn startups using high-tech and non-high-tech technologies. The second line gives labor demand from adolescent VC- and bank-funded firms using high-tech technologies. The third line replicates the second line for the conventional technology. The fourth and fifth lines repeat the second and third lines for adult firms. The last line is the endogenous labor supply. Appendix D.3 states the equilibrium definition formally.

6 Quantitative Analysis

The big picture for the quantitative analysis is this. Most startups begin small and remain small, consistent with the findings of Hurst and Pugsley (2011)—see also the recent work on Danish firms by Akcigit et al. (2025). By contrast, high-tech VC-financed firms grow to be very large and contribute disproportionately to employment despite representing only a tiny share of firms. VC-backed firms that use conventional technologies also become large, but not as big as the high-tech ones. They contribute non-negligibly to employment, yet are still a fraction of firms. Last, most firms start off as bank financed. They are numerous and account for the majority of employment. Bank-financed, high-tech firms are bigger than the ones using conventional technologies, but are still much smaller than VC-financed firms. Bank-financed firms are numerically dominant and account for the majority of employment in aggregate. The modal firm—bank-financed, non-high-tech—is very small individually, but contributes substantially to employment by sheer volume.

The model is calibrated to replicate a rich set of data targets. The vast majority of data targets are grouped into three categories of firms: newborn (under age 3), adolescent (ages 3–10), and adult (age 11+). A period in the model is taken to be a year. Standard parameter values are applied where available. The annual real interest rate is given a value of 4% implying that $\iota = 0.04$. From the U.S. Census Bureau's Business Dynamics Statistics (BDS), the annual survival rates for newborns, adolescents, and adults are $\mathfrak{s}_n = 0.859$, $\mathfrak{s}_a = 0.920$, and $\mathfrak{s}_e = 0.949$. Hence, the annual survival-adjusted discount factors within the three phases are $0.859/(1.04) = 0.826$, $0.920/(1.04) = 0.885$ and $0.949/(1.04) = 0.913$. The annual depreciation rate of capital is taken to have a value of 8%, so

that the rental rate on capital is $r = 0.04 + 0.08 = 0.12$. Appendices H to J derive the key formulas used for computing the model and matching it with the data.

Since the three phases are of different lengths some adjustments have to be made to theory in order to match the data. Recall that each period a unit mass of new startups is born. If the annual survival rate for newborns is $\mathfrak{s}_n$, then $\mathfrak{s}_n^3$ of these will survive into the adolescent phase. By summing across the 3 periods in the newborn phase, the mass of newborn startups is $(1-\mathfrak{s}_n^3)/(1-\mathfrak{s}_n)$. Suppose that the annual survival rate for an adolescent startup is $\mathfrak{s}_a$. Then, the mass of startups surviving into adulthood is $\mathfrak{s}_n^3\mathfrak{s}_a^8$. Taking into account that adolescent startups potentially have eight periods of life implies that there will be $\mathfrak{s}_n^3(1-\mathfrak{s}_a^8)/(1-\mathfrak{s}_a)$ of them. Last, there will be $\mathfrak{s}_n^3\mathfrak{s}_a^8/(1-\mathfrak{s}_e)$ adult firms, where $\mathfrak{s}_e$ is the annual survival rate. When taking the theory to data, the survival-adjusted discounted profits for each phase need to be computed and the labor-market-clearing condition has to be modified to take into account the mass of firms in each phase—see Appendix G for the details.

6.1 Adolescent Startups, age 3 to 10 yrs

Now, start with data targets for adolescent startups.[22] The facts for them are presented in Table 5. For a given method of financing, adolescent startups using advanced technologies are much larger in terms of employment than those using conventional technologies. VC-backed startups are bigger than bank-financed ones, regardless of the technology used. The standard deviation of employment is large for all types of adolescent startups. For a given level of financing, the variance of employment is larger for high-tech startups. Holding the type of technology fixed, the variance of employment for VC-funded startups is bigger than for bank-financed ones. Not surprisingly, high-tech adolescent startups do not account for a large percentage of firms ($< 4\%$). VC-funded startups comprise a very small fraction of firms. The annual exit rate for adolescent startups is $100 \times (1 - \mathfrak{s}_a) = 8.0\%$. Last, to compute the average equity share earned by venture capitalists, the sample of firms that had a first VC deal before 2010 was analyzed. The average equity share for a firm's last deal before age 10 was 55%. Some intuition about how these data targets help to identify some of the model's parameters is provided now.

High-tech startups. Start with high-tech adolescent startups. Data targets T1, T2, T5, T6, and T9 in Table 5 are useful for pinning down the mean and variance of high-tech startup's potentials, μ_{p_h} and $\sigma^2_{p_h}$, the variance of the second-period random productivity shock for high-tech firms, $\sigma^2_{\epsilon h}$, and for computing the VC threshold for high-tech startups, p^*_h. Intuitively, data target T9 is instrumental for determining the threshold for VC funding, p^*_h. Given this threshold, targets

[22] These empirical moments are calculated using the main sample of firms from the ABS 2018–2022. Within this sample, firms are classified as adopters or non-adopters based on whether they reported adoption in any of these ABS waves, regardless of when adoption occurred. Information on the timing of adoption is only available (within intervals) in the ABS 2023 survey. While one could use the 2023 data alone to identify adoption timing, doing so would result in a smaller sample and an understated adoption rate, given the narrower range of technologies covered in that survey. The model abstracts from adoption dynamics and assumes that the adoption decision occurs early in a firm's life cycle. This assumption is broadly consistent with the data: as shown in Figure 1, most adopting firms do so in their early years—around 70% of high-tech firms adopt before reaching age 10.

Table 5: Calibration Targets, Adolescent Startups, 3 to 10yrs

Target		**U.S. Data**	**Model**
Employment Shares (% of all employment)			
T1	High-Tech, VC financed	0.28 (57.13)	0.28
T2	High-Tech, Bank financed	2.398 (16.39)	2.398
T3	Non-High-Tech, VC financed	0.29 (39.36)	0.29
T4	Non-High-Tech, Bank financed	10.62 (9.446)	10.62
Standard Deviation of ln *Employment*			
T5	High-Tech, VC financed	1.528	1.302
T6	High-Tech, Bank financed	1.302	1.302
T7	Non-High-Tech, VC financed	1.47	1.15
T8	Non-High-Tech, Bank financed	1.15	1.15
Share of Startups (% of all firms)			
T9	High-Tech, VC financed	0.1147	0.1109
T10	High-Tech, Bank financed	3.398	3.285
T11	Non-High-Tech, VC financed	0.1712	0.1736
T12	Non-High-Tech, Bank financed	26.12	26.48
Equity Share of Venture Capitalists (%)			
T13	All VC financed firms	55	65

Notes: Numbers in parenthesis refer to absolute average employment size.

T1, T5, and T6 provide information on employment that can be used to back out the properties of the productivity distributions that determine the distributions for employment.

Non-high-tech startups. Likewise, for non-high-tech adolescent startups, data targets T3, T4, T7, T8, and T11 provide information for calibrating $\mu_{p_n}, \sigma^2_{p_n}, \sigma^2_{\epsilon n}$ and p^*_n.

Costs and benefits of VC. The information provided by data targets T1, T3, and T9–T12 helps to pin down the venture capitalist's overseeing costs parameters, α_h and α_n, and the benefit from using VC, γ_{hv} and γ_{nv}.[23] Heuristically speaking, a venture capitalist's share of an adolescent venture reflects the benefits and costs of using VC. While γ_{hv} and γ_{nv} are directly targeted to match the employment shares of VC-backed firms, the calibrated ordering $\gamma_{hv} > \gamma_{nv}$ is consistent with the larger VC treatment effect for technology adopters found in Table 4.

High-tech adoption cost. Last, the share of high-tech startups ties down the scale parameter, $\mathfrak{g}$, for the Gumbel distribution, which governs the fixed cost for a high-tech startup.

Adolescent survival rate. This is calculated using data from the BDS.

VC Equity Share. This number is useful for calibrating the venture capitalist's bargaining power, $1 - \eta$.

[23]The indifference condition (17) between using bank and VC funding for each technology implies that two of these variables can be solved for in terms of the others.

Table 6: Calibration Targets, Newborn Startups, $\leq$ 2yrs

Target	**U.S. Data**	**Model**
Employment Shares (% of all employment)		
T14 High-Tech	0.73 (8.167)	0.73
T15 Non-High-Tech	4.23 (6.026)	4.23
Standard Deviation of ln *Employment*		
T16 High-Tech	1.141	1.141
T17 Non-High-Tech	1.05	1.05
Share of Startups (% of all firms)		
T18 High-Tech	2.078	2.287
T19 Non-High-Tech	16.31	17.95

Notes: Numbers in parenthesis refer to absolute average employment size.

6.2 Newborn Startups, age ≤ 2 yrs

A set of stylized facts is also collected for newborn startups—see Table 6. The facts concerning employment are now just broken down by technology. Newborn startups are much smaller than adolescent ones. They haven't had time to grow. Still the ones using advanced technologies are bigger than those using conventional ones. The standard deviation of employment is also large for newborn startups. It is larger for the high-tech newborn startups relative to the non-high-tech ones. Unsurprisingly, newborn startups have a high exit rate of $100 \times (1 - \mathfrak{s}_n) = 14.1\%$. These facts are useful for pinning down the mean and variance, $\mu_{z_\tau^1}$ and $\sigma^2_{z_\tau^1}$ for $\tau = h, n$, of a newborn startup's productivity.

6.3 Adult Firms, age 11+ yrs

Last, a limited set of facts is provided for adult firms—Table 7. High-tech adult firms are much larger than non-high-tech ones, holding fixed the method of finance. High-tech, VC-financed firms average almost 3,000 employees. VC-backed firms are much larger than bank-financed ones, regardless of the technology used. By comparison average firm size in the United States is only about 23 employees. VC-backed firms (using either advanced or conventional technologies) are only a small fraction of all firms ($< 0.2\%$). Yet, they still account for roughly 12.6% of employment. High-tech, VC-backed firms make up only 0.07% of firms in the economy, but they still comprise 8.6% of employment. Bank-financed adult firms using conventional technologies comprise by far the largest slice of firms in the economy and these firms tend to be small; actually, smaller than the average firm size in the economy. Bank-financed, high-tech firms are bigger than the ones using conventional technologies, but they are still much smaller than VC-funded firms regardless of the technology used by the latter. VC-funded firms are 3 times more likely to adopt high-tech than bank-financed ones.

The lefthand side panel of Figure 6 shows the model generated firm-size distributions for each of the four types of adult firms. As can be clearly seen, there is a greater mass of VC-funded firms in the right tail of the firm-size distributions for employment relative to bank-funded firms,

Table 7: Calibration Targets, Adult Firms, 11+yrs

Target		**U.S. Data**	**Model**
Employment Shares (% of all employment)			
T20	High-Tech, VC financed	8.63 (2,944)	8.63
T21	High-Tech, Bank financed	26.72 (104)	26.72
T22	Non-High-Tech, VC financed	3.96 (736.8)	3.96
T23	Non-High-Tech, Bank financed	42.13 (21.43)	42.13
Share of Adult Firms (% of all firms)			
T24	High-Tech, VC financed	0.06807	0.183
T25	High-Tech, Bank financed	5.967	5.434
T26	Non-High-Tech, VC financed	0.1247	0.287
T27	Non-High-Tech, Bank financed	45.66	43.8

Notes: Numbers in parenthesis refer to absolute average employment size.

regardless of the technologies that firms use. This is due to both selection and synergy effects. For a given type of finance, the firm-size distributions for high-tech firms essentially dominate those using conventional technologies.

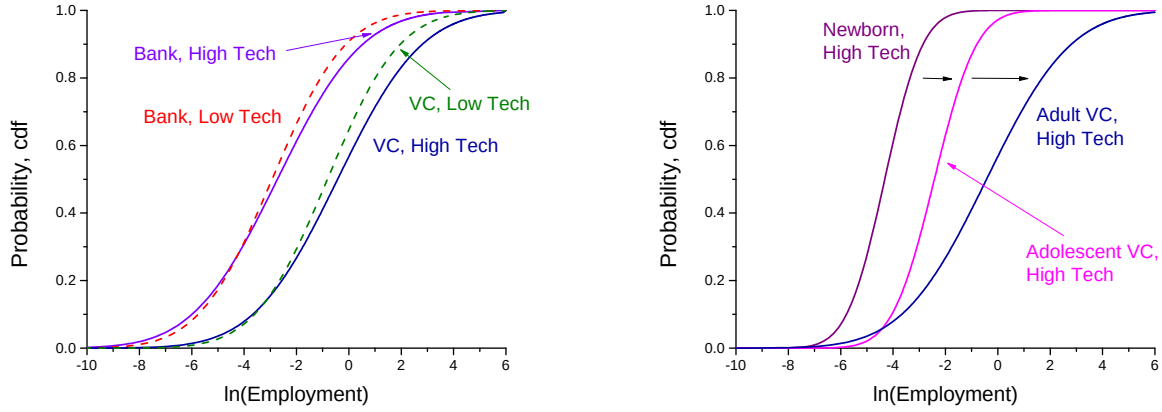


Figure 6: Firm-size distributions in the model measured by *ln* employment.
Notes: The plots are in cumulative distribution function form. Left panel, the firm-size distributions are shown for the four types of adult firms. Right panel, the growth in the firm-size distributions from a newborn, high-tech startup to an adult, VC-financed, high-tech firm.

The fact that VC-funded adult firms are punching well above their weight is evident from Table 8, which displays the odds ratios for the various types of firms. The odds ratios give each type of firm's share of employment relative to their share of the number of firms. The odds ratios for VC-funded adult firms are large, especially for VC firms using advanced technologies. Additionally, bank-financed, high-tech adult firms also contribute more to employment than their numbers warrant. Bank-financed firms using conventional technologies underperform in terms of employment; i.e., their odds ratio is less than 100%. Last, both high- and non-high-tech newborn firms are underachievers

Table 8: Odds Ratios for Employment

Phase	**Odds Ratios (%)**			
Adolescent Startups	High-Tech, VC	High-Tech, Bank	Non-High-Tech, VC	Non-High-Tech, Bank
	246.00	70.58	169.49	40.68
Newborn Startups	High-Tech		Non-High-Tech	
	35.17		25.94	
Adult Firms	High-Tech, VC	High-Tech, Bank	Non-High-Tech, VC	Non-High-Tech, Bank
	12,677.04	447.83	3,172.71	92.28

in terms of generating employment just because their employment is very low when starting out.

The shares of employment for the various types of adult firms are useful for calibrating the growth factors, $\chi_{\tau f}$ for $\tau = h, n$ and $f = b, v$. From Tables 5 and 7 it can be calculated that, contingent on survival, VC-funded, high-tech firms grow a phenomenal 52 times between the adolescent and adult phases. This is followed by VC-funded, non-high-tech firms that increase by a factor of 19 times. Bank-financed, high-tech firms have a growth factor of 6 times. Bank-financed, non-high-tech firms are relative laggards, only roughly doubling in size. The annual exit rate for adult firms is $100 \times (1 - \mathfrak{s}_e) = 5.1\%$. Exit rates decline with age; i.e., $5.1 < 8.0 < 14.1\%$. The evolution, or rightward shifts, in the employment distributions starting from a newborn, high-tech startup to an adult, high-tech, VC-financed firm is shown in the righthand side panel of Figure 6. The parameter values obtained from the calibration are displayed in Table 9.

7 Thought Experiments

A series of thought experiments starts off by quantifying the macroeconomic roles of VC, advanced technology, and the VC/high-tech synergy effect, and then examines the reallocation effects across firm funding/technology profiles induced by tax and subsidy policies. Before proceeding, the model's measures of welfare, reallocation effects, and total factor productivity (TFP) are introduced.

Welfare. The equivalent variation (EV), ε, associated with a shift from regime A to regime B is given by

$$\varepsilon = 100\% \times \frac{[c^B - \upsilon(l^B)^{1+\theta}/(1+\theta)] - [c^A - \upsilon(l^A)^{1+\theta}/(1+\theta)]}{c^A},$$

where c^j and l^j, for $j = A, B$, are the consumptions and labor supplies in the two scenarios. This measures the amount, in terms of a percentage of regime A's consumption, that either a person would be willing to pay or have to be compensated to move from A to B.

Reallocation. The change in aggregate employment (or in fact income and the capital stock) can be decomposed into the difference in each type of firm's average employment and the shift in

Table 9: Calibrated Parameter Values

Parameter Value	**Description**	**Identification**
Production function—all firms		
$\lambda = 0.6$	Labor share	Standard
$\kappa = 0.2$	Capital share	Standard
$\zeta = 0.2$	Profit share	Standard
$m = 0.1$	Entrepreneurial capital	Normalization
Production shocks, adolescent startups		
$\mu_{p_h} = -2.953, \sigma_{p_h} = 0.34, \sigma_{\epsilon_h} = 2.527$	Potential means, variances—high-tech	T1, T2, T5, T6
$\mu_{p_n} = -3.174, \sigma_{p_n} = 0.391, \sigma_{\epsilon_n} = 2.169$	Potential means, variances—non-high tech	T3, T4, T7, T8
Production shocks, newborn startups		
$\mu_{z_h^1} = -3.831, \mu_{z_n^1} = -4.239$	Productivity means, newborns	T14, T15
$\sigma_{z_h^1} = 2.282, \sigma_{z_n^1} = 2.100$	Productivity variances, newborns	T16, T17
Discount factors, rental rates, survival rates—annual		
$r = 0.04 + 0.08 = 0.12$	Capital rental rate, $r = \iota + \mathfrak{d}$	Standard
$\mathfrak{s}_n = 0.859, \mathfrak{s}_a = 0.920, \mathfrak{s}_e = 0.949$	Survival rates	BDS
$\delta^1 = 0.826, \delta^2 = 0.885, \delta^3 = 0.913$	Discount factors, $\mathfrak{s}^i/(1.04)$	Surv Adj
Venture capital		
$\alpha_h = 3.619$	Oversight cost, constant, high tech	T9, T10
$\alpha_n = 1.087$	Oversight cost, constant, non-high tech	T11, T12
$\xi = 0.5$	Oversight cost, slope	Imposed
$\gamma_{hv} = 0.502, \gamma_{nv} = 0.386$	Synergy effect	T1, T3
$\eta = 0.75$	Entrepreneur's bargaining power	T13
High-tech adoption cost		
$\mathfrak{g} = 0.33$	Gumbel distribution, scale	T18, T19
Adult firm growth		
$\chi_{hv} = 3.748, \chi_{hb} = 1.366$	Growth factors, high-tech	T20, T21
$\chi_{nv} = 2.542, \chi_{nb} = 0.739$	Growth factors, non-high-tech	T22, T23

the share of each type of firm in the economy. The formula for doing this is

$$l^B - l^A = \sum_{j=1}^{10}[(\frac{\#_j^B + \#_j^A}{2})(l_j^B - l_j^A) + (\frac{(l_j^B + l_j^A)}{2})(\#_j^B - \#_j^A)],$$

where l_j^A and l_j^B are the average employments for a type-j firm in the two situations and $\#_j^A$ and $\#_j^B$ are the measures of each firm type. Reallocation effects discussed below relate to the distortion-induced misallocation effects emphasized by Guner, Ventura, and Xu (2008), Hsieh and Klenow (2009), and Restuccia and Rogerson (2008).

TFP. Aggregate TFP is measured as $\boldsymbol{z} = \boldsymbol{o}/(\boldsymbol{k}^\kappa \boldsymbol{l}^\lambda)$, where $\boldsymbol{z}$ is TFP, $\boldsymbol{o}$ is GDP, $\boldsymbol{k}$ is the aggregate capital stock, and $\boldsymbol{l}$ is aggregate labor supply.

7.1 No Venture Capital, No High Tech, and No VC/High-Tech Synergy Effect

Consider first the effect of removing the three key forces in the model, VC, advanced technology, and the VC/high-tech synergy effect.

No VC. Venture capital is shut down by making it prohibitively expensive. Figure 7, left panel, shows the results. The impact on the macro-economy is substantial. GDP drops by 4.6%. The loss in welfare is high, with the equivalent variation being -3.2%. This occurs because the synergy effect from VC has been forfeited. Surprisingly, the adoption of high tech increases by 4.5%. This transpires because non-high-tech, VC-funded startups switch into high-tech, bank-funded ones in order to maintain profitability. As a result, TFP falls because high-tech firms are less productive on average due both to the absence of the VC synergy effect and the fact that these firms are less suitable for high technology.

No advanced technology. Similarly, the adoption of advanced technologies is turned off by making it prohibitively expensive. The upshot for the macro-economy is shown in Figure 7, right panel. GDP drops by 12.9% and employment by 8.3%. Measured TFP is lower by 5.5%. The loss in welfare is huge. The equivalent variation is -8.9%. It may seem surprising that switching off high-tech has a bigger effect than eliminating VC, because VC-funded firms have the highest levels of employment. Note, however, that startups using VC funding are a much smaller fraction of firms than startups that use high tech.

No VC/high-tech synergy effect. Finally, the macroeconomic importance of the additional synergy effect that VC backing provides to high technology adopters, relative to non-adopters, is examined in Figure 8. The calibrated synergy parameters imply that the benefits of VC are larger for firms that adopt advanced technology than for those that do not ($\gamma_{hv} > \gamma_{nv}$). The counterfactual eliminates this complementarity by setting γ_{hv} to γ_{nv}. The plot shows that GDP declines by 1.9% and employment by 1.2%, with an equivalent variation of –1.3%. The EV drop is approximately 40% of the overall VC effect found in the no-VC experiment. This highlights

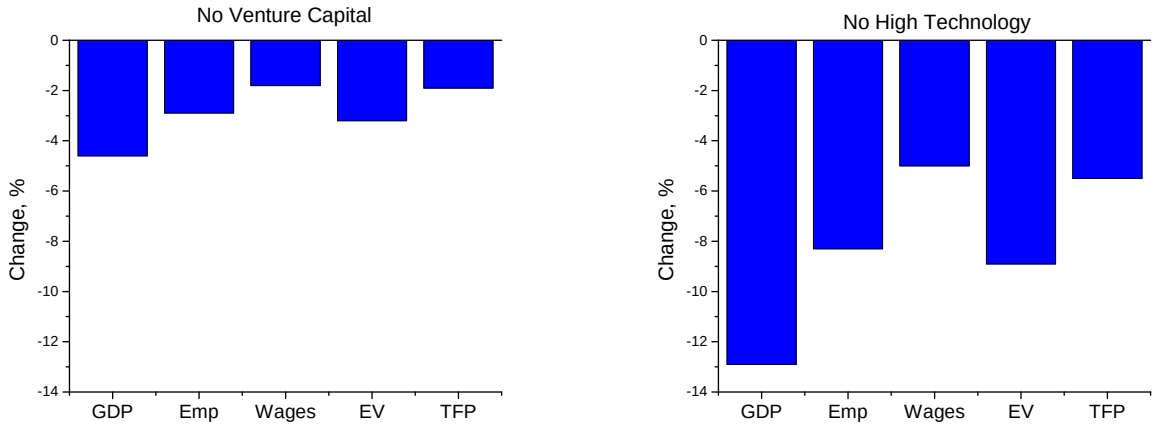


Figure 7: No Venture Capital and No High Tech Experiments.
Notes: Left panel, the bar chart shows the impact in the model of eliminating VC on some key macroeconomic variables. Right panel, the impact in the model of eliminating high technology on some key macroeconomic variables.

the substantial macroeconomic importance of the complementarity between VC and technology adoption, which transpires as firms at the margin switch from VC to bank funding and from high tech to non-high tech in the counterfactual economy.

7.2 Tax rates

Startups may be organized as C corporations or partnerships.[24] C corporations are favored by venture capitalists, with 60% of VC-funded startups adopting this form; partnerships are favored by other startups (80%). When operating as a C corporation, an adult firm will pay corporate income tax at the rate τ_c. Traditional public finance theory suggests that the corporate income tax is nondistorting. As a profit tax, corporate income taxation does not affect the choice of capital and labor in the adult firm problem (1), because it just multiplies the maximand by $1-\tau_c$. It influences the type of financing and technologies used by startups, however. When a startup is sold, the sellers are taxed at the capital gains tax rate, τ_g. The presence of the corporate income tax reduces the sale value of a startup by a factor of $1-\tau_c$. This, combined with the capital gains tax, implies that the proceeds from the sale of a startup are effectively lessened by the factor $(1-\tau_c)(1-\tau_g)$. Alternatively, when operating as a partnership, profits are taxed at the personal income tax rate, τ_l. Qualified business income can be deducted at the rate d. So, which business organization form is preferred for tax purposes depends on whether $(1-\tau_c)(1-\tau_g) \gtrless 1-\tau_l(1-d)$.

Currently, the corporate income tax is 21% and capital gains are taxed at 20%. Partnerships are taxed at a personal income tax rate of 30% with a deduction for qualified business income of 20%.

[24] Abraham et al. (2023) analyze the choice of a firm's organizational form.

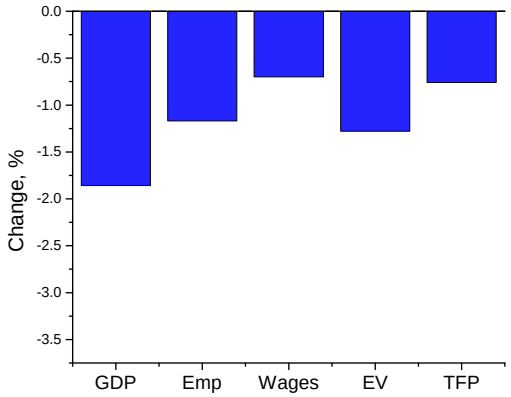


Figure 8: No Additional VC Synergy for Technology Adopters.
Notes: The bar chart shows the impact in the model of eliminating the additional synergy effect of VC for technology adopters on some key macroeconomic variables.

The model is recalibrated assuming the above business organizational structure and these tax rates. A startup's organizational structure is assigned randomly conditional on the source of funding, in line with the population averages in the data.[25]

Raising the corporate and capital gains tax rates

Consider raising both the corporate income tax rate and the capital gains tax rate from their current values of 21% and 20%, respectively, to a common rate of 28%.[26] Tax receipts are rebated back to consumers via lump-sum transfer payments. The macroeconomic implications of the change in the tax rates are displayed in the left panel of Figure 9. The aggregate effects are substantial: GDP falls by 2.3%, employment by 1.5%, and TFP by 1.0%. The high-tech adoption rate falls by 1.2%. The welfare loss corresponds to an equivalent variation of –1.6%. The excess burden of the tax change—welfare loss per dollar of additional revenue—is 33.6.

The macroeconomic results mask important reallocation effects. The reallocation effects can be gleaned from Table 10. The movement away from VC-financed to bank-financed firms is strong. As can be seen from column 3, VC-funded adult firms are large contributors to the fall in employment. The large drop in the fraction of adult VC-funded firms is a major factor in the fall of employment, as reflected in column 2. VC-funded adult firms are highly productive enterprises hiring a lot of labor.

[25]Accountants generally consider the partnership structure to be more advantageous for startups under U.S. tax law [Erickson et al. (2020)]. However, venture capitalists tend to favor the corporate form—a preference that remains somewhat puzzling. In Spain, where the comparable legal forms (S.A. and S.L.) face identical tax rates, the more successful firms nonetheless gravitate toward the S.A. corporate structure [Rios-Rull and Rodriguez-Lopez (2025)].

[26]The common rate of 28 percent is chosen solely to provide a sizable perturbation to both tax margins. While this rate is arbitrary, it lies within the range of values considered in previous tax rate proposals.

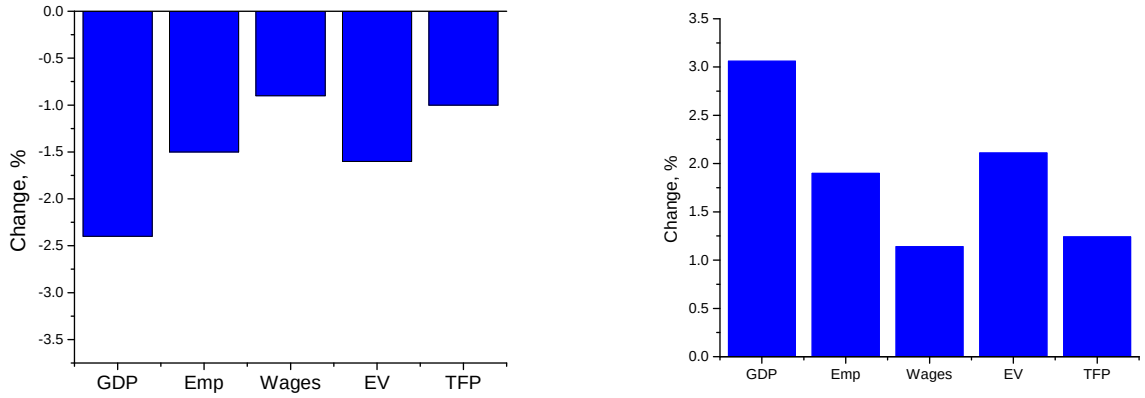


Figure 9: Tax Experiments.

Notes: In the left panel, the bar chart shows the impact of raising the corporate and capital gains tax rates on some key macroeconomic variables in the model. In the right panel, the bar chart shows the impact on the same key macroeconomic variables of eliminating the capital gains tax for high-tech C corporations.

While it is true that the number of adolescent VC-funded startups also falls, at such a young stage they don't hire much labor. Still, the decline in adolescent VC-funded firms plays an important role because they grow up to be adult firms. Surprisingly, the average size of VC-funded firms actually increases because the threshold for funding, p_τ^*, rises. This works to increase their employment—column 1. The rise in average employment by adult bank-financed firms offsets significantly the decline in aggregate employment. This occurs for two reasons. First, there is a reallocation of some high productivity firms away from VC to bank financing. Second, the wage rate has fallen. Both of these effects operate to stimulate employment by adult bank-financed firms.

Eliminating capital gains tax for high-tech C corporations

Reductions in capital gains taxation have been proposed as a means of stimulating investment in capital-intensive small businesses. The Qualified Small Business Stock (QSBS) program is a prominent example [see Campello and Junqueira (2025) for an analysis]. A central feature of QSBS is the elimination of capital gains taxes on qualifying investments in small businesses organized as C corporations. Eligibility is restricted to firms operating in specific sectors—including technology, biotechnology, and information and media—and to firms whose gross assets do not exceed $50 million when the stock is issued.

The macroeconomic effects from eliminating capital gains taxation for high-tech C corporations are large (see the right panel of Figure 9). GDP grows by 3.1%. Total factor productivity rises by 1.2%, partly spurred on by a climb in high-tech adoption of 4.0%. There is also a sizable increase in employment of 1.9%, motivated by a 1.1% rise in real wages. Welfare rises by 2.1%. The elimination

Table 10: Reallocation Effect: Tax Experiment

Decomposition of Δ Employment, %			
	Δ Empl	**Δ Firms**	**Δ Total**
	1	***2***	***3***
Newborn Startups			
High-Tech	-1.1	0.6	-0.5
Non-High-Tech	-6.5	-0.4	-6.9
Adolescent Startups			
High-Tech, VC	-1.8	10.1	8.2
High-Tech, Bank	-8.4	-0.8	-9.2
Non-High-Tech, VC	-1.9	10.5	8.6
Non-High-Tech, Bank	-30.1	-3.5	-33.6
Adult Firms			
High-Tech, VC	-56.2	307.5	251.3
High-Tech, Bank	-93.8	-8.5	-102.3
Non-High-Tech, VC	-25.8	143.6	117.8
Non-High-Tech, Bank	-119.4	-14.0	-133.4

Notes: Since the change in aggregate employment is *negative*, for the newborn, adolescent, and adult categories, a *negative* number means that the entry *increased* employment, while a *positive* one implies it *decreased* it.

of capital gains taxation works to offset the effect of distortional taxation levied on businesses. The excess burden associated with eliminating the capital gains tax for high-tech C corporations is 13.9, so for every dollar lost in revenue there is a gain in welfare of 13.9 dollars.

Behind the curtain are substantial reallocation effects. Table 14 in Appendix E.1 shows that the fraction of high-tech, VC-funded firms soars at the expense of non-high-tech firms. Note that average employment by high-tech firms actually declines because at the margin less productive startups are adopting high tech and also because the real wage has risen.

7.3 Subsidies

Two subsidy experiments are considered. The first provides a 10% capital cost subsidy to all adolescent startups; the second targets the same subsidy exclusively at high-tech adolescent startups. Both are implemented as a reduction in the rental rate r for adolescent startups.

Subsidizing all startups. The broad subsidy produces moderate aggregate gains: GDP rises by 0.7%, employment by 0.5%, and the high-tech adoption rate by 0.5%. TFP falls negligibly (–0.04%), as the subsidy redirects resources at the margin toward relatively low-productivity adolescent startups. Welfare rises by 0.3%, with an excess burden of 0.8, meaning each dollar of subsidy cost yields $0.80 in welfare gains—reflecting partial offsetting of distortionary corporate and personal income taxes. Reallocation analysis shows that non-high-tech, bank-financed adolescent firms account for a large share of employment gains, which explains the slight TFP decline—see Table 15 in Appendix E.2.

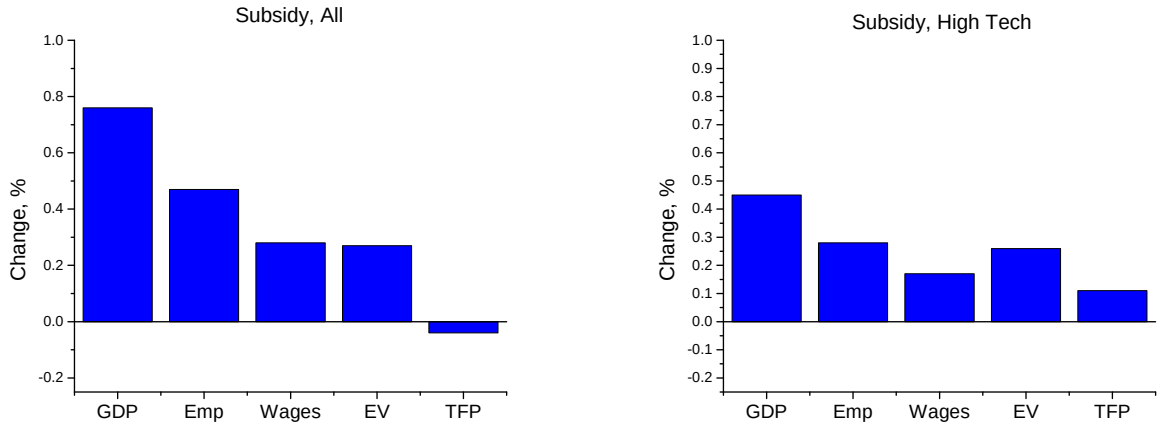


Figure 10: Subsidy Experiments.

Notes: Left panel, the bar chart shows the impact in the model of providing subsidies to all adolescent startups on some key macroeconomic variables. Right panel, subsidies are provided to just high-tech adolescent startups.

Subsidizing only high-tech startups. The targeted subsidy produces smaller but qualitatively similar aggregate effects—GDP +0.5%, employment +0.3%—as it applies to a narrower set of firms. However, the high-tech adoption rate rises by 2.3%. TFP increases modestly (0.1%) because the subsidy is concentrated in the most productive segment of the economy. Welfare again rises by 0.3%, but the excess burden is 35.4, meaning each dollar of revenue foregone generates $35.40 in welfare—reflecting the high productivity of the targeted group. Reallocation analysis—Table 16 in Appendix E.2—shows that the targeted subsidy reallocates employment from non-high-tech to high-tech firms. From the model's perspective, subsidizing high-tech startups is effective because it focuses on the most productive part of the economy.

8 Closing

This study examines how advanced technology adoption and VC financing jointly shape firm growth and macroeconomic performance. Recently available U.S. Census Bureau microdata show that both are associated with stronger firm outcomes, but their combination also matters: employment gains following VC funding are especially large among technology adopters. This pattern points to a complementarity between advanced technology and the capital, expertise, and strategic guidance venture capitalists provide.

A quantitative startup model formalizes this interaction by making technology adoption and financing choices endogenous. When calibrated to the empirical patterns, the model attributes sizable contributions to output and employment to both VC and advanced technology, and implies that their complementarity itself carries material macroeconomic weight. The tax and subsidy counter-

factuals reveal substantial reallocation across firms with different combinations of technology and financing. Recognizing these heterogeneous effects is essential for designing policies that promote innovation and entrepreneurship while accounting for their broader economic implications.

The analysis has some limitations. The empirical estimates cannot fully rule out selection on unobserved firm characteristics, and the model treats technology choice as a one-time, early-life decision—it does not allow technology upgrading [say as in Parente (1994)] or direct VC influence on technology choice after financing is obtained. Addressing these limitations offers natural directions for future research. Nevertheless, the empirical evidence and the model point in the same direction: finance and technology are not separate forces. The contribution of VC depends partly on the technologies firms use, while the adoption of and returns to advanced technologies depend partly on the financing and support available to startups. As technology continues to advance and VC markets evolve, the interplay between finance and technology adoption will remain central to economic growth and innovation. This research lays the groundwork for deeper exploration into how they shape firm performance and impact the macro-economy.

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Supplemental Appendix

A Data

The empirical analysis uses data from the Annual Business Survey (ABS) and PitchBook. The technological variables are obtained from the ABS. For the most part, information on venture capital funding is harvested from PitchBook with a limited amount of facts taken from the ABS.

A.1 The Use of Technology by Firms

The ABS collects data from firms regarding their use of various technologies for the period 2017-2022, with this information obtained from ABS surveys conducted between 2018-2023. The specific questions asked about the use of technology vary by survey year. Only the technologies examined in the current analysis are listed for each question.

- **ABS (yr1 - 2018) Business Technologies**. The question asked was: *In 2017, to what extent did this business use the following technologies in producing goods or services?*
  Technologies included in the analysis: Augmented reality, Automated guided vehicles (AGV) or AGV systems, Automated storage and retrieval systems, Machine learning, Machine vision software, Natural language processing, Radio-frequency identification (RFID) inventory system, Robotics, and Voice recognition software. The extent of adoption was gauged by the choice selected in the following list: *No use; Testing but not using in production or service; In use for less than 5% of production or service; In use for between 5%–25% of production or service; In use for more than 25% of production or service; Don't know.* In the analysis the technology is counted as in use if the firm indicated in "use for less than 5%" or higher.
  Technologies excluded from the analysis: The following technology is excluded in the analysis because it is too common: Touchscreens/ kiosks for customer interface (Examples: self-checkout, self-check-in, touchscreen ordering).

- **ABS (yr2 - 2019) Production Technology for Goods and Services**: The question asked was: *During the three years 2016 to 2018, to what extent did this business use the following technologies in production processes for goods or services?*
  Technologies included in the analysis: Artificial Intelligence, Robotics. Extent was gauged by the choice selected in the following list: *Did not use; Tested, but did not use in production or service; Low use; Moderate use; High use; Don't know.* In the analysis the technology is counted as in use if the firm indicated "low use" or higher.
  Technologies excluded from the analysis: Cloud-Based Computing Systems and Applications, Specialized Software, and Specialized Equipment are excluded. In general, the year-2 survey sampled a different set of firms in 2018 than the year-1 survey.

- **ABS (yr3 - 2020) Use of Digital Technologies**: The question asked was: *During the three years 2017 to 2019, to what extent does this business use the following digital technologies for innovation activities?*

  Technologies included in the analysis: Artificial Intelligence, Digital technologies for distributed ledgers (blockchain). Extent was gauged by the choice selected in the following list: *A great extent; To some extent; To a small extent; Not at all.* A technology was counted as in use if the firm indicated to "some extent" or higher.

  Technologies excluded from the analysis: Computer infrastructure (server technologies), cloud computing, automation, Internet-connected devices, mobile communication technologies, the use of digital technologies for collaboration, communication (i.e., through social media), and digital technologies for planning and management (i.e., enterprise resource planning, customer relationship management).

- **ABS (yr4 - 2021) Business Technologies**: The question asked was: *In 2020, did this business produce goods or provide services by using or applying any of the following technologies?* The technology module on this survey had a similar structure to that in ABS 2018.

  Technologies included in the analysis: Augmented reality, Automated guided vehicles (AGV) or AGV systems, Machine learning, Machine vision, Natural language processing, Radio-frequency identification (RFID) system, Robotics, Voice recognition software, Additive manufacturing (3D printing), including prototyping. As in the ABS 2018, Artificial intelligence was defined as the collection of Machine learning, Machine vision software, Natural language processing, Augmented reality, AGVs, and Voice recognition software. The extent of adoption was gauged by the respondent's choice selected from the following list: *In use; In testing, but not in use; Not in use nor testing; Don't know.* The technology is counted as "In use" if the firm indicated "In use."

- **ABS (yr5 - 2022) Use of Technologies:** The question asked was: *During 2021, to what extent did this business use the following technologies?*

  Technologies included in the analysis: Advanced sensing (e.g., machine vision, voice recognition, networked sensors and sensing, millimeter-wave radar, LIDAR, RFID, biointegrated sensors, electric grid measurement), Artificial intelligence (e.g., machine learning, planning, reasoning, and decision making), Autonomous systems and robotics (e.g., industrial robotics, automated guided vehicles (surface, aerospace, maritime)), Additive manufacturing (e.g., additive manufacturing (3-D Printing), smart manufacturing), Biotechnology (e.g., genetic engineering, DNA synthesis, genetic sequencing, tissue engineering, biomanufacturing, bioinformatics), Human-machine interfaces (e.g., augmented reality, virtual reality, brain-computer interfaces, human-machine teaming), Communication and networking technologies (e.g., radio frequency and mixed signal circuits, antennas and components, spectrum management technologies, communications and network security, mesh networks /infrastructure

independent communication technologies), Advanced financial technologies (e.g., digital technologies for distributed ledgers, blockchain), Advanced semiconductors and microelectronics (e.g., beyond CMOS electronics (including next generation semiconductor materials), design and electronic design automation (EDA) tools, manufacturing technologies and tooling, advanced lithography), Advanced engineering materials (e.g., materials by design, metamaterials, nanomaterials, smart materials, AM alloys, biomimetic, flexible electronics, material property characterization additive manufactured parts), Renewable energy generation and storage (e.g., wind, solar, and bio-based generation, electric and hybrid engines, batteries and grid backup/storage), Advanced gas turbine engine technologies [e.g., aero, marine, industrial (power generation), enabling component technologies], and Advanced nuclear energy technologies [e.g., aero, marine, industrial (power generation), enabling component technologies]. Extent was gauged by the choice selected in the following list: *A lot; Somewhat; A little; Not at all.* The technology is counted as in use if the firm indicated "a little" or higher.
TECHNOLOGIES EXCLUDED FROM THE ANALYSIS: Advanced computing (e.g., supercomputing, edge computing, cloud computing, data storage, advanced computing architectures).

- **ABS (yr6 - 2023) Production Technology for Goods and Services**: The question asked was: *During the three years 2020 to 2022, did this business adopt/use the following technologies?* The technology module on this survey had a similar structure to that in ABS 2019.
  TECHNOLOGIES INCLUDED IN THE ANALYSIS: Artificial Intelligence and Robotics. For each technology, the survey asks about the timing of adoption. For example,
  Timing of Adoption for Artificial Intelligence Technology—Processes and Methods: Approximately what year did this business first adopt or use Artificial Intelligence in processes and methods?
  Prior to 1990, 1991–1995, 1996–2000, 2001–2005, 2006–2010, 2011–2015, 2016–2020, 2021–Present, Don't know.
  TECHNOLOGIES EXCLUDED FROM THE ANALYSIS: Cloud-Based Computing Systems and Applications, Specialized Software, and Specialized Equipment are excluded, mainly because they are more commonplace as shown in Acemoglu et al. (2023).

A.2 Venture Capital Funding for Firms

Data on venture capital funding is primarily sourced from PitchBook, which collects information on venture capital financing through public sources as well as its extensive network. As a leading provider of VC data, PitchBook's datasets are also used by the National Venture Capital Association in its annual reports. This data is then merged with the Census Bureau's Business Register using name and address matching, utilizing company details such as name, state, city, zip code, and street address. According to PitchBook's glossary, venture capital is defined as "a type of private equity

investing that targets startups and early-stage companies with high growth potential." For the year 2018, PitchBook's data is supplemented by responses to a specific question from the ABS.

- **ABS (yr1 - 2018) Capital Funding**: The question asked was: *What was the source(s) of capital used to start or initially acquire this business*?:
  Personal/family savings of owner(s), Personal/family assets other than savings of owner(s), Personal/family home equity loan, Personal credit card(s) carrying balances, Business credit card(s) carrying balances, Government-guaranteed business loan from a bank or financial institutions, including SBA-guaranteed loans, Business loan from a bank or financial institution, Business loan from a federal, state, or local government, Business loan/investment from family/friend(s), Investment by venture capitalist(s), Grants, Other source(s) of capital, Don't know, None needed.

B The Advanced Technologies Studied

Five advanced technologies are highlighted as *examples* of the technologies studied in the empirical analysis; namely, additive manufacturing, artificial intelligence (AI), distributed ledgers, radio-frequency identification (RFID), and robotics.

B.1 RFID (Radio Frequency Identification)

RFID is a technology where a tag attached to an object allows it to be identified and tracked. The tag, once activated by an electromagnetic field, transmits information to a radio receiver. Mario Cardullo received the first patent for an RFID device in 1973, with an initial vision for applications in credit cards and toll systems. Today, RFID technology is used in a wide array of applications including access control, biometric data retrieval from passports and driver's licenses, contactless credit card payments, inventory management, and tracking of livestock, pets, and shipments.

B.2 Robotics

The history of robotics dates back to 1949, when William Grey Walter developed battery-powered robots with three wheels that could navigate around obstacles. These robots, which resembled tortoises, were capable of phototaxis, or moving toward light, and could return to their charging station when their battery was low. The fundamental elements of these early robots—sensor technologies, feedback loops, and decision-making—remain integral to modern robots. A decade later, General Motors introduced the first industrial robotic arm, designed to lift and stack hot metal parts. In 1972, engineers at the Stanford Research Institute created "Shakey," the first robot that incorporated AI. Shakey could break down commands into actionable steps, such as navigating to a specified room and moving an object to a desired location. Today, robots are widely used in man-

ufacturing, healthcare (e.g., surgical assistance and food delivery in hospitals), law enforcement, military operations, and space exploration.

B.3 Artificial Intelligence (AI)

The concept of AI was first contemplated by Alan Turing in 1950, but it wasn't until 1956 that a computer program called The Logic Theorist was developed by Allen Newell, Cliff Shaw, and Herbert A. Simon, proving 38 theorems from *Principia Mathematica* by Alfred North Whitehead and Bertrand Russell. Despite its significance, the program was not well received at the 1956 Dartmouth Summer Research Project on Artificial Intelligence. An important milestone in AI came in 1967 when Joseph Weizenbaum created ELIZA, an early natural language processing program that could communicate with people using pattern matching. AI development was initially limited by computing power, but as computer technology advanced, breakthroughs occurred, such as IBM's Deep Blue defeating world chess champion Garry Kasparov in 1997. AI is now applied in various fields, from personalized advertising and autonomous vehicles to fraud detection, healthcare diagnostics, facial recognition, and voice assistants like Alexa.

B.4 Additive Manufacturing (3D Printing)

Additive manufacturing, or 3D printing, traces its origins to Johannes F. Gottwald's 1971 patent for the Liquid Metal Recorder, a modified inkjet printer that used liquid metal to create shapes. This technology revolutionized manufacturing by enabling rapid prototyping and direct production from design files. Additive manufacturing allows for complex shapes and custom designs, reduces material waste (since it doesn't require cutting or milling), and cuts down on assembly steps. Additionally, products can be manufactured on demand, which is particularly beneficial for specialized or low-volume items.

B.5 Distributed Ledgers

A distributed ledger is a decentralized system that records and verifies transactions across multiple locations and institutions through peer-to-peer networks, using cryptography for security. Every node in the network stores an identical copy of the ledger, and updates to the ledger require verification by a majority of nodes before they are recorded across the entire network. This system offers increased security and transparency, and eliminates the need for a central authority to oversee transactions. The concept of distributed ledgers was introduced by Satoshi Nakamoto in 2008, primarily for use in cryptocurrencies like Bitcoin.

These technologies represent a core group of innovations that have had a profound impact on various industries. While their applications continue to evolve, they are already reshaping fields such as manufacturing, healthcare, transportation, and security.

C Additional Empirical Results

Building on the baseline specification in Table 2, the regression analysis in Table 11 controls for a large number of business owner characteristics and firm business strategies/motivations related to innovation and growth. The regression examines, for robustness, the extent to which the relationships found in Table 2 are explained away by these intrinsic characteristics of the businesses that may be correlated with both VC backing and firm outcomes. The large set of control variables is drawn from the 2018 ABS and defined as follows: "Adv degree" is whether the business owner has a master's or higher degree; "Prior business" is whether the business owner has prior business ownership; "Age 35–54" is whether the business owner's age is between 35 and 54; "Age 55+" is whether the business owner's age is above 55; "Lifestyle" is whether the proprietor owns a business for a lifestyle reason (i.e., flexibility or work-life balance); "Process innov" is whether the business had process innovation (i.e., introduction or improvement in (i) methods of manufacturing, (ii) logistics, delivery or distribution methods, or (iii) supporting activities for processes); "Product innov" is whether the business had product innovation (the introduction or improvement of goods or services); "Patents" is whether the business owns patents or has pending patents; "IP important" is whether intellectual property is important for the business; and "Growth" is whether the business has a strategy to grow.[27, 28]

VC-backed firms have a higher technology adoption rate than non-VC-backed firms even after controlling for detailed business characteristics, as Table 11 shows. The coefficient on the VC-financed dummy declines from 0.106 in column (1) to 0.061 in column (3), where all control variables are employed. Firms' innovation activities are controlled for in column (3). In particular, process innovation is strongly associated with technology adoption. Columns (4)-(9) explore the relationships between the VC financing/technology adoption status and firm outcomes. The difference in firm size between VC high-tech firms and the omitted group (i.e., non-VC, non-high-tech firms) attenuates as more business characteristics are controlled for, but remains significant (statistically and economically) in the regression with all control variables. A similar pattern is observed for the comparison between VC-backed, non-high tech firms, and the omitted group, and for the comparison between non-VC, high-tech firms and the omitted group.

The regression analysis in Table 12 exploits information on the timing of technology adoption. The ABS 2023 asked firms about the timing of AI adoption. The response options were five-year intervals (prior to 1990, 1991–1995, ..., 2016–2020, 2021–present). This data is linked to the Longitudinal Business Database (LBD) using firm identifiers. The dummy variable, Adoption

[27] Similar control variables are also used in McElheran et al. (2024) in their analysis of AI adoption. Here, the definition of technology includes a broad set of advanced technologies beyond AI. Moreover, firm outcomes are examined as a function of the interaction between VC backing and technology adoption.

[28] A business owner is defined as the person who owns the largest percentage in the business. If several owners have the same percentage in the business, "Owner 1" in the ABS form is chosen as the owner.

Table 11: Regression with detailed control variables using ABS (2018)

	(1) adoption	(2) adoption	(3) adoption	(4) ln(emp)	(5) ln(emp)	(6) ln(emp)	(7) ln(rev)	(8) ln(rev)	(9) ln(rev)
VC-financed	0.106***	0.102***	0.0606***						
	(0.00837)	(0.00836)	(0.00819)						
VC high-tech				0.999***	0.919***	0.638***	0.821***	0.730***	0.362***
				(0.0485)	(0.0486)	(0.048)	(0.0761)	(0.0768)	(0.0774)
VC non-high-tech				0.661***	0.604***	0.459***	0.686***	0.618***	0.428***
				(0.0287)	(0.0286)	(0.0284)	(0.0384)	(0.0386)	(0.0386)
Non-VC high-tech				0.397***	0.384***	0.276***	0.484***	0.469***	0.327***
				(0.00681)	(0.00677)	(0.00678)	(0.00895)	(0.00889)	(0.00894)
Adv degree		0.0232***	0.0153***		0.131***	0.109***		0.174***	0.146***
		(0.00183)	(0.0018)		(0.00629)	(0.00619)		(0.00878)	(0.00864)
Prior business		0.0194***	0.0131***		0.181***	0.162***		0.184***	0.159***
		(0.00121)	(0.00119)		(0.00423)	(0.00419)		(0.0059)	(0.00583)
Age 35–54		0.0013	0.00908***		0.011	0.0316***		0.0218	0.0496***
		(0.00258)	(0.00256)		(0.00907)	(0.00902)		(0.0128)	(0.0128)
Age 55+		-0.00402	0.00857**		-0.172***	-0.134***		-0.291***	-0.240***
		(0.00269)	(0.00266)		(0.00948)	(0.00943)		(0.0134)	(0.0133)
Lifestyle		-0.000642	-0.00774***		-0.156***	-0.207***		-0.163***	-0.232***
		(0.00113)	(0.00113)		(0.00417)	(0.00414)		(0.00569)	(0.00565)
Process innov			0.0905***			0.155***			0.215***
			(0.00176)			(0.00521)			(0.00714)
Product innov			0.0176***			-0.00345			0.000273
			(0.00108)			(0.00401)			(0.00552)
Patents			0.0372***			0.261***			0.349***
			(0.0052)			(0.0152)			(0.0211)
IP important			0.0872***			0.273***			0.328***
			(0.00192)			(0.00574)			(0.00777)
Growth			0.0222***			0.301***			0.411***
			(0.0011)			(0.00415)			(0.00574)
+ Fixed effects									
R-squared	0.0363	0.0377	0.0719	0.2086	0.2203	0.2472	0.1745	0.1860	0.2132
N (rounded)	346,000	346,000	346,000	346,000	346,000	346,000	346,000	346,000	346,000
Adopt rate	10.03%								
VC-adopt rate	22.98%								

Notes: Included fixed effects are: year×NAICS (4 digits), state, and firm age. All independent variables are binary variables. The regressions are weighted by the LBD weights. Standard errors are in parentheses and are clustered by firmid. * p<0.05 ** p<0.01 *** p<0.001. N is rounded to protect confidentiality.

Table 12: Regression with Timing of AI Adoption (Two-Way Fixed-Effect Model)

	(1)	**(2)**
	ln(**emp**)	ln(**rev**)
Adoption (during)	0.136***	0.174***
	(0.0116)	(0.0146)
Adoption (post)	0.168***	0.260***
	(0.0291)	(0.0379)
VC (during)	0.266***	0.118
	(0.0453)	(0.103)
VC (post)	0.844***	1.103***
	(0.0516)	(0.102)
+ Fixed effects		
R-squared	0.871	0.894
N (rounded)	6,590,000	4,800,000

Notes: The included fixed effects are: firm, year×NAICS (4 digits), and firm age. The sample consists of firms in ABS (2023) linked to LBD (1978-2021). Revenue is obtained from the LBD (1997-2021). The regressions are weighted by sampling weights [tabulation weights in ABS (2023) in the first column and by tabulation weights × probability weights associated with LBD revenue in the second column]. Standard errors are shown in parentheses and are clustered by firmid. * p<0.05 ** p<0.01 *** p<0.001. N is rounded to protect confidentiality.

(during), indicates that the year for the dependent variable, either employment or revenue, was within the five-year interval during which AI adoption occurred, and the dummy variable, Adoption (post), indicates that the year was after the adoption interval. These two dummy variables take on a value of zero for the years before the adoption interval and in all years for firms that have never adopted AI. Similarly, the dummy variable, VC (during), indicates that the firm raised its first VC financing in the year recorded for either employment or revenue, and the dummy variable, VC (post), means that the firm had raised VC financing before the year. Similar to the adoption timing case, the omitted category here is all years before VC financing and all years for firms that had no VC funding. The linear regression absorbs fixed effects of the firm, year-industry interactions, and firm age. Therefore, the coefficient on Adoption (during) examines how firm size changes during the years of AI adoption relative to years before AI adoption within the firm, controlling for year-industry effects and firm age effects. The table shows that firm size, measured as ln(employment) and ln(revenue), increases during AI adoption and even further after AI adoption. The size of VC-backed firms also increases after the VC funding year. The magnitudes of the estimated effects are larger for VC financing compared to AI adoption.

The findings are in line with a growing literature that documents that the adoption of automation technologies is associated with an increase in employment at the firm level—this literature is surveyed in Restrepo (2024). This literature is further extended here by documenting the increase in employment and revenue after technology adoption in a representative sample of U.S. firms.

To assess the robustness of Figures 2 and 3, Figure 11 and Figure 12 display the dynamic treatment effects of VC backing and technology adoption, respectively, using two alternative methods in

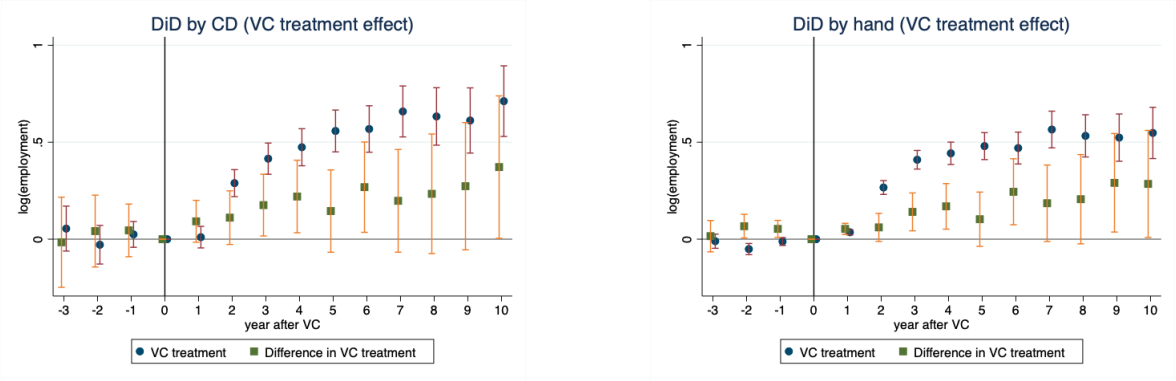


Figure 11: VC Treatment Effects.

Notes: VC treatment effects are estimated using the DiD method developed by de Chaisemartin and d'Haultfoeuille (CD) and DiD by hand based on the sample average of the difference-in-differences between treated-control pairs. Difference in VC treatment refers to the difference in the impact of VC treatment on high-tech adopters versus non-high-tech ones.

Table 13: Difference-in-Differences Analyses (Treatment Effect at $\tau = 10$)

	Methodologies		
	TWFE	**CD**	**DiD by hand**
VC Treatment Effect at $\tau = 10$	0.705	0.712	0.548
	(0.073)	(0.093)	(0.067)
VC Heterogeneity at $\tau = 10$	0.495	0.372	0.285
	(0.120)	(0.187)	(0.141)
High-Tech Treatment Effect at $\tau = 10$	0.135	0.134	0.067
	(0.024)	(0.031)	(0.020)

Notes: The outcome variable is ln(employment). Standard errors are in parentheses. The DiD analysis is conducted three ways: namely, with (i) two-way fixed effects (TWFE) regressions, (ii) estimators developed by de Chaisemartin and d'Haultfoeuille (CD), and (iii) DiD by hand based on the sample average of the difference-in-differences between treated-control pairs. Observations are weighted by the LBD weights.

place of TWFE. The methodologies are discussed in the main text. The figures show little evidence of systematic pre-trends and illustrate employment gains following both treatments. Table 13 reports estimates of the treatment effect in the 10th year after the treatment events. The treatment effect in the 10th year is larger than the average effect over the post-treatment periods from $\tau = 1$ to $\tau = 10$.

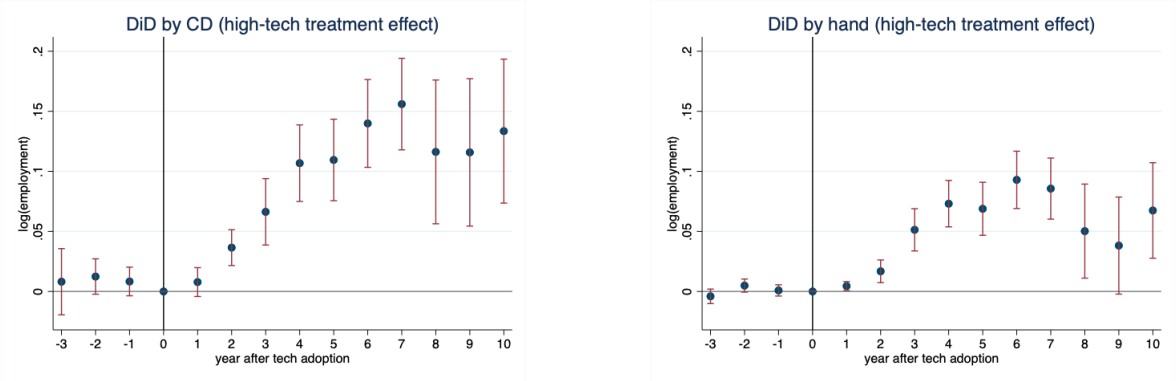


Figure 12: High-tech Treatment Effects.
Notes: High-tech treatment effects are estimated using the DiD method developed by de Chaisemartin and d'Haultfoeuille (CD) and DiD by hand based on the sample average of the difference-in-differences between treated-control pairs.

D Theory

D.1 Nash Bargaining—Lemma 1, Proof

The first-order conditions for $k^2_{\tau v}$,$l^2_{\tau v}(z^2_{\tau v})$, and s_τ associated with the Nash bargaining problem (5) between an entrepreneur and a venture capitalist are (for $\tau = h, n$):

$$\begin{aligned}\eta E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \mathfrak{b}_\tau | p_\tau\Big]^{\eta-1}(1-s_\tau)E[\kappa(z^2_{\tau v})^\zeta (k^2_{\tau v})^{\kappa-1} l^2_{\tau v}(z^2_{\tau v})^\lambda - r|p_\tau] \\ \times E\Big[s_\tau[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \alpha_\tau - \xi p_\tau | p_\tau\Big]^{1-\eta} \\ = E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \mathfrak{b}_\tau | p_\tau\Big]^{\eta} \\ \times (1-\eta)E\Big[s_\tau[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \alpha_\tau - \xi p_\tau | p_\tau\Big]^{-\eta} \\ \times s_\tau E[\kappa(z^2_{\tau v})^\zeta (k^2_{\tau v})^{\kappa-1} l^2_{\tau v}(z^2_{\tau v})^\lambda - r|p_\tau], \quad (25)\end{aligned}$$

$$\begin{aligned}\eta E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \mathfrak{b}_\tau | p_\tau\Big]^{\eta-1}(1-s_\tau)[\lambda(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^{\lambda-1} - w] \\ \times E\Big[s_\tau[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \alpha_\tau - \xi p_\tau | p_\tau\Big]^{1-\eta} \\ = E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \mathfrak{b}_\tau | p_\tau\Big]^{\eta} \\ \times (1-\eta)E\Big[s_\tau[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \alpha_\tau - \xi p_\tau | p_\tau\Big]^{-\eta} \\ \times s_\tau[\lambda(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^{\lambda-1} - w], \quad (26)\end{aligned}$$

and

$$\eta E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \mathfrak{b}_\tau | p_\tau\Big]^{\eta-1}$$
$$\times E[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}|p_\tau]$$
$$\times E\Big[s_\tau[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \alpha_\tau - \xi p_\tau | p_\tau\Big]^{1-\eta}$$
$$= E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \mathfrak{b}_\tau | p_\tau\Big]^{\eta}$$
$$\times (1-\eta)E\Big[s_\tau[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \alpha_\tau - \xi p_\tau | p_\tau\Big]^{-\eta}$$
$$\times E[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}|p_\tau]. \quad (27)$$

Start with the first order condition (25). It is automatically satisfied when (6) holds. Likewise, (7) will guarantee that (26) is fulfilled. To derive the solution for s_τ note that the term $E[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}|p_\tau]$ cancels out on both sides of (27). Then, divide both sides of equation (27) by $E\Big[(1-s_\tau)[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \mathfrak{b}_\tau | p_\tau\Big]^{\eta-1}$ and $E\Big[s_\tau[(z^2_{\tau v})^\zeta (k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}] - \alpha_\tau - \xi p_\tau | p_\tau\Big]^{-\eta}$, and then solve for s_τ to get equation (8).

D.2 Bank Financing—Lemma 2, Proof

In the bank financing problem (13) the entrepreneur will make the interest payment $\tilde{r}_\tau(k^2_{\tau b}; p_\tau)$ with probability $\Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)$. Solving out for $\tilde{r}_\tau(k^2_{\tau b}; p_\tau)$ in (13) by using the bank's zero-profit condition (12) gives

$$E[\pi^2_{\tau b}|p_\tau] = \max_{k^2_{\tau b}, l^2_{\tau b}(z^2_{\tau b})} \Big\{ \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau) E[(z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^\lambda - wl^2_{\tau b}(z^2_{\tau b}) + \delta^2\pi^3_{\tau b} | z^2_{\tau b} \geq z^{2*}_\tau, p_\tau]$$
$$- rk^2_{\tau b} + [1 - \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)] E[i_\tau(z^2_{\tau b}, k^2_{\tau b}) | z^2_{\tau b} < z^{2*}_\tau, p_\tau] \Big\}.$$

Next, use (10) to substitute out for $i_\tau(z^2_{\tau b}, k^2_{\tau b})$ in the above maximization problem, which yields

$$E[\pi^2_{\tau b}|p_\tau] = \max_{k^2_{\tau b}, l^2_{\tau b}(z^2_{\tau b})} \Big\{ \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau) E[(z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^\lambda - wl^2_{\tau b}(z^2_{\tau b}) + \delta^2\pi^3_{\tau b} | z^2_{\tau b} \geq z^{2*}_\tau, p_\tau]$$
$$- rk^2_{\tau b} + [1 - \Pr(z^2_{\tau b} \geq z^{2*}_\tau | p_\tau)] E[(z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^\lambda - wl^2_{\tau b}(z^2_{\tau b}) + \delta^2\pi^3_{\tau b} | z^2_{\tau b} < z^{2*}_\tau, p_\tau] \Big\}.$$

Finally, this gives the maximization problem shown below which has the associated first-order conditions (14) and (15).

$$E[\pi^2_{\tau b}|p_\tau] = \max_{k^2_{\tau b}, l^2_{\tau b}(z^2_{\tau b})} \Big\{ E[(z^2_{\tau b})^\zeta (k^2_{\tau b})^\kappa l^2_{\tau b}(z^2_{\tau b})^\lambda - rk^2_{\tau b} - wl^2_{\tau b}(z^2_{\tau b}) + \delta^2\pi^3_{\tau b} | p_\tau] \Big\}. \quad (28)$$

D.3 Equilibrium Definition

Definition. An equilibrium consists of a solution for: (i) the fractions of newborn startups using the advanced and conventional technologies, $\Pr\left[E[\pi^1|h]-\phi \geq E[\pi^1|n]\right]$ and $\Pr\left[E[\pi^1|h]-\phi < E[\pi^1|n]\right]$; (ii) the labor hired by newborn startups using the high tech and conventional technologies, $l_h^1(z_h^1)$ and $l_n^1(z_n^1)$; (iii) the fractions of high-tech adopting adolescent startups funded by VC and banks, $\Pr[p_h \geq p_h^*]$ and $\Pr[p_h < p_h^*]$; (iv) the capital and labor hired by such adolescent startups, $k_{hv}^2(p_h \geq p_h^*)$, $k_{hb}^2(p_h < p_h^*)$, $l_{hv}^2(z_{hv}^2)$, and $l_{hb}^2(z_{hb}^2)$; (v) the fractions of conventional technology adopting adolescent startups funded by VC and banks, $\Pr[p_n \geq p_n^*]$ and $\Pr[p_n < p_n^*]$; (vi) the capital and labor hired by such adolescent startups, $k_{nv}^2(p_n \geq p_n^*), k_{nb}^2(p_n < p_n^*)$, $l_{nv}^2(z_{nv}^2)$, and $l_{nb}^2(z_{nb}^2)$; (vii) the threshold rules for VC funding of advanced and conventional technology projects, p_h^* and p_n^*; (viii) the amounts of capital, $k_{hv}^3(z_{hv}^3), k_{hb}^3(z_{hb}^3), k_{nv}^3(z_{nv}^3)$, and $k_{nb}^3(z_{nb}^3)$, and labor hired by adult firms, $l_{hv}^3(z_{hv}^3), l_{hb}^3(z_{hb}^3), l_{nv}^3(z_{nv}^3)$, and $l_{nb}^3(z_{nb}^3)$; and (ix) the wage rate, w. These allocations are determined such that:

1. The fractions of newborn startups using the advanced and conventional technologies, $\Pr\left[E[\pi^1|h]-\phi \geq E[\pi^1|n]\right]$ and $\Pr\left[E[\pi^1|h]-\phi < E[\pi^1|n]\right]$, are determined by the technology choice decision (20).

2. Newborn high-tech and conventional startups hire labor, $l_h^1(z_h^1)$ and $l_n^1(z_n^1)$, to maximize the entrepreneur's profits in accordance with (19).

3. The fractions of advanced technology adolescent startups funded by venture capitalists and banks, $\Pr[p_h \geq p_h^*]$ and $\Pr[p_h < p_h^*]$, are governed by the financing decision (16).

4. Adolescent high-tech and conventional startups that are funded by venture capitalists hire labor, $l_{hv}^2(z_{hv}^2)$ and $l_{nv}^2(z_{nv}^2)$, in keeping with the solution to the Nash Bargaining problems as specified by (7).

5. The fractions of conventional technology adolescent startups funded by venture capitalists and banks, $\Pr[p_n \geq p_n^*]$ and $\Pr[p_n < p_n^*]$, are ruled by the financing decision (16).

6. Adolescent startups that are funded by banks hire labor, $l_{hb}^2(z_{hb}^2)$ and $l_{nb}^2(z_{nb}^2)$, to maximize the entrepreneur's profits as stated by (15).

7. The threshold rules for VC funding for advanced and conventional technologies, p_h^* and p_n^*, are governed by (17).

8. Capital is hired by VC-funded adolescent startups, $k_{hv}^2(p_h \geq p_h^*)$ and $k_{nv}^2(p_n \geq p_n^*)$, in line with the outcome of the Nash Bargaining problem or with equation (6).

9. Capital is hired by bank-funded adolescent startups, $k_{hb}^2(p_h < p_h^*)$ and $k_{nb}^2(p_n < p_n^*)$, as dictated by (14), to maximize the entrepreneur's profits.

Table 14: Reallocation Effect: No Capital Gains Tax Experiment

Decomposition of Δ Employment, %			
	Δ Empl	**Δ Firms**	**Δ Total**
	1	***2***	***3***
Newborn Startups			
High-Tech	-1.1	1.5	0.4
Non-High-Tech	-6.2	-1.1	-7.3
Adolescent Startups			
High-Tech, VC	-3.1	15.3	12.3
High-Tech, Bank	-8.7	0.5	-8.2
Non-High-Tech, VC	-0.2	-3.6	-3.8
Non-High-Tech, Bank	-23.4	-2.0	-25.4
Adult Firms			
High-Tech, VC	-94.0	469.2	375.2
High-Tech, Bank	-97.1	5.8	-91.2
Non-High-Tech, VC	-2.2	-49.1	-51.3
Non-High-Tech, Bank	-92.9	-7.8	-100.7

10. Adult firms hire capital, $k^3_{hv}(z^3_{hv})$, $k^3_{hb}(z^3_{hb})$, $k^3_{nv}(z^3_{nv})$, and $k^3_{nb}(z^3_{nb})$, and labor, $l^3_{hv}(z^3_{hv})$, $l^3_{hb}(z^3_{hb})$, $l^3_{nv}(z^3_{nv})$, and $l^3_{nb}(z^3_{nb})$, to maximize profits as specified by (2) and (3).

11. The labor market clears in accordance with (24). This determines wages, w.

12. The rental rate on capital, r, and the survival-adjusted discount factors, δ^1 and δ^2, are pinned down by (22) and (23).

E Additional Thought Experiments

E.1 Reallocation effects of no capital gains taxes for high-tech C corporations

Removing capital gains taxes for high-tech C corporations generates substantial reallocation, as Table 14 shows. The fraction of high-tech, VC-funded firms soars at the expense of non-high-tech firms (column 2). Since high-tech, VC-funded firms are very productive, they account for the rise in employment and GDP as column 3 establishes—note that the contribution of essentially every other type of startups to employment is negative. The average employment of high-tech firms actually declines (see column 1), as less productive startups adopt advanced technologies and the real wage rises.

E.2 Reallocation effects of subsidies

In the experiment that subsidizes all adolescent startups (subsection 7.3), it is clear from Table 15 that reallocation effects are important. The rise in aggregate employment is primarily driven by the

Table 15: Reallocation Effect: Subsidy, All

Decomposition of Δ Employment, %			
	Δ Empl	**Δ Firms**	**Δ Total**
	1	***2***	***3***
Newborn Startups			
High-Tech	-1.1	0.7	-0.4
Non-High-Tech	-6.3	-0.5	-6.9
Adolescent Startups			
High-Tech, VC	6.2	-0.9	5.2
High-Tech, Bank	51.7	2.9	54.5
Non-High-Tech, VC	6.2	0.4	6.6
Non-High-Tech, Bank	226.6	-1.5	225.1
Adult Firms			
High-Tech, VC	-15.8	-26.9	-42.6
High-Tech, Bank	-60.7	30.5	-30.3
Non-High-Tech, VC	-10.2	5.6	-4.6
Non-High-Tech, Bank	-100.9	-5.8	-106.7

increase in average employment by adolescent startups, as displayed in column 1. In particular, non-high tech, bank-funded adolescent firms increase their employment significantly and this accounts for most of the increase in aggregate employment, as can be deduced from columns 1 and 3. These startups on average have the lowest levels of productivity, however. When using bank funding an entrepreneur reaps all of the benefit from the subsidy. By contrast, the entrepreneur must share part of the benefit with the venture capitalist when using VC funding. There is a reduction in employment for all types of adult firms—again see column 1. This transpires for two reasons. First, the subsidy drives up the wage rate, and second, adult firms do not receive the subsidy. As column 2 illustrates, the drop in the fraction of both adolescent and adult high-tech, VC-funded firms works to decrease aggregate employment. Also note that the number of non-high-tech, bank-funded firms declines—again see column 2—as there is a shift toward high-tech, bank-financed ones and non-high-tech, VC-funded ones.

In the experiment that subsidizes only high-tech adolescent startups, reallocation effects once again play a major role. The subsidy stimulates both a rise in employment for high-tech adolescent startups and their numbers, as Table 16, columns 1 and 2 show. These extra startups grow into adult firms. The rising share of adult high-tech firms contributes significantly to the increase in aggregate employment, as can be gleaned from columns 2 and 3. Average employment for these types of firms, however, actually decreases—column 1. At the margin, less productive startups are enticed to adopt advanced technology and labor is now more expensive. The net increase in employment—column 3—occurs because adult high-tech firms are large on average. This comes at the expense of other types of firms. Non-high-tech, bank-financed adult firms provide the biggest offset to the rise in employment, because of the decline in their average employment and in their

Table 16: Reallocation Effect: Subsidy, High Tech

Decomposition of Δ Employment, %			
	Δ Empl	**Δ Firms**	**Δ Total**
	1	***2***	***3***
Newborn Startups			
High-Tech	-1.1	6.2	5.1
Non-High-Tech	-6.3	-4.5	-10.9
Adolescent Startups			
High-Tech, VC	10.5	2.8	13.3
High-Tech, Bank	89.5	21.2	110.7
Non-High-Tech, VC	-0.2	-4.3	-4.4
Non-High-Tech, Bank	-24.0	-10.4	-34.4
Adult Firms			
High-Tech, VC	-22.0	81.0	59.0
High-Tech, Bank	-65.3	223.8	158.5
Non-High-Tech, VC	-2.5	-58.0	-60.5
Non-High-Tech, Bank	-95.0	-41.4	-136.4

share in the total number of firms—see columns 1, 2, and 3.

F Supplemental Material, Households

Behind the scenes is a representative household residing in a stationary equilibrium. The household solves the following intertemporal maximization problem:

$$\max_{c_t, l_t, k_{t+1}} \sum_{t=0}^{\infty} \beta^t \ln(c_t - \upsilon \frac{l^{1+\theta}}{1+\theta}),$$

subject to

$$c_t + k_{t+1} = w_t l_t + r_t k_t + \pi_t + (1 - \mathfrak{d}) k_t,$$

where c_t, l_t, k_t, and π_t are period-t aggregate consumption, labor supply, capital, and profits. The solution to this problem gives the consumption Euler equation and the consumption/labor efficiency condition

$$\frac{1}{c_t - \upsilon l_t^{1+\theta}/(1+\theta)} = \beta \frac{1}{c_{t+1} - \upsilon l_{t+1}^{1+\theta}/(1+\theta)} (r_t + 1 - \mathfrak{d})$$

and

$$\upsilon l_t^{\theta} = w_t, \text{ cf. equation (21).}$$

F.1 Stationary Equilibrium

It is trivial to deduce from the consumption Euler equation that in a stationary equilibrium,

$$r = 1/\beta - 1 + \mathfrak{d} = \iota + \mathfrak{d}, \text{ cf. equation (22)},$$

where the subjective rate of time preference is $\iota \equiv 1/\beta - 1$. The consumer's budget constraint can be written as

$$c = wl + rk + \pi - \mathfrak{d}k.$$

Now, the national income identity implies that aggregate output, o, is given by,[29]

$$o = wl + rk + \pi$$

so that

$$c = o - \mathfrak{d}k.$$

G Supplemental Material, Adjusting for Period Length

When the model is matched with the U.S. data the 3 phases are of different potential lengths: the newborn (3 years), adolescent (8 years), and adult (∞ years). Some adjustments are required to the labor-market-clearing conditions, discounted profits, and employment.

G.1 Labor-Market-Clearing Condition

From Section 6, the mass of newborn startups is $\mathfrak{m}_n = (1-\mathfrak{s}_n^3)/(1-\mathfrak{s}_n)$, the mass of adolescent startups is $\mathfrak{m}_a = \mathfrak{s}_n^3(1-\mathfrak{s}_a^8)/(1-\mathfrak{s}_a)$, and the mass of adult firms is $\mathfrak{s}_n^3\mathfrak{s}_a^8/(1-\mathfrak{s}_e)$. Given this, the labor-market-clearing condition (24) rewrites as

$$\begin{aligned}
&\mathfrak{m}_n\{\Pr\Big[E[\pi^1|h]-\phi \geq E[\pi^1|n]\Big]E[l_h^1(z_h^1)] + \Pr\Big[E[\pi^1|h]-\phi < E[\pi^1|n]\Big]E[l_n^1(z_n^1)]\} \\
&+\mathfrak{m}_a\Big\{\Pr\Big[E[\pi^1|h]-\phi \geq E[\pi^1|n]\Big]\{\Pr[p_h \geq p_h^*]E[l_{hv}^2(z_{hv}^2)|p_h \geq p_h^*]+\Pr[p_h < p_h^*]E[l_{hb}^2(z_{hb}^2)|p_h < p_h^*]\}\Big\} \\
&+\mathfrak{m}_a\Big\{\Pr\Big[E[\pi^1|h]-\phi < E[\pi^1|n]\Big]\{\Pr[p_n \geq p_n^*]E[l_{nv}^2(z_{nv}^2)|p_n \geq p_n^*]+\Pr[p_n < p_n^*]E[l_{nb}^2(z_{nb}^2)|p_n < p_n^*]\}\Big\} \\
&+\mathfrak{m}_e\Big\{\Pr\Big[E[\pi^1|h]-\phi \geq E[\pi^1|n]\Big]\{\Pr[p_h \geq p_h^*]E[l_{hv}^3(z_{hv}^3)|p_h \geq p_h^*]+\Pr[p_h < p_h^*]E[l_{hb}^3(z_{hb}^3)|p_h < p_h^*]\}\Big\} \\
&+\mathfrak{m}_e\Big\{\Pr\Big[E[\pi^1|h]-\phi < E[\pi^1|n]\Big]\{\Pr[p_n \geq p_n^*]E[l_{nv}^3(z_{nv}^3)|p_n \geq p_n^*]+\Pr[p_n < p_n^*]E[l_{nb}^3(z_{nb}^3)|p_n < p_n^*]\}\Big\} \\
&= l
\end{aligned}$$

[29] For each firm j it is the case that $o_j = wl_j + rk_j + \pi_j$. So, the national income identity just sums over all firms.

G.2 Discounted Profits and Employments

The annual survival-adjusted discount factors for each phase are $\delta_n = \mathfrak{s}_n/(1+\iota)$, $\delta_a = \mathfrak{s}_a/(1+\iota)$, and $\delta_e = \mathfrak{s}_e/(1+\iota)$. There are two relevant concepts: discounted profits (left) and employment (right) for each type of newborn startup.

1. Type-τ newborn startups

$$(1+\delta_n+\delta_n^2)\pi_\tau^1 = \frac{1-\delta_n^3}{1-\delta_n}\pi_\tau^1 \text{ and } (1+\mathfrak{s}_n+\mathfrak{s}_n^2)E[l_\tau^1(z_\tau^1)] = \frac{1-\mathfrak{s}_n^3}{1-\mathfrak{s}_n}E[l_\tau^1(z_\tau^1)];$$

2. Type-τf adolescent startups

$$\frac{1-\delta_a^8}{1-\delta_a}\pi_{\tau f}^2 \text{ and } \frac{1-\mathfrak{s}_a^8}{1-\mathfrak{s}_a}E[l_{\tau f}^2(z_{\tau f}^2)];$$

3. Type-τf adult firms

$$\frac{1}{1-\delta_e}\tilde{\pi}_{\tau f}^3 \text{ and } \frac{1}{1-\mathfrak{s}_e}E[l_{\tau f}^3(z_{\tau f}^3)].$$

H Supplemental Material, Firms

Formulas from the firms' problems are derived that are used to compute the model's equilibrium.

H.1 Adult Firms

By combining (2) and (3), the solutions for capital and labor for an adult firm are

$$k_{\tau f}^3(z_{\tau f}^3) = z_{\tau f}^3[(\frac{\kappa}{r})^{1-\lambda}(\frac{\lambda}{w})^{\lambda}]^{\frac{1}{\zeta}}$$

and

$$l_{\tau f}^3(z_{\tau f}^3) = z_{\tau f}^3[(\frac{\kappa}{r})^{\kappa}(\frac{\lambda}{w})^{1-\kappa}]^{\frac{1}{\zeta}}. \tag{29}$$

Accordingly, by substituting these solutions into (1), momentary profits during the adult phase are given by

$$\tilde{\pi}_{\tau f}^3(z_{\tau f}^3) = (1-\kappa-\lambda)z_{\tau f}^3[(\frac{\kappa}{r})^{\kappa}(\frac{\lambda}{w})^{\lambda}]^{1/\zeta}.$$

H.2 Adolescent Startups

From (7), (6), (14), and (15), it can be seen that the generic first-order conditions for an adolescent startup's capital and labor read

$$\lambda(z_{\tau f}^2)^{\zeta}(k_{\tau f}^2)^{\kappa}l_{\tau f}^2(z_{\tau f}^2)^{\lambda-1} = w \tag{30}$$

and

$$\kappa E[(z_{\tau f}^2)^{\zeta}(k_{\tau f}^2)^{\kappa-1} l_{\tau f}^2 (z_{\tau f}^2)^{\lambda} | p_\tau] = r.$$

Combining the two first-order conditions yields the following expression for capital investment:

$$k_{\tau f}^2 = \left[\left(\frac{\kappa}{r}\right)^{1-\lambda} \left(\frac{\lambda}{w}\right)^{\lambda} \right]^{\frac{1}{\zeta}} E\left[(z_{\tau f}^2)^{\frac{\zeta}{1-\lambda}} | p_\tau \right]^{\frac{1-\lambda}{\zeta}}. \tag{31}$$

To use this equation requires knowledge of the conditional expectation $E\left[(z_{\tau f}^2)^{\frac{\zeta}{1-\lambda}} | p_\tau\right]$. This can be computed using the properties of the log-normal distribution.

To this end, let $\tilde{z}_{\tau f} \equiv (z_{\tau f}^2)^{\frac{\zeta}{1-\lambda}}$. Then,

$$\ln \widetilde{z}_{\tau f} = \frac{\zeta}{1-\lambda} \ln z_{\tau f}^2 = \frac{\zeta}{1-\lambda} (\ln p_\tau + \ln \varepsilon_{\tau f}).$$

Now, the sum of two independently distributed normal variables is normal, with mean and variance given by the sum of the means and the variances of the two original distributions. Thus,

$$\ln \widetilde{z}_{\tau f} | p_\tau \sim \mathcal{N}(\mu_{\tau f}, \sigma_{\tau f}^2),$$

where $\mu_{\tau f} = \frac{\zeta}{1-\lambda}(\ln p_\tau + \gamma_{\tau f})$ and $\sigma_{\tau f}^2 = \frac{\zeta^2}{(1-\lambda)^2}\sigma_{\varepsilon_\tau}^2$ (note at this stage the variance of p_τ is zero). Then, using the formula for the expected value of a variable that is distributed according to a log-normal distribution gives

$$E\left[(z_{\tau f}^2)^{\frac{\zeta}{1-\lambda}} | p_\tau\right] = E[\tilde{z}_{\tau f} | p_\tau] = \exp\left\{ \mu_{\tau f} + \frac{1}{2}\sigma_{\tau f}^2 \right\}.$$

Formula (31) for $k_{\tau f}^2$ now appears as

$$k_{\tau f}^2(p_\tau) = p_\tau \exp\left\{ \gamma_{\tau f} + \frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2} \right\} \left[\left(\frac{\kappa}{r}\right)^{1-\lambda} \left(\frac{\lambda}{w}\right)^{\lambda} \right]^{\frac{1}{\zeta}}. \tag{32}$$

By substituting (32) into (30), a solution can be derived for labor, $l_{\tau f}^2(z_{\tau f}^2)$, conditional both on potential, p_τ, and the productivity shock, $\varepsilon_{\tau f}$. Specifically,

$$l_{\tau f}^2(z_{\tau f}^2) = p_\tau \varepsilon_{\tau f}^{\frac{\zeta}{1-\lambda}} \exp\left\{ \frac{\kappa}{1-\lambda}\gamma_{\tau f} + \frac{\kappa\zeta}{(1-\lambda)^2}\frac{\sigma_{\varepsilon_\tau}^2}{2} \right\} \left(\frac{\kappa}{r}\right)^{\frac{\kappa}{\zeta}} \left(\frac{\lambda}{w}\right)^{\frac{\zeta+\lambda\kappa}{(1-\lambda)\zeta}}. \tag{33}$$

Last, the adolescent startup's expected profits, conditional on its potential, read

$$E[\hat{\pi}_{\tau f}^2 | p_\tau] \equiv E\left[(z_{\tau f}^2)^{\zeta} \left(k_{\tau f}^2(p_\tau)\right)^{\kappa} l_{\tau f}^2 (z_{\tau f}^2)^{\lambda} - r k_{\tau f}^2(p_\tau) - w l_{\tau f}^2(z_{\tau f}^2) | p_\tau \right].$$

These profits may *not* be what either an entrepreneur or a financier earns. By using the policy functions (32) and (33), it follows that

$$E[\hat{\pi}^2_{\tau f}|p_\tau] = p_\tau(1-\lambda-\kappa)\exp\left\{\gamma_{\tau f} + \frac{\zeta}{1-\lambda}\frac{\sigma^2_{\varepsilon_\tau}}{2}\right\}\left[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^\lambda\right]^{\frac{1}{\zeta}}. \tag{34}$$

Expected Selling Value

The selling value of a startup at the end of the adolescent phase, conditional on its potential is $E[\pi^3_{\tau f}|p_\tau]$. Now,

$$\pi^3_{\tau f} = \frac{1}{1-\delta^3}\tilde{\pi}^3_{\tau f} = \frac{1}{1-\delta^3}(1-\lambda-\kappa)z^3_{\tau f}[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^\lambda]^{1/\zeta},$$

where $z^3_{\tau f} = \chi_{\tau f} z^2_{\tau f} = \chi_{\tau f} p_\tau \varepsilon_{\tau f}$. So to compute the expected selling value, $E[\pi^3_{\tau f}|p_\tau]$, requires a solution for $E[z^3_{\tau f}|p_\tau]$. By using the properties of the log-normal, $E[z^3_{\tau f}|p_\tau]$ can be rewritten as

$$E[z^3_{\tau f}|p_\tau] = \chi_{\tau f} p_\tau E[\varepsilon_{\tau f}|p_\tau] = \chi_{\tau f} p_\tau \exp\left\{\gamma_{\tau f} + \frac{1}{2}\sigma^2_{\varepsilon_\tau}\right\}.$$

Thus, the expected selling value of an adolescent startup rewrites as

$$E[\pi^3_{\tau f}|p_\tau] = \frac{1}{1-\delta^3}(1-\lambda-\kappa)\chi_{\tau f} p_\tau \exp\left\{\gamma_{\tau f} + \frac{1}{2}\sigma^2_{\varepsilon_\tau}\right\}[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^\lambda]^{1/\zeta}, \tag{35}$$

where $f = v$, if $p_\tau \geq p^*_\tau$, and $f = b$, if $p_\tau < p^*_\tau$.

Entrepreneur's Expected Profits, Bank Financing

It is easy to deduce that in the adolescent phase the entrepreneur's expected profits from bank financing are

$$E[\pi^2_{\tau b}|p_\tau] = E[\hat{\pi}^2_{\tau b}|p_\tau] + \delta^2 E[\pi^3_{\tau b}|p_\tau],$$

where momentary expected profits are given by $E[\hat{\pi}^2_{\tau b}|p_\tau]$ and the discounted expected selling value by $\delta^2 E[\pi^3_{\tau b}|p_\tau]$. Equations (34) and (35) allow this to be modified to

$$E[\pi^2_{\tau b}|p_\tau] = p_\tau(1-\lambda-\kappa)\left[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^\lambda\right]^{\frac{1}{\zeta}}\left[\exp\{\gamma_{\tau b} + \frac{\zeta}{1-\lambda}\frac{\sigma^2_{\varepsilon_\tau}}{2}\} + \frac{\delta^2}{1-\delta^3}\chi_{\tau b}\exp\{\gamma_{\tau b} + \frac{1}{2}\sigma^2_{\varepsilon_\tau}\}\right]. \tag{36}$$

Entrepreneur's Expected Profits, Venture Capital Financing

From the Nash Bargaining problem (5) it is clear that the entrepreneur's expected profits in the adolescent phase from venture capital financing are

$$E[\pi^2_{\tau v}|p_\tau] = E\left[\Big(1-s_\tau(p_\tau)\Big)[(z^2_{\tau v})^\zeta(k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}]|p_\tau\right].$$

Equation (8) in turn implies that

$$E\left[\Big(1-s_\tau(p_\tau)\Big)[(z^2_{\tau v})^\zeta(k^2_{\tau v})^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v} - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}]|p_\tau\right]$$
$$= (1-\eta)E[\pi^2_{\tau b}|p_\tau]+\eta E\left[(z^2_{\tau v})^\zeta\left(k^2_{\tau v}(p_\tau)\right)^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v}(p_\tau) - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v} - \alpha_\tau - \xi p_\tau|p_\tau\right]. \tag{37}$$

Following steps parallel to the derivation of (36), it can be established that

$$E\left[(z^2_{\tau v})^\zeta\left(k^2_{\tau v}(p_\tau)\right)^\kappa l^2_{\tau v}(z^2_{\tau v})^\lambda - rk^2_{\tau v}(p_\tau) - wl^2_{\tau v}(z^2_{\tau v}) + \delta^2\pi^3_{\tau v}|p_\tau\right] =$$
$$p_\tau(1-\lambda-\kappa)\left[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^\lambda\right]^{\frac{1}{\zeta}}\left[\exp\{\gamma_{\tau v}+\frac{\zeta}{1-\lambda}\frac{\sigma^2_{\varepsilon_\tau}}{2}\}+\frac{\delta^2}{1-\delta^3}\chi_{\tau v}\exp\{\gamma_{\tau v}+\frac{1}{2}\sigma^2_{\varepsilon_\tau}\}\right]. \tag{38}$$

Finally, plugging (38) into (37) and rearranging yields the expected profits from venture capital financing:

$$E[\pi^2_{\tau v}|p_\tau] = p_\tau(1-\lambda-\kappa)\left[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^\lambda\right]^{\frac{1}{\zeta}}\times$$
$$\left\{\exp\{\frac{\zeta}{1-\lambda}\frac{\sigma^2_{\varepsilon_\tau}}{2}\}\left[\eta(e^{\gamma_{\tau v}}-e^{\gamma_{\tau b}})+e^{\gamma_{\tau b}}\right]+\frac{\delta^2}{1-\delta^3}\exp\{\frac{1}{2}\sigma^2_{\varepsilon_\tau}\}\chi_{\tau b}\left[\eta(\frac{\chi_{\tau v}}{\chi_{\tau b}}e^{\gamma_{\tau v}}-e^{\gamma_{\tau b}})+e^{\gamma_{\tau b}}\right]\right\}-\eta(\alpha_\tau+\xi p_\tau). \tag{39}$$

H.3 Newborn Startups

From (19) the solution for the labor hired by a newborn startup is

$$l^1_\tau(z^1_\tau) = \left[\frac{\lambda}{w}(z^1_\tau)^\zeta m^\kappa_\tau\right]^{\frac{1}{1-\lambda}}. \tag{40}$$

Using this in (18) then gives the momentary profits for a newborn startup:

$$\pi^1_\tau(z^1_\tau) = (1-\lambda)\left[\left(\frac{\lambda}{w}\right)^\lambda(z^1_\tau)^\zeta m^\kappa_\tau\right]^{\frac{1}{1-\lambda}}. \tag{41}$$

Entrepreneur's Expected Profits

For a newborn startup the entrepreneur's unconditional expected profits from using technology τ are given by

$$E[\pi^1|\tau] = E[\pi^1_\tau] + \delta^1 E[\pi^2_\tau],$$

where

$$E[\pi^2_\tau] = \Pr[p_\tau \geq p^*_\tau]E[\pi^2_{\tau v}|p_\tau \geq p^*_\tau] + \Big[1-\Pr[p_\tau \geq p^*_\tau]\Big]E[\pi^2_{\tau b}|p_\tau < p^*_\tau].$$

Here $E[\pi_\tau^1]$ is the expected momentary profits from the newborn phase and $E[\pi_\tau^2]$ is the expected profits from the adolescent phase. The terms for $E[\pi_\tau^1]$ and $E[\pi_\tau^2]$ are now computed, starting with the latter.

By using (36) and (39), the expected profits from the adolescent phase are

$$\begin{aligned}E[\pi_\tau^2] = \left[1 - \Pr[p_\tau \geq p_\tau^*]\right] \times E[p_\tau | p_\tau < p_\tau^*](1-\lambda-\kappa)\left[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^\lambda\right]^{\frac{1}{\zeta}} \\ \times \left\{\exp\{\gamma_{\tau b} + \frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\} + \frac{\delta^2}{1-\delta^3}\chi_{\tau b}\exp\{\gamma_{\tau b} + \frac{1}{2}\sigma_{\varepsilon_\tau}^2\}\right\} \\ + \Pr[p_\tau \geq p_\tau^*] \times \{E[p_\tau | p_\tau > p_\tau^*](1-\lambda-\kappa)\left[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^\lambda\right]^{\frac{1}{\zeta}} \times \\ \left[\exp\{\frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\}\left[\eta(e^{\gamma_{\tau v}} - e^{\gamma_{\tau b}}) + e^{\gamma_{\tau b}}\right] + \frac{\delta^2}{1-\delta^3}\exp\{\frac{1}{2}\sigma_{\varepsilon_\tau}^2\}\chi_{\tau b}\left[\eta(\frac{\chi_{\tau v}}{\chi_{\tau b}}e^{\gamma_{\tau v}} - e^{\gamma_{\tau b}}) + e^{\gamma_{\tau b}}\right]\right] \\ - \eta\left(\alpha_\tau + \xi E[p_\tau | p_\tau > p_\tau^*]\right)\},\end{aligned}$$

Next, using the formula for the expected value of a variable with a truncated log-normal distribution (see Appendix J) allows the expected values for the potentials, $E[p_\tau | p_\tau < p_\tau^*]$ and $E[p|p > p^*]$, to be put forth as

$$E[p_\tau | p_\tau < p_\tau^*] = E\left[e^{\ln p_\tau} | \ln p_\tau < \ln p_\tau^*\right] = \exp\left\{\mu_{p_\tau} + \frac{\sigma_{p_\tau}^2}{2}\right\}\frac{\Phi_{\mu_{p_\tau}^*, \sigma_{p_\tau}^2}(\ln p_\tau^*)}{\Phi_{\mu_{p_\tau}, \sigma_{p_\tau}^2}(\ln p_\tau^*)} \tag{42}$$

and

$$E[p_\tau | p_\tau > p_\tau^*] = E\left[e^{\ln p_\tau} | \ln p_\tau > \ln p_\tau^*\right] = \exp\left\{\mu_{p_\tau} + \frac{\sigma_{p_\tau}^2}{2}\right\}\frac{1 - \Phi_{\mu_{p_\tau}^*, \sigma_{p_\tau}^2}(\ln p_\tau^*)}{1 - \Phi_{\mu_{p_\tau}, \sigma_{p_\tau}^2}(\ln p_\tau^*)}, \tag{43}$$

where $\Phi_{\mu_{p_\tau}^*, \sigma_{p_\tau}^2}$ denotes the cumulative distribution function for a normal distribution with mean $\mu_{p_\tau}^* \equiv \mu_{p_\tau} + \sigma_{p_\tau}^2$ and variance $\sigma_{p_\tau}^2$.

Last, using (41), the unconditional momentary profits from the newborn phase, $E[\pi_\tau^1]$, can be expressed as

$$E[\pi_\tau^1] = (1-\lambda)\left[\left(\frac{\lambda}{w}\right)^\lambda m_\tau^\kappa\right]^{\frac{1}{1-\lambda}} E\left[(z_\tau^1)^{\frac{\zeta}{1-\lambda}}\right].$$

The properties of the bivariate log-normal distribution allow this to read

$$E\left[(z_\tau^1)^{\frac{\zeta}{1-\lambda}}\right] = \exp\left\{\frac{\zeta}{1-\lambda}\mu_{z_\tau^1} + \left(\frac{\zeta}{1-\lambda}\right)^2\frac{\sigma_{z_\tau^1}^2}{2}\right\}.$$

I Supplemental Material, Data Targets

Formulas for the data targets are presented here. In what follows, let $\Phi_{\mu,\sigma^2}(x)$ represent the cumulative normal distribution for a variable x with mean μ and variance σ^2. The associated density function is denoted by $\phi_{\mu,\sigma^2}(x)$. When subscripts are omitted, $\Phi(x)$ and $\phi(x)$ refer to the cumulative distribution and density functions for the standard normal distribution with mean zero and variance of one. Finally, $\mu^*_{p_\tau} \equiv \mu_{p_\tau} + \sigma^2_{p_\tau}$ where μ_{p_τ} and $\sigma^2_{p_\tau}$ are the mean and variance of the marginal distribution for the log of potential, $\ln p_\tau$.

I.1 Average Employment

Newborn Startups

From equation (40), average employment in a newborn startup can be expressed as

$$E[l^1_\tau] = \left[\frac{\lambda}{w} m^\kappa_\tau\right]^{\frac{1}{1-\lambda}} E\left[(z^1_\tau)^{\frac{\zeta}{1-\lambda}}\right],$$

where by using the properties of a log-normal distribution it can be calculated that

$$E\left[(z^1_\tau)^{\frac{\zeta}{1-\lambda}}\right] = \exp\left\{\frac{\zeta}{1-\lambda}\mu_{z^1_\tau} + \left(\frac{\zeta}{1-\lambda}\right)^2 \frac{\sigma^2_{z^1_\tau}}{2}\right\}.$$

Adolescent Startups, Bank Financing

By using (33), average employment in an adolescent bank-backed startup is

$$E[l^2_{\tau b}] = E[p_\tau | p_\tau < p^*_\tau] E\left[\varepsilon_{\tau b}^{\frac{\zeta}{1-\lambda}}\right] \exp\left\{\frac{\kappa}{1-\lambda}\gamma_{\tau b} + \frac{\kappa\zeta}{(1-\lambda)^2}\frac{\sigma^2_{\varepsilon_\tau}}{2}\right\} \left(\frac{\kappa}{r}\right)^{\frac{\kappa}{\zeta}} \left(\frac{\lambda}{w}\right)^{\frac{\zeta+\lambda\kappa}{(1-\lambda)\zeta}}. \tag{44}$$

Exploiting the properties of the log-normal distribution gives

$$E\left[\varepsilon_{\tau f}^{\frac{\zeta}{1-\lambda}}\right] = \exp\left\{\frac{\zeta}{1-\lambda}\gamma_{\tau f} + \left(\frac{\zeta}{1-\lambda}\right)^2 \frac{\sigma^2_{\varepsilon_\tau}}{2}\right\}. \tag{45}$$

Therefore, substituting in for $E[p_\tau | p_\tau < p^*_\tau]$, by using (42), allows (44) to be rewritten as

$$E[l^2_{\tau b}] = \exp\left\{\gamma_{\tau b} + \mu_{p_\tau} + \frac{\sigma^2_{p_\tau}}{2} + \frac{\zeta}{1-\lambda}\frac{\sigma^2_{\varepsilon_\tau}}{2}\right\} \left(\frac{\kappa}{r}\right)^{\frac{\kappa}{\zeta}} \left(\frac{\lambda}{w}\right)^{\frac{\zeta+\lambda\kappa}{(1-\lambda)\zeta}} \frac{\Phi_{\mu^*_{p_\tau},\sigma^2_{p_\tau}}(\ln p^*_\tau)}{\Phi_{\mu_{p_\tau},\sigma^2_{p_\tau}}(\ln p^*_\tau)}. \tag{46}$$

Adolescent Startups, VC Financing

Equation (33) implies that average employment in an adolescent VC-backed startup is

$$E[l_{\tau v}^2] = E[p_\tau | p_\tau > p_\tau^*] E\left[\varepsilon_{\tau v}^{\frac{\zeta}{1-\lambda}}\right] \exp\left\{\frac{\kappa}{1-\lambda}\gamma_{\tau v} + \frac{\kappa\zeta}{(1-\lambda)^2}\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\}\left(\frac{\kappa}{r}\right)^{\frac{\kappa}{\zeta}}\left(\frac{\lambda}{w}\right)^{\frac{\zeta+\lambda\kappa}{(1-\lambda)\zeta}}.$$

Next, using (43) and (45) results in

$$E[l_{\tau v}^2] = \exp\left\{\gamma_{\tau v} + \mu_{p_\tau} + \frac{\sigma_{p_\tau}^2}{2} + \frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\}\left(\frac{\kappa}{r}\right)^{\frac{\kappa}{\zeta}}\left(\frac{\lambda}{w}\right)^{\frac{\zeta+\lambda\kappa}{(1-\lambda)\zeta}}\frac{1-\Phi_{\mu_{p\tau}^*,\sigma_{p\tau}^2}(\ln p_\tau^*)}{1-\Phi_{\mu_{p_\tau},\sigma_{p_\tau}^2}(\ln p_\tau^*)}.$$

Adult Firms, Bank Financing

Using (29) average employment in an adult bank-backed firm can be expressed as

$$E[l_{\tau b}^3] = \chi_{\tau b} E[p_\tau | p_\tau < p_\tau^*] E[\varepsilon_{\tau b}][(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^{1-\kappa}]^{\frac{1}{\zeta}}.$$

The above expression can be rewritten, using (42) and the properties of the log-normal, as

$$E[l_{\tau b}^3] = \chi_{\tau b}\exp\left\{\gamma_{\tau b} + \frac{1}{2}\sigma_{\varepsilon_\tau}^2 + \mu_{p_\tau} + \frac{1}{2}\sigma_{p_\tau}^2\right\}[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^{1-\kappa}]^{\frac{1}{\zeta}}\frac{\Phi_{\mu_{p\tau}^*,\sigma_{p\tau}^2}(\ln p_\tau^*)}{\Phi_{\mu_{p_\tau},\sigma_{p_\tau}^2}(\ln p_\tau^*)}.$$

Adult Firms, VC Financing

Average employment in an adult VC-backed firm can be expressed using (29) as

$$E[l_{\tau v}^3] = \chi_{\tau v} E[p_\tau | p_\tau > p_\tau^*] E[\varepsilon_{\tau v}][(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^{1-\kappa}]^{\frac{1}{\zeta}}.$$

Using (43) together with the properties of the log-normal permits the following rewrite:

$$E[l_{\tau v}^3] = \chi_{\tau v}\exp\left\{\gamma_{\tau v} + \frac{1}{2}\sigma_{\varepsilon_\tau}^2 + \mu_{p_\tau} + \frac{1}{2}\sigma_{p_\tau}^2\right\}[(\frac{\kappa}{r})^\kappa(\frac{\lambda}{w})^{1-\kappa}]^{\frac{1}{\zeta}}\frac{1-\Phi_{\mu_{p\tau}^*,\sigma_{p\tau}^2}(\ln p_\tau^*)}{1-\Phi_{\mu_{p_\tau},\sigma_{p_\tau}^2}(\ln p_\tau^*)}.$$

I.2 Variances

Newborn Startups

It is straightforward to see from equation (40) that the variance of log employment for a newborn startup is

$$V\left(\ln l_\tau^1\right) = \left(\frac{\zeta}{1-\lambda}\right)^2\sigma_{z_\tau}^2.$$

Adolescent Startups, Bank Financing

Using (33), the variance of log employment in adolescent bank-backed startup can be written as

$$V(\ln l_{\tau b}^2) = V\left(\ln p_\tau | \ln p_\tau < \ln p_\tau^*\right) + \left(\frac{\zeta}{1-\lambda}\right)^2 \sigma_{\varepsilon_\tau}^2.$$

The first term is

$$V\left(\ln p_\tau | \ln p_\tau < \ln p_\tau^*\right) = E\left[(\ln p_\tau)^2 | \ln p_\tau < \ln p_\tau^*\right] - E[\ln p_\tau | \ln p_\tau < \ln p_\tau^*]^2.$$

Let $\tilde{p_\tau} \equiv (\ln p_\tau^* - \mu_{p_\tau})/\sigma_{p_\tau}$. Using the formula for the variance of a variable distributed according to a truncated normal distribution (see Appendix J), it transpires that

$$E\left[(\ln p_\tau)^2 | \ln p_\tau < \ln p_\tau^*\right] = \sigma_{p_\tau}^2 + \mu_{p_\tau}^2 - \frac{\sigma_{p_\tau}^2 \tilde{p_\tau} \phi(\tilde{p_\tau})}{\Phi(\tilde{p_\tau})} - 2\mu_{p_\tau}\sigma_{p_\tau}\frac{\phi(\tilde{p_\tau})}{\Phi(\tilde{p_\tau})}.$$

Then, using the formula for the mean of a truncated normal distribution (Appendix J), one can derive that

$$E[\ln p_\tau | \ln p_\tau < \ln p_\tau^*] = \mu_{p_\tau} - \sigma_{p_\tau}\frac{\phi(\tilde{p_\tau})}{\Phi(\tilde{p_\tau})}.$$

Therefore, the variance of log-employment can be written as follows

$$V\left(\ln l_{\tau b}^2\right) = \sigma_{p_\tau}^2 + \mu_{p_\tau}^2 - \frac{\sigma_{p_\tau}^2 \tilde{p_\tau} \phi(\tilde{p_\tau})}{\Phi(\tilde{p_\tau})} - 2\mu_{p_\tau}\sigma_{p_\tau}\frac{\phi(\tilde{p_\tau})}{\Phi(\tilde{p_\tau})} - \left(\mu_{p_\tau} - \sigma_{p_\tau}\frac{\phi(\tilde{p_\tau})}{\Phi(\tilde{p_\tau})}\right)^2 + \left(\frac{\zeta}{1-\lambda}\right)^2 \sigma_{\varepsilon_\tau}^2.$$

Adolescent Startups, VC Financing

This derivation parallels the one above. The variance of log employment in adolescent VC-backed startup can be expressed, using (33), as

$$V(\ln l_{\tau v}^2) = V\left(\ln p_\tau | \ln p_\tau > \ln p_\tau^*\right) + \left(\frac{\zeta}{1-\lambda}\right)^2 \sigma_{\varepsilon_\tau}^2.$$

Rewrite the first term as

$$V\left(\ln p_\tau | \ln p_\tau > \ln p_\tau^*\right) = E\left[(\ln p_\tau)^2 | \ln p_\tau > \ln p_\tau^*\right] - E[\ln p_\tau | \ln p_\tau > \ln p_\tau^*]^2.$$

Again, let $\tilde{p_\tau} \equiv (\ln p_\tau^* - \mu_{p_\tau})/\sigma_{p_\tau}$. Using the formula for the variance of a truncated normal distribution (Appendix J) delivers

$$E\left[(\ln p_\tau)^2 | \ln p_\tau > \ln p_\tau^*\right] = \sigma_{p_\tau}^2 + \mu_{p_\tau}^2 + \frac{\sigma_{p_\tau}^2 \tilde{p_\tau} \phi(\tilde{p_\tau})}{1 - \Phi(\tilde{p_\tau})} + 2\mu_{p_\tau}\sigma_{p_\tau}\frac{\phi(\tilde{p_\tau})}{1 - \Phi(\tilde{p_\tau})}.$$

Then, using the formula for the mean of a truncated normal distribution (Appendix J) results in

$$E[\ln p_\tau | \ln p_\tau > \ln p_\tau^*] = \mu_{p_\tau} + \sigma_{p_\tau} \frac{\phi(\tilde{p_\tau})}{1 - \Phi(\tilde{p_\tau})}.$$

The variance of log-employment therefore is

$$V\left(\ln l_{\tau v}^2\right) = \sigma_{p_\tau}^2 + \mu_{p_\tau}^2 + \frac{\sigma_{p_\tau}^2 \tilde{p_\tau} \phi(\tilde{p_\tau})}{1 - \Phi(\tilde{p_\tau})} + 2\mu_{p_\tau}\sigma_{p_\tau} \frac{\phi(\tilde{p_\tau})}{1 - \Phi(\tilde{p_\tau})} - \left(\mu_{p_\tau} + \sigma_{p_\tau} \frac{\phi(\tilde{p_\tau})}{1 - \Phi(\tilde{p_\tau})}\right)^2 + \left(\frac{\zeta}{1-\lambda}\right)^2 \sigma_{\varepsilon_\tau}^2.$$

I.3 VC's Profit Share

The formula for a venture capitalist's share of a type-τ adolescent startup's profits is derived now. From (8), it can be seen that a venture capitalist's share of profits is

$$s(p_\tau) = \frac{\eta(\alpha_\tau + \xi p_\tau) + (1-\eta)\left[E\left[(z_{\tau v}^2)^\zeta \left(k_{\tau v}^2(p_\tau)\right)^\kappa l_{\tau v}^2 (z_{\tau v}^2)^\lambda - r k_{\tau v}^2(p_\tau) - w l_{\tau v}^2(z_{\tau v}^2) + \delta^2 \pi_{\tau v}^3 | p_\tau\right] - E[\pi_{\tau b}^2 | p_\tau]\right]}{E\left[(z_{\tau v}^2)^\zeta \left(k_{\tau v}^2(p_\tau)\right)^\kappa l_{\tau v}^2 (z_{\tau v}^2)^\lambda - r k_{\tau v}^2(p_\tau) - w l_{\tau v}^2(z_{\tau v}^2) + \delta^2 \pi_{\tau v}^3 | p_\tau\right]}. \tag{47}$$

Using (36) and (38), it can be shown that

$$(1-\eta)\frac{\left[E\left[(z_{\tau v}^2)^\zeta \left(k_{\tau v}^2(p_\tau)\right)^\kappa l_{\tau v}^2 (z_{\tau v}^2)^\lambda - r k_{\tau v}^2(p_\tau) - w l_{\tau v}^2(z_{\tau v}^2) + \delta^2 \pi_{\tau v}^3 | p_\tau\right] - E[\pi_{\tau b}^2 | p_\tau]\right]}{E\left[(z_{\tau v}^2)^\zeta \left(k_{\tau v}^2(p_\tau)\right)^\kappa l_{\tau v}^2 (z_{\tau v}^2)^\lambda - r k_{\tau v}^2(p_\tau) - w l_{\tau v}^2(z_{\tau v}^2) + \delta^2 \pi_{\tau v}^3 | p_\tau\right]} =$$
$$\frac{(1-\eta)}{e^{\gamma_{\tau v}}} \frac{\exp\{\frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\}(e^{\gamma_{\tau v}} - e^{\gamma_{\tau b}}) + \frac{\delta^2}{1-\delta^3}\exp\{\frac{1}{2}\sigma_{\varepsilon_\tau}^2\}(\chi_{\tau v} e^{\gamma_{\tau v}} - \chi_{\tau b} e^{\gamma_{\tau b}})}{\exp\left\{\frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\} + \frac{\delta^2}{1-\delta^3}\chi_{\tau v}\exp\left\{\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\}}. \tag{48}$$

Additionally, one can express

$$\frac{\eta(\alpha_\tau + \xi p_\tau)}{E\left[(z_{\tau v}^2)^\zeta \left(k_{\tau v}^2(p_\tau)\right)^\kappa l_{\tau v}^2 (z_{\tau v}^2)^\lambda - r k_{\tau v}^2(p_\tau) - w l_{\tau v}^2(z_{\tau v}^2) + \delta^2 \pi_{\tau v}^3 | p_\tau\right]} =$$
$$\frac{\eta(\alpha_\tau p_\tau^{-1} + \xi)}{(1-\lambda-\kappa)e^{\gamma_{\tau v}}\left[(\frac{\kappa}{r})^\kappa (\frac{\lambda}{w})^\lambda\right]^{\frac{1}{\zeta}}\left\{\exp\left\{\frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\} + \frac{\delta^2}{1-\delta^3}\chi_{\tau v}\exp\left\{\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\}\right\}}. \tag{49}$$

Finally, to compute $E[s(p_\tau)]$ requires solving for $E[1/p_\tau | p_\tau > p_\tau^*]$. Using the formula for the mean of a truncated normal distribution (Appendix J) gives the average share of profits for a type-τ project or

$$E[s(p_\tau)] = \frac{(1-\eta)}{e^{\gamma_{\tau v}}} \frac{\exp\{\frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\}(e^{\gamma_{\tau v}} - e^{\gamma_{\tau b}}) + \frac{\delta^2}{1-\delta^3}\exp\{\frac{1}{2}\sigma_{\varepsilon_\tau}^2\}(\chi_{\tau v} e^{\gamma_{\tau v}} - \chi_{\tau b} e^{\gamma_{\tau b}})}{\exp\left\{\frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\} + \frac{\delta^2}{1-\delta^3}\chi_{\tau v}\exp\left\{\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\}} +$$
$$+ \frac{\eta}{(1-\lambda-\kappa)e^{\gamma_{\tau v}}\left[(\frac{\kappa}{r})^\kappa (\frac{\lambda}{w})^\lambda\right]^{\frac{1}{\zeta}}} \times \frac{\alpha_\tau E\left[p_\tau^{-1} | p_\tau > p_\tau^*\right] + \xi}{\left\{\exp\left\{\frac{\zeta}{1-\lambda}\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\} + \frac{\delta^2}{1-\delta^3}\chi_{\tau v}\exp\left\{\frac{\sigma_{\varepsilon_\tau}^2}{2}\right\}\right\}}. \tag{50}$$

J Supplemental Material, Properties of the Normal and Log-Normal Distributions

Three properties of the normal and the log-normal distribution are listed here.[30] In what follows, let $\Phi(x)$ and $\phi(x)$ refer to the standard normal cumulative distribution and density functions with mean zero and variance of one for the random variable x.

1. Expected values for one-sided truncations of a normally distributed variable with mean μ and standard deviation σ:

$$E[x|x > a] = \mu + \sigma \frac{\phi\Big((a-\mu)/\sigma\Big)}{1 - \Phi\Big((a-\mu)/\sigma\Big)}$$

and

$$E[x|x < a] = \mu - \sigma \frac{\phi\Big((a-\mu)/\sigma\Big)}{\Phi\Big((a-\mu)/\sigma\Big)}.$$

2. Variances for one-sided truncations of a normally distributed variable with mean μ and standard deviation σ:

$$V(x|x > a) = \sigma^2\{1 + [(a-\mu)/\sigma]\frac{\phi\Big((a-\mu)/\sigma\Big)}{1 - \Phi\Big((a-\mu)/\sigma\Big)} - [\frac{\phi\Big((a-\mu)/\sigma\Big)}{1 - \Phi\Big((a-\mu)/\sigma\Big)}]^2\}$$

and

$$V(x|x < a) = \sigma^2\{1 - [(a-\mu)/\sigma]\frac{\phi\Big((a-\mu)/\sigma\Big)}{\Phi\Big((a-\mu)/\sigma\Big)} - [\frac{\phi\Big((a-\mu)/\sigma\Big)}{\Phi\Big((a-\mu)/\sigma\Big)}]^2\}.$$

3. Expected values for one-sided truncations of a log-normally distributed variable x with mean μ and standard deviation σ:

$$E[x|x > a] = e^{\mu+\sigma^2/2} \frac{\Phi\Big((\mu + \sigma^2 - \ln a)/\sigma\Big)}{1 - \Phi\Big((\ln a - \mu)/\sigma\Big)}$$

and

$$E\left[x|x < a\right] = e^{\mu+\sigma^2/2} \frac{\Phi\Big((\ln a - \mu - \sigma^2)/\sigma\Big)}{\Phi\Big((\ln a - \mu)/\sigma\Big)}.$$

[30] See https://en.wikipedia.org/wiki/Truncated_normal_distribution
and
https://en.wikipedia.org/wiki/Log-normal_distribution.