ABSTRACT

Title of Dissertation: ESSAYS ON CORPORATE VENTURE CAPITAL, FIRM DYNAMICS, AND AGGREGATE GROWTH

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This dissertation studies the impact of corporate venture capital (CVC) on firm dynamics, innovation, and aggregate economic growth. In Chapter 1, I examine whether and how CVC enables funded young firms to rapidly grow, relative to the effect of traditional venture capital (TVC). I formalize the hypothesis that CVC can improve young firm outcomes through demand and/or technology spillovers using a simple model of VC financing and young firm innovation. To test the hypothesis, I assemble a micro-level dataset that links each U.S. VC-funded firm to its funder(s) and subsequent patenting and exit outcomes. To address endogenous investment relationships and to separately identify the causal effects of CVC and TVC in the presence of CVC-TVC syndication, I employ a shift-share research design that predicts both forms of investment at the industry level using the interaction of the initial market shares of different funders and several instruments for funder-specific supply shifts. My estimates reveal that the effect of CVC is as large as the effect of TVC. Moreover, the effect of CVC is found to be

stronger when the funded firm is upstream with respect to the CVC funder in the Input-Output matrix and downstream in the patent citation matrix, lending support to the hypothesized demand and technology channels of CVC.

Chapter 2 investigates the effect of CVC on one form of strategic payoffs to funding firms: corporate innovation. I construct and analyze a micro-level dataset that links CVC investments to U.S. publicly traded firms and their patenting activities. I track the funding firms before and after starting CVC, in comparison to a group of control firms defined by firm size, age, industry, and prior growth. I find that CVC leads to an increase in patenting rate at the funding firms. Importantly, much of the effect is driven by smaller-sized funding firms, informing the potential relationship between CVC and internal innovation across the firm size distribution.

Chapter 3 explores the implications of CVC for aggregate economic outcomes. I develop a growth model featuring CVC and endogenous firm innovation that is consistent with a set of facts on U.S. CVC, including (i) the selection of large and highly innovative firms into making CVC investment and (ii) positive treatment effects associated with CVC on both the funded and funding firms, measured by innovation outcomes. In equilibrium, firms engaged in CVC benefit from positive treatment that makes them innovate more, whereas other firms reduce innovation as they face more intense competition. These forces in turn affect firm selection and the incentives for new entrepreneurship. Quantitative analysis suggests that a higher level of CVC activity leads to an overall increase in aggregate growth, a fall in entry, and a fattening of the firm size distribution at both tails.

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by

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Dedication

To my wonderful parents.

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Chapter 1: The Effect of Corporate Venture Capital on Young Firm Outcomes

1.1 Introduction

Most business startups exit within their first ten years or remain small conditional on survival; a small fraction of young firms expand rapidly, and these so-called high-growth young firms contribute considerably to U.S. job creation, productivity growth, and innovation (Acemoglu et al., 2018; Akcigit and Kerr, 2018; Decker et al., 2014, 2016; Haltiwanger et al., 2017). What makes a high-growth young firm?

Venture capital (VC) financing has been shown to be a key contributing factor supporting high-growth young firms. VC is a form of minority equity financing particularly suited to deal with the high risks involved in financing risky but growth-oriented young businesses. Lerner and Nanda (2020) document that while less than 0.5 percent of firms each year in the United States receive VC financing, they represent nearly half of the entrepreneurial firms that become publicly traded.[1] Using a quantitative growth model, Akcigit et al. (2019) show that in a counterfactual economy without VC financing, the U.S. annual growth rate would fall from 1.8 to 1.3 percent.

However, existing work, including the studies quoted above, has by and large only considered VC investments made by *financial* VC firms, which account for about three quarters of total

[1] Entrepreneurial IPOs are defined as non-financial, non-reverse LBO (leveraged buyout), non-REIT (real estate investment trust), and non-SPAC (special purpose acquisition company) IPOs

U.S. VC investments. The neglected quarter is comprised of corporate VC investments made by *non-financial* firms. Corporate VC funders include some of the largest and most innovative non-financial firms in the U.S. economy, spanning the manufacturing, communications, retail, and services industries, such as Intel, Comcast, Amazon, and Microsoft. Crucially, unlike traditional VC, which serves as a form of financial intermediation, corporate VC entails a match between non-financial firms that may be motivated by demand and/or technology synergies beyond a pure financing relationship. For example, Comcast invested in DocuSign, the digital signature company, and has since become one of the largest customers of DocuSign. As another example, Intel has invested in a number of drone startups, as drones require powerful chips and Intel has the technology to offer.

These observations motivate the central question in the paper: Does corporate VC matter for high-growth young firms, and how might the size and channels of these effects differ from traditional VC? Despite being a large and alternative source of VC financing, corporate VC (referred to as CVC hereafter) has received little academic attention, in contrast to a long-standing literature on traditional VC (referred to as TVC hereafter).

Answers to the question posed above have important implications along at least three dimensions. First, given that CVC amounts to a quarter of total VC and given the magnitude of the effect of TVC described earlier, CVC could have a meaningful impact on high-growth young firms and the macroeconomy. Second, as more than 10 percent of TVC investments are in fact syndicated/co-invested with CVC, not considering CVC risks attributing some of the treatment effect arising from CVC to TVC. Third, the channels of CVC can shed light on the extent to which frictions in young firms' access to markets, customers, and technology-based intangibles are critical in the growth process, thus helping inform the design of entrepreneurship policies.

A priori, why should we expect the effect of CVC to be different from TVC, or to exist at all? I formalize the hypothesis that CVC can positively affect a young firm's innovation rate and exit outcomes in a simple model featuring VC financing and endogenous innovation by outside entrepreneurs. In the model, an outside entrepreneur needs to innovate and build up demand for her product before the product can be commercialized. The entrepreneur is assumed to lack her own means to finance research and development (R&D) expenditures. She can be funded by either a corporate or a traditional venture capitalist. Assuming that the corporate venture capitalist is able to increase the appeal of the entrepreneur's product through demand synergies and/or improve the research capability of the entrepreneur through technology synergies, the model suggests that the entrepreneur would innovate at a higher rate under CVC financing than under TVC financing, everything else equal. The intuition relates to the profit incentives that are the central driving force of the rate and direction of innovation in endogenous growth models dating back to Acemoglu (2002); Acemoglu and Linn (2004); Aghion and Howitt (1992); Grossman and Helpman (1991); Romer (1990).

In addressing the role of CVC empirically, this paper makes a first attempt at separately identifying the causal effects of CVC and TVC on young firm outcomes. The task is challenging both due to an inherent selection bias and the nature of staged and syndicated financing. Since CVC and TVC funders tend to select high-quality firms to invest in, the funded firms may perform well even in the absence of any VC financing, biasing ordinary least squares estimates of causal effects. In the lack of exogenous or quasi-experimental shocks to the formation of investment relationships, the TVC literature has commonly pursued an event study approach. This approach compares the outcomes of TVC-funded firms to those of observationally similar non-TVC funded firms, with the control group of non-TVC funded firms constructed based on firm characteristics at the time TVC-funded firms *first* receive TVC. Unfortunately, this approach is not well suited to answer the question at hand for two related reasons. First, because a funded firm may raise multiple rounds of financing and receive either TVC or CVC, or both, it is not immediately clear how an event study approach would accommodate *different* types of events (i.e., first receiving TVC versus first receiving CVC). Second, the possibility of syndication implies that a TVC recipient may *first* receive TVC in conjunction with CVC and, conversely, a CVC recipient may *first* receive CVC in conjunction with TVC, making it difficult for an event study approach to disentangle the effects coming from CVC versus TVC.

I instead propose an industry-level specification to mitigate the selection bias and the complications arising from staged VC financing and syndication. Specifically, my empirical model relates aggregate young firm outcomes in an industry over a period of time to lagged CVC and TVC investments in that industry, controlling for a rich set of fixed effects and other lagged industry-level covariates. To instrument for the likely endogenous quantities of CVC and TVC, I employ a shift-share (Bartik-style) research design that predicts CVC and TVC investments using the interaction of the initial market shares of different funders investing in the industry and idiosyncratic funder supply shifts. The funder supply shifts are constructed in two ways to isolate the component of VC investments driven by the abundance of funder capital, rather than being driven by young firm quality or technological opportunities in a specific industry. The first approach adds up a funder's national changes in VC investments, leaving out the industry in observation. More systematically, the second approach uses a regression framework to extract a set of funder-specific effects by first purging the common industry effects that likely reflect selection.

Implementing the empirical strategy requires data linking VC funders, funded firms, and measures of young firm outcomes. I construct such a dataset by combining a variety of commercial and public data sources. I obtain data on U.S. VC activity between 1980 and 2018 from Thomson Reuters VentureXpert and merge in data on initial public offerings (IPOs) and acquisitions from Thomson Reuters SDC Platinum to identify the subset of funded firms that experience a successful exit event. I also merge in patent and citation data from the United States Patent and Trademark Office (USPTO) to examine the innovative outputs of funded firms. Since my empirical strategy requires variation in VC investments at the parent firm level, I additionally obtain firm ownership information from Standard & Poor's Capital IQ and identify the ultimate corporate parent of a CVC or TVC unit, referred to as the funder throughout the paper.

My empirical estimates reveal an economically and statistically significant effect of CVC on young firm outcomes. Specifically, a one percent increase in CVC investments at the four-digit Standard Industrial Classification (SIC) industry level leads to a 0.4 percent increase in the number of successful patent applications or the citation-weighted number of patents issued by the funded firms in subsequent years. There is also a 0.2 percent increase in the number of successful future exits via an IPO or an acquisition. Crucially, the empirical model cannot reject the null hypothesis that the effect of CVC is as large as the effect of TVC at conventional levels of statistical significance.

Consistent with the hypothesized channels, much of the effect of CVC stems from strong demand and technology linkages between the CVC funders and the funded firms. I measure demand-side linkages using the Input-Output (I-O) Accounts maintained by the U.S. Bureau of Economic Analysis (BEA). Technology-side linkages are measured using an industry-level patent citation matrix that I build from the USPTO data. Measured this way, I find that the effect of CVC is stronger in industries where more of the funded firms are upstream with respect to their CVC funders in the I-O matrix, lending support to the hypothesis of demand spillovers running from funders to the funded firms getting CVC. Additionally, the effect of CVC is found to be stronger in industries where more of the funded firms are downstream with respect to their CVC funders in the patent citation matrix, supporting the hypothesis of technology spillovers associated with getting CVC.

My findings are quantitatively relevant for the macroeconomy. To see how, consider the following simple back-of-the-envelope calculation. Given that (i) CVC amounts to a quarter of total VC, (ii) the absence of TVC would lead to a 0.5 percentage point drop in the U.S. annual growth rate as estimated by Akcigit et al. (2019), and (iii) the empirically identified effect of CVC is as large as the effect of TVC, it follows that the absence of CVC would cause at least a 0.2 percentage point drop in the U.S. annual growth rate. An interesting and subtle point, however, is that CVC has also been shown to positively affect the growth outcomes of funders (Dushnitsky and Lenox, 2005; Liu, 2021c; Ma, 2020), suggesting that the aggregate implications of CVC are potentially larger than what the back-of-the-envelope calculation implies. I tackle this potentially very involved question in a separate project (Liu, 2021a). In that project, I develop an endogenous growth model that reflects both aspects of CVC. The key tradeoff in the model is that while firms engaged in CVC become more innovative as they benefit from synergies, other firms are discouraged as they face more intense competition. These forces in turn affect firm selection and the incentives for new entrepreneurship. The aggregate impact of CVC thus becomes a quantitative question.

Contribution to literature This paper makes a direct contribution to the literature on VC-backed growth. A rich body of work has analyzed the impact of TVC on high-growth young firms and the aggregate economy, using either empirical or quantitative methods (see, for example, Akcigit et al., 2019; Bernstein et al., 2015; Chemmanur et al., 2011; Gornall and Strebulaev, 2015; Greenwood et al., 2018; Hellman and Puri, 2002; Hochberg et al., 2007; Kaplan and Lerner, 2010; Kortum and Lerner, 2000; Lerner and Nanda, 2020; Opp, 2019; Puri and Zarutskie, 2012; Samila and Sorenson, 2011).

Findings from the TVC literature, however, are unlikely to be readily applicable to CVC given that the latter involves a match between non-financial firms seeking synergies. Moreover, as described previously, the nature of staged financing and CVC-TVC syndication suggests that existing empirical studies on TVC using the event study approach run the risk of conflating the effects of CVC and TVC.

A handful of studies address the role of CVC directly. Gompers and Lerner (2000) and Gompers (2002) document a positive association between getting CVC funding and exit outcomes for young firms. Chemmanur et al. (2014) focus on CVC-funded firms that went public between 1980 and 2004 and construct a matched sample of TVC-funded firms that also went public, based on observable characteristics at the IPO year. The authors then track the innovation performance of the two groups of firms over time and find that the CVC-funded group achieves better innovation outcomes in post-IPO years.[2]

Relative to Chemmanur et al. (2014), the shift-share strategy proposed in this paper has several advantages. First, my strategy is not limited to publicly traded firms and, in fact, treats going public as an outcome itself. Second, my strategy can control for unobserved and time-varying confounding factors affecting young firm outcomes that may not be fully controlled for

[2] Ivanov and Xie (2010) employ a similar matching strategy on the set of publicly traded firms that were once funded by CVC and study the effect of CVC on IPO valuations.

by matching on observable characteristics. Third, my strategy is robust to CVC-TVC syndication while matching CVC-funded firms with TVC-funded firms is generally not.

More broadly, my results inform the debate about the sources of firm growth. On the one hand, the large literature tying productivity and firm performance has recently emphasized demand-based fundamentals as a key factor in explaining cross-sectional differences in firm size and growth (Eslava and Haltiwanger, 2020; Foster et al., 2016; Gourio and Rudanko, 2014; Hottman et al., 2016; Moreira, 2016; Sedláček and Sterk, 2017). These studies identify demand fundamentals using plant- or firm-level price data or business cycle fluctuations and have found demand frictions to be particularly relevant in the early stages of the firm lifecycle. My work identifies demand linkages from the production structure and corroborates the demand channel.

On the other hand, scholars such as Nicholas Bloom have highlighted the role of management practices in explaining the large and persistent productivity differences across firms (Bender et al., 2018; Bloom et al., 2013, 2019, 2021). The TVC literature cited previously has provided abundant evidence that a key channel through which TVC enables high-growth young firms is by providing managerial services. To the extent that the effect of TVC identified in my analysis reflects managerial services, my results indicate that demand- and management–based explanations are both relevant in the context of high-growth young firms.

Outline of the paper I begin the analysis with a brief description of the institutional background of VC, followed by a simple model of VC financing and young firm innovation in Section 1.2. The model formalizes the hypothesized demand and technology channels of CVC. I then describe the data in Section 1.3. In Section 1.4, I document three stylized facts on U.S. CVC that are relevant for the empirical analysis. I first highlight the prevalence of staged financing and CVC-

TVC syndication in the data. I next gauge the degree of selection by showing that CVC funders tend to select more innovative firms to invest in, relative to TVC funders. I then illustrate the potential scope for demand and technology spillovers by juxtaposing the industry distributions of the CVC funders and the funded firms against the I-O matrix and the patent citation matrix. I proceed to Section 1.5 with causal analysis on the effect and channels of CVC. Finally, I offer concluding remarks in Section 1.6.

1.2 Background and Motivating Theory

1.2.1 Institutional Background

TVC is a form of minority equity financing provided by financial venture capital firms to start-up and young businesses that are deemed to have high growth potential. A venture capital firm is typically structured as a limited partnership comprised of several venture capitalists, also called the "general partners." The general partners raise funds from so-called "limited partners" such as pension funds, college endowments, and wealthy individuals. Each fund has a life span of about 10 years. The general partners invest on behalf of the limited partners and hold preferred stocks in the funded businesses. When a funded business successfully exits the investment through an IPO or an acquisition by another firm, the general partners sell their equity holdings, give the promised returns back to the limited partners, and receive a profit share or carry.

CVC differs from TVC along several dimensions. While TVC funds are raised from limited partners, CVC funds are provided by *non-financial* parent firms.[3] A CVC unit can be structured as a division within the corporate structure or as an external entity with the corporate parent being

[3]Banks and real estate companies may also engage in CVC activity. I exclude these firms in my analysis.

the sole limited partner (Gompers, 2002). Regardless of the structure, the objective of the CVC unit is to bring strategic payoffs or synergies to the corporate parent beyond simple financial returns. While TVC has been found to add value to funded businesses by recruiting outside managers (Hellman and Puri, 2002), restructuring the board of directors (Lerner, 1995), helping develop business plans (Kaplan and Strömberg, 2001), and connecting the funded firms to future investors (Gompers et al., 2020), CVC may be additionally advantageous by providing funded firms with access to the funder's business resources and technologies.

Because the financing of high-potential businesses can be risky, both traditional and corporate venture capitalists rely on intensive screening before making an investment. More importantly, instead of providing all the necessary capital upfront, venture capitalists invest in stages and preserve the option to not refinance. Refinancing is typically conditional on the funded firm's ability to achieve certain milestones. In addition, VC financial contracts typically allocate various forms of control rights to the venture capitalists should the funded firm perform poorly (Kaplan and Strömberg, 2003).

Syndication is another key institutional strategy for venture capitalists to mitigate investment risks. Several venture capitalists may jointly fund a deal to share risks; there could also be additions of more venture capitalists at later rounds of funding. It is common for traditional and corporate venture capitalists to syndicate deals, although the latter typically join the syndicate at later rounds. The possibility of syndication presents a challenge in separately identifying the effects of CVC and TVC, an issue that I tackle in my research design.

1.2.2 A Motivating Model

In this section, I develop a simple partial-equilibrium model featuring CVC, TVC, and endogenous innovation by the funded firm. The model formalizes the hypothesis that CVC can have a positive effect on young firm outcomes through demand and/or technology spillovers.

Environment Time is continuous. Consider a customer who demands an aggregate of a continuum of varieties:

$$Y(t) = \left(\int_{\mathcal{N}(t)} \varphi_j(t)^{\frac{1}{\epsilon}} y_j(t)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1.1}$$

where j indexes a commercialized variety, φ is a variety-specific demand shifter that reflects the appeal of the variety, y is the quantity demanded, $\epsilon > 1$ is the elasticity of substitution across varieties, and $\mathcal{N}$ is the measure of varieties that expands over time as outside entrepreneurs commercialize new varieties with the help of CVC or TVC. In the model, I do not take a stand on whether the customer is a consumer or a producer, although my empirical analysis uses the production structure to identify demand-based fundamentals. Without loss of generality, I assume that each variety is supplied by a single entrepreneur and that each entrepreneur owns one variety at each point in time. In what follows, I drop the time index t when it causes no confusion.

Suppose that the customer has decided on the ideal amount of the aggregate $\bar{Y}$, which is taken to be the numeraire.[4] She then chooses the quantity of each variety y to minimize the cost of obtaining $\bar{Y}$. The solution yields the inverse demand function for each variety:

$$p_j = \bar{Y}^{\frac{1}{\epsilon}} \varphi_j^{\frac{1}{\epsilon}} y_j^{-\frac{1}{\epsilon}}, \tag{1.2}$$

[4]Exactly how $\bar{Y}$ is determined is not relevant for the purpose of my analysis. As one example, if Equation (1.1) also stands for the instantaneous utility function of the customer, then $\bar{Y}$ could be obtained by maximizing the lifetime discounted version of Equation (1.1) subject to a flow budget constraint of the customer.

where p_j is the price of variety j set by the entrepreneur supplying the variety.

Once commercialized, variety j can be produced by the entrepreneur with a linear technology:

$$y_j = l_j, \tag{1.3}$$

where l_j is the number of production workers employed. Suppose that the wage rate facing production/unskilled workers is given by w_u. Given that Equation (1.2) is isoelastic, the entrepreneur finds it optimal to charge a constant markup over her marginal cost: $p_j = \frac{\epsilon}{\epsilon-1} w_u$. The entrepreneur's profits are therefore given by:

$$\begin{aligned} \Pi(\varphi_j) &= \frac{1}{\epsilon - 1} \left(\frac{\epsilon - 1}{\epsilon} \right)^{\epsilon} \bar{Y} {w_u}^{1-\epsilon} \varphi_j \\ &\equiv \pi \varphi_j. \end{aligned} \tag{1.4}$$

Naturally, profits are increasing in the appeal of the variety.

Now, consider the value of a commercialized variety. The continuous-time Hamilton-Jacobi-Bellman equation is given by:

$$rV(\varphi_j) - \dot{V}(\varphi_j) = \pi \varphi_j, \tag{1.5}$$

where r is the market interest rate and $\dot{V} \equiv \partial V / \partial t$. Since the model is cast in an expanding-variety framework and new varieties do not replace existing ones, the value of a variety is simply the net present discounted value of flow profits. With some innocuous assumptions on the supply of production workers, Appendix A.3 shows that the value function (1.5) admits a closed-form solution that is linear in appeal:

$$V(\varphi_j) = \nu \varphi_j, \tag{1.6}$$

where ν is a function of model primitives and equilibrium objects that are taken as given.

Commercializing a variety An outside entrepreneur starts with a business plan with baseline appeal φ_0. To commercialize the business plan, the entrepreneur needs to engage in R&D to further improve the appeal of her product. Upon a successful innovation, the appeal of the product increases by a proportional step size $\lambda > 1$:

$$\varphi = \lambda \varphi_0. \tag{1.7}$$

The product is then commercialized, yielding a value of $V(\lambda\varphi_0)$, where V is given by Equation (1.6).

Performing R&D requires hiring skilled labor at the wage rate w_s. To innovate at a flow rate x, the entrepreneur needs to hire $x^2/2\eta$ researchers, where $\eta > 0$ parameterizes the research capability of the entrepreneur.[5] The R&D expenditures are therefore given by:

$$R(x \mid \eta) = \frac{x^2}{2\eta} w_s. \tag{1.8}$$

Crucially, the entrepreneur is assumed to lack her own means to finance the R&D expenditures. She therefore needs to raise funding from either a corporate venture capitalist—an incumbent entrepreneur who currently own a commercialized variety—or a traditional venture capitalist.

[5] The assumption of a quadratic R&D technology simplifies the derivation; the curvature value is also typically used in quantitative endogenous growth models. See, for example, Acemoglu et al. (2018) and Akcigit and Kerr (2018).

Both types of venture capitalists are assumed to be representative. To simplify the analysis, I assume that the project is financed by a single venture capitalist.

The contracting scheme is kept as simple as possible. First, I assume that the entrepreneur's R&D activity is perfectly verifiable and thus contractable, and I focus on the case of complete contracts (the first best from the viewpoint of the entrepreneur). Next, I abstract from search and matching frictions. Conditional on being matched with a venture capitalist, the entrepreneur chooses her effort level and makes a contract offer $\{x, R\}$ to the venture capitalist. The offer stipulates that the entrepreneur is obligated to hire the necessary number of researchers in order to deliver the optimal innovation rate, x, that maximizes the joint payoffs to the entrepreneur and the venture capitalist; meanwhile, the venture capitalist is obligated to pay for the associated R&D expenditures, R. Note that I abstract from the venture capitalist's participation constraint, so how the entrepreneur and the venture capitalist split the joint payoffs is irrelevant for the entrepreneur's innovation decision. This justifies the absence of the payoff shares in the contract. Otherwise, the entrepreneur's problem would become the maximization of her own payoffs subject to the venture capitalist's participation constraint, which would require the payoff shares to be stipulated in the contract, which would complicate the analysis.[6]

The entrepreneur's innovation decision The entrepreneur's problem can be expressed as:

$$\max_{x} \; x \cdot V\left(\lambda \varphi_0\right) - R(x \mid \eta). \tag{1.9}$$

[6]In reality, a venture capitalist's equity share is arguably not the most critical factor influencing an entrepreneur's efforts. Typically, the equity share is determined the following way. Suppose that the estimated investment need for a startup is \$x million. The venture capitalist expects the startup to have a successful exit by year n at a value of \$y million. The venture capitalist then converts the expected exit value to the present value using her desired rate of return. Suppose that the discounted present value, referred to as "post-money" valuation, is \$z million. The venture capitalist's equity share is then x/z.

She chooses her innovation rate to maximize the joint payoffs to herself and the venture capitalist, which is equal to the value of a new variety net of the R&D costs. Solving the problem is straightforward and yields the entrepreneur's optimal innovation rate:

$$x(\eta, \lambda \mid \varphi_0) = \frac{\eta \nu \lambda \varphi_0}{w_s}. \tag{1.10}$$

Conditional on the entrepreneur's initial quality (φ_0), the optimal innovation rate is an increasing function of her research capability (η) and the size of the improvement in product appeal:

$$\frac{\partial x(\eta, \lambda \mid \varphi_0)}{\partial \eta} > 0 \quad \text{and} \quad \frac{\partial x(\eta, \lambda \mid \varphi_0)}{\partial \lambda} > 0. \tag{1.11}$$

The intuition behind Result (1.11) is straightforward. On the demand side, when the entrepreneur expects a higher demand for her product once the product is commercialized, she will have stronger incentives to innovate ex ante. Market size to increase has been a central driving force of the pace and direction of technological progress in endogenous growth models dating back to, for example, Acemoglu (2002); Acemoglu and Linn (2004); Aghion and Howitt (1992); Grossman and Helpman (1991); Romer (1990). On the technology side, when the entrepreneur becomes more productive at performing R&D, she will spend more on innovation, as R&D becomes more cost effective at generating innovation.

Empirical implications Result (1.11) implies that a CVC-funded entrepreneur will have a higher innovation rate than a TVC-funded entrepreneur, everything else equal, if CVC can (i) help the entrepreneur increase her product appeal by a larger step size through demand-based spillovers and/or (ii) make the entrepreneur more capable at performing R&D through technology spillovers. If higher appeal can be thought of as a reasonable proxy for a successful exit, we would also expect CVC to increase the likelihood of a successful exit for the funded entrepreneur. Note that the model abstracts from any treatment effect of TVC on the entrepreneur. A realistic extension would be to assume that TVC may also increase the entrepreneur's step size of innovation by, for example, improving the managerial efficiency of the entrepreneur. Consequently, the causal effect of CVC can be identified by controlling for the quality of the entrepreneur and the amount of TVC financing. Section 1.5 proposes an empirical strategy that seeks to identify the causal effect of CVC, in light of the model implications. Additionally, Section 1.5 proposes a specification to test the hypothesized demand and technology channels of CVC.

1.3 Data Sources and Measurement

Testing the causal effects and channels of CVC requires a comprehensive dataset of VC activity that links each funded firm to its funders, growth outcomes, and the degree of demand and technology linkages with the funders in case of CVC investments. I draw on a variety of commercial and public data sources to construct the dataset. This section describes the data sources, the main procedures for linking records across data sources, the sample selection criteria, and the resulting measures used in subsequent analysis. More details on the construction of the dataset are provided in Appendix A.1.

Tracking VC activities Data on VC investments come from VentureXpert, a proprietary product of Thomson Reuters. VentureXpert tracks the investments of CVC and TVC funds on a global basis, drawing information from public news releases, private equity newsmakers, official filings, and investor surveys that may contain information not presented in official deal statements (Röhm et al., 2020). The database was started in 1977 and has since then been backfilled through the 1960s (Chen et al., 2010). Because venture capitalists are not required to disclose their investments to any regulatory agency, coverage is always a concern in VC research (Kaplan and Lerner, 2016). However, VentureXpert has been shown to offer the most comprehensive coverage among competing databases (Maats et al., 2011). For this reason, this database has been extensively used in VC research.

VentureXpert contains rich information at the investment deal or financing round level (deal and round are used interchangeably). For each deal, I observe the date of the deal, the funding amount, and identifying information for the funded firm and the investors. While each deal involves a single funded firm, there can be multiple investors participating in the deal. Unfortunately, VentureXpert does not identify the lead investor, nor does it provide details on the funding contribution by each investor, only the total funding amount. Core identifying information for a funded firm includes firm name, detailed location, founding year, and four-digit SIC code. Core identifying information for an investor includes firm name, detailed location, and firm type (CVC or TVC). I extract from VentureXpert all deals made by U.S. based CVC and TVC units in U.S. based firms between 1980 and 2018. Following common practice in VC research, funded firms are restricted to those coded in VentureXpert as being "Startup/Seed", "Early Stage", "Expansion", or "Later Stage" in their first observed financing round. This restriction filters out deals involving bridge loans, open market purchases, private investments in public equity, and other stages of venture investments for more mature firms. Appendix A.1 provides details on the filters that I use for the raw extraction.

Identifying the ultimate parent of an investing entity I merge the set of CVC and TVC units in VentureXpert to Standard & Poor's Capital IQ to identify the ultimate parent of an investing entity, referred to as the "funder" throughout the paper. Capital IQ provides ownership and operating information for both public and a large number of private firms worldwide. Because my empirical strategy uses variation in VC investments at the funder level, this step is crucial, especially when a CVC funder invests via one or multiple subsidiaries. For example, Alphabet Inc, the holding company of Google Inc, has three CVC arms: Gradient Ventures LLC, CapitalG Management Company LLC, and GV Management Co LLC. I need to correctly assign all the investments made by these three CVC arms to Alphabet.[7]

By default, ownership information in Capital IQ is based on a firm's current status. I need instead a history of the firm's ownership changes to assign deals made by the firm at different points in time to the right parent. For example, Compaq Computer Corp was a publicly listed firm until 2001 when it got acquired by HP Inc. While the current corporate parent of Compaq Computer is HP, deals made by Compaq Computer prior to 2001 should be linked to Compaq Computer itself, not HP. Appendix A.1 describes an automated procedure that I use to track ownership changes over time for each investing firm. Once the funder is identified, I retrieve from Capital IQ additional information such as the funder's primary four-digit SIC code.[8]

Obtaining outcomes of the funded firms My empirical analysis focuses on the innovative and exit outcomes of the funded firms. Innovative output is measured using patent and citation data from PatentsView, a public data repository maintained by the United States Patent and Trademark

[7]While TVC units are typically structured as independent partnerships, linking TVC units in VentureXpert to Capital IQ is nonetheless necessary for consistently identifying a firm. For example, First Star Ventures LLC, formerly known as Procyon Ventures, has both names recorded in VentureXpert. By linking the two records to the same unique firm identifier in Capital IQ, I can correctly associate the two records with the same firm.

[8]I also retrieve information on firm type (e.g., "Public Company," "Private Company," "Private Investment Firm," and "Corporate Investment Arm"). I use the information to cross check investor type in VentureXpert. In the rare occasions of a disagreement between VentureXpert and Capital IQ, I manually verify the record using Google search.

Office (USPTO). I obtain from PatentsView the universe of utility patents filed to USPTO and granted between 1976 (the earliest year available) and 2019.[9] Core data items include the date a patent was applied for and granted, the technology class of the patent, the number of citations made and received by the patent, and the entity to which the patent is assigned (namely, the assignee). I link the list of funded firms in VentureXpert to the list of assignees in PatentsView to identify the subset of funded firms that are patenting firms and obtain their histories of patent applications and citations. As standard in the literature, I date a patent by its application date rather than the grant date, as the actual timing of invention is closer to the application data than the subsequent grant date.

A successful exit is defined as an event in which the funded firm goes public or gets acquired post-VC financing. I do not have information on bad exits such as write-offs or failed ventures. IPO data come from Thomson Reuters SDC Platinum Global New Issues. The database tracks new issues of securities on a global scale, using data from regulatory filings, prospectuses, surveys of underwriters, and news sources. I obtain from the database U.S. public offerings from 1970 (the earliest year available) up to 2018. Following convention, I consider only completed IPOs that involve the issuance of ordinary common shares.[10] I link the list of funded firms in VentureXpert to the list of U.S. issuers in SDC Platinum Global New Issues to identify whether a funded firm went public, and if so, when the IPO took place.

Acquisition data are taken from Thomson Reuters SDC Platinum Mergers and Acquisitions. The database tracks M&A transactions worldwide, using data from regulatory filings, news sources, and surveys of investment banks and law firms. Data for transactions involving U.S.

[9]Following the literature, I do not consider plant or design patents.

[10]The excluded categories are IPOs that are withdrawn or completed IPOs that involve, for example, unit offering, closed-end fund, real estate investment trust, or an American depository receipt. See Appendix A.1 for more details.

targets go back to 1979. I obtain from this database the list of completed transactions up to 2018 that involve the acquisition of more than 50% of the target firm's stocks or assets.[11] I then link the list of the VC funded firms to U.S. M&A targets to identify whether and when a funded firm was acquired. Since a funded firm may go public and later get acquired, or may get acquired multiple times by different acquirors, the exit status is based on whichever event comes first.

In practice, the set of funded firms in VentureXpert are first linked to Capital IQ before being linked to PatentsView or SDC Platinum. Doing so is necessary for consistently identifying a funded firm, hence its outcomes. Consider the example of the Wisconsin-based software startup Expressume Inc that changed its name to Montage Talent Inc in 2011. Both names are recorded in VentureXpert as the startup raised financing rounds before and after 2011. By linking the two records to the same unique firm identifier in Capital IQ, I can consistently identify the firm.

Linking across databases The preceding paragraphs suggest a need to link VentureXpert with Capital IQ, PatentsView, and SDC Platinum. To do so, I implement a standard name and address matching procedure that follows Akcigit et al. (2019), Davis et al. (2014), Davis et al. (2019), and Dinlersoz et al. (2019), among others. I briefly describe the procedure here and leave further details to Appendix A.1. Essentially, two firms in different databases are linked together or deemed to be the same firm if their firm names and locations are sufficiently similar to each other. Therefore, firm name, street address, city, state, and zip code variables in each database are first standardized to facilitate string comparison across databases. Record linking is then performed though multiple rounds of matching, from the strictest criteria requiring a perfect match on firm name and location to progressively looser criteria that allow for fuzzy matching (exact firm name and fuzzy location, fuzzy firm name and exact location, etc.). Successfully matched records are

[11] Appendix A.1 provides details on the filters that I use to extract qualifying transactions.

then removed from the set of records to be matched in the next round. When available, founding year and SIC variables are used to validate links.

Assessing match rate against prior studies Table 1.1 reports the match rate across databases. The top row shows the raw extraction from VentureXpert for the period 1980–2018. Slightly under 80% of the funded firms in VentureXpert are linked to Capital IQ, a match rate comparable to prior studies that use a name and address matching procedure to link TVC-funded firms in VentureXpert to other micro-level datasets such as the Longitudinal Business Database (LBD) at the U.S. Census Bureau.[12] For example, Puri and Zarutskie (2012) report a match rate of 80% and Akcigit et al. (2019) have a match rate of 70%. The match rate for investing entities is higher, at about 90%, reflecting the fact that investing entities are in general more established firms and are therefore either better covered in Capital IQ or have more consistent identifying information across databases.[13]

Conditional on being linked to Capital IQ, 88% of the CVC funders and 41% of the funded firms are identified as patenting firms by being linked to PatentsView. I do not perform a similar match for TVC funders as they are financial firms. The match rate for funded firms is once again comparable to prior studies that link TVC-funded firms in VentureXpert to PatentsView using a similar matching procedure. Specifically, Akcigit et al. (2019) report that among the firms financed by TVC between 1980 and 2012 that can be linked to the LBD, 34% have patents. When I restrict my sample to TVC-funded firms during the same period, 39% have patents. The higher rate in my sample is possibly due to a higher representation of good firms in Capital IQ relative to the LBD, although it could also be the case that some assignees whose patent applications have

[12] The LBD is an administrative data source that contains the universe of firms and establishments in the non-farm business sector with at least one paid employee.

[13] For example, 69% of the matched CVC funders are publicly listed firms that can in turn be linked to Compustat.

just recently been granted are present in my dataset but not in Akcigit et al. (2019).

With respect to the match rate of SDC Platinum, 9% of the VentureXpert-Capital IQ linked funded firms are identified as having exited through an IPO while 32% exit through an acquisition by the end of 2018. Puri and Zarutskie (2012) report that among TVC-funded firms in their sample that can be linked to the LBD, 7% went public and 26% were acquired as of 2005.[14]

Overall, my match rates are in the ballpark of the previous literature. While Capital IQ may overrepresent good firms relative to the firm population, this should not be a serious concern for my analysis as long as the overrepresentation of good firms applies both to CVC- and TVC-funded firms.

Table 1.1: Match Rate, 1980–2018

	#CVC Units	#TVC Units	#Funded
VentureXpert	922	3,356	31,261
Linked to:			
Capital IQ	94%	89%	78%
PatentsView	88%	n/a	41%
SDC Platinum Global New Issues (or M&As)	n/a	n/a	9% (32%)

Notes: The top row reports statistics for the raw extraction from VentureXpert. The raw extraction is restricted to U.S. based CVC and TVC units investing in U.S. based firms that are in startup/seed, early, expansion, or later stage in their first observed financing round. The last two rows are conditional on being linked to Capital IQ. The 88% in the second-to-last row pertains to VentureXpert-Capital IQ linked CVC *funders*.

Sample restrictions I impose two fairly minimal restrictions on the analysis sample. First, I focus on funders and funded firms that can be linked to Capital IQ. This restriction ensures

[14] More precisely, Puri and Zarutskie (2012) use the union of VentureXpert and VentureSource, a product of Dow Jones, to identify TVC funded firms between 1981 and 2005. While the universe of TVC-funded firms in my sample is different from theirs, when I restrict my sample to TVC-funded firms during the same period, 13% went public and 23% were acquired as of 2005.

consistent identification of a firm, as explained previously. Second, I focus on funded firms and CVC funders in the non-farm, non-financial private business sector.[15]

The resulting full sample consists of about 121,000 deal-funder-funded observations, 60,000 deals, 21,000 funded firms, 610 CVC funders, and 2,600 TVC funders between 1980 and 2018. Among the funded firms in this sample, 97 percent received TVC financing and 23 percent received CVC financing. Figure A.1 plots the share of CVC investments over time. Despite large cyclical variation, CVC accounts for between 15 to 30 percent of total VC investments on an annual basis.

Correcting for truncations The full sample is subject to a truncation bias associated with the outcomes of the funded firms. For patenting activity, the time lag between patent applications and grants implies that as the sample moves closer to the end, there is an increasing incidence of patents filed in recent years that have not yet been granted. Similarly, the number of IPOs and acquisitions declines towards the end of the sample, as firms receiving VC funding in more recent years have not had enough time to mature.

My baseline regression sample is therefore limited to funded firms whose first financing round occurs before the end of 2014. For patents applied for between 1980 and 2014, 98% were granted prior to 2019 when my patent data stops.[16] For IPOs, the median time span between an IPO and the first financing round is four years while the 75th percentile is seven years, conditional on having had an IPO by 2018 when my IPO data stops. For acquisitions, the corresponding median and 75th percentile is five and eight years. I therefore also consider

[15] Specifically, I drop funded firms and CVC funders that are either missing SIC information or come from (i) the Crop and Animal Production industry group (SIC 0100-0200); (i) the Finance, Insurance, and Real Estate industry group (6000-6799) or (iii) the Public Administration industry group (SIC 9100-9999).

[16] The median application-grant lag is two years; the mean is three years.

an alternative regression sample in which funded firms are limited to those whose first financing round is before the end of 2009, leaving nine years until 2018 for exit outcomes to realize.

To correct for a similar truncation bias associated with patent citations, (i.e., more recent patents have not had enough time to receive citations compared to older patents), I restrict the citation window to three or five years after the application date. Self-citations are dropped. Additionally, all citations are scaled by the average citations received by other patents applied for in the same year and the same technology class as defined by the Cooperative Patent Classification (CPC) at the section level.[17] This adjustment purges the citation data of effects due to truncation, systematic changes over time in the propensity to cite, and changes in the number of patents making citations.

Measuring demand and technology linkages Testing the hypothesized channels of CVC requires measures of the demand- and technology-side linkages for each CVC funder-funded pair. I turn to two data sources to construct measures of these linkages. The first is the 1992 Benchmark Input-Output (I-O) Account maintained by the U.S. Bureau of Economic Analysis (BEA). The I-O Account shows the flows of sales and purchases of industry outputs, allowing me to trace upstream and downstream linkages between industries.[18] I choose the year 1992 because it is the last vintage in which the BEA compiled I-O tables based on the SIC system, which is compatible with the rest of my data. Staring from 1997, the I-O tables are based on the North

[17] The CPC is a joint effort between the USPTO and the European Patent Office to harmonize patent classification. Since January 2015, the USPTO stopped classifying new utility patents using the old United States Patent Classification (USPC) scheme and began only using the CPC scheme. CPC classes have been retrospectively applied to older patents. There are nine CPC sections (Human Necessitates, Physics, Electricity, etc.). The aggregation level is similar to the six technology classes defined by Hall et al. (2001), which is widely used in the literature to adjust patent citations.

[18] The I-O Account in its original form shows the production of *commodities* by industries (the "make" table) and the consumption of *commodities* by industries (the "use" table). I use the concordance provided by the BEA to map commodities to four-digit SIC industries. In doing so, certain SIC industries are aggregated such that each resulting industry maps to non-overlapping commodities. See Appendix A.1 for more details.

American Industry Classification System (NAICS).

Consider a CVC-funded firm from industry i whose CVC funder is from industry j. Since industry i could be both buying from and selling to industry j, I construct two measures of I-O linkages to reflect such relationships:

$$\begin{aligned} IO_{ij}^{Down} &= \frac{sales_{i\to j}}{\sum_{j'} sales_{i\to j'}} = \text{demand share from funder's industry} \\ IO_{ij}^{Up} &= \frac{sales_{j\to i}}{\sum_{j'} sales_{i\to j'}} = \text{input cost share from funder's industry.} \end{aligned} \tag{1.12}$$

In Equation (1.12), IO_{ij}^{Down} measures the importance of the CVC funder's industry as a buyer for the outputs of the funded firm's industry, where the term $sales_{i\to j}$ is the 1992 "use" value in the BEA I-O Account for the value of industry i's outputs purchased by industry j. Conversely, IO_{ij}^{Up} measures the importance of the CVC funder's industry as a supplier of inputs to the funded firm's industry. Note that the summation in the denominator again runs over industry i's total sales, so IO_{ij}^{Up} could also be thought of as a cost share.

For technology linkages, I first use the citation data from PatentsView to compute a citation matrix at the industry level. The citation matrix has a similar structure to the I-O matrix, but captures the flows of knowledge rather than goods between industries.[19] Because citations are between patents defined at the technology class level, I use the concordance developed by Goldschlag et al. (2019) to map each technology class to a four-digit SIC industry. Appendix A.1 describes the procedure in depth. Once the industry citation matrix is computed, I define two measures of technology linkages between a CVC-funded firm from industry i and its CVC funder from

[19]To be consistent with the I-O matrix, I restrict the citations to those among patents applied up to 1992 (conditional on being granted by 2019). I am exploring the robustness of my results with alternative time windows.

industry j, analogously to how I define the I-O linkage measures:

$$\begin{aligned} Tech_{ij}^{Down} &= \frac{citations_{j\to i}}{\sum_{j'} citations_{j'\to i}} = \text{knowledge demand from funder's industry} \\ Tech_{ij}^{Up} &= \frac{citations_{i\to j}}{\sum_{j'} citations_{i\to j'}} = \text{knowledge input from funder's industry.} \end{aligned} \quad (1.13)$$

The variable $Tech_{ij}^{Down}$ is the share of citations made by the CVC funder's industry to the funded firm's industry in the total citations received by the funded firm's industry; it therefore captures the degree to which the CVC funder's industry demands knowledge from the funded firm's industry. Conversely, $Tech_{ij}^{Up}$ is the share of citations made by the funded firm's industry to the CVC funder's industry in the total citations made by the funded firm's industry. Hence, the variable indicates the importance of knowledge flows from the CVC funder's industry to the funded firm's industry.

1.4 Stylized Facts on U.S. CVC

Armed with this data, I first document three stylized facts on U.S. CVC that are relevant for the empirical analysis. First, I highlight the prevalence of syndication between CVC and TVC funders and emphasize that this feature of the data needs to be taken seriously when estimating the causal effects of CVC and TVC on young firm outcomes. Next, I show that CVC funders tend to select more innovative firms in which to invest, relative to TVC funders. Making a causal statement about the effects of CVC therefore requires an empirical strategy that controls for endogenous selection. Lastly, I compare the industry distributions of CVC funders and their funded firms to the I-O matrix and the patent citation matrix. By doing so, I suggest that there is scope for CVC to influence young firm outcomes through demand and technology spillovers.

Causal analysis on the effects and channels of CVC follows in Section 1.5.

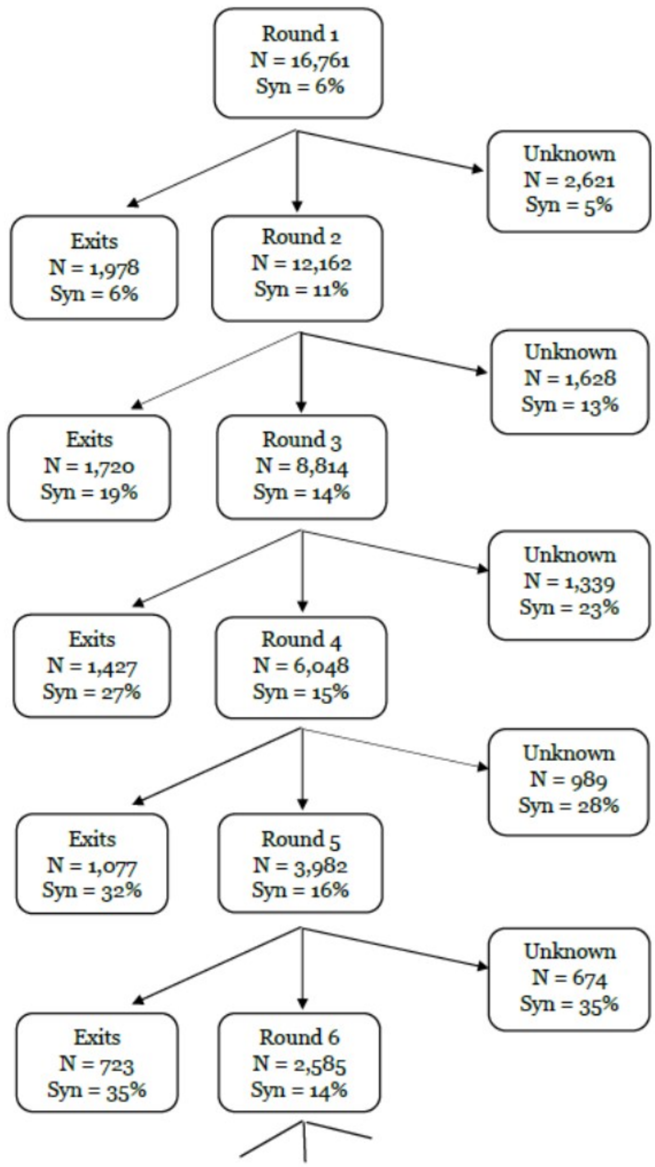
Prevalence of staged financing and CVC-TVC syndication Figure 1.1 shows what happens to the funded firms in the baseline sample round by round. While about 12 percent of the firms successfully exit via an IPO or an acquisition after the first round of VC financing, two-thirds go on to get a second VC deal. Of the firms that survive to round two, about 14 percent proceed to an exit event, while 72 percent go on to a third round. Overall, the median number of rounds is three, while the 75th percentile is four.

While only 6 percent of firms receive both CVC and TVC in the first round, that share increases to 11 percent among firms that survive to round two. By the end of round two, 19 percent of the exits involve firms that received both CVC and TVC. Conditional on surviving to round three, the share of CVC-TVC-syndicated firms further increases to 14 percent, and these firms represent 27 percent of the exits by the end of round three. Taken together, about 11 percent of the rounds involve CVC-TVC syndicates, and 22 percent of funded firms receive both CVC and TVC at some point (not necessarily in the same round). Conditional on getting CVC at some point, 49 percent of funded firms have CVC in their first round, while 69 percent have CVC in their last round.

Selection of innovative firms Figure 1.2 tracks the share of CVC- and TVC-funded firms that are in high-tech industries over time. High-tech industries are defined as in Hecker (2005) and Haltiwanger et al. (2014) and are listed in Appendix A.1. We can see from Figure 1.2 that CVC funders have consistently exhibited a stronger investment focus on high-tech firms, relative to TVC funders.

To further gauge the degree of selection, I compare CVC- and TVC-funded firms along

Figure 1.1: Staged Financing and CVC-TVC Syndicates



Notes: The sample is comprised of VC funded firms whose first observed financing round is between 1980 and 2014. The status of each firm is tracked through December 2018. An "exit" is defined as an IPO or an acquisition. "Unknown" refers to the case in which the funded firm neither experiences an exit event nor appears in the next round, which could either be a genuine write-off or a coverage issue. "Syn" stands for syndication and refers to the share of firms that receive both CVC and TVC financing (not necessarily in the same round).

Figure 1.2: Share of Funded Firms in High-Tech Industries

Notes: Figure plots the share of CVC- and TVC-funded firms that are in high-tech industries over the full sample period 1980-2018. High-tech industries are defined as in Hecker (2005) and Haltiwanger et al. (2014).

some key characteristics in Table 1.2. Because of staged financing and to avoid conflating treatment with selection, I slice the data by funded firms that have CVC in their *first* round versus those that do not. Judging from the number of patents and the citation-weighted number of patents by the funded firms, it does seem to be the case that CVC funders tend to select more innovative firms than TVC funders.[20]

Additionally, I experiment with classifying funded firms into three mutually exclusive groups to explicitly account for syndication. These three groups are comprised of firms that receive (i) both CVC and TVC (not necessarily in the same round), (ii) TVC alone, and (iii) CVC alone. Table A.2 in the Appendix confirms that the syndicated group and the CVC-alone group exhibits stronger patenting records than the TVC-alone group.

[20]In unreported analysis, I find that the patterns broadly hold within two-digit SIC industries and within states.

Table 1.2: Characteristics of Funded Firms by Funder Type

	CVC in 1st round [N=1,329]	Otherwise [N=11,267]	P-val on diff
Characteristics			
Age at 1st round	2.6	2.6	0.605
% in high-tech industries	74.9	72.9	0.132
# Patents at 1st round	1.0	0.6	0.000
# Citations at 1st round	1.9	1.1	0.000
Outcomes			
Total funding $ (mln)	34.0	30.0	0.000
# Patents 5yr after 1st round	4.2	3.6	0.008
# Citations 5yr after 1st round	8.7	7.1	0.008
% IPO	11.4	11.9	0.607
% Acquired	33.4	34.8	0.307

Notes: Table reports statistics from a t-test of equality in means. The sample is restricted to funded firms that received their first funding round between 1980 and 2009, to account for right truncation of the outcome variables. Firm age is winsorized at the 1st and 99th percentiles; funding amount is deflated to 2015 U.S. dollars using the GDP deflator and winsorized at the 1st and 99th percentiles; high-tech sectors are defined as by Hecker (2005) and Haltiwanger et al. (2014); and patent measures are winsorized at the 99th percentile. Among funded firms that had CVC in their first round, 55 percent also had TVC.

Scope for demand and technology spillovers Figure 1.3 plots the distribution of CVC deals across 32 symmetric industries defined at the two-digit SIC level. The y-axis denotes the industries of the CVC funders, and the x-axis denotes the industries of the CVC-funded firms. All entries in the matrix sum up to 100 percent. The matrix is quite sparse. The majority of deals are made in the business services industry by funders engaged in (i) business services (like Microsoft), (ii) communications (like Comcast), (iii) the manufacturing of electronic equipment (like Intel), and (iv) the manufacturing of industrial machinery (like Cisco Systems). Within business services (two-digit SIC 73), investments are concentrated in prepackaged software (SIC 7372) and information retrieval services (SIC 7375). Separately, funders from the pharmaceutical industry invest heavily within their own industry.[21]

In Figure 1.4, I present the I-O matrix and the patent citation matrix for the same set of industries as in Figure 1.3. Panel (a) depicts the I-O demand shares, IO_{ij}^{Down}, defined in Equation (1.12); Panel (b) depicts the knowledge input shares, $TECH_{ij}^{Up}$, defined in Equation (1.13). Each row of these matrices sums up to unity. A visual comparison of Panel (a) against Figure 1.3 suggests that while demand for goods stems primarily from within industries, many industries also demand inputs from the business services industry (which contains most of the funded firms). Hence, there is scope for CVC to bring demand-based spillovers to funded firms. Similarly, comparing Panel (b) against Figure 1.3 reveals that while most flows of knowledge are within industries, the manufacturing industry broadly defined (which contains many CVC funders) supplies a significant amount of knowledge to the rest of the economy, including to the business services industry. It is therefore reasonable to expect technology-based spillovers benefiting funded firms after getting CVC.

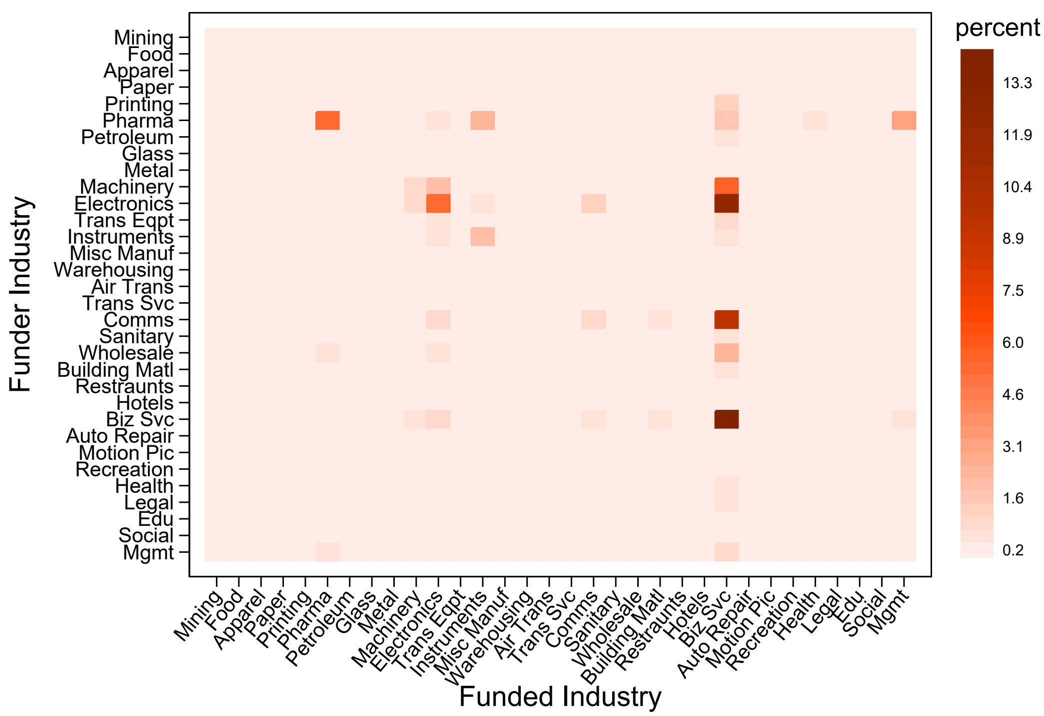
1.5 Causal Evidence on the Effects and Channels of CVC

The preceding section suggests the potential for CVC to influence young firm outcomes via demand and/or technology linkages. To establish a causal link, this section lays out a shift-share (Bartik-style) research design that deals with endogenous selection and the complications arising from staged financing and CVC-TVC syndication. The shift-share research design has a wide range of applications in economics.[22] My approach is most closely related to Davis and

[21]Figure A.2 in the Appendix plots the industry distribution of TVC deals.

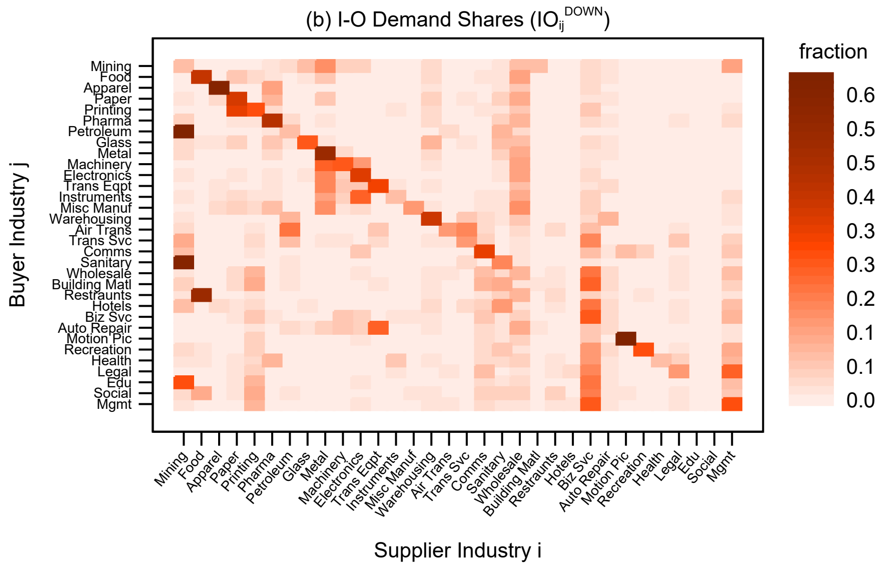
[22]In labor economics, international trade, and macroeconomics see Acemoglu and Linn (2004); Acemoglu and Restrepo (2020); Acemoglu et al. (2016); Autor et al. (2020, 2013); Bartik (1991); Blanchard and Katz (1992); Card (2009); Davis and Haltiwanger (2019); Greenstone et al. (2020); Hummels et al. (2014); Nunn and Qian (2014); Peri et al. (2015), for example.

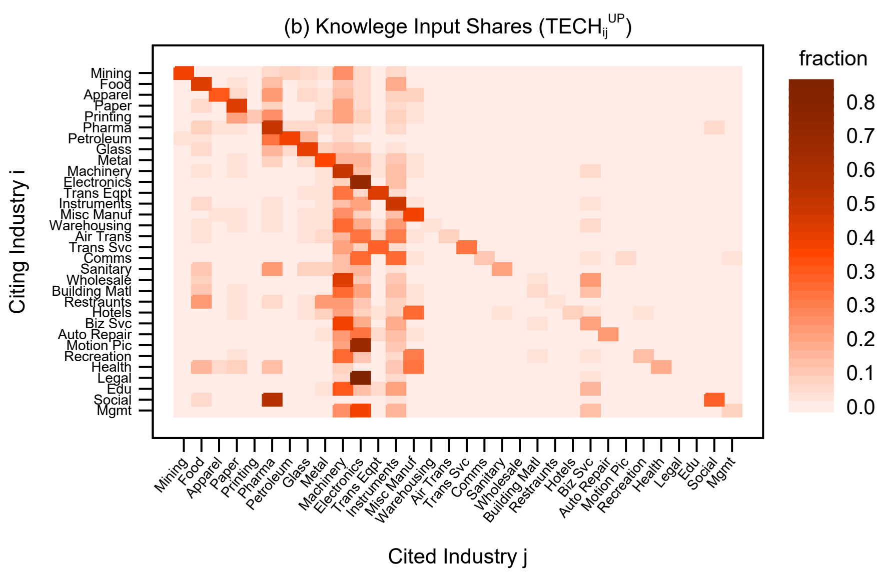
Figure 1.3: Industry Distribution of CVC Deals



Notes: Figure plots the distribution of CVC deals across 32 symmetric funder and funded industries defined at the two-digit SIC level. Certain industries are slightly aggregated to ensure symmetry of the matrix. Matrix entries sum up to 100 percent.

Figure 1.4: Input-Output and Patent Citation Matrices





Notes: Panel (a) plots the I-O demand shares, IO_{ij}^{Down}, as defined in Equation (1.12). Each row sums up to unity. The shares are computed using the 1992 BEA benchmark make and use tables. Industries are defined at the two-digit SIC level, with slight aggregation of certain industries to ensure symmetry of the matrix. Panel (b) plots the citation shares, $Tech_{ij}^{Up}$, as defined in Equation (1.13). Each row sums up unity. The shares are computed using USPTO data, restricting citations to those among patents applied up to 1992 (conditional on being granted by 2019). Industries are defined the same way as in Panel (a).

Haltiwanger (2019) and Greenstone et al. (2020).

Overarching methodological choices I begin with describing two overarching methodological choices in my empirical study. First, I focus on low-frequency movements in the data since both young firm outcomes and staged VC financing can be lumpy. Specifically, I partition the data into several five-year intervals. I reserve the first five years in my dataset between 1980 and 1984 as the initial period and use it to compute baseline quantities that are then used to construct the proposed instrumental variables; I do not use this period in the regression sample. Additionally, as described in the data section, I limit the regression sample to funded firms whose first observed financing round occurs before the end of 2014. Doing so leaves time for young firm outcomes to realize before my dataset stops in 2018. I also consider an alternative regression sample ending in 2009 to explore the robustness of the baseline results.

Second, I estimate my regressions at the four-digit SIC industry level rather than at the individual firm level. In the absence of an exogenous or quasi-experimental shock to the formation of VC relationships, identifying the causal effects of CVC and TVC using a firm-level specification could involve comparing the outcomes of CVC- and TVC-funded firms to observationally similar non-VC funded firms. My dataset does not include non-VC funded firms, unfortunately. Alternatively, identification could come from comparing the outcomes of CVC-funded firms to observationally similar TVC-funded firms. The control group of TVC-funded firms would then be constructed based on firm characteristics at the time CVC-funded firms *first* receive CVC, following a typical event study approach. However, conditional on getting any CVC, about 72 percent of the recipients first receive CVC in conjunction with TVC. This syndication makes it difficult for an event study approach to disentangle the treatment effects arising from CVC versus TVC.

The industry-level specification presented below features both CVC and TVC investments as explanatory variables. For exposition purposes, I use "VC" as an umbrella term to illustrate the workings of the shift-share instruments, which I then use to instrument both CVC and TVC analogously.

Setting the stage Consider the following regression specification:

$$\ln(Y)_{i\tau} = \alpha \ln(TVC)_{i\tau} + \beta \ln(CVC)_{i\tau} + \alpha_i + \alpha_{j\tau} + X_{i\tau} + \epsilon_{i\tau}, \tag{1.14}$$

where i indexes a four-digit SIC industry, τ a five-year period, and j the broader two-digit SIC industry that i belongs to. The dependent variable Y is young firm outcomes at the industry level, as measured either by (i) the number of patents or citation-weighted patents applied for by the funded firms or (ii) the number of IPOs and acquisitions among funded firms within the four years following the first funding event (which happens in period τ). The main regressors TVC and CVC are, respectively, the number of TVC- and CVC-funded firms or deals in industry i over period τ.[23] As described in the data section, I do not have information on the funding contribution from each investor, and hence I cannot measure the dollar amounts of TVC and CVC separately. The specification focuses on within-industry variation over time by featuring a set of four-digit SIC industry fixed effects (α_i). The specification also controls for broader macroeconomic conditions over time by including a set of two-digit SIC industry-by-period fixed effects ($\alpha_{j\tau}$). Finally, $X'_{i\tau}$ is a set of other industry-level covariates besides VC that might affect young firm outcomes. Specifically, $X'_{i\tau}$ includes the average age of the funded firms at the first funding event, which controls for firm lifecycle dynamics. The coefficients of interest are α and

[23]Following convention, I add one to Y, CVC, and TVC if the cell is zero before taking logs.

β; they can be loosely interpreted as the elasticities of young firm outcomes with respect to TVC and CVC at the industry level. The difference between the two coefficients gives an indication of the differential effect of CVC relative to TVC.

Direct ordinary least squares (OLS) estimates of Equation (1.14) could not be interpreted as yielding causal estimates of α and β, because realized CVC and TVC investments are likely correlated with the unobserved error term in Equation (1.14). For example, both CVC and TVC funders may tend to select promising young firms that would perform well even in the absence of any VC financing, leading to an upward bias in estimated α and β. Alternatively, there could be unobserved and time-varying technological shocks at the industry level that influence the amount of VC investments and young firm outcomes simultaneously.

A shift-share style research design To deal with the endogeneity of both forms of VC investment, I consider a shift-share style research design that instruments CVC and TVC using the interaction of the initial market shares of different funders investing in an industry with measures of funder supply shifts. Specifically, the instrument takes the form:

$$\widehat{VC}_{i\tau} = \sum_k \underbrace{\omega_{ik}}_{\text{funder market shares}} \times \underbrace{s_{k\tau}}_{\text{funder supply shifts}}, \tag{1.15}$$

where k indexes a funder, i a four-digit SIC industry, and τ a five-year period.

The "share" component in Equation (1.15), ω_{ik}, is funder k's initial market share in industry i. Ideally, I would like to use the share from the previous period or the initial sample period to mitigate simultaneity bias. However, because the set of four-digit SIC industries a typical funder invests in has expanded over time, using the previous period or the initial period alone results in many missing cells. I therefore use the average market share of a funder between period $\tau - 1$ and τ. The market share is measured in terms of the number of funded firms or deals. As described below, my identification strategy does not necessarily require the exogeneity of the shares.

The "shift" component in Equation (1.15), $s_{k\tau}$, is a set of funder-specific supply shifts that I construct below. Intuitively, these funder supply shifts are meant to isolate the component of VC investments that reflects a funder's abundance of capital, rather than being driven by young firm quality or technological opportunities in an industry. One could think of these supply shifts as capturing, for example, idiosyncratic productivity shocks to funders or differences in CEO visions, which in turn determine how much capital is available for and devoted to VC investment independent of funded firm characteristics.

I use two approaches to construct the funder supply shifts $s_{k\tau}$ in Equation (1.15). The first is to simply add up a funder k's investments to all industries except to the industry i in observation. Specifically:

$$s^1_{k\tau} = \sum_{i' \neq i} VC_{i'k\tau}, \tag{1.16}$$

where the superscript denotes the first among the two approaches. When constructed this way, $s^1_{k\tau}$ is meant to capture a funder's overall abundance of capital and can be argued as plausibly exogeneous with respect to conditions in a specific funded industry. One concern with Equation (1.16) is that there may be correlated industry shocks, so that the leave-one-out procedure is not enough to remove correlations between funder and funded industry disturbances. For robustness, I consider leaving out the broader three- or two-digit SIC industry that i falls into.

The second approach uses a generalization of the leave-one-out procedure. I leverage the fact that a typical funder invests across multiple four-digit SIC industries, as shown in Table A.3

in the Appendix, so that I can first purge the common industry effects that likely reflect selection. Specifically, I run the following regression period by period:

$$VC_{ik\tau} = \delta_{i\tau} + \delta_{k\tau} + \epsilon_{ik\tau}, \tag{1.17}$$

where $VC_{ik\tau}$ is funder k's investments in industry i over period τ, $\delta_{i\tau}$ is a set of industry-specific effects, and $\delta_{k\tau}$ is a set of funder-specific effects. Since the industry fixed effects, $\delta_{i\tau}$, measure the variation in VC investments that is common across funders investing in the same industry, they likely reflect young firm quality or technological opportunities in an industry. Consequently, the funder fixed effects, $\delta_{k\tau}$, capture the component of funder k's VC investments that is purged of effects driven by young firm quality or technological opportunities in a funded industry. The funder supply shifts are then taken to be the estimated funder-specific effects:

$$s^2_{k\tau} = \hat{\delta}_{k\tau}, \tag{1.18}$$

where the superscript differentiates the second approach from the first.

In sum, I instrument both CVC and TVC investment using the instrumental variable outlined in Equation (1.15), where the funder supply shifts $s_{k\tau}$ are constructed in two ways as given by Equation (1.16) and Equation (1.18). The purging regression in Equation (1.17) is run separately for CVC and TVC funders, and likewise the market shares ω_{ik} in Equation (1.15) are computed separately within each type of funder.

Probing the validity of the research design Recent work has discussed the validity and inference of shift-share style instruments (see, for example, Adão et al., 2019; Andrews et al., 2017; Barrett and Christian, 2012; Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018). Specifically, Goldsmith-Pinkham et al. (2020) derive theoretical results showing that the validity of the shift-share instrument could come from the exogeneity of the shares. Borusyak et al. (2021), instead, show that validity could stem from the quasi-random assignment of the shocks. My identifying assumption is more aligned with Borusyak et al. (2021). Since the funder supply shifts that I construct are essentially a set of idiosyncratic shocks, my instruments are valid to the extent that the funder supply shifts are (i) as-good-as-randomly assigned conditional on included covariates, (ii) mutually uncorrelated, and (iii) large in number and sufficiently dispersed, according to the conditions derived by Borusyak et al. (2021).

To probe the assumption of quasi-random shocks, I conduct a falsification test by regressing predetermined young firm outcomes on the shift-share instruments. If the funder supply shifts are as-good-as-randomly assigned to industries within periods, one would expect the instruments to not predict predetermined variables. Specifically, I regress industry-level young firm outcomes in period τ on the two-, three-, and four-period ahead instruments.[24] Table 1.3 reports the reduced-form IV estimates. By and large, I do not find statistically significant relationships between the predetermined outcomes and the shift-share instruments, bolstering our confidence in the exogeneity of the funder supply shifts.

To gauge the degree of correlation between the funder supply shifts, I regress funder k's supply shift on the average supply shift of other funders investing in the same industries in which k invests. To compute the average supply shift of peers, I first calculate market-share-weighted funder supply shifts excluding funder k's own effect in every industry in which k invests. I

[24]Because the outcomes are collected within a four-year window since the first funding event, I do not regress period-τ outcomes on the one-period ahead instruments to mitigate simultaneity bias.

then aggregate these averages to the funder level, weighting each observation by the share of funder k's investments in each industry. Table 1.4 shows no statistically significant correlations when I measure the supply shifts using purging approach. However, there is a mildly significant correlation when I use the leave-one-out approach for CVC funders and a highly significant correlation for TVC funders. Consistent with a priori expectations, the purging approach is better at isolating the idiosyncratic component of funder investments than the leave-one-out approach.

Finally, the validity of the research design hinges on there being a sufficient number of funder-level supply shocks, and a small average exposure to each funder across industries. The average exposure to funder k can be computed simply as $e_k = \frac{1}{N}\sum_i \omega_{ik}$, where ω_{ik} is funder k's baseline market share in industry i defined in Equation (1.15) and N is the total number of industries in which funder k invests. Following Borusyak et al. (2021), I compute the inverse of the Herfindahl-Hirschman Index (HHI) of the exposure shares as a simple check on dispersion.[25] Table 1.5 shows that the inverse of the HHI is quite high across funder-by-period cells. For comparison, the inverse of the HHI in the Autor et al. (2013) setting that features 794 industry-by-period shocks is 191.6 (Borusyak et al., 2021).

Taken together, the falsification, correlation, and dispersion exercises suggest that my shift-share instruments can be reasonably viewed as leveraging exogenous variation. In light of the unsatisfactory performance of the leave-one-out instrument in the correlation test, however, I take the purging instrument as my preferred instrument. I nonetheless report results using both instruments in what follows for the purpose of robustness.

Results on the causal effect of CVC relative to TVC Table 1.6 reports the OLS and IV two-

[25] Note that the exposure shares are computed period by period. For the purpose of the exercise, all the exposure shares are stacked and normalized to sum up to one across all periods. The inverse of the HHI is then computed as $1/\sum_{k\tau} e_{k\tau}^2$.

stage least squares (2SLS) estimates of Equation (1.14), focusing on patent-based metrics as outcomes. Columns (1) to (3) use raw patent counts as the dependent variable while columns (4) and (5) use citation-weighted patent counts to properly reflect the scientific impact of the patents. As a benchmark, column (1) presents an OLS estimation that includes four-digit industry effects and two-digit industry-by-period effects, with no other industry controls. Column (2) features the same set of regressors as used in column (1) but instruments CVC and TVC using the funder supply shifts constructed with the leave-one-out approach in Equation (1.16), excluding the broad two-digit industry. Relative to column (2), column (3) uses the funder supply shifts constructed with the purging approach in Equation (1.18). Judging from the 2SLS estimates in columns (2) and (3), both CVC and TVC investments are found to have a statistically significant effect on the number of (ultimately) successful patent applications by the funded firms in subsequent years. The magnitudes of the estimates are stable across the two instruments. More precisely, a one percent increase in CVC deals at the industry level leads to a roughly 0.4 percent increase in subsequent successful patent applications by the funded firms. Importantly, the model cannot reject the null hypothesis that the effect of CVC is as large as the effect of TVC. The effects are robust to using citation-weighted patent counts, as shown in column (4); they are also robust to including other industry level covariates, as shown in column (5).

The IV 2SLS estimates in Table 1.6 are in general larger than the OLS estimates. This result may seem counterintuitive, considering that the OLS estimates should overstate the effects of CVC and TVC due to the omission of controls for young firm quality or technological opportunities at the industry that are positively correlated with young firm outcomes (upward bias). A classical reason why IV estimates may be larger than their OLS counterparts is measurement errors in the independent variables. In my case, however, the independent variables, such as the number of

CVC and TVC deals, can be precisely measured conditional on the sample. A more plausible explanation is that while the OLS estimates measure the *average* effects of CVC and TVC, the IV estimates measure the *local* effects on the *marginal* young firms. Given how the instruments are constructed, they influence the young firms that would not have been funded had the funders lacked sufficient capital. If these marginal young firms have lower quality than the average firm in the VC-funded cohort, CVC and TVC could be more beneficial to these firms, consistent with the IV estimates being larger than the OLS estimates.

Note that the F statistics that measure instrument relevance are all above the conventional threshold of ten. Further details on the first-stage regressions are reported in Table A.4 in the Appendix. The table shows a strong correlation between the instruments and the endogenous variables, conditional on included covariates. Moreover, the R squared values are quite high, strengthening the claim of a strong first stage.

With a similar structure, Table 1.7 reports the estimated effects of CVC and TVC on the exit outcomes of funded firms. Columns (1) to (3) combine the number of IPOs and acquisitions together while columns (4) and (5) examine IPOs and acquisitions separately. All columns feature the full set of controls. The IV estimates suggest that a one percent increase in CVC deals at the industry level leads to a roughly 0.2 percent increase in subsequent successful exits. The effect is more pronounced with acquisitions than with IPOs.[26]

Testing the channels of CVC The preceding section establishes a causal effect of CVC on young firm outcomes that is as large as the effect of TVC. To test whether this effect stems from demand and/or technology synergies as hypothesized in the model section, I run the following

[26] I am currently investigating whether CVC funders invest solely to attempt to acquire the funded firms down the road. Click the link in the first page for the latest version of the paper.

regression:

$$
\begin{aligned}
\ln(Y)_{i\tau} &= \ln(TVC)_{i\tau} + \ln(CVC)_{i\tau} + \gamma\Omega_{i\tau} \times \ln(CVC)_{i\tau} + \Omega_{i\tau} \\
&+ \alpha_i + \alpha_{j\tau} + X_{i\tau} + \epsilon_{i\tau}, \qquad (1.19)
\end{aligned}
$$

where $\Omega_{i\tau}$ is a stand-in for the linkage measures defined below and all other variables are defined in the same way as in Equation (1.14). As described in the data section, because a CVC funder's industry could both buy from and sell to (or cite from and be cited by) the funded firm's industry, I compute separate downstream and upstream linkage measures for a CVC funder-funded pair, as shown in Equation (1.12) and Equation (1.13). These pairwise linkage measures need to be aggregated to obtain $\Omega_{i\tau}$ in Equation (1.19).

Consider first the downstream I-O linkage, denoted by $\Omega_{i\tau}^{IO-Down}$. For each funded industry i whose CVC funders come from industries $j \in \mathcal{J}$, I compute:

$$
\Omega_{i\tau}^{IO-Down} = \sum_{j \in \mathcal{J}} \underbrace{IO_{ij}^{Down}}_{\text{demand share in Equation (1.12)}} \times \underbrace{W_{j\tau}}_{\text{funding share}}, \qquad (1.20)
$$

where IO_{ij}^{Down} is the demand share as defined in Equation (1.12) and W measures total CVC funding from industry j to i relative to all CVC funding received by i (in terms of the number of funded firms or deals). Essentially, $\Omega_{i\tau}^{IO-Down}$ is the weighted average of the demand from each CVC funder's industry to the funded industry.

In a similar vein, the upstream I-O measure, $\Omega_{i\tau}^{IO-Up}$, is computed using Equation (1.20) but replacing IO_{ij}^{Down} with IO_{ij}^{Up}, the input cost share, as defined in Equation (1.12). The variable $\Omega_{i\tau}^{IO-Up}$ therefore measures the average importance of the CVC funders' industries in supplying inputs to the funded firms.

To construct the technology counterparts, $\Omega_{i\tau}^{Tech-Up}$ and $\Omega_{i\tau}^{Tech-Down}$, I replace the I-O demand share in Equation (1.20) with the knowledge input share ($Tech_{ij}^{Up}$) or the knowledge demand share ($Tech_{ij}^{Down}$) as defined in Equation (1.13).

Finally, I compute two measures to capture the *net* effects of the I-O and technology linkages, denoted by $\Omega_{i\tau}^{IO-NetDown}$ and $\Omega_{i\tau}^{Tech-NetUp}$. Specifically, $\Omega_{i\tau}^{IO-NetDown}$ is constructed by replacing the demand share in Equation (1.20) with the net downstream importance of the CVC funder's industry with respect to the funded firm's industry in the I-O matrix, as measured by $IO_{ij}^{Down} - IO_{ij}^{Up}$. Because of the linearity in Equation (1.20), $\Omega_{i\tau}^{IO-NetDown} = \Omega_{i\tau}^{IO-Down} - \Omega_{i\tau}^{IO-Up}$. The variable $\Omega_{i\tau}^{Tech-NetUp}$ is constructed analogously.

Table 1.8 reports the IV estimates of Equation (1.19) for patenting outcomes. Given the large number of endogenous variables including the interaction terms, Equation (1.19) is estimated as a reduced-form equation. All columns include the full set of controls and use the purging instrument of funder supply shifts as defined in Equation (1.18). Columns (1) and (2) focus on I-O linkages and suggest that the effect of CVC on patent counts is stronger in funded industries for which the CVC funders have stronger downstream relationships with the funded firms, lending support to the hypothesized demand channel. Columns (3) and (4) focus on the technology linkages and suggest that the effect of CVC on patent counts is stronger in funded industries in which funded firms draw knowledge more heavily from the funding industries, lending support to the hypothesized technology channel. When both the I-O and technology linkage measures are included in column (5), both channels hold up. Finally, column (6) looks at citation-weighted patent counts and shows that the demand channel persists.

In unreported analysis, I do not find evidence that demand and technology channels matter for exit outcomes at conventional levels of statistical significance. While successful exits may be a reasonable proxy for young firm growth, which is ultimately what I am interested in, there may be considerations beyond the scope of this paper that influence the decisions to go IPO or to be acquired. A large literature examines the motives of M&A in general (Faria, 2008; Jovanovic and Rousseau, 2002, 2008; Rhodes-Kropf and Robinson, 2008) or in the specific context of innovation (Acemoglu et al., 2010; Aghion and Tirole, 1994; Aghion et al., 2006; Bena and Li, 2014).

Robustness checks The baseline results are robust to a host of tests reported in Appendix A.2. First, I use the short regression sample ending in 2009 to leave more time for firm outcomes to realize. Panel (A) of Table A.5 presents the estimated effects of CVC and TVC on the patenting outcomes of funded firms while Panel (A) of Table A.6 presents the estimates for successful exits. The identified effects shown in Table 1.6 and 1.7 continue to hold in the short sample. In fact, the magnitudes of the estimates are slightly larger in the short sample, consistent with a longer time window further alleviating the truncation problem.

Second, I explore the sensitivity of the baseline results to pooling CVC and TVC funders when running the purging regression in Equation (1.17). In the baseline, Equation (1.17) is run separately for each type of funder to allow for potential differences in the screening ability across funder types. To the extent that CVC funders possess industry knowledge and in-house technologies, they may be better at screening young firms than TVC funders. Having two separate sets of industry fixed effects in the baseline estimation accommodates such a possibility. In Panel (B) of Table A.5 and A.6, I report results when the purging regression is run pooling together both types of funders and subjecting them to the same set of industry fixed effects. The estimates are quite close to the baseline results, and the F statistics are in fact slightly larger than their baseline counterparts.

Third, I experiment with weighting the purging regression in Equation (1.17) by each funder's baseline investments in industry i.[27] Doing so allows an observation's influence to be proportional to its investments. The results for patenting outcomes and successful exits are reported respectively in Panel (C) of Table A.5 and A.6. The estimates are once again close to the baseline results.

Fourth, instead of log-transforming the dependent variable and fitting a log-linear regression for Equation (1.14), I use the untransformed dependent variable and implement a Poisson pseudo-maximum likelihood (PPML) procedure. Relative to a log-linear regression, the PPML procedure is recommended in the presence of nonnegative and count data with possibly many zeros (Blackburn, 2007; Gourieroux et al., 1984; Manning and Mullahy, 2001; Silva and Tenreyro, 2006; Wooldridge, 1999). The procedure requires minimal assumptions about the distribution of the data, unlike the negative binomial (NB) regression, a popular alternative to estimating count data models.[28,29] Because the PPML procedure and other existing methods for estimating count models in a panel setting cannot yet handle 2SLS, I report the reduced-form PPML estimates in Table A.7. Reassuringly, the baseline results hold up well with this alternative estimation procedure.

Finally, I investigate the channels of CVC using unweighted linkage measures. I replace the funding share, W, in Equation (1.20) with $1/N$, where N is the number of funding industries

[27] As described previously, the set of four-digit SIC industries a typical funder invests in has expanded over time. I therefore use the average amount of investments between period $\tau - 1$ and τ as the weights.

[28] The NB model introduces a dispersion parameter that can better deal with the overdispersion of count data—i.e., the conditional variance is larger than the conditional mean—than a Poisson model. However, the Poisson model can accommodate fixed effects in a panel setting whereas the NB model with fixed effects does not qualify as a true fixed effects method (Allison and Waterman, 2002; Greene, 2005; Guimarães, 2008).

[29] I use the Stata command *ppmlhdfe* to implement the PPML procedure with fixed effects in a panel setting. See Correia et al. (2020) for a detailed user manual.

for industry i in observation. The results are reported in Table A.8. As in the baseline case, both the demand the technology channels are found to be statistically significant for patenting outcomes.

1.6 Concluding Remarks

CVC is an important funding source for risky innovation, representing about a quarter of total U.S. VC investments. Unlike TVC, which serves as a form of financial intermediation, CVC entails a match between non-financial firms seeking synergies beyond a simple financing relationship. Despite the large size and unique nature of CVC, the role of CVC is a relatively unchartered territory in the economics, business, or finance literature.

This paper provides causal evidence that CVC is as important as TVC in the making of high-growth young firms. The result is obtained by leveraging a unique dataset and a shift-share empirical strategy that is plausibly robust to a set of issues plaguing empirical VC research, including the presence of staged financing, CVC-TVC syndication, and endogenous selection. Importantly, the identified channels of CVC support the notion that demand-based conditions and technology-related intangibles matter in the growth process of young firms. A natural policy implication is that frictions in young firms' access to markets, customers, and technological intangibles may need to be addressed more seriously by policies aiming to promote high-quality entrepreneurship.

This paper leaves behind open and interesting questions about other aspects of CVC. Why do funders engage in CVC activity? Is there a feedback loop between CVC and in-house R&D or acquisitions? What are the aggregate implications of CVC, and is CVC an efficient vehicle for promoting long-run economic growth? I scratch the surface of some of these issues in Liu (2021a,c). More systematic studies on these questions point to promising directions for future research.

Table 1.3: Falsification Tests

	$\ln(Patents)$				$\ln(Exits)$			
	Reduced-form IV 1		Reduced-form IV 2		Reduced-form IV 1		Reduced-form IV 2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Two-period ahead instruments								
$\ln(CVC)$	-0.070*	-0.057	-0.089	-0.071	-0.014	-0.015	-0.013	-0.013
	(0.040)	(0.039)	(0.081)	(0.079)	(0.018)	(0.018)	(0.037)	(0.037)
$\ln(TVC)$	-0.070	-0.060	-0.037	-0.045	-0.053	-0.050	-0.060	-0.063
	(0.055)	(0.053)	(0.120)	(0.118)	(0.032)	(0.031)	(0.067)	(0.066)
Observations	728	728	728	728	728	728	728	728
R-squared	0.816	0.822	0.814	0.821	0.801	0.804	0.800	0.802
Three-period ahead instruments								
$\ln(CVC)$	0.006	-0.006	0.050	0.036	-0.016	-0.017	0.009	0.009
	(0.049)	(0.050)	(0.092)	(0.095)	(0.022)	(0.022)	(0.043)	(0.043)
$\ln(TVC)$	-0.083	-0.032	-0.063	0.014	-0.027	-0.016	-0.049	-0.033
	(0.100)	(0.099)	(0.221)	(0.212)	(0.048)	(0.048)	(0.099)	(0.099)
Observations	516	516	516	516	516	516	516	516
R-squared	0.812	0.820	0.812	0.820	0.800	0.801	0.799	0.801
Four-period ahead instruments								
$\ln(CVC)$	0.040	0.045	0.162**	0.159*	-0.020	-0.017	-0.009	-0.009
	(0.042)	(0.043)	(0.080)	(0.084)	(0.027)	(0.026)	(0.053)	(0.051)
$\ln(TVC)$	0.032	0.018	0.073	0.078	0.013	0.007	-0.023	-0.020
	(0.072)	(0.070)	(0.164)	(0.151)	(0.044)	(0.043)	(0.091)	(0.090)
Observations	312	312	312	312	312	312	312	312
R-squared	0.854	0.865	0.856	0.867	0.822	0.832	0.822	0.831
Four-digit industry effects	y	y	y	y	y	y	y	y
Two-digit industry by period effects	y	y	y	y	y	y	y	y
Industry controls	n	y	n	y	n	y	n	y

Notes: The table reports reduced-form IV estimates of modified Equation (1.14). Specifically, the outcome variables in period τ are regressed on the instruments for period $\tau + n$, where $n \in [2,\ 4]$. The dependent variables are (log) patent counts or (log) IPO and acquisition counts. Outcomes are restricted to a four-year window after the first funding event. CVC and TVC are measured by the number of deals. Industry controls include the average age of funded firms at the first funding event. IV 1 uses the leave-one-out approach to compute the funder supply shifts as given by Equation (1.16), excluding the broad two-digit SIC industry. IV 2 uses the purging approach to compute the funder supply shifts as given by Equation (1.18). Robust standard errors are clustered at the four-digit SIC level. *** p<0.01; ** p<0.05; * p<0.1.

Table 1.4: Testing for Correlated Funder Supply Shifts

	IV 1		IV 2	
Funder supply shifts	CVC	TVC	CVC	TVC
Average supply shift of the peers investing in industries where the funder invests	0.027*	0.034***	-0.172	0.151
	(0.016)	(0.006)	(0.115)	(0.099)
Observations	986	4,377	908	4,006
R-squared	0.010	0.011	0.086	0.021
Period fixed effects	y	y	y	y

Notes: The estimates are obtained by regressing a funder's supply shift on the average supply shift of other funders investing in the same industries. The regression sample is an unbalanced panel defined by the funder id and the time period. Because the funder supply shifts are constructed period by period, all specifications use within-period variation by controlling for period fixed effects. IV 1 refers to the leave-one-out approach to constructing the funder supply shifts as given by Equation (1.16), excluding the broad two-digit SIC industry. IV 2 refers to the purging approach as given by Equation (1.18). Robust standard errors are clustered at the funder level. *** p<0.01; ** p<0.05; * p<0.1.

Table 1.5: Characteristics of Shock Exposures

	IV 1		IV 2	
	CVC	TVC	CVC	TVC
1/(Herfindahl-Hirschman Index of the exposure shares)	152.1	940.8	154.3	810.2
# funder-by-period shocks	985	4,315	925	4,006
# funders	495	1863	492	1859

Notes: The average exposure to funder k across industries is computed as $e_k = \frac{1}{N}\sum_i \omega_{ik}$, where ω_{ik} is funder k's baseline market share in industry i as defined in Equation (1.15) and N is the total number of industries in which funder k invests. The exposure shares are computed period by period and normalized to sum up to one across all periods. Following Borusyak et al. (2021), the inverse of the Herfindahl index is computed as $1/\sum_{k\tau} e_{k\tau}^2$. IV 1 refers to the leave-one-out approach to constructing the funder supply shifts as given by Equation (1.16), excluding the broad two-digit SIC industry. IV 2 refers to the purging approach as given by Equation (1.18).

Table 1.6: The Causal Effects of CVC and TVC on Patenting Outcomes

$\ln(Patents)$	(1) OLS Counts	(2) 2SLS IV 1 Counts	(3) 2SLS IV 2 Counts	(4) 2SLS IV 2 Citation-wgt	(5) 2SLS IV 2 Citation-wgt
$\ln(CVC)$	0.313***	0.402***	0.386***	0.379**	0.415***
	(0.059)	(0.112)	(0.123)	(0.152)	(0.156)
$\ln(TVC)$	0.432***	0.468***	0.442***	0.550***	0.472***
	(0.044)	(0.100)	(0.112)	(0.128)	(0.157)
P-val on diff	0.188	0.725	0.793	0.489	0.837
Observations	1,527	1,527	1,527	1,527	1,527
R-squared	0.827	0.211	0.214	0.167	0.176
Kleibergen-Paap F stat	n/a	60.301	46.908	46.908	33.329
Four-digit industry effects	y	y	y	y	y
Two-digit industry-by-period effects	y	y	y	y	y
Industry controls	n	n	n	n	y

Notes: The table reports OLS and IV 2SLS estimates of Equation (1.14). The dependent variable is (log) patent counts or citation-weighted patent counts. CVC and TVC are measured by the number of deals. Patents are restricted to those applied for within a four-year window after the first funding event. Citations are restricted to a three-year window after the application date and scaled by technology field-by-year means. Self-citations are excluded. Industry controls include the average age of funded firms at the first funding event. Column (2) uses the leave-one-out approach to construct the funder supply shifts as given by Equation (1.16), excluding the broad two-digit SIC industry. Columns (3)-(5) use the purging approach to construct funder supply shifts as given by Equation (1.18). Robust standard errors are clustered at the four-digit SIC level. *** p<0.01; ** p<0.05; * p<0.1.

Table 1.7: The Causal Effects of CVC and TVC on Successful Exits

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
		IV 1	IV 2	IV 2	IV 2
$\ln(Exits)$	IPO+M&A	IPO+M&A	IPO+M&A	IPO	M&A
$\ln(CVC)$	0.220***	0.181***	0.210***	0.071*	0.167***
	(0.037)	(0.049)	(0.052)	(0.038)	(0.051)
$\ln(TVC)$	0.178***	0.096*	0.079	0.002	0.100**
	(0.022)	(0.050)	(0.055)	(0.041)	(0.050)
P-val on diff	0.340	0.328	0.172	0.344	0.451
Observations	1,527	1,527	1,527	1,527	1,527
R-squared	0.844	0.218	0.216	0.019	0.213
Kleibergen-Paap F stat	n/a	48.301	33.329	33.329	33.329
Four-digit industry effects	y	y	y	y	y
Two-digit industry-by-period effects	y	y	y	y	y
Industry controls	y	y	y	y	y

Notes: The table reports OLS and IV 2SLS estimates of Equation (1.14). The dependent variable is (log) number of successful exits, either counting IPOs and M&As together (columns 1-3) or separately (columns 4-5), among funded firms within the four years following the first funding event. CVC and TVC are measured by the number of deals. All specifications control for four-digit SIC industry fixed effects, two-digit SIC industry-by-period fixed effects, and industry-level controls that include the average age of funded firms at the first funding event. Column (2) uses the leave-one-out approach to construct the funder supply shifts as given by Equation (1.16), excluding the broad two-digit SIC industry; columns (3) to (5) use the purging approach as given by Equation (1.18). Robust standard errors are clustered at the four-digit SIC level. *** p<0.01; ** p<0.05; * p<0.1.

Table 1.8: The Channels of CVC on Patenting Outcomes

$\ln(Patents)$	(1) IV 2 Reduced-form Counts	(2) IV 2 Reduced-form Counts	(3) IV 2 Reduced-form Counts	(4) IV 2 Reduced-form Counts	(5) IV 2 Reduced-form Counts	(6) IV 2 Reduced-form Citation-wgt
$\ln(CVC)$	0.380***	0.388***	0.342***	0.321***	0.395***	0.447***
	(0.065)	(0.073)	(0.060)	(0.062)	(0.063)	(0.090)
$\ln(TVC)$	0.161**	0.162**	0.170**	0.175**	0.158**	0.163**
	(0.073)	(0.073)	(0.076)	(0.076)	(0.073)	(0.081)
$\ln(CVC) \times \Omega^{IO-NetDown}$	0.114***				0.097**	0.114**
	(0.035)				(0.039)	(0.054)
$\ln(CVC) \times \Omega^{IO-Down}$		0.100**				
		(0.042)				
$\ln(CVC) \times \Omega^{IO-Up}$		-0.125***				
		(0.048)				
$\ln(CVC) \times \Omega^{Tech-NetUp}$			0.250**		0.252**	0.268
			(0.119)		(0.123)	(0.169)
$\ln(CVC) \times \Omega^{Tech-Up}$				0.265**		
				(0.112)		
$\ln(CVC) \times \Omega^{Tech-Down}$				-0.260**		
				(0.113)		
Observations	932	932	932	932	932	932
R-squared	0.834	0.835	0.832	0.832	0.837	0.804
Four-digit IO industry effects	y	y	y	y	y	y
Two-digit IO industry-by-period effects	y	y	y	y	y	y
Industry controls	y	y	y	y	y	y

Notes: The table reports reduced-form IV estimates of Equation (1.19), using the purging approach to construct funder supply shifts as given by Equation (1.18). The dependent variable is (log) patent counts or citation-weighted patent counts. Patents are restricted to those applied for within a four-year window after the first funding event. Citations are restricted to a three-year window after the application date and scaled by technology field-by-year means. Self-citations are excluded. Industry controls include the main effects of the linkage terms and the average age of funded firms at the first funding event. See Appendix A.1 for details on mapping SIC industries and patent technology classes to I-O industries. Robust standard errors are clustered at the four-digit I-O industry level. *** p<0.01; ** p<0.05; * p<0.1.

Chapter 2: Learning by Investing: Corporate Venture Capital and Corporate Innovation

2.1 Introduction

Non-financial firms fund start-up and young businesses through corporate venture capital (CVC), a form of minority equity investment modeled on the traditional approach to venture capital but often times motivated by strategic payoffs in addition to pure financial returns.[1] This paper investigates the effect of CVC on one form of strategic payoffs to the funding firms: corporate innovation. CVC is widely viewed as part of corporate research and development (R&D) strategies, by enabling the funding firms to engage with the entrepreneurial sector (see Da Rin et al., 2013; Drover et al., 2017, for review) As of 2016, aggregate CVC investment reached $38 billion, amounting to about 10 percent of U.S. private R&D expenditures (NSF, 2018; NVCA, 2019).

A small but growing body of work has examined the link between CVC and the innovation outcomes of the funding firms. Dushnitsky and Lenox (2005) make early contributions. They construct a sample of U.S. publicly traded firms that invested in CVC or patented during the period of 1969–1999. Using within-firm variation, they find that forward citation-weighted

[1] Some banks and real estate companies also engage in CVC activity. I exclude these financial firms in my analysis.

patenting outcomes are positively related to the level of lagged CVC investment. Ma (2020) uses a more recent sample of U.S. publicly traded firms to show that firms launch CVC units following a period of deteriorated internal innovation and terminate CVC units when innovation begins to recover. For a source of exogenous variation, the author instruments a firm's CVC decisions using the degree of knowledge obsolescence in the firm's predetermined knowledge stock.[2] The positive relationship between CVC and funder innovation is also supported by industry studies (Smith and Shah, 2013; Wadhwa and Kotha, 2006).[3]

My strategy to overcome the endogeneity of CVC is to form a group of control firms that could provide a measure of the counterfactual outcomes for CVC funders had the latter not engaged in CVC activity. To do so, I construct and analyze a micro-level dataset that links CVC investments to U.S. publicly traded firms and their patenting activity. I track the funding firms before and after starting CVC, in comparison to a group of control firms that match the CVC firms in firm size, age, industry, and prior patenting performance. I find that CVC leads to an increase in the patenting rate at the funding firms. Importantly, much of the effect is driven by smaller-sized funding firms, suggesting potential complementarity between CVC and R&D activities, as smaller firms have been shown to be more innovation intensive than their larger counterparts and account disproportionately for major inventions (see Akcigit and Kerr, 2018; Cohen and Klepper, 1996, for example).

Relative to existing studies, the matching strategy strengthens the causal interpretation in Dushnitsky and Lenox (2005). Additionally, my estimates can be interpreted as the average treatment effect of CVC engagement on funders' innovation outcomes, which complements Ma

[2]A firm i's predetermined knowledge stock at year t is proxied by the set of all patents cited by firm i but not belonging to i up to year $t-\tau$. The degree of knowledge obsolescence is then measured by the change in the number of citations (excluding self-citations) received by this predetermined knowledge stock from year $t-\tau$ to t.

[3]For a more comprehensive review of CVC research, see Da Rin et al. (2013) and Drover et al. (2017).

(2020) that identifies the local average treatment effect of CVC based on firms that were induced to start (terminate) CVC by the incremental increase (decrease) in knowledge obsolescence. Moreover, the estimated heterogeneous effects of CVC across the firm size distribution helps inform the debate about firm size and innovation.

The remainder of the paper is organized as follows. Section 2.2 provides a brief overview of the institutional background of CVC. Section 2.3 describes the data sources and the analysis sample. Section 2.4 presents a number of stylized facts on the funder side of the CVC market. Section 2.5 discusses the empirical strategy that I use to estimate the treatment effect of CVC on funders' innovation outcomes, followed by the results and open questions. Finally, Section 2.6 offers concluding remarks.

2.2 Institutional Background

To facilitate the contrast between CVC and traditional venture capital (TVC), I begin with a brief overview of the TVC industry.[4] Like any other financial intermediary, traditional venture capitalists channel funds from investors to entrepreneurs who have productive ideas but no money. Committed capital to venture funds primarily comes from wealthy individuals, pension funds, and college endowments (called limited partners), with each fund having a life span of about 10 years (Samila and Sorenson, 2011). Traditional venture capitalists screen and invest in high-potential start-ups on behalf of the limited partners; they hold preferred stock and get paid before the common stock that entrepreneurs and other less privileged investors hold (Kaplan and Strömberg, 2003). When a portfolio start-up issues an initial public offering (IPO) or gets acquired by another firm, traditional venture capitalists turn their equity holding into realized returns. They then return

[4]Further details about how TVC works can be found in the large-scale survey study by Gompers et al. (2020).

capital to the limited partners and receive a profit share or carry.

Because the financing of young firms is intrinsically risky, traditional venture capitalists rely on intensive screening and monitoring to mitigate risks. Most notably, once they decide to invest, they disburse the funds in stages. The refinancing of the funded firm is conditional on the firm's performance. Staged financing thus allows traditional venture capitalists to monitor how their money is being used and gather timely information on the likelihood of a venture's success. In addition, financing contracts would allocate various forms of control rights to the venture capitalists should the portfolio start-up performs poorly (Kaplan and Strömberg, 2003).

Post investment, traditional venture capitalists actively add value to their portfolio firms. For example, they facilitate the recruitment of outside managers (Hellman and Puri, 2002), participate in the structuring of the boards of directors (Lerner, 1995), and help develop business plans (Kaplan and Strömberg, 2001). In a recent survey study, Gompers et al. (2020) show that traditional venture capitalists also play a key role in connecting their portfolio firms to customers and future investors.

CVC units share many of the operational characteristics with traditional venture capitalists. For example, CVC units also rely heavily on screening and staged financing. Often times, CVC units are staffed by individuals with backgrounds resembling traditional venture capitalists. Moreover, it is not uncommon for corporate and traditional venture capitalists to share deal flows or syndicate deals.

However, CVC and TVC differ along several key dimensions. The first is funding source and organizational structure. While TVC firms raise funds from limited partners, CVC units are funded by their corporate parents. A CVC unit can be structured as an internal division and funded directly from the corporate parent's balance sheet. Alternatively, a CVC unit can be structured as an external entity, with the corporate parent being the sole limited partner (Gompers, 2002).

The most important difference lies in investment objectives. Specifically, CVC units are not so much driven by pure financial returns as TVC firms do; they are more likely driven by product market or technological synergies with the funded firms. For example, Intel Capital, the venture arm of Intel Corporation and one of the most active CVC funders, has invested in a number of drone start-ups in the recent past.[5] Because drones require powerful chips, Intel can accumulate demand for its own products through making these investments. As another example, consider 7-Ventures, the venture arm of 7-Eleven that is a subsidiary of the Japanese retail group Seven & i Holdings Company. 7-Ventures recently invested in KeyMe, a start-up with a patented technology that allows customers to scan keys with their smartphone and pick up duplicates in a smart kiosk. Not surprisingly, these kiosks can be found in 7-Eleven nowadays.[6]

Last but not least, CVC units are arguably well positioned to push the funded firms to rapidly grow, considering the spillovers from the CVC funders' business resources, customer capital, and technological capabilities. Gompers and Lerner (2000) show that CVC-funded firms are as likely to go public as TVC-funded firms. In a more recent study, Chemmanur et al. (2014) identify CVC-backed IPO firms and construct a matched sample of TVC-backed IPO firms based on observable characteristics at the IPO year. They find that conditional on going public, CVC-backed companies produce more patents and receive higher citations per patent in post-IPO years.

[5] See `https://www.businessinsider.com/intel-investing-in-drones-2015-8`

[6] For a news article, see `https://www.vcnewsdaily.com/keyme/venture-capital-funding/jqjflwgyjt`

2.3 Data

To study the impact of CVC on the innovation outcomes of the funding firms, I construct a dataset that links CVC transaction level data with U.S. publicly traded firms and their patenting activity. The exercise is limited to CVC funding firms that are publicly traded, because data on private firms are limited. In what follows, I briefly describe the data sources, the procedures for merging firms across databases, and the sample selection criteria. More details on the construction of the dataset are provided in Appendix B.1.

Data sources and merging procedures The main data source that I use to obtain information on venture capital activity is VentureXpert, a product of Thomson Reuters. The database tracks venture capital investments on a global basis, drawing information from public news releases, private equity newsmakers, official filings, and investor surveys that may contain information not presented in official deal statements (Röhm et al., 2020). The database was started in 1977 and has since then been backfilled through the 1960s (Chen et al., 2010). Because venture capitalists are not required to disclose their investments to any regulatory agency, coverage is always a concern in VC research (Kaplan and Lerner, 2016). However, VentureXpert has been shown to offer the most comprehensive coverage among competing databases (Maats et al., 2011). For this reason, the database has been extensively used in venture capital research.

For each venture capital deal or financing round, I observe the date of the deal, the funding amount, and identifying information for the funded firms and the funding entities. Core identifying information for a funded firm includes firm name, detailed location, four-digit Standard Industrial Classification (SIC) code, and founding year. Core identifying information for an investing entity includes firm name, detailed location, and type (corporate or traditional).[7] I extract from VentureXpert all venture capital deals that involve U.S. based CVC units investing in U.S. based firms between 1980 and 2018. Appendix B.1 describes how I define a U.S. based CVC unit in VentureXpert.

To identify the ultimate corporate parent of a CVC unit, referred to as the "funder" throughout the paper, I utilize the corporate ownership information in Capital IQ. Capital IQ is a product of Standard & Poor's; it provides ownership information, among other data items, for both public and a large number of private firms worldwide. CVC units in VentureXpert are first merged with firms in Capital IQ using a name and address matching procedure as described in Appendix B.1. For merged entities, I extract their ultimate corporate parents from Capital IQ, with unique firm identifiers. I then link these parent firms to Compustat using the crosswalk of firm identifiers maintained by Standard & Poor's. Finally, I obtain financial data for the linked parent firms in Compustat.

By default, ownership information in Capital IQ is based on a firm's current status. Such information may mask past changes in firm ownership through mergers and acquisitions (M&As). To deal with this complication, I check whether the duration of each CVC unit — the time period between the first and last dates when the CVC unit is observed to make an investment in VentureXpert — overlaps with the life span of the corporate parent in Compustat. In cases where an overlap is not detected, I back track the previous parent(s) using M&A information either in Capital IQ or the Thomson Reuters SDC Platinum Mergers and Acquisitions database. SDC Platinum covers the near universe of M&A transactions worldwide, sourcing data from

[7] While each deal involves a single funded firm, there may be multiple investors participating in the deal. Unfortunately, VentureXpert does not identify the lead investor, nor does it provide details on the funding contribution by each investor.

regulatory filings, news sources, and surveys of investment banks and law firms.

Data on firm-level innovation outcomes are taken from Autor et al. (2020). The authors study the impact of the competitive shock emanating from Chinese import penetration on U.S. domestic innovation. They match patent assignee records maintained by the United States Patent and Trademark Office (USPTO) to Compustat firms. The matching algorithm leverages a web search engine that is able to link many company name variants found on patent records to a single firm in Compustat. The matched patenting data contains longitudinal records on the number of patents granted to Compustat firms between 1975 and March 2013.[8]

Sample selection criteria After merging VentureXpert with Compustat, I obtain 408 non-financial, public firms that engage in CVC activity between 1980 and 2018. Table 2.1 shows the match rate in detail. The top row reports statistics for traditional venture capital to help benchmark the magnitude of CVC. The second row reports the raw number of U.S. based CVC units that invested in U.S. based start-ups in VentureXpert during this period. The last row reports the number of parent firms that are successfully linked to Compustat. The matched sample accounts for slightly over half of the total CVC activity. Among unmatched CVC units, about two thirds are affiliated with foreign parents; the rest are either affiliated with U.S. private parents or are unable to be linked to Capital IQ. The match rate is comparable to prior studies that link CVC units in VentureXpert to Compustat. For example, Dushnitsky and Lenox (2005) focus on the period from 1969 to 1999 and identify 247 CVC parent firms in Compustat. Ma (2020) focuses on a more recent period from 1980 to 2015 and identifies 381 parent firms in Compustat.

The raw analysis sample is comprised of the VentureXpert-Compustat merged CVC parent

[8]I have extended the match to patents granted up to 2019, and will use the extended data in future versions of the project.

Table 2.1: VentureXpert-Compustat Match Rate, 1980–2018

	# Investors	# Deals	Deal Value (bln $)
Traditional VC	3,403	100,807	945.9
CVC	966	17,202	311.6
Compustat-merged CVC	408	9,040	185.6

Notes: Deal value is normalized to 2015 U.S. dollars using the GDP deflator. Financial firms (SIC 6000-6799) are excluded from the set of VentureXpert-Compustat merged CVC firms.

firms and all other Compustat firms observed between 1980 and 2018. I use this sample to document a set of stylized facts on U.S. CVC in Section 2.4. Separately, I focus on a subsample of patenting firms to study the treatment effects of CVC engagement on the innovation outcomes of the funding firms in Section 2.5. As described below, the treatment effects are identified using an event study approach. The event is defined as the year when a firm makes its first CVC investment.

The event study approach requires additional restrictions on the raw sample. First, the time period is limited to 1980–2012 to utilize the patenting data. Second, I focus on firms that patented at least once between 1980 and 2012. Third, I restrict the sample to firms that are observed for at least three years before starting CVC (the pre-period) and five years afterwards (the post-period). The post-period is used to assess the effects of CVC on a funder's subsequent innovation performance. The pre-period is needed to test for confounding pre-trends that may bias the estimation. This implies that non-CVC firms need to have at least nine years of operating history to remain in the sample as potential control firms (described in detail in Section 2.5). Table 2.2 shows the attrition rate associated with each additional sample restriction.

Table 2.2: Raw Sample and Event Study Sample

	CVC	Non-CVC
Raw Sample, 1980-2018	408	22,865
1980-2012	369	21,430
Patenting firms	322	7,558
Nine-year history	190	4,814
Coarsened exact matching	99	245
Event study sample	99	245

Notes: The table shows the attrition rate associated with each additional sample selection criterion. The first row refers to the raw sample that is comprised of VentureXpert-Compustat merged CVC parent firms and all other Compustat firms observed between 1980 and 2018. The second row limits the time period to 1980–2012 to utilize patenting data. The third row focuses on firms that patented at least once between 1980 and 2012. The fourth row restricts CVC parent firms to those observed for at least three years prior to starting CVC and five years afterwards; non-CVC firms are restricted to those having at least nine years of operating history. The fifth row shows the fraction of CVC and non-CVC firms that are successfully matched in the coarsened exact matching procedure described in Section 2.5. By construction, the event study sample is a weakly balanced panel with 3,096 firm-by-year observations.

2.4 Stylized Facts on CVC Funders

Firm-level characteristics I begin with a non-parametric comparison between CVC parent firms and their Compustat peers along some key dimensions. Table 2.3 presents the results from t-tests of equality in means. The table shows that the two sets of firms are markedly different. CVC parent firms are on average larger, as measured by global employment or sales; they are also older, more productive as measured by (log) labor productivity, more profitable as measured by return on assets, less leveraged, and less tangible. While CVC parent firms apply more patent each year, they are on average less R&D-intensive, consistent with existing work showing that

R&D intensity tends to decline with firm size (see, for example, Akcigit and Kerr, 2018). One aspect where CVC parent firms do not differ significantly from their non-CVC peers is liquidity, as measured by cash-to-assets ratios.[9]

Table 2.3: Univariate Tests of Equality in Means, Raw Sample

	CVC	Obs	Non-CVC	Obs	Diff	
Log employment	8.58	[408]	5.68	[21,467]	2.90	***
Log sale	7.26	[408]	4.02	[21,803]	3.24	***
Age since IPO	11.57	[408]	5.17	[22,865]	6.41	***
Log labor productivity	5.65	[408]	5.19	[20,629]	0.46	***
Patents applied per year	58.39	[348]	6.46	[7,532]	51.94	***
Capital expenditure/sales	0.13	[407]	0.27	[21,746]	-0.14	***
R&D expenditure/sales	0.24	[325]	0.76	[13,007]	-0.52	***
Cash/assets	0.22	[408]	0.21	[22,818]	0.01	
ROA	0.08	[408]	-0.29	[22,727]	0.37	***
Total debt/assets	0.23	[408]	0.40	[22,806]	-0.17	***
Property, plant, equipment/assets	0.24	[408]	0.29	[22,815]	-0.05	***

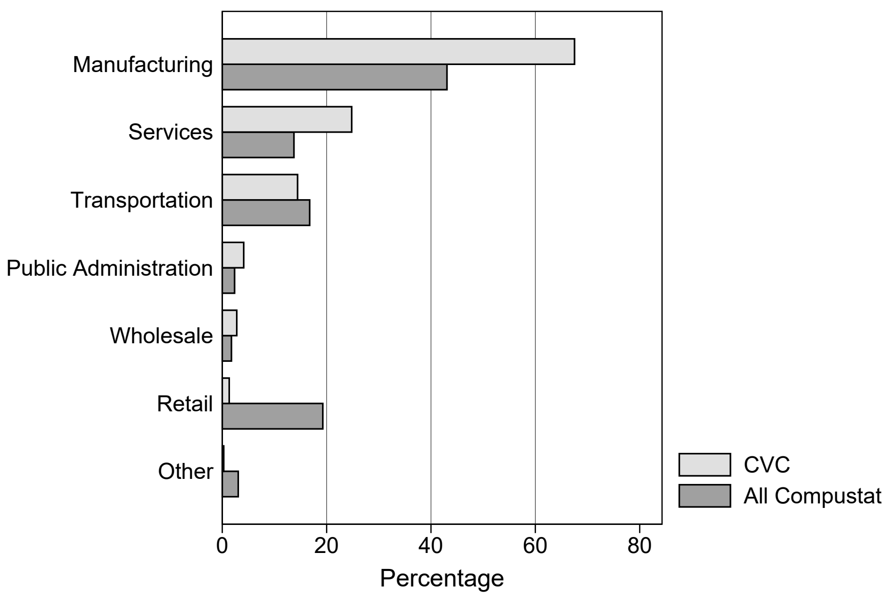
Notes: Sales are expressed in millions of 2015 U.S. dollars; Labor productivity is measured as real revenue per worker, where revenue is expressed in thousands of 2015 U.S. dollars; Patents are restricted to those granted between 1975 and March 2013 as in Autor et al. (2020); ROA (return on assets) is calculated as EBITDA/assets. All nominal variables are converted to real value using the GDP deflator. R&D-over-sales ratio is winsorized at the top and bottom two percentiles. All other variables are winsorized at the top and bottom one percentiles. *** indicates statistical significance at the 0.1% level.

Sectoral distribution Figure 2.1 plots the distribution of CVC parent firms across seven broadly defined sectors. Each light grey bar represents the percentage of deals made by CVC funders from a given sector. Each dark grey bar represents the employment share of that sector in Compustat. Clearly, CVC funders are overrepresented in manufacturing and services sectors; they are underrepresented in retail trade. Within the manufacturing sector, funders are concentrated

[9] In unreported analysis, I implement the t-test separately on firms within the manufacturing and services sectors. I find that the patterns in Table 2.3 hold broadly within the two sectors, suggesting that the differences are not driven by sectoral composition of CVC funders.

in the manufacturing of electronic equipment (SIC 36), chemical products (SIC 28), and industrial machinery (SIC 35), which together accounts for about 83% of all deals made by the manufacturing sector. Within the services sector, more than 90% of deals are made by funders engaged in business services (SIC 73), notably computer and data processing services (SIC 7370) and prepackaged software (SIC 7372).

Figure 2.1: Sectoral Distribution of CVC Funders, Raw Sample



Notes: Sectors are classified based on the two-digit SIC code. The category "Other" consists of Agriculture, Mining, and Construction. Each light grey bar represents the percentage of deals made by CVC funders from a given sector. The light grey bars sum up to slightly more than one as certain deals involve several CVC funders. Each dark grey bar represents the percentage of (global) employment accounted for by a given sector in Compustat. All the dark grey bars sum up to unity.

Investment patterns Do CVC funders mostly invest in start-ups from the same industry? Figure 2.2 plots the industry overlap between CVC funders and their funded firms in a matrix form. The matrix features 31 symmetric industries defined roughly at the two-digit SIC level.[10] Each row shows where CVC funders from a given industry invest. Entries in each row sum up to unity. A darker shading indicates a higher investment share. The matrix is quite sparse. Both the mean and the median number of industries that a CVC funder invests in is four, conditional on the funded industry representing more than 5% of the total investments.

While a nontrivial fraction of investments is made within industries, as indicated by the dark shadings along the diagonal, most investments go to the business services industry, regardless of the funder's industry. Within business services, investments concentrate in prepackaged software (SIC 7372), computer programming services (SIC 7371), and information retrieval services (SIC 7375).

Taken together, the descriptive analysis suggests that selection into CVC is likely not random. CVC funders are larger, older, and possess larger patent portfolios. Moreover, CVC funders invest heavily in high-tech industries, pointing to a motive of information/technology acquisition. To formally test whether CVC engagement improves a funder's innovation outcomes, one needs a strategy that mitigates endogenous selection, which I turn to next.

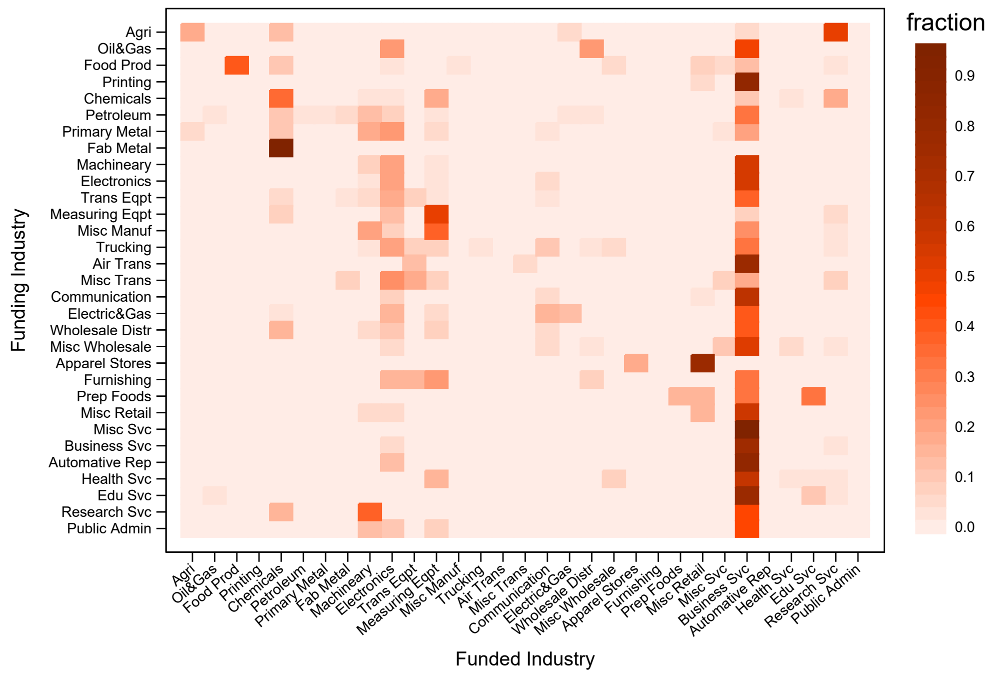
2.5 Estimating the Treatment Effects of CVC

2.5.1 Identification

What are the effects of starting CVC on a funder's subsequent innovation performance? Estimating these effects is challenging due to an inherent selection bias associated with the

[10] In the raw sample, CVC funders span 35 industries at the two-digit SIC level; their funded firms span 55 industries at the 2-digit SIC level. To make the investment matrix symmetric, certain adjacent industries are aggregated.

Figure 2.2: Industry Overlap between CVC Funders and Their Funded Firms, Raw Sample



Notes: The figure plots the industry distributions of Compustat CVC funders and their funded firms. There are 31 symmetric industries on both axes, defined at the two-digit SIC level. Each row shows where CVC funders from a given industry invest. Entries in each row sum up to unity. A higher fraction is shaded by a darker color. In the raw sample, CVC funders span 35 industries at the two-digit SIC level; their funded firms span 55 industries at the two-digit SIC level. To make the matrix symmetric, certain adjacent industries are aggregated. In addition, funded firms from the construction sector are dropped because no CVC funders are from the construction sector. Dropped investments represent less than 0.06% of all investments.

decision to start CVC. As Section 2.4 makes clear, the distribution of funders across business characteristics and industries is likely not random. In the absence of an instrument or exogenous shock to the decision of starting CVC, I construct a group of non-CVC firms that matches CVC funders along several key dimensions. I then compare the changes in firm-level outcomes at the funding firms around starting CVC to contemporaneous changes at the matched control firms, using a difference-in-differences method.

The baseline regression specification takes the form:

$$Y_{it} = \alpha_i + \lambda_{jt} + X_{it}'\gamma + \beta\, CVCPost_{it} + \epsilon_{it}, \tag{2.1}$$

where Y_{it} is the measured innovation outcome of firm i (from industry j) in year t; α_i is a vector of firm fixed effects; λ_{jt} is a vector of industry-by-year effects; and X_{it} comprises observable and time-varying firm-level covariates that may affect a firm's capacity to innovate. Crucially, $CVCPost_{it}$ is the treatment dummy that takes on the value of one if a firm ever engages in CVC activity and the observation is in a year post starting CVC; the dummy is equal to zero otherwise.[11]

A few remarks on the baseline specification are in order. First, firm fixed effects are used to control for selection into CVC based on unobserved and fixed factors such as the quality or openness of a firm's management team. Second, by including industry-by-year fixed effects, I control for industry-specific and time-varying conditions or shocks.[12] Third, the validity of the difference-in-differences strategy hinges on the control firms being a good measure of the counterfactual innovation rates of CVC funders had the latter group not engaged in CVC activity (parallel trends assumption). If the parallel trends assumption is satisfied, the estimated β coefficient recovers the average treatment effect on the treated firms conditional on the set of included

[11]By definition, $CVCPost_{it}$ is equal to zero for non-CVC firms across all years; it is also equal to zero for a CVC firm in years prior to starting CVC.

[12]If the outcome variable is (log) assets or sales, adding industry by year fixed effects effectively controls for industry-specific deflators; it also acts as a control for industry-specific variation in intermediate input shares, as discussed by Haltiwanger et al. (2017). When the outcome variable is (log) patent stock or the number of flow patents, industry-by-year effects control for industry-specific technological opportunities that may arise at different points in time. For example, Webb et al. (2018) and Autor et al. (2020) show that industries tend to exhibit markedly different patterns in patent applications over time.

covariates in Equation (2.1).

To put the control and treated firms on common trajectories, I consider two sets of criteria when constructing the control group. The first set of criteria requires the control firms to match the treated firms on key observed characteristics at the time when the latter group starts CVC. These characteristics include firm size as measured by (log) assets, firm age since IPO, and firm industry defined at the three-digit SIC level. These characteristics are chosen as previous studies have found that firm growth and volatility vary greatly by firm size, age, and industry (Davis et al., 1996; Haltiwanger et al., 2013). Moreover, technologies and innovation rates also differ by firm size, age, and industry (see, for example, Akcigit and Kerr, 2018; Autor et al., 2020; Webb et al., 2018). The second set of criteria is used to strengthen the parallel trends assumption more directly. Specifically, Roberts and Whited (2013) recommend matching on the growth rates of the outcome variables to ensure similarity in pre-trends. Following their recommendation, I require that the control firms also match the treated firms in the growth rates of patent stock prior to year t (the event year). I use the Davis-Haltiwanger-Schuh (DHS) methodology to measure growth rates (see Davis et al., 1996), as this methodology has attractive features and is widely used in the firm dynamics literature.[13]

More concretely, control firms are identified using coarsened exact matching techniques that follow Akcigit et al. (2019); Davis et al. (2019, 2014), among others. Specifically, each funding firm that started CVC in a given year is matched with one or several non-CVC firms in the same year and in the same cell defined by the full cross product of ten firm size categories,

[13] The DHS growth rate for any outcome variable Y_{it} is calculated as $\frac{Y_{it}-Y_{it-1}}{0.5*(Y_{it}+Y_{it-1})}$. This measure is a second order approximation of the log difference for growth rates around zero, and it has the added advantage of (i) accommodating entry and exit and (ii) mitigating the problem of regression to the mean. Note that this measure is symmetric and bounded between -2 (exit) and 2 (entry). For details, see Törnqvist et al. (1985), Davis et al. (1996), and Haltiwanger et al. (2013).

five firm age categories, slightly under 250 industry categories, and four prior DHS growth rate categories.[14] More details of the procedure are provided in Appendix B.2.

Of the 190 CVC firms and 4,814 non-CVC firms in the subsample, 99 CVC firms are matched with 245 non-CVC firms that form the control group, as shown in Table 2.2. Together, the matched CVC firms and their control firms form the regression sample. By construction, the regression sample is a (weakly) balanced panel: Each firm is observed for three years in the pre-period and five years in the post-period, with the event year varying across firms.

Lastly, I augment the baseline regression with an event-study framework:

$$Y_{it} = \alpha_i + \lambda_{jt} + X_{it}'\gamma + \sum_{\tau=1}^{5} \beta_{-\tau} CVC_{i,t-\tau} + \sum_{\tau=1}^{3} \beta_{+\tau} CVC_{i,t+\tau} + \epsilon_{it}, \tag{2.2}$$

where the sums on the right-hand side allow for five lags or post-treatment effects ($\beta_{-\tau}$) and three leads or anticipatory effects ($\beta_{+\tau}$). Other variables in Equation (2.2) are defined the same way as in the baseline specification (2.1). The event-study framework has two attractive features. First, I can perform a formal check on the parallel trends assumption, by testing whether future events granger cause changes in the outcome variables, conditional on included covariates (i.e., whether β_{+1}, β_{+2}, and β_{+3} are statistically and significantly different from zero). Second, the pattern of post-treatment effects can be traced out by the estimated $\beta_{-\tau}$ coefficients. A priori, there does not seem to be a strong reason for expecting the treatment effect to accumulate or fade over time.[15]

[14] In the baseline regressions, I do not impose one-to-one matching, i.e., a treated firm can be matched to as many control firms as suitable based on the matching criteria. In sensitivity tests as described shortly, I weight the control firms given that certain cells may have more control firms than the treated.

[15] The specification in Equation (2.2) treats the value of β's as the effects of CVC engagement relative to the event year. Note that without a control group, Equation (2.2) is not identified with both firm and year fixed effects. This is because the firm fixed effect defines the event time, which, together with the dummies indicating the years surrounding the event, uniquely determines the year. Having a control group that never experiences the treatment in the regression sample solves the under-identification problem, because the control group can be used to estimate the year effects independently of the causal effect of treatment. See Hall et al. (2007) and Borusyak and Jaravel (2017)

2.5.2 Results

Table 2.4 reports the estimates of Equation (2.1) and Equation (2.2), using (log) patent stock as the outcome variable.[16] The first column fits the difference-in-differences specification in Equation (2.1), conditional on just firm and industry-by-year fixed effects. Column (2) fits the event study specification in Equation (2.2), controlling for firm and industry-by-year effects. Column (3) adds onto column (2) firm-level control variables, including firm size as measured by (log) assets, (log) labor productivity as measured by revenue per worker, R&D intensity as measured by the ratio of flow R&D expenditures to sales, liquidity as measured by cash-to-assets ratio, and leverage as measured by total-debt-to-assets ratio. Column (4) uses one-year lagged values of firm-level controls to mitigate simultaneity bias. As a result, the coefficient on year $t-3$ is not identified.

As Table 2.4 suggests, CVC funders experience an average annual increase in patent stock that ranges from 9% to 16% in the five years post starting CVC, depending on specification. Adding firm-level covariates tends to reduce the size the effect and delay the onset and peak of the effect. Nonetheless, the effect persists through the fifth year. Importantly, we do not see statistically significant and diverging pre-trends in patenting activity between the treated and control firms, bolstering confidence in the estimated coefficients.

for more detailed discussions on this issue.

[16]Following the literature as summarized by Hall et al. (2010), patent stock is calculated using a perpetual inventory method with a depreciation rate of 15%. Specifically, $PatentStock_{it} = NewPatents_{it} + (1 - \delta)PatentStock_{it-1}$, where $NewPatents_{it}$ is the number of eventually granted patents applied by firm i in year t, and δ is the depreciation rate. The initial patent stock for a given firm is calculated as the average number of patents applied by the firm between 1980 and 1985. Following convention, I add one to the patent stock before logging it to accommodate zero entries. In unreported analysis, I experiment with using the flow number of patents, $\log(1+NewPatents_{it})$, as an alternative outcome variable. The estimated treatment effects are qualitatively similar to those reported in the main text, although less persistent. I am working on estimating Equation (2.1) and Equation (2.2) using Poisson models to better deal with the count nature of the data.

Table 2.4: Estimated Treatment Effects of CVC

$\log(1 + PatentStock)$	(1)	(2)	(3)	(4)
β (POST)	0.164**			
	(0.081)			
β_{+3} (Pre, 3yr)		-0.040	0.078	
		(0.073)	(0.072)	
β_{+2} (Pre, 2yr)		-0.070	-0.005	-0.008
		(0.060)	(0.058)	(0.057)
β_{+1} (Pre, 1yr)		-0.025	0.019	0.019
		(0.034)	(0.035)	(0.036)
β_{-1} (Post, 1yr)		0.099***	0.069*	0.058
		(0.037)	(0.036)	(0.036)
β_{-2} (Post, 2yr)		0.125**	0.132***	0.067
		(0.053)	(0.048)	(0.049)
β_{-3} (Post, 3yr)		0.153**	0.152**	0.128**
		(0.068)	(0.060)	(0.060)
β_{-4} (Post, 4yr)		0.142*	0.157**	0.129*
		(0.082)	(0.069)	(0.068)
β_{-5} (Post, 5yr)		0.154*	0.159**	0.159**
		(0.091)	(0.077)	(0.077)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-by-year effects	Yes	Yes	Yes	Yes
Firm-level controls	No	No	Yes	No
Firm-level controls, lagged	No	No	No	Yes
Observations	3,096	3,096	3,096	2,752
R-squared	0.557	0.558	0.624	0.585

Notes: The table reports estimates of Equation (2.1) and Equation (2.2) on the matched sample of CVC and observationally similar non-CVC firms. Match is based on firm size as measured by (log) assets, firm age since IPO, three-digit SIC industry, and the growth rate of patent stock in the two years prior to the event. The coefficients are relative to the event year (the omitted base). Firm-level control variables include firm size as measured by (log) assets, (log) labor productivity as measured by revenue per worker, R&D intensity as measured by the ratio of flow R&D expenditures to sales, liquidity as measured by cash-to-assets ratio, and leverage as measured by total-debt-to-assets ratio. To maintain a constant sample size over all specifications, missing values for firm-level control variables are replaced with a value of zero, and an indicator variable for each missing control is added to the regression. In column (4), the coefficient on year $t - 3$ is not identified due to the inclusion of lagged firm-level covariates. Robust standard errors are clustered at the firm level. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

One comment pertains to regression weights. The estimates in Table 2.4 are obtained from unweighted regressions. We might be interested in recovering the average treatment effects that reflect a firm's share in aggregate activity, which involves weighting the treated firms as well as their control firms within a given cell. Weighting the treated firms reflects the distribution of funder activity levels over cells. Weighting the control firms within a given cell is desirable since one treated firm may be associated with multiple control firms. Following Davis et al. (2014) and Davis et al. (2019), I use an activity-weighting scheme. Specifically, I weight each treated firm by its share of aggregate funder activity in the regression sample, where each funder's activity level is defined as the average of its assets at the start and end of the time interval under consideration. To weight control firms, I first compute for each control firm in a given cell its activity share among all the control firms in that cell. I then multiply these shares with the associated funder weight such that the sum of weights on control firms is set equal to the funder's activity share. Alternatively, I experiment with assigning equal weights across the control firms in a given cell.

In unreported analysis, I find no statistically significant treatment effect using weighted regressions. This result suggests that the relationship between CVC engagement and funder innovation outcomes might vary systematically across the firm size distribution. In particular, funders that are relatively larger in size may not benefit from CVC as much as funders that are smaller in size. I investigate this issue more formally next.

2.5.3 Heterogeneous Effects across the Firm Size Distribution

To test the heterogeneous effects of CVC on funder innovation across the firm size distribution, I use the following specification:

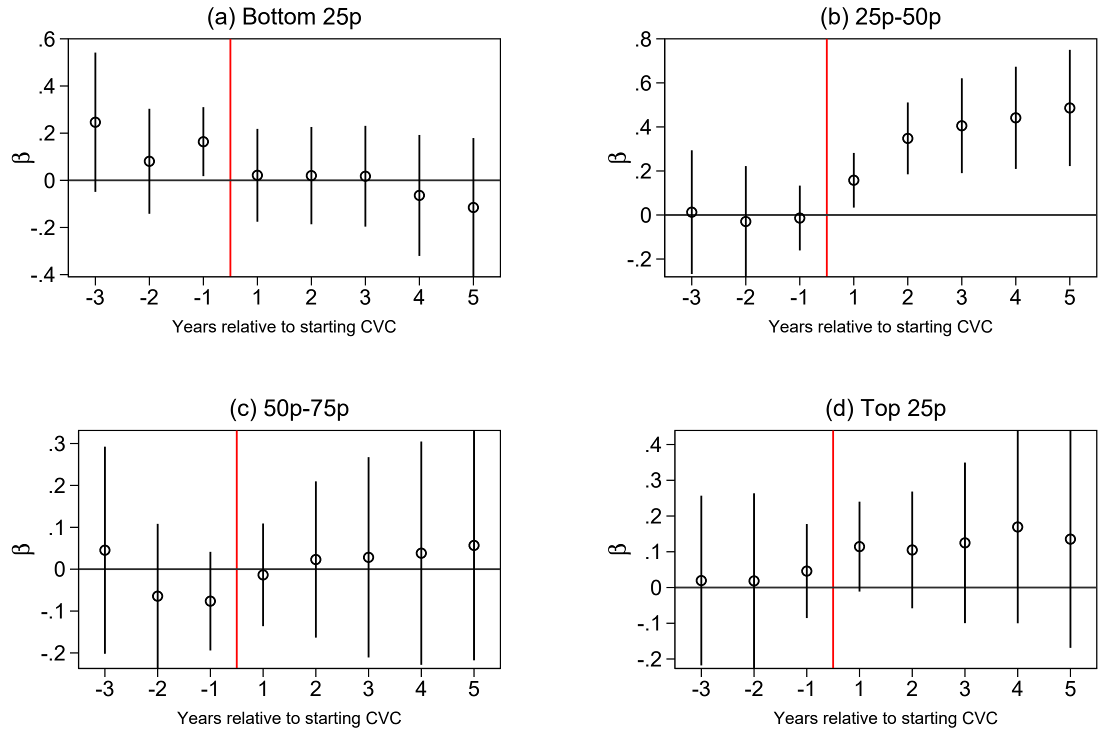
$$Y_{it} = \alpha_i + \lambda_{jt} + X'_{it}\gamma + \sum_{\tau=1}^{5}\sum_{k=1}^{4} \mathbb{1}(i \in Q_k)\, \beta^k_{-\tau} CVC_{i,t-\tau} + \sum_{\tau=1}^{3}\sum_{k=1}^{4} \mathbb{1}(i \in Q_k)\, \beta^k_{+\tau} CVC_{i,t+\tau} + \epsilon_{it}, \tag{2.3}$$

where Q_k denotes firm size categories and all other variables are defined as before. In practice, firms are sorted into four size categories defined by the 25th, 50th, and 75th percentiles of (log) assets as of year $t-1$ (one year before the event year).

The estimated coefficients of Equation (2.3) are presented visually in Figure 2.3. The figure shows that the treatment effects of CVC concentrate among funders in the second size bin (25th-50th percentile). The effects intensify over time, reaching up to an annual increase in patent stock of about 50% in the fifth year post starting CVC. Funders in other size categories do not experience a statistically significant improvement in patenting outcomes.

Taking Figure 2.3 as given, that smaller-sized funders benefit from CVC more than larger-sized funders raise an interesting question of why it is the case. Industry composition is unlikely the driving force behind the result. Except for the top quartile, which is disproportionately represented by firms from the Transportation and Communications sectors (about 60%), the rest of the size bins each has about 60% manufacturing firms and 30% services firms, which is broadly representative of the sectoral distribution of CVC funders in the raw sample as depicted in Figure 2.1. One possible explanation may be related to systematic differences in innovation behaviors across the firm size distribution. A vast literature documents that small firms are on average more

Figure 2.3: Heterogeneous Effects of CVC across the Firm Size Distribution



Notes: The figure plots the estimated coefficients in Equation (2.3) by firm size categories. Estimation is performed on the matched sample of CVC firms and observationally similar non-CVC firms. Firm size categories are defined by the 25th, 50th, and 75th percentiles of (log) assets as of year $t-1$ (one year before the event year). The regression controls for firm fixed effects, three-digit SIC industry by year fixed effects, and contemporaneous firm-level covariates that include log assets, log labor productivity, R&D-to-sales ratio, cash-to-assets ratio, and total-debt-to-assets ratio. The red vertical line indicates the event year. All coefficients are relative to the event year, which is normalized at zero. Circles are point estimates. Bars are 95% confidence intervals.

innovation intensive than large firms, and the former group accounts for a larger share of major inventions (see, for example, Akcigit and Kerr, 2018; Cohen and Klepper, 1996). Thus, it may be the case that CVC and R&D are complimentary activities.

2.5.4 Open Questions

In addition to how to interpret the heterogeneous effects of CVC on funder innovation outcomes across the firm size distribution, I discuss three other issues that are under investigation. First, the estimated effects of starting CVC on a funder's subsequent patenting rates are quite rapid, taking place a year or two after the first investment. Innovation, however, is slow moving. Moreover, it arguably takes some organizational learning before a funder can internalize the strategic payoffs from CVC. Both arguments raise the concern of whether the estimated causal effects of starting CVC are spurious. Lack of data on the contractual terms of CVC prevents me from directly checking whether the funded start-ups agree to file patents on behalf of the CVC funder(s). However, to the extent that patents filed by the funded start-up are sold outright to the CVC funder(s), these transactions should be reflected in patent assignment data, which can be examined empirically.[17]

Second, the empirical specification can be strengthened by controlling for each funder's M&A activity. Recent studies find that M&A may lead to improved patenting outcomes at the acquiring firms (Bena and Li, 2014; Sevilir and Tian, 2012). If CVC funders simultaneously conduct more acquisitions post starting CVC, or if they become more capable of selecting highly innovative targets post starting CVC, then omitting M&A would overestimate the treatment effects of CVC on funder innovation. M&A data can be obtained from Thomson Reuters SDC Platinum, which I have access to. Additionally, I can check the extent to which CVC funders eventually acquire their funded firms, a common (mis)conception that CVC funders invest solely to screen future acquisition targets.

[17]Patent reassignment data have been used by Akcigit et al. (2016) and Figueroa and Serrano (2019), among others. The raw data are publicly available and can be obtained from Google Patents Beta.

Third, the sorting patterns between CVC funders and their funded firms are worth investigating. One hypothesis is that there is positive sorting on innovative capabilities, so highly innovative start-ups match with highly innovative funders, which tends to be smaller in firm size. Such a sorting pattern could contribute to the strong treatment effect of CVC on the patenting outcomes of smaller-sized funders. Empirically, I can merge patent data with CVC-funded firms using the name and address matching procedure described in Section 2.3 and Appendix B.1. I can then study the sorting patterns between CVC funders and their funded firms based on patent related metrics.

2.6 Concluding Remarks

This paper contributes to a sparse literature on CVC. Using merged venture capital, Compustat, and patenting data from 1980 to 2012, I first document a set of stylized facts on CVC funding firms. I show that CVC funders are larger, older, and more innovative than their non-CVC counterparts, and CVC funders tend to invest within their own industries and the business services industry. To estimate the treatment effect of CVC on funder innovation, I construct a group of observationally similar non-CVC firms defined by firm size, age, industry, and prior patenting performance. I then compare the changes in innovation outcomes at the funding firms after starting CVC to contemporaneous changes at the matched control firms. The estimates suggest a sizable effect: CVC funders experience an average annual increase in patent stock that ranges between 9% and 16% post starting CVC. Importantly, the effects are heterogeneous across the firm size distribution, with firms of smaller size receiving the strongest treatment.

Several open questions present interesting avenues for future research. First, the sources or mechanisms underlying the treatment effect of CVC on funder innovation deserve further investigation. Second, a growing body of work has documented the secular rise in corporate cash holdings. To what extent is this trend linked to the notable increase in CVC over the past few decades? Third and relatedly, how do firms allocate the increased cash holdings between in-house R&D and external investment via CVC? Is CVC an efficient vehicle for spurring funder innovation, given the opportunity cost of R&D and the search and matching frictions in the CVC market? Answers to these questions may help inform the relationship between firm size and innovation, the rise in corporate cash holdings, and the boundaries of the firm.

Chapter 3: The Aggregate Implications of Corporate Venture Capital

3.1 Introduction

In the Schumpeterian growth paradigm, entrants and incumbents are pure rivals: entrants engage in innovation to "creatively destroy" the incumbents. Over the last few decades, however, a growing share of innovation involves established corporations partnering with high-growth start-ups, particularly in the high-tech sectors. Start-up companies often embody more innovative and disruptive ideas than their established counterparts, yet large businesses have greater access to customers, distribution networks, and capital, which new ventures lack.

A prominent approach to innovation partnership has been corporate venture capital (CVC) —minority equity investment made by non-financial firms in start-up and young businesses.[1] Large corporations like AT&T, Google, Intel, Microsoft, and Pfizer have been active players in the CVC market for several years. In addition to funding, the investing firm typically provides a start-up with mentoring services and access to the firm's internal resources. Meanwhile, the start-up supplies external knowledge to the investing firm. For example, Google Ventures invested \$258 million in the ride-sharing company Uber in 2013. While Uber benefited from Google's

[1]Other forms of partnership arrangements do not necessarily involve corporate ownership. One example is corporate accelerators. An accelerator provides start-ups with light financing and a few months of access to a corporation's technological and business infrastructure, mentoring services, and network-building opportunities, culminating in a demo day attended by corporate managers and external investors. Chesbrough and Weiblen (2015) provide detailed discussion of such arrangements. Among the 30 top companies in seven of the largest industries, almost half had an accelerator in 2015, up from just 2% in 2010 (HBR, 2017).

map services, Google later launched its own self-driving service company, Waymo.

As of 2018, aggregate CVC investment reached \$67 billion, roughly 51% of the total investment made by the venture capital industry, up from \$16 billion in 2000 and almost doubling the CVC investment of \$37 billion in 2017 (Dushnitsky and Lenox, 2006; NVCA, 2019).[2] To put these figures in perspective, U.S. private businesses spent \$375 billion on R&D in 2016 (NSF, 2018).

A small but growing body of work documents the micro-level gains from CVC (see, for example, Chemmanur et al., 2014; Dushnitsky and Lenox, 2005; Liu, 2021b,c; Ma, 2020). These studies provide evidence suggesting (i) sizable treatment effects associated with a CVC relationship on both the start-up and the investing firms, especially based on patent-related measures and (ii) potential sorting of highly innovative start-up firms to incumbents that are larger and more innovative.

While CVC represents an important vehicle for spurring firm-level innovation, its impact on the macroeconomy remains unexamined. This paper takes a first attempt at studying the aggregate implications of CVC through the lens of a highly stylized endogenous growth model. The model builds upon the framework of endogenous firm innovation in the spirit of Klette and Kortum (2004) and Lentz and Mortensen (2008), but extends the canonical framework to incorporate features of the CVC market that are broadly consistent with the micro-level findings described above.

In the model, incumbent firms have heterogeneous research capacities. High-type incumbents are more capable in their innovation efforts than low-type incumbents. Moreover, high-type

[2]The National Venture Capital Association classifies CVC deals as financing rounds that saw firms investing via established CVC arms, or using off balance sheet or other non-CVC methods.

incumbents can nurture innovation in entrant firms whereas low-type incumbents cannot. An incumbent has the option to match with an entrant firm and gain access to a more advanced innovation technology, subject to paying a fixed cost. In equilibrium, larger high-type incumbents are selected into CVC, consistent with the empirical pattern.

While potential entrants are ex-ante homogenous, conditional on entering, an entrant firm that is matched with a CVC partner benefits from a higher likelihood of entering as a high-type firm than otherwise. By influencing the permanent type of entrant firms, CVC is assumed to have a persistent treatment effect on entrant firms beyond the entry stage. Thus, entrant firms with a CVC partner are expected to have a higher survival rate on average and grow faster conditional on survival, relative to entrant firms that enter the economy independently.

Given this setup, CVC presents a tradeoff. On the one hand, firms engaged in CVC benefit from positive treatment effects that make them innovate more. On the other hand, the rest of the firms reduce innovation as they face more intense competition. These forces in turn affect firm selection and the incentives for new entrepreneurship in the general equilibrium. The overall effect of CVC therefore becomes a quantitative question.

The model is calibrated to match key features of the U.S. aggregate economy and the CVC market, such as firm entry rates, exit rates, employment growth rates conditional on firm size and age, and the growth and exit profiles of firms engaged in CVC. The main comparative statics exercise that I perform is to compare the calibrated economy to counterfactual economies with varying levels of CVC activity. I find that the economy with a higher level of CVC exhibits greater competition, as driven by (i) the increase in innovation efforts by larger, high-type incumbents and the associated shift of the firm size distribution towards those firms; and (ii) the increase in the fraction of entrants that enter as high-type firms. Greater competition translates into higher aggregate growth, as in standard endogenous growth models. Entry, however, is depressed because although the prospects for outside entrepreneurs to enter as a high-type firm have improved, intensified competition makes small firms substantially more likely to exit regardless of firm type, reducing the incentives for entry.

As a starting point, the current model is a crude representation of CVC. Notably, the model abstracts from the financing aspect of CVC, and the effect of CVC on the entrant firm is modeled through a single reduced-form parameter (a higher likelihood of entering as a high-type firm than otherwise). This simplification implies that I do not distinguish the sources of the treatment effect of CVC on the entrant firm. For one thing, the effect could arise from a financing channel, considering that CVC helps relax the credit constraint of the entrant firm. Separately, there could be synergies between the funded and the funding firm that result from both demand- and technology-side linkages, as shown empirically by Liu (2021b). Moreover, the model abstracts from ex-ante heterogeneity among entrants, thus cannot speak to the determinants of selection on the entrants' side. While adding richer features of CVC may change the quantitative implications of the model, the central forces described in the preceding paragraph is likely to carry over to an extended model.

Related literature This paper builds upon models of endogenous firm innovation and firm dynamics in general equilibrium, as pioneered by Aghion and Howitt (1992); Klette and Kortum (2004); Lentz and Mortensen (2008). Since then, the endogenous growth framework has been extended to allow for substantially richer firm heterogeneity and dynamics (see, for example, Acemoglu et al., 2021, 2018; Akcigit and Kerr, 2018; Akcigit et al., 2021). The framework has been applied in the context of traditional venture capital (by financial venture capital firms) to study its impact on young firms and the aggregate economy (Akcigit et al., 2019; Ates, 2014; Greenwood et al., 2018; Opp, 2019). However, results from these models are unlikely to be readily applicable to CVC, given that traditional venture capital represents financial intermediation whereas CVC represents a match between non-financial firms seeking synergies beyond a pure financing relationship.

More recently, Akcigit et al. (2020) introduce foreign CVC into the endogenous growth framework and examine the aggregate implications of knowledge spillovers to foreign competitors making CVC investment in U.S. start-ups. I am not aware of existing theoretical work that incorporates domestic CVC into the endogenous growth framework to study the incentives and outcomes of domestic firms.

How I model CVC is guided by empirical studies on U.S. CVC patterns. This literature documents several stylized findings. First, the investing firms are typically large and innovation-intensive in terms of patenting activity (Liu, 2021c; Ma, 2020). Second, CVC investment is found to enhance innovation outcomes of the investing firm (Dushnitsky and Lenox, 2005; Liu, 2021c; Ma, 2020). Third, CVC investors are found to nurture innovation in start-ups at least as well as traditional venture capitalists do (Chemmanur et al., 2014; Liu, 2021b). In the model, I introduce a set of reduced-form assumptions that replicate most of these patterns. Specifically, I replicate the double treatment effect (on both entrant and incumbent firms) and the selection of larger and more innovative incumbents into CVC. For simplicity, however, I abstract from ex-ante heterogeneity on the entrants' side in the current model.

Layout The rest of the paper proceeds as follows. Section 3.2 presents the model and characterizes the stationary equilibrium. Section 3.3 describes the calibration strategy and evaluates the aggregate implications of CVC through a comparative statics exercise. Section 3.4 discusses issues with the current model and directions for follow-up work. Finally, Section 3.5 offers concluding remarks. Details of proofs and omitted derivations in the main text are provided in the Appendix.

3.2 Model

In this section, I develop a variant of Klette and Kortum (2004)'s model of endogenous firm innovation to incorporate partnerships between incumbent and entrant firms via CVC. The basic setup in Section 3.2.1–3.2.3 follows Klette and Kortum (2004) almost exactly—including household preferences, final good production, intermediate good production, and market structure. I introduce CVC-specific features in Section 3.2.4 and characterize firms' value functions, policy functions, and the invariant size distribution of firms in Section 3.2.5–3.2.6. Lastly, Section 3.2.7 provides a formal definition of the stationary equilibrium.

3.2.1 Preferences

Consider a closed economy in continuous time. There is a representative household with logarithmic preferences:

$$U = \int_0^\infty \exp(-\rho t) \ln C(t) dt, \tag{3.1}$$

where $\rho > 0$ is the discount factor and $C(t)$ is aggregate consumption at time t.

The representative household is endowed with two types of labor, both supplied inelastically. Specifically, unskilled labor L_U, whose supply is exogenous and is normalized to 1, is used in the production of a final good discussed below. The fixed exogenous supply of skilled labor, L_S, is employed by both incumbent firms (total labor demand denoted by S_I) and outside entrepreneurs (total labor demand denoted by S_E) to perform R&D functions. Naturally, the labor market-clearing condition for each type of labor is:

$$L_U = 1 \quad \text{and} \quad S_I + S_E = L_S. \tag{3.2}$$

All firms in the economy including entrant firms are owned by the representative household. The flow budget constraint of the household therefore is:

$$\dot{A}(t) + C(t) \leq r(t)A(t) + w_u(t) + w_s(t)L_S, \tag{3.3}$$

where $A(t) = \int_0^1 V_j(t)dj$ denotes the asset position of the household, $V_j(t)$ is the value of firm j at time t, $w_u(t)$ is the unskilled wage rate, $w_s(t)$ is the skilled wage rate, and $r(t)$ is the interest rate.

The household maximizes her lifetime discounted utility in Equation (3.1) subject to her flow budget constraint in Equation (3.3) and the no-Ponzi condition $\int_0^\infty \exp(-r(t)t)A(t)dt \geq 0$. This maximization problem yields the standard Euler equation:

$$\frac{\dot{C}}{C} = r - \rho, \tag{3.4}$$

where I have dropped the time index as I focus on stationary equilibria. Hereafter, the time index will be dropped when there is no confusion.

3.2.2 Final Good Technology

The final good that the household consumes, Y, is a Cobb-Douglas composite of a continuum of intermediate varieties indexed by $j \in [0,1]$:

$$\ln Y = \int_0^1 \ln y_j dj, \tag{3.5}$$

where y_j denotes the quantity of variety j.

Throughout, I normalize the price of the final good to 1. With logarithmic preferences, the inverse demand function for variety j has unitary elasticity:

$$y_j^d = \frac{Y}{p_j}, \tag{3.6}$$

where p_j denotes the price of variety j set by the intermediate good producer of j.

As will be discussed, the final good is also used to pay the fixed costs for starting CVC, incurred by the incumbents, in addition to household consumption. Since all other expenses in the economy are in terms of labor, the resource constraint is:

$$Y = C + \Phi, \tag{3.7}$$

where Φ denotes the aggregate spending on fixed costs for starting CVC.

3.2.3 Intermediate Good Technology

Each intermediate variety, also referred to as a product line or simply a product, is produced monopolistically by the latest innovator with the best technology (productivity) in that variety. By hiring l_j units of unskilled labor, the latest innovator in variety j can produce according to:

$$y_j = q_j l_j, \tag{3.8}$$

where q_j denotes the variety-specific productivity of the latest innovator and evolves endogenously as a result of innovation. Note that Equation (3.8) implies a marginal cost of production equal to w_u/q_j.

What happens to market leadership, prices, and profits following an innovation? The latest innovator over variety j will improve the variety-specific productivity by a proportional step size $\gamma > 1$:

$$q_j(t + \Delta t) = \gamma q_j(t). \tag{3.9}$$

Since each product market is characterized by Bertrand competition and the previous innovator will charge at least her marginal cost, w_u/q_j, the latest innovator will charge the marginal cost of the previous innovator. It is then straightforward to compute the profits of the latest innovator:

$$\begin{aligned} \Pi_j &= [p_j - MC_j]y_j = \left[\frac{w_u}{q_j} - \frac{w_u}{\gamma q_j}\right]\frac{Yq_j}{w_u} \\ &= \frac{\gamma - 1}{\gamma}Y, \end{aligned} \tag{3.10}$$

where I have used the inverse demand function (3.6) in deriving the second equality. In what follows, I set $\pi \equiv (\gamma - 1)/\gamma$ to save notation.

Under this market structure, a firm is defined as a collection of its products, $\mathcal{J}_f = \{j : j \text{ is owned by firm } f\}$. A firm has the incentive to innovate over other firms' products and consequently steal the monopoly profits associated with operating those products; a firm never has the incentive to innovate over its existing product(s) as such action cannibalizes its own profits.

In the model, a natural proxy for firm size is the number of products a firm operates, denoted by n. Note that the profits of a firm with n products are:

$$\Pi^f(n) = \sum_{j \in \mathcal{J}_f} \Pi_j = n\pi Y. \tag{3.11}$$

Hence, firm profits are proportional to the number of its products. Moreover, as Section C.2.1 of the Appendix shows, firm employment (both skilled and unskilled) is also proportional to the number of its products.

At any point in time, there are: (i) a set of incumbent firms whose measure will be determined in equilibrium; and (ii) a unit mass of outside entrepreneurs who do not currently operate any product but engage in R&D in order to enter the market upon a successful innovation. Exit happens when an incumbent firm has lost all its product(s). Hereafter, I will drop the firm index, f, when there is no confusion.

3.2.4 R&D Investment and CVC Relationships

As described in the previous section, monopoly leadership in a product market results from successful innovation. In this section, I discuss how firms (incumbent and entrant) innovate—through

R&D investment and formation of CVC relationships. Standard models in the spirit of Klette and Kortum (2004) and Lentz and Mortensen (2008) feature incumbent and entrant firms conducting R&D activity independently.[3] My key departure from the standard model is to bridge the entrepreneurial and the incumbent sectors through CVC. In what follows, I first describe the R&D technology of incumbents. I then describe how CVC relationships are formed and what the associated impacts are on the innovation outcomes of the matched firms. Lastly, I describe entry R&D.

3.2.4.1 Incumbent R&D

Incumbents conduct in-house R&D as in the standard model. Following recent endogenous growth models, I assume that there is firm heterogeneity in innovative capacities.[4] Specifically, upon successful entry, each firm draws its permanent type $\theta \in \{\theta_H, \theta_L\}$, corresponding to a high-type or a low-type firm. As will become clear, firm type affects the CVC technology.

In addition, firm type affects R&D efficiency as follows. When a θ-type firm hires S units of skilled labor (researchers), the firm can generate a Poisson arrival rate of innovation, Z, according to:

$$Z(n, \theta) = (\theta S)^{\frac{1}{\zeta}} n^{1-\frac{1}{\zeta}}, \tag{3.12}$$

where $\zeta > 1$ parameterizes the concavity of the innovation production function.

Three remarks are in order. First, with $\theta_H > \theta_L > 0$, high-type incumbents are assumed to be more productive in their R&D efforts than low-type incumbents, per any given amount of skilled labor hired. One can thus think of θ as (skilled) labor-augmenting. Second, the flow rate

[3] A branch of the endogenous growth literature features strategic interactions between incumbent firms. See for example, Acemoglu and Akcigit (2012); Aghion et al. (1997, 2005, 2001); Akcigit and Ates (2019); Akcigit et al. (2018).

[4] For recent endogenous growth models with firm heterogeneity in research capacities, see Acemoglu et al. (2021, 2018); Akcigit et al. (2021).

of innovation also depends on the number of existing products a firm operates, n. Here, the idea is to use n to proxy for the firm-specific, non-transferable and non-tradable knowledge stock that is used as an input in the innovation process. Third, the innovation production function has constant returns to scale (RTS). Akcigit and Kerr (2018) show that depending on whether the innovation production function has constant RTS or decreasing RTS, a firm's innovation intensity—the per-product flow rate of innovation—can be constant or decreasing in firm size. In the baseline model, I work with constant RTS as this specification admits sharper analytic solutions and helps build intuition. In my numerical analysis, I also solve a generalized version of the model with decreasing RTS. I will show that the results obtained from the baseline model hold qualitatively in the generalized model.

Note that Equation (3.12) implies the following cost (wage bill) of R&D:

$$C(z, n, \theta) = \frac{z^{\zeta} n w_s}{\theta}, \tag{3.13}$$

where $z \equiv Z/n$ denotes the per-product innovation intensity of the firm and w_s is the skilled wage rate.

R&D efforts are assumed to be undirected. Conditional on innovating, a firm improves the productivity of a randomly selected product other than the firm's own product(s) by a proportional step size $\gamma > 1$, as in Equation (3.9), and adds that product to the firm's existing product portfolio.

3.2.4.2 Formation of CVC Relationships

Incumbent and entrant firms can form CVC relationships to seek synergies. Recall that CVC relationships have been found to have a positive treatment effect on start-up as well as investing firms, especially as measured by patent-related outcomes. Moreover, there is some evidence of sorting of highly innovative start-up firms to established firms that are larger and more innovative.

I do not aim at micro-founding these characteristics of CVC in the model. As a starting point, my approach is to take these patterns as given and analyze how their presence affects aggregate outcomes. To that end, I introduce a number of assumptions below that replicate the empirical patterns in a highly stylized fashion. Essentially, Assumptions 3.1 and 3.4 replicate the double treatment effect of CVC on incumbents and entrants, while Assumptions 3.2 and 3.3 replicate the selection of larger, more innovative incumbents into CVC. I abstract from any selection on the entrants' side. In Section 3.4, I revisit this simplification and discuss the potential issues associated with it.

Assumption 3.1 (Positive treatment to incumbent firms) *Through partnering with a potential entrant, an incumbent improves its R&D capacity according to:*

$$\hat{Z}(n, \theta) = (\kappa \theta S)^{\frac{1}{\zeta}} n^{1-\frac{1}{\zeta}}, \tag{3.14}$$

where $\kappa > 1$ governs the magnitude of the capacity gain from CVC.

In this specification, a CVC relationship is (skilled) labor-augmenting; it raises the odds for an incumbent to innovate successfully relative to an incumbent not engaged in CVC. Intuitively, one can think of this capacity gain as coming from CVC enabling an incumbent to access new and disruptive technologies, to gain market intelligence, or to become more agile in the product development cycle, all of which make the incumbent's R&D efforts more productive.

Assumption 3.2 (Selection of larger incumbents into CVC) *In order for a CVC relationship to form, there is a fixed cost, $c_p Y$, incurred by the incumbent, which can be interpreted as any legal, financial, or reputational hurdle that the incumbent has to overcome.*

A couple of remarks are in order. First, much like an export cost in a Melitz (2003)-type model that generates an endogenous cutoff in productivity for exporters, here the fixed cost of starting CVC will lead to an endogenous threshold in firm size such that larger firms will find it optimal to incur the fixed cost in return for the capacity gain. I will formally describe how this threshold is determined when I describe firms' value functions. Second, the fixed cost parameter, c_p, is scaled up by output Y such that aggregate spending on the fixed costs for CVC is a constant fraction of aggregate output along a balanced growth path.

A main comparative statics exercise in this paper will be a decline in the fixed cost parameter, c_p, which induces higher levels of CVC in the model economy.

Assumption 3.3 (Selection of more innovative incumbents into CVC) *High-type incumbents are able to nurture innovation in entrant firms (detailed in Assumption 3.4) whereas low-type incumbents are not. In equilibrium, high-type incumbents are selected into CVC.*

Here, I assume that low-type incumbents have nothing to offer to entrant firms in terms of technological or demand-side synergies. Entrants therefore are indifferent between partnering with low-type incumbents or not, in which case CVC relationships are assumed to not take place for simplicity. On the other hand, an entrant firm has an incentive to partner with a high-type incumbent because doing so is advantageous, as discussed next.

Assumption 3.4 (Positive treatment to entrants) *Outside entrepreneurs are ex-ante homogeneous.*

However, conditional on entering, an entrant firms that is partnered with a high-type incumbent has a higher probability of drawing a high type than otherwise.

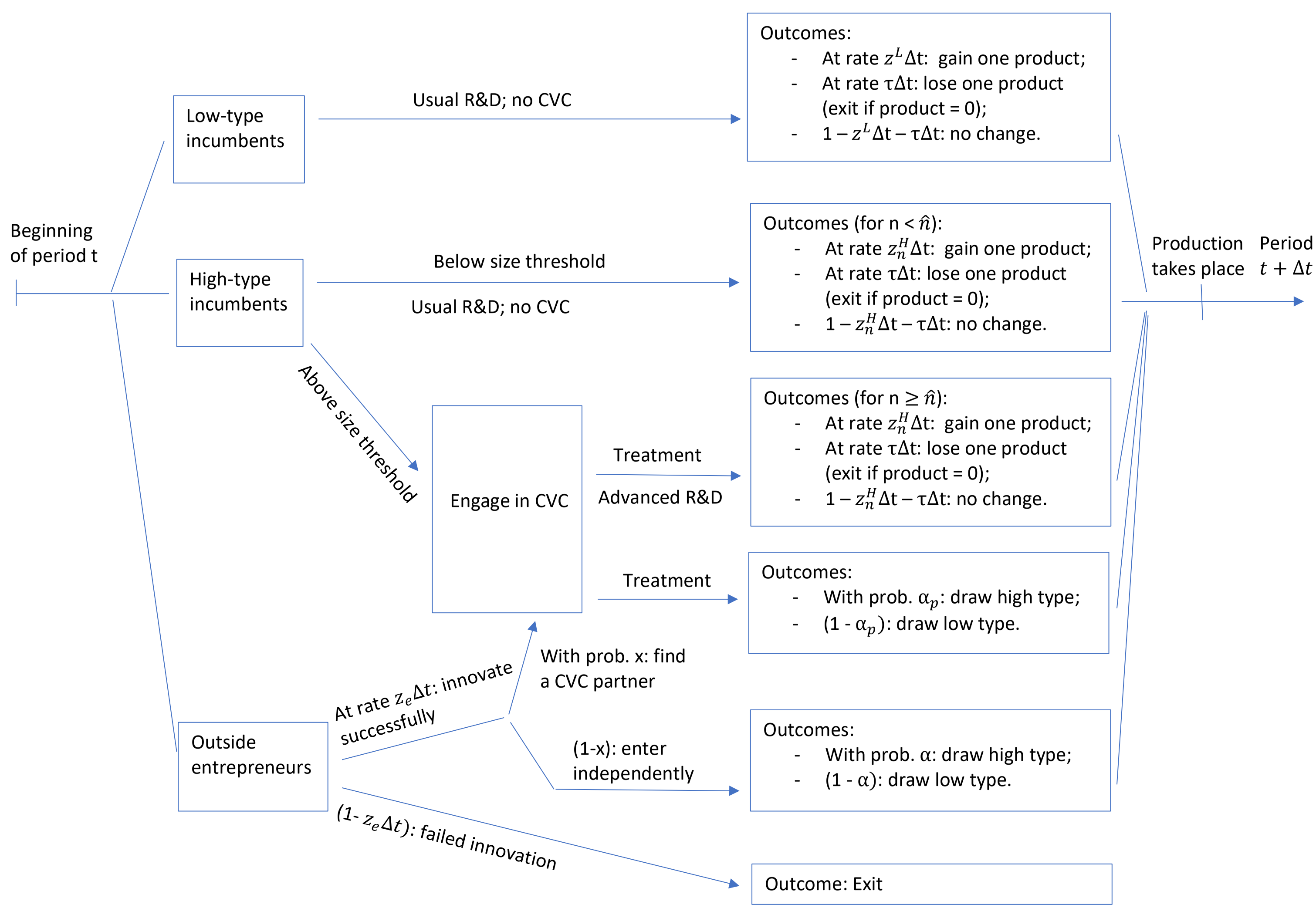
By influencing the permanent type of entrant firms, CVC is assumed to have a persistent treatment effect on entrant firms beyond the entry stage. Thus, entrant firms that are backed by (high-type) incumbents are expected to have a higher survival rate on average and grow faster conditional on survival, relative to entrant firms that enter the economy independently.

Finally, for tractability reasons, I abstract from search and matching frictions. High-type incumbents that are large enough to opt for CVC will each match with an entrant firm. In equilibrium, the fraction of entrants with a CVC partner is determined by the measure of high-type incumbents above the endogenous size threshold for selection into CVC.

Timing of events To summarize, low-type incumbents conduct R&D as in the standard model and do not engage in CVC. High-type incumbents of different sizes face the decision of whether to partner with an entrant or not. The presence of a fixed cost for CVC leads to a threshold in firm size such that larger (high-type) incumbents opt for CVC. Each high-type incumbent above the size threshold matches with one entrant at a time. Absent search and matching frictions, the probability for an entrant firm to find a CVC partner is equal to the measure of high-type incumbents above the size threshold.[5] Figure 3.1 summarizes the timing of events.

[5]Recall that the measure of entrant firms is normalized to 1 and the measure of incumbent firms will be determined in equilibrium. Since an incumbent firm can own multiple products, the measure of incumbent firms will be less than 1. It is thus guaranteed that the measure of (high-type) incumbents above the size threshold is smaller than the measure of entrants.

Figure 3.1: Timeline of Events



3.2.4.3 Entry R&D

At any point in time, a unit mass of outside entrepreneurs invests in R&D in order to enter the economy. Outside entrepreneurs have access to an innovation technology similar to that of an incumbent firm with one product. Specifically, the innovation intensity, equivalent to the flow rate of innovation in the case of outside entrepreneurs, is given by:

$$z_e = (\theta_e S_e)^{\frac{1}{\zeta}}, \tag{3.15}$$

where θ_e denotes the innovative capacities of outside entrepreneurs and S_e the amount of skilled labor (researchers) hired. Entrants enter the economy with a single, randomly selected product line and the realization of $\theta \in \{\theta_H, \theta_L\}$ is revealed only after entering the market.

Crucially, conditional on successfully innovating, an outside entrepreneur may match with a high-type incumbent and enhance her likelihood of drawing a high type, echoing Assumption 3.4. Let α_p and α denote, respectively, the probability that an entrant with and without a CVC partner will draw a high type. I impose $\alpha_p > \alpha$.

Thus, the equilibrium entry flow rate is given by:

$$\begin{aligned} z_e &= \operatorname{argmax}_z \left\{ -\frac{z^{\zeta} w_s}{\theta_e} + z\mathbb{E}V_1 \right\} \\ &= \left[\frac{\theta_e \mathbb{E}V_1}{\zeta w_s} \right]^{\frac{1}{\zeta - 1}}, \end{aligned} \tag{3.16}$$

where $\mathbb{E}V_1$ denotes the expected value of a one-product firm and the expectation is taken over firm type. Specifically:

$$\mathbb{E}V_1 = \underbrace{\left[F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H \alpha_p + (1 - F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H)\alpha\right]}_{A} V_1^H + (1-A)V_1^L, \tag{3.17}$$

where F^H denotes the measure of high-type incumbents, $\hat{n}$ the size threshold for CVC, μ_n^H the share of high-type incumbents with n products, V_1^L the value of a low-type incumbent with one product, and V_1^H the value of a high-type incumbent with one product, all of which will be determined endogenously.

Equation (3.17) states that the expected value of entry is the weighted average value of a high-type firm with one product and a low-type firm with one product, where the weights are the probabilities of drawing a high or low type. For notational convenience, I denote by A (and $1-A$) the endogenous probability of entering as a high-type (and low-type) firm. Note that an entrant can enter as a high-type firm under two cases: (i) if the entrant firm matches with a high-type incumbent, which happens with probability $F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H$, it has a higher chance of drawing a high type, given by α_p; (ii) if the entrant does not match with a high-type incumbent, it can still enter as a high-type firm, albeit at a lower probability α.

CVC may have two countervailing effects on entry. On the one hand, higher levels of CVC raise A, which encourages entry as outside entrepreneurs internalize the improved prospects for entering as a high-type firm, everything else equal. On the other hand, higher levels of CVC tend to reduce V_1^L and V_1^H, largely through intensified competition that makes one-product firms more likely to exit. Therefore, the net effect of CVC on entry can be positive or negative. In my numerical analysis, I find that the negative force dominates.

Thus far, I have completed the description of the model environment. I next turn to firms' value functions.

3.2.5 Value Functions

Low-type Recall that low-type incumbents do not engage in CVC; their problem is the same as in the standard model. Let V_n^L and z_n^L denote, respectively, the value and the innovation intensity of a low-type incumbent with n products. Note that there is an abuse of notation here—both the value and the innovation intensity are actually functions of firm type and firm size, hence should be more precisely written as $V(n, \theta_L)$ and $z(n, \theta_L)$. On that note, the continuous-time Hamilton-Jacobi-Bellman equation for a low-type incumbent is:

$$\begin{aligned} rV_n^L - \dot{V}_n^L = \max_{z_n^L \geq 0} \quad & \Bigg\{ \quad n\pi Y - \frac{(z_n^L)^\zeta n w_s}{\theta_L} \\ & + \quad n z_n^L \left(V_{n+1}^L - V_n^L \right) + n\tau \left(V_{n-1}^L - V_n^L \right) \Bigg\}, \end{aligned} \tag{3.18}$$

where $\dot{V}_n^L = \partial V_n^L / \partial t$ and τ denotes the equilibrium average rate of innovation, also referred to as the creative destruction rate, which is the rate at which a given product of the firm is replaced by a higher-quality one from another firm (incumbent or entrant).

Equation (3.18) states that the value of a low-type incumbent with n products is composed of three parts. First, the firm receives flow profits from operating its current products and incurs a flow cost of doing R&D. At the chosen flow rate nz_n^L, the firm successfully innovates and expands its number of products from n to $n+1$, leading to a capital gain. At the same time, the firm loses a given product in its portfolio due to creative destruction at a flow rate $n\tau$, leading to a capital loss.

The following proposition characterizes the value of a low-type incumbent and its optimal R&D intensity.

Proposition 3.1 *Let $\omega_s \equiv w_s/Y$ denote the normalized skilled wage and let $v_n^L \equiv V_n^L/Y$ denote the normalized value function of a low-type incumbent with n products. The normalized value function is linear in firm size:*

$$v_n^L = n\nu_L, \tag{3.19}$$

where ν_L denotes the franchise value of each product and can be expressed implicitly as the sum of a production value and an innovation option value:

$$\nu_L = \frac{\pi}{\rho+\tau} + \frac{1}{(\rho+\tau)}(\zeta-1)\left(\frac{\theta_L}{\omega_s}\right)^{\frac{1}{\zeta-1}}\left(\frac{\nu_L}{\zeta}\right)^{\frac{\zeta}{\zeta-1}}. \tag{3.20}$$

Moreover, the optimal R&D intensity is independent of firm size:

$$z^L = \left[\frac{\theta_L \nu_L}{\zeta \omega_s}\right]^{\frac{1}{\zeta-1}}. \tag{3.21}$$

Proof 3.1 *See Appendix C.1.*

The above results are entirely standard. Here, the linearity of firm value in firm size follows from the constant-RTS property of the innovation production function, as does the independence of research intensity in firm size.

Using these analytic results, I highlight two forces that help build intuition for the problems of high-type incumbents and outside entrepreneurs, which do not admit closed-form solutions. First, *holding the skilled wage rate fixed*, the partial derivatives of franchise value and innovation intensity with respect to the creative destruction rate are negative, i.e., $\partial \nu_L/\partial \tau < 0$ and $\partial z^L/\partial \tau < 0$, as shown in Appendix Section C.2.1. Thus, greater competition leads to a fall in franchise value and innovation effort, everything else equal. Intuitively, if a firm exerts costly innovation effort only to be easily replaced by a competitor ex-post, that reduces the firm's effort ex-ante. Moreover, if the realized gain from successful innovation is short-lived, that decreases the franchise value itself. Second, *holding the creative destruction rate fixed*, the partial derivatives of franchise value and innovation intensity with respect to the normalized skilled wage are negative, i.e., $\partial \nu_L/\partial \omega_s < 0$ and $\partial z^L/\partial \omega_s < 0$, also as shown in Appendix Section C.2.1. Not surprisingly, the more costly is R&D, the less effort a firm exerts and the lower the franchise value becomes, everything else equal.

High-type High-type incumbents solve a similar R&D problem but face the additional decision of whether to engage in CVC or not. Let V_n^H and z_n^H denote, respectively, the value and the innovation intensity of a high-type incumbent with n products. The value satisfies the following Hamilton-Jacobi-Bellman equation:

$$
\begin{aligned}
rV_n^H - \dot{V}_n^H \;=\; n\pi Y \;&+\; \max\left\{\begin{array}{l} \max_{z_n^H\geq 0}\left\{-(z_n^H)^{\zeta} n w_s/\theta_H + n z_n^H\left(V_{n+1}^H - V_n^H\right)\right\}; \\ \max_{z_n^H\geq 0}\left\{-(z_n^H)^{\zeta} n w_s/(\kappa\theta_H) - c_p Y + n z_n^H\left(V_{n+1}^H - V_n^H\right)\right\} \end{array}\right\} \\
&+\; n\tau\left(V_{n-1}^H - V_n^H\right). \qquad (3.22)
\end{aligned}
$$

A high-type incumbent's value in (3.22) is similar to that of a low-type incumbent except that it involves an additional choice between partnering with an entrant or not as represented by the outer maximization.

While there is no longer a closed-form solution for the problem facing high-type incumbents, the next proposition establishes the existence of a size threshold for CVC.

Proposition 3.2 *Let $\omega_s \equiv w_s/Y$ denote the normalized skilled wage and let $v_n^H \equiv V_n^H/Y$ denote the normalized value function of a high-type incumbent with n products. There exists an integer, $\hat{n}$, such that high-type incumbents with $n \geq \hat{n}$ products pursue CVC, while those with $n < \hat{n}$ products do not. The normalized value and innovation intensity satisfy:*

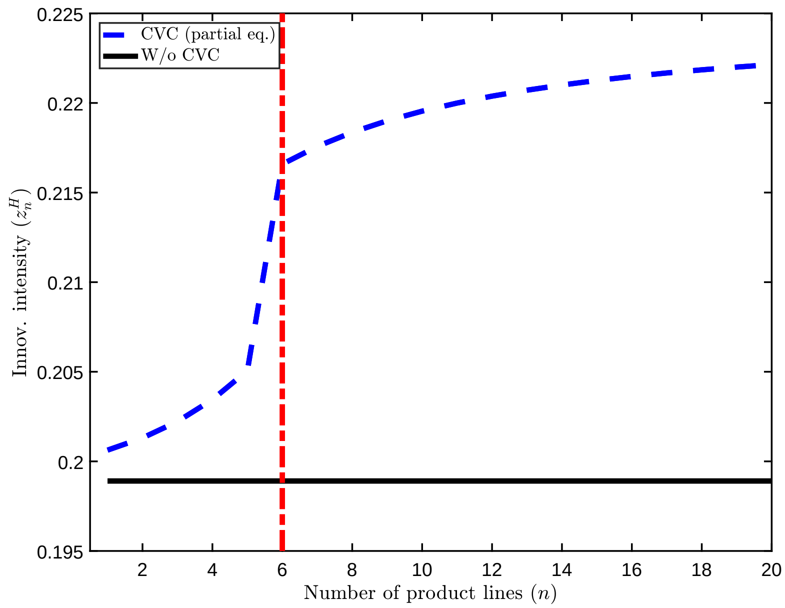
$$\begin{aligned} \rho v_n^H = n\pi \quad &+ \quad \left\{ \begin{array}{ll} \max_{z_n^H \geq 0} \left\{ -(z_n^H)^\zeta n \omega_s/\theta_H + n z_n^H \left(v_{n+1}^H - v_n^H \right) \right\} & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \left\{ -(z_n^H)^\zeta n \omega_s/(\kappa\theta_H) - c_p + n z_n^H \left(v_{n+1}^H - v_n^H \right) \right\} & \text{for } n \geq \hat{n} \end{array} \right\} \\ &+ \quad n\tau \left(v_{n-1}^H - v_n^H \right). \end{aligned} \tag{3.23}$$

Proof 3.2 *See Appendix C.1.*

How does the option of CVC alter the incentive to innovate for high-type incumbents, relative to a standard economy in which there is no CVC activity? Figure 3.2 provides a visual illustration. The solid black line plots the optimal innovation intensity of high-type incumbents as a function of firm size (n) in an economy without CVC, which is flat as one would expect. The dashed blue line plots the optimal innovation intensity of high-type incumbents with the option of CVC, solved under the same parameterization and the same skilled wage rate (ω_s) and creative destruction rate (τ) as in the solid black line. Therefore, the difference between the two lines represents the partial equilibrium effect of CVC. Everything else equal, the option of CVC induces an increase in innovation intensity across the entire size distribution of high-type firms, represented by the higher level of the dashed blue line relative to the solid black line.

More importantly, due to the option value of CVC, high-type incumbents have an innovation intensity schedule that is S-shaped. To the left of the size threshold, the innovation intensity is

Figure 3.2: Optimal Innovation Intensity, High-Type (z_n^H)



Notes: The solid black line plots the optimal innovation intensity of high-type incumbents as a function of firm size (n) in an economy without CVC activity, solved using the baseline parameterization but with a high value of c_p, the fixed cost for CVC, which renders $\hat{n} = \infty$. The dashed blue line plots the optimal innovation intensity of high-type incumbents with the option of CVC, solved under the baseline parameterization and the same skilled wage rate (ω_s) and creative destruction rate (τ) as in the solid black line. The size threshold for CVC, $\hat{n} = 6$, is indicated by the red dash-dot vertical line. The difference between the solid black line and the dashed blue line represents the partial equilibrium effect of CVC.

increasing and convex in firm size. To gain intuition, think of a high-type incumbent with five products and another high-type incumbent with three products, with the size threshold for CVC being $\hat{n} = 6$. With just one successful innovation, the five-product firm will reach the size threshold and match with an entrant to gain access to a more advanced innovation technology. Meanwhile, it takes three consecutive successful innovations for the three-product firm to reach the size threshold. Therefore, the marginal return to a successful innovation is higher for the five-product firm than for the three-product firm, inducing greater effort by the former. The jump in innovation intensity is steepest at the threshold both because the incentive is the strongest and because of the direct effect of the realized capacity gain, κ.

To the right of the size threshold, the innovation intensity is increasing and concave in firm size. Intuitively, the closer a high-type incumbent is to the threshold (from the right), the greater incentive it has to innovate and grow in size in order not to fall back below the threshold. Once a high-type incumbent has accumulated enough products and the prospect of falling back is perceived to the very low, innovation effort will barely increase in firm size.

To summarize, the option value of CVC induces (i) an increase in innovation efforts by high-type incumbents across the entire size distribution, holding competition and skilled wages fixed; and (ii) an S-shaped policy function. In general equilibrium, however, the levels of competition and skilled wages will rise due to the presence of CVC, disincentivizing innovation. As a result, the dashed blue line will shift downward and may even cross the solid black line, suggesting the possibility that small high-type incumbents may end up exerting less effort than they would in an economy without CVC activity. I defer further discussion until the numerical analysis section and next characterize the invariant firm size distribution.

3.2.6 Invariant Firm Size Distribution

In a stationary equilibrium, though individual firms enter, exit, and change size, the overall measure of firms in different states stays the same. This implies that and flows into and out of each state should balance each other.

I first work with the case of low-type firms. Specifically, let μ_n^L denote the share of low-type firms with n products, F^L the total measure of low-type firms, and z^L their optimal innovation intensity (which is not a function of n, as shown in Proposition 3.1). Naturally, $\sum_{n=1}^{\infty} \mu_n^L = 1$ for μ_n^L to be a proper distribution.

The invariant size distribution of low-type firms can be represented by a set of differential equations below. In the first equation, the left-hand side and the right-hand side equate the mass of entering and exiting low-type firms. For $n = 1$, the inflows are made up of (i) entrants that draw a low type; and (ii) current two-product, low-type firms that lose one of their products due to creative destruction. The outflows are made up of current one-product, low-type firms that either successfully innovate or lose their single product to another firm. A similar interpretation holds for the case of $n \geq 2$.

State	Inflow = Outflow
Entry/Exit:	$z_e \underbrace{\left[F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H (1-\alpha_p) + (1 - F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H)(1-\alpha)\right]}_{1-A} = F^L \mu_1^L \tau$
$n = 1:$	$z_e(1-A) + F^L \mu_2^L 2\tau = F^L \mu_1^L (z^L + \tau)$
$n \geq 2$:	$F^L \mu_{n-1}^L (n-1) z^L + F^L \mu_{n+1}^L (n+1)\tau = F^L \mu_n^L n (z^L + \tau)$

The characterization for high-type firms is similar. Let μ_n^H denote the share of high-type firms with n products, F^H the total measure of high-type firms, and z_n^H their optimal innovation intensity (which is a function of n in this case). Again, consistency requires that $\sum_{n=1}^{\infty} \mu_n^H = 1$. The invariant size distribution of high-type firms satisfies the following flow equations:

The interpretation of the above flow equations is analogous to that of the low-type firms. I simply note that the rate at which a high-type firm flows into or out of a particular state varies by

State	Inflow = Outflow
Entry/Exit:	$z_e \underbrace{\left[F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H \alpha_p + (1 - F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H)\alpha\right]}_{A} = F^H \mu_1^H \tau$
$n = 1:$	$z_e A + F^H \mu_2^H 2\tau = F^H \mu_1^H (z_1^H + \tau)$
$n \geq 2$:	$F^H \mu_{n-1}^H (n-1) z_{n-1}^H + F^H \mu_{n+1}^H (n+1)\tau = F^H \mu_n^H n (z_n^H + \tau)$

firm size.

The next proposition shows that the stationary firm size distribution for each type has a closed-form expression.

Proposition 3.3 *Consider a stationary equilibrium and let the flow rate of entry (z_e), the optimal innovation intensities of low- and high-type firms (z^L and z_n^H), and the creative destruction rate (τ) be given. The distributions of low- and high-type firms are, respectively:*

$$\mu_n^L = \frac{\frac{1}{n}\left(\frac{z^L}{\tau}\right)^n}{\ln\left(\frac{\tau}{\tau - z^L}\right)} \quad \textit{and} \quad \mu_n^H = \frac{\frac{1}{n}\prod_{j=1}^{n-1}\left(\frac{z_j^H}{\tau}\right)}{\sum_{n=1}^{\infty}\frac{1}{n}\frac{\tau}{z_n^H}\prod_{j=1}^{n}\left(\frac{z_j^H}{\tau}\right)} \tag{3.24}$$

Proof 3.3 *See Appendix C.1.*

Finally, note that the aggregate spending on fixed costs for CVC is:

$$\Phi = F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H c_p Y. \tag{3.25}$$

3.2.7 Stationary Equilibrium

I now characterize the labor market-clearing condition, the creative destruction rate, and the aggregate growth rate of this economy. I then provide a formal definition of the stationary equilibrium.

Labor market clearing First note that the supply and demand for unskilled labor must be equal:

$$1 = \int_0^1 l_j dj = \frac{1}{\gamma \omega_u}, \tag{3.26}$$

where $\omega_u \equiv w_u/Y$ denotes the normalized unskilled wage.

Similarly, the supply and demand for skilled labor must be equal:

$$\begin{aligned} L_S = \quad & F^L \sum_{n=1}^{\infty} \frac{1}{\theta_L}(z^L)^{\zeta} n \mu_n^L + F^H \sum_{n=1}^{\hat{n}-1} \frac{1}{\theta_H}(z_n^H)^{\zeta} n \mu_n^H \\ + \quad & F^H \sum_{n=\hat{n}}^{\infty} \frac{1}{\kappa \theta_H}(z_n^H)^{\zeta} n \mu_n^H + \frac{z_e^{\zeta}}{\theta_e}. \end{aligned} \tag{3.27}$$

The right-hand side of Equation (3.27) shows that the total demand for skilled labor comes low-type incumbents (first term), from high-type incumbents below the size threshold for CVC (second term), from high-type incumbents at and above the threshold (third term), and from outside entrepreneurs (last term).

Creative destruction and aggregate growth The equilibrium rate of creative destruction, τ, is given by:

$$\tau = F^L \sum_{n=1}^{\infty} n z^L \mu_n^L + F^H \sum_{n=1}^{\infty} n z_n^H \mu_n^H + z_e. \tag{3.28}$$

Essentially, the creative destruction rate is the sum of average innovation efforts by each incumbent (of low- or high-type) and the realized entry rate.

Creative destruction translates into aggregate growth. The following proposition shows that aggregate growth is in fact the product of the frequency and size of innovations (as in the standard model).

Proposition 3.4 *Along a balanced growth path, the growth rate of the economy is equal to:*

$$g = \tau \ln \gamma. \tag{3.29}$$

Proof 3.4 *See Appendix C.1.*

I now summarize the stationary equilibrium of this economy.

Definition 3.1 *A stationary equilibrium of the economy is a tuple*

$$\{v_n^L, z^L, v_n^H, z_n^H, \hat{n}, z_e, \mu_n^L, \mu_n^H, F^L, F^H, \tau, g, r, \omega_s\} \tag{3.30}$$

such that: (i) the normalized value and innovation intensity of low-type firms (v_n^L and z^L) are given by Proposition 3.1; (ii) the normalized value and innovation intensity of high-type firms (v_n^H and z_n^H), along with the size threshold for CVC ($\hat{n}$), satisfy Proposition 3.2; (iii) the realized entry rate, z_e, satisfies the normalized version of Equation (3.16), with the expected value of entry given by the normalized version of Equation (3.17);[6] *(iv) the stationary firm size distributions*

[6] The normalized version of Equation (3.16) is given by:

$$z_e = \left[\frac{\theta_e \mathbb{E} v_1}{\zeta \omega_s}\right]^{\frac{1}{\zeta - 1}}, \tag{3.31}$$

(μ_n^L and μ_n^H)) are given by Proposition 3.3; (v) Firm measures (F^L and F^H) are such that the mass of entering and exiting low- and high-type firms are equated as in Section 3.2.6; (vi) the creative destruction rate (τ) is given by Equation (3.28); (vii) the aggregate growth rate (g) is given by Proposition 3.4; (viii) the interest rate (r) satisfies the Euler equation (3.4); and (ix) the normalized skilled wage (ω_s) is consistent with the labor market-clearing condition in Equation (3.27).

Taking stock The analysis so far points to some key forces through which a rise in CVC activity may affect the process of firm entry, exit, and expansion. For entry, a rise in CVC improves the prospects for outside entrepreneurs to enter as a high-type firm, encouraging entry R&D. On the other hand, higher levels of CVC tend to intensify competition and raise skilled wages, discouraging entry R&D. For high-type incumbents, while the partial equilibrium effect of CVC tends to induce more innovation (with an S-shaped schedule), the general equilibrium effect from greater competition and higher skilled wages works in the opposite direction. For low-type incumbents, their innovation efforts are expected to fall following a rise in CVC, due to greater competition and higher wages. To quantitatively assess the strength of these countervailing forces, I turn to the numerical analysis next.

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where $\mathbb{E}v_1 = \mathbb{E}V_1/Y$ and the normalized version of Equation (3.17) is given by:

$$\mathbb{E}v_1 = \underbrace{\left[F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H \alpha_p + (1 - F^H \sum_{n=\hat{n}}^{\infty} \mu_n^H)\alpha\right]}_{A} v_1^H + (1-A)v_1^L. \tag{3.32}$$

3.3 Numerical Analysis

This section studies the model's quantitative implications by conducting numerical simulations for a baseline parameterization. I first outline the computational algorithm for solving the stationary equilibrium and then describe the calibration strategy. I next carry out the main comparative statics exercise—a decline in the cost of starting CVC, c_p.

3.3.1 Computer Algorithm

I solve the stationary equilibrium as a fixed point over the normalized skilled wage (ω_s), the realized entry rate (z_e), and the creative destruction rate (τ). The algorithm is made up of the following steps:

1. **Outer loop**: Guess $\{\omega_s, z_e, \tau\}$

2. Solve for ν_L and z^L in Proposition 3.1.

3. Solve v_n^H, z_n^H, and $\hat{n}$ in Proposition 3.2 using the uniformization method.[7]

4. Solve μ_n^L, μ_n^H, F^L and F^H using the bisection method over A (with the maximal number of products a firm can operate set to 35):

   (a) Guess A.

   (b) Guess μ_1^k for $k = \{L, H\}$.

   (c) Compute F^k and μ_n^k for $k = \{L, H\}$ using the flow equations in Section 3.2.6.

   (d) Solve for μ_1^k such that $\sum_{n=1}^{35} \mu_n^k = 1$ for $k = \{L, H\}$.

[7] I follow Akcigit and Kerr (2018).

(e) Compute implied A in 3.17.

(f) Update A until convergence.

5. Compute implied L_S using Equation (3.27), implied z_e using Equation (3.16), and implied τ using Equation (3.28).

6. **Close outer loop:** End the equilibrium solver.

Once the equilibrium is solved, I simulate the evolution of a panel of 8192 (2^{13}) firms until they reach the approximate stationary equilibrium after 25,000 iterations, corresponding to 500 years. At each iteration, firms gain and lose products according to the flow probabilities specified in the model. I then simulate the model for another 250 iterations, corresponding to five years, and use those years to compute the moments of interest.[8]

3.3.2 Calibration

The model has 11 parameters:

$$\{\underbrace{\zeta, \theta_L, \theta_H, \theta_e}_{\text{R\&D}}, \underbrace{\kappa, c_p, \alpha_p, \alpha}_{\text{CVC}}, \underbrace{\gamma, \rho, L_S}_{\text{Macro}}\}. \tag{3.33}$$

The first four parameters are related to the R&D technology: the convexity of the cost function (ζ), the type-specific innovation capacities (θ_L and θ_H), and the entry capacity (θ_e). The next four parameters capture the various aspects of the CVC technology: the capacity gain to incumbents (κ), the fixed cost incurred by incumbents (c_p), and the treatment to entrant firms (α_p relative to

[8]Since many of the empirical moments I use are collected from Acemoglu et al. (2018) and their moments are computed over five-year windows, I follow the same procedure so that the model moments are consistently defined.

α). Lastly, the remaining three parameters relate to macro dynamics: the innovation step size (γ), the patience of the household (ρ), and the measure of skilled labor supply (L_S).

The calibration proceeds in two steps. First, a subset of parameter values is set using direct empirical evidence or are taken from the literature. Specifically, I set the R&D curvature parameter to $\zeta = 2$, following the microeconomic innovation literature.[9] The household discount rate is set to $\rho = 0.02$, which roughly corresponds to an annual discount factor of 0.97, a standard value used in the endogenous growth literature. In addition, following Acemoglu et al. (2018), I take $L_S = 0.166$, which matches the share of managers, scientists and engineers in the workforce in 1990. Table 3.1 summarizes the externally calibrated parameters.

Table 3.1: Externally Calibrated Parameters

#	Parameter	Description	Value	Source
1	ζ	Curvature in R&D function	2	Literature
2	ρ	Discount factor	0.02	Literature
3	L_S	Measure of skilled labor	0.166	Acemoglu et al. (2018)

In the second step, the remaining eight parameters are jointly calibrated using simulated method of moments (SMM). The parameter values are chosen to minimize the distance between the target data moments and the corresponding model-implied counterparts:

$$\min \sum_{i=1}^{10} \frac{|\text{model (i)} - \text{data (i)}|}{\frac{1}{2}|\text{model (i)}| + \frac{1}{2}|\text{data (i)}|}. \tag{3.34}$$

The SMM procedure targets 10 data moments collected from a mixture of existing studies. Although these moments jointly determine the eight parameter values, I discuss the intuition

[9] Acemoglu et al. (2018); Akcigit and Kerr (2018) discuss the microeconomic evidence in detail.

behind the identification of each parameter, building upon heuristics and what has commonly been implemented in the literature. Table 3.2 reports the values of the internally calibrated parameters.[10]

Table 3.2: Internally Calibrated Parameters

#	Parameter	Description	Value	Target
1	θ_L	Innovative capacity, low-type	0.18	Life-cycle firm growth
2	θ_H	Innovative capacity, high-type	0.3	Life-cycle firm growth
3	θ_e	Innovative capacity, entrants	0.14	Entry rate
4	κ	CVC gain to incumbents	1.05	Differential growth of incumbents with CVC *
5	c_p	Cost of CVC	0.02	Matching prob. of CVC **
6	α_p	Prob. of high-type entry w/ a CVC partner	0.7	Differential exit/growth of entrants with a CVC partner *
7	α	Prob. of high-type entry w/o a CVC partner	0.6	Age vs. exit profile
8	γ	Innovation step size	1.16	Aggregate growth rate

Notes: * indicates moment that would help identify a given parameter but not actually used in the calibration (work in progress). ** indicates moment in the context of traditional venture capital financing and will be replaced by the CVC counterpart in follow-up work.

Identifying θ_L, θ_H, and θ_e The innovative capacities of incumbents, θ_H and θ_L, are mostly identified from the profile of incumbents' life-cycle growth. The higher the innovative capacities, the faster firms will grow conditional on survival. Hence, I target employment growth rates by firm age conditional on firm size. The innovative capacity of potential entrants, θ_e, largely governs how effective outside entrepreneurs are in successfully replacing incumbent producers, and therefore is mostly identified from the aggregate entry rate.

Identifying κ The capacity gain parameter, κ, embodies the treatment associated with CVC to high-type incumbents. Data moments related to the differential growth performances between firms with and without CVC would help identify κ. For example, Dushnitsky and Lenox (2005)

[10] This version of the calibration does not use CVC specific moments, which I am currently working on.

regress (log) patenting outcomes on lagged (log) CVC investment and a set of control variables. Because my model lacks the financing aspect of CVC, I cannot replicate this regression with my simulated firm panel. Alternatively, Liu (2021c) and Ma (2020) provide causal evidence of the effect of CVC on the funding firms, using either an event study approach or an instrumental variable strategy. I am working on incorporating these empirical moments into my calibration. At the moment, however, the effect of κ will be partly reflected in the profile of incumbents' life-cycle growth used to identify θ_L and θ_H.

Identifying c_p The fixed cost for CVC, c_p, generates a threshold in firm size above which larger high-type incumbents opt for making CVC investment. The lower is c_p, the lower the size threshold, and consequently the easier it becomes for an entrant to match with a high-type incumbent. Hence, c_p is closely related to the probability that an entrant will be in a CVC relationship. Ideally, one would like to target, for example, the share of incumbent firms engaged in CVC activity or the share of entrant firms obtaining a CVC deal. While I am computing these empirical moments, I use the statistic from Ates (2014) in the context of traditional venture capital for the time being. Specifically, roughly one out of a hundred applicants succeeds in securing traditional venture capital funding. Note that the model counterpart to this statistic is the measure of high-type incumbents above the size threshold, given that there is no selection on the entrants' side and every meeting between an entrant and a high-type incumbent above the size threshold results in a successful match.

Identifying α and α_p To identify α, the probability for an entrant firm without a CVC partner to draw a high type, I focus on the age profile of exit rates conditional on firm size. Without type heterogeneity, the likelihood of exit would be independent of age conditional on size. In the presence of firm heterogeneity, however, there is endogenous selection in the sense that the share of high-type firms within a given cohort increases as the cohort ages. To identify α_p, the probability for an entrant firm with a CVC partner to draw a high type, one would like to target the difference in exit rates or the difference in growth profiles between entrant firms with and without backing from an incumbent. This is because the model predicts that entrant firms with a CVC partner have on average (i) a lower exit rate and (ii) a higher growth rate conditional on survival. For the time being, I target instead the share of firms aged five years or below. The higher is α_p, the larger the share of young firms should be conditional on α.

Identifying γ The innovation step size, γ, directly translates firms' innovation outcomes to aggregate growth. Therefore, γ is chosen to match a growth rate of about 2% in the United States, as provided by Acemoglu et al. (2018); Akcigit et al. (2021).[11]

3.3.3 Goodness of Fit

Table 3.3 reports the targeted moments in the data and their model-implied counterparts. With the limitation of missing data moments discussed in preceding paragraphs, the model replicates the data to some extent. However, the model generates too much aggregate growth but too little employment growth among small and young firms, likely due to an unrealistically high creative destruction rate under the current parameterization.

To get a sense of the magnitude of the treatment effects associated with CVC, I report in the bottom panel of Table 3.3 model-implied moments relating to the growth and exit rates of firms engaged in CVC. There is a three-percentage point growth differential between large, old

[11] Akcigit et al. (2021) rely on publicly available data from the Business Dynamics Statistics from 2012. Acemoglu et al. (2018) measure the growth rate of output per worker in their sample of firms during the 1987-1997 period as changes between Census of Manufacturer years expressed in per annum terms.

Table 3.3: Model and Data Moments

#	Moment	Data	Model	Data Source
1	Aggregate growth rate (%)	2.22	3.91	Acemoglu et al. (2018)
2	Entry rate (%)	7.35	8.32	Akcigit et al. (2021)
3	Emp. growth rate (small-young)	0.106	0.038	Acemoglu et al. (2018)
4	Emp. growth rate (small-old)	0.035	0.037	Acemoglu et al. (2018)
5	Emp. growth rate (large-old)	-0.05	-0.039	Acemoglu et al. (2018)
6	Firm exit rate (small-young)	0.107	0.133	Acemoglu et al. (2018)
7	Firm exit rate (small-old)	0.077	0.129	Acemoglu et al. (2018)
8	Firm exit rate (large-old)	0.036	0.066	Acemoglu et al. (2018)
9	Matching prob. of CVC **	0.01	0.026	Ates (2014)
10	5-year entrant share	0.393	0.506	Acemoglu et al. (2018)
Model-implied moments related to CVC:				
	Emp. growth rate (large-old-partnered)	n.a.	-0.009	
	Firm exit rate (5-year entrant)	n.a.	0.112	
	Firm exit rate (5-year-partnered)	n.a.	0.102	

Notes: ** indicates moments in the context of traditional venture capital financing. Following Acemoglu et al. (2018), large (small) firms are defined to be those above (below) the median firm size in the sample. Old (young) firms are defined to be those aged above (below) 10 years.

firms with and without CVC. In addition, there is a one-percentage point difference in the exit rate between young firms (aged five years and below) with and without a CVC partner.

3.3.4 Comparative Statics

To assess the net impact of CVC in general equilibrium, I perform a comparative statics exercise by solving the model under the baseline parameterization with different values of c_p, the fixed cost parameter for CVC. In what follows, I first report and discuss the aggregate results from this exercise. I then turn to the firm-level decision rules to rationalize the aggregate dynamics.

Aggregate dynamics Table 3.4 reports selected aggregate moments corresponding to different size thresholds for CVC $\hat{n}$ induced by a gradual decline in the fixed cost parameter c_p. From left to right, we go from a model economy without CVC ($\hat{n} = \infty$) to a model economy in which every high-type incumbent opts for CVC ($\hat{n} = 1$), with intermediate cases in between.

Table 3.4: Aggregate Dynamics Following a Decline in c_p

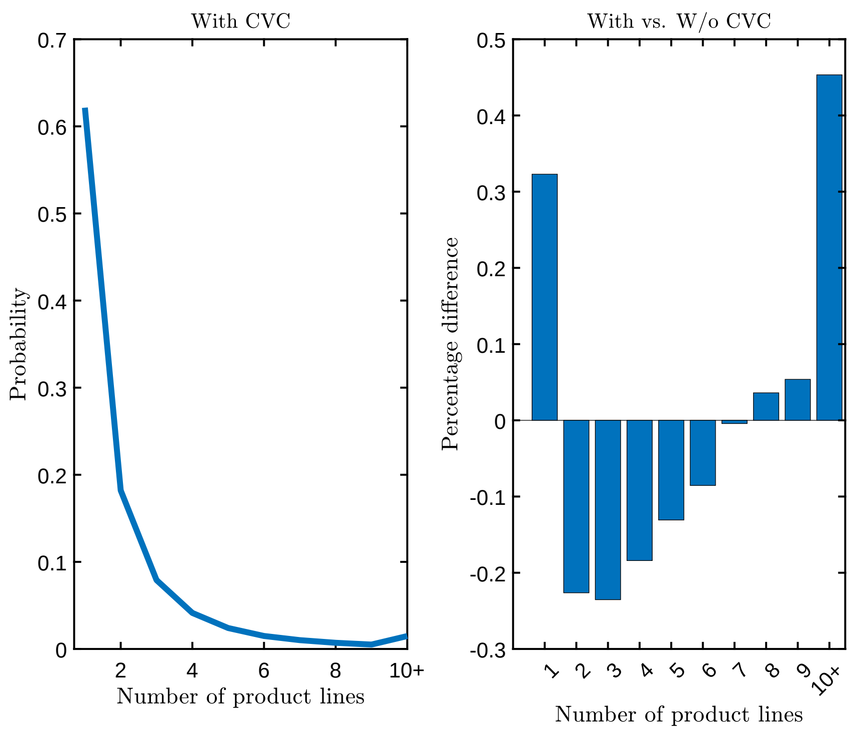
Variable	Data	$\hat{n} = \infty$ ($c_p = 0.12$)	$\hat{n} = 13$ ($c_p = 0.05$)	$\hat{n} = 6$ ($c_p = 0.02$)	$\hat{n} = 3$ ($c_p = 0.01$)	$\hat{n} = 1$ ($c_p = 0$)
Growth rate (%)	2.22	3.89	3.89	3.91	3.93	3.97
Creative destruction rate (%)	n.a.	26.21	26.23	26.34	26.49	26.72
Entry rate (%)	7.35	8.44	8.42	8.32	8.24	8.28
Prob. of high type (%)	n.a.	60	60.02	60.26	60.95	63.72
Normalized val. of one-prod. low-type (%)	n.a.	58.46	58.40	58.03	57.57	56.81
Normalized val. of one-prod. high-type (%)	n.a.	75.50	75.32	74.43	73.65	74.42
Normalized skilled wage (%)	n.a.	56.94	56.96	57.13	57.21	57.52
Emp. growth rate (small-young)	0.106	0.038	0.039	0.038	0.038	0.028
Emp. growth rate (small-old)	0.035	0.038	0.045	0.037	0.055	0.028
Emp. growth rate (large-old)	-0.05	-0.042	-0.031	-0.039	-0.045	-0.035
Emp. growth rate (large-old-partnered)	n.a.	na.	-0.013	-0.009	-0.013	-0.032
Firm exit rate (small-young)	0.107	0.133	0.128	0.133	0.133	0.132
Firm exit rate (small-old)	0.077	0.133	0.126	0.129	0.133	0.136
Firm exit rate (large-old)	0.036	0.069	0.063	0.066	0.065	0.067
Firm exit rate (5-year entrant)	n.a.	0.111	0.116	0.112	0.115	0.113
Firm exit rate (5-year-partnered)	n.a.	na.	0.091	0.101	0.107	0.108
5-year entrant share	0.393	0.497	0.504	0.505	0.498	0.496

Notes: Large (small) firms are defined to be those above (below) the median firm size in the sample. Old (young) firms are defined to be those aged above (below) 10 years.

Overall, for higher levels of CVC, the economy exhibits (i) greater competition, as represented by higher creative destruction rates; (ii) higher growth rates; (iii) higher skilled wages; and (iv) lower entry rates. The results confirm that the general equilibrium forces from increased competition and skilled wages discourage outside entrepreneurs from entry, despite a better prospect for entering as a high-type firm. There are, however, a significant amount of non-monotonicities when it comes to the growth and exit profiles, which I am still exploring.

In addition, CVC affects the macroeconomy through a change in the size distribution of firms, depicted in Figure 3.3. There is a fattening of the firm size distribution at the left and the right tails, accompanied by a hollowing-out in the middle. The fattening in the left tail is largely due to increased creative destruction that makes it hard for one-product firms to grow quickly. The fattening in the right tail is mostly driven by large, high-type firms that engage in CVC and expand in size at the expense of smaller firms.

Figure 3.3: Firm Size Distribution



Notes: The left-hand-side panel plots the theoretical invariant firm size distribution under the baseline parameterization with $\hat{n} = 6$. The right-hand-side panel plots the percentage differences in the theoretical invariant firm size distribution between $\hat{n} = 6$ and $\hat{n} = \infty$.

Together, lower realized entry and a fattening at the tails of the firm size distribution suggest that large high-type incumbents engaged in CVC must be the primary driving force behind the increase in competition (Recall that the creative destruction rate is the sum of the average of innovation efforts by each type of incumbent and the realized entry rate). The following firm-level results confirm this intuition.

Firm-level dynamics Figure 3.4 plots the optimal R&D intensity by high- and low-type incumbents in (i) an economy without CVC activity ($\hat{n} = \infty$) and (ii) an economy in which high-type incumbents with $n \geq 6$ products opt for CVC ($\hat{n} = 6$).

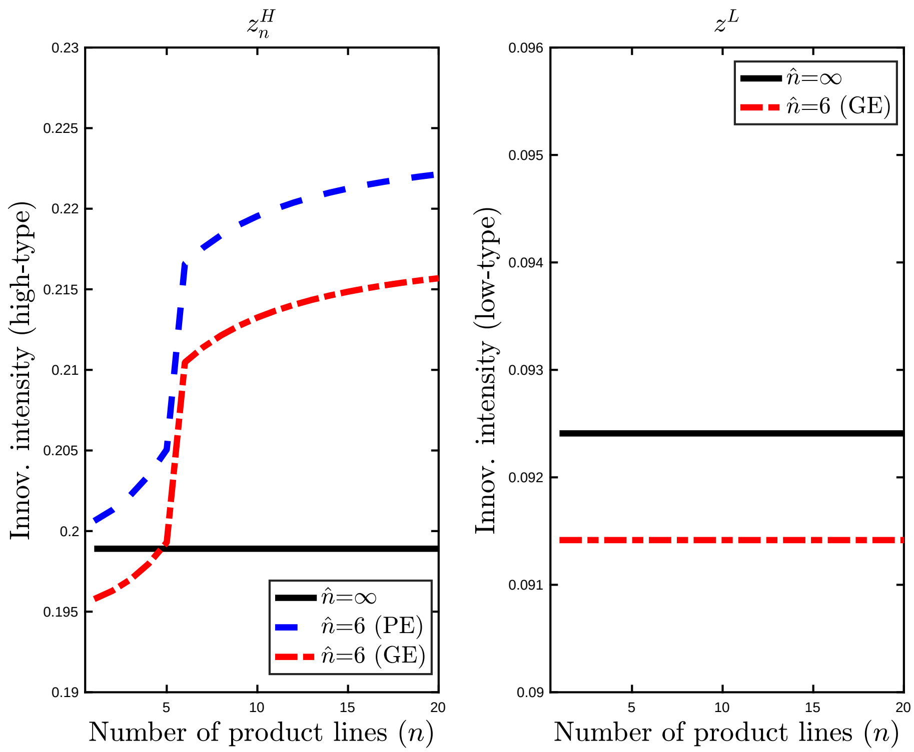
For high-type incumbents, recall that the partial-equilibrium effect of CVC leads to an increase in innovation effort across the entire size distribution, represented by the higher level of the dashed blue line relative to the solid black line. In general equilibrium, however, increased competition and skilled wages depress innovation efforts to the extent that small high-type incumbents end up exerting less effort in an economy with the option of CVC, relative to a counterfactual economy without CVC, as the left end of the dotted red line falls below the solid black line. Low-type incumbents, not surprisingly, experience a uniform decrease in innovation intensity as a result of increased competition and skilled wages.

3.3.5 Robustness

One assumption in the baseline model is that the innovation production function has constant RTS. Akcigit and Kerr (2018) show that when the innovation production function features decreasing RTS, the optimal innovation intensity is decreasing in firm size—more in line with the empirical observation that small firms tend to be more R&D-intensive. I now check robustness by solving a generalized version of the model with decreasing RTS. Specifically, the generalized innovation production function takes the form:

$$\tilde{Z}(n, \theta) = (\theta S)^{\tilde{\zeta}} n^{\tilde{\sigma}}, \quad \theta \in \{\theta_H, \theta_L\} \tag{3.35}$$

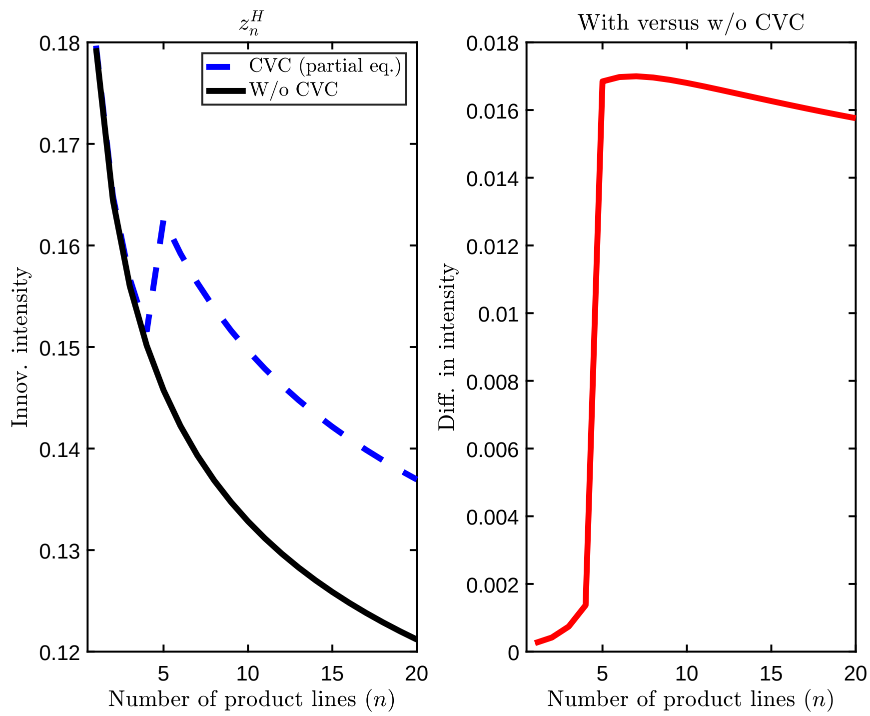
Figure 3.4: CVC and Innovation Intensity



Notes: In the left-hand-side panel, the red dash-dot line plots the optimal innovation intensity of high-type incumbents using the baseline parameterization, with the size threshold for CVC being $\hat{n} = 6$. The solid black line plots the optimal innovation intensity of high-type incumbents in an economy without CVC activity, solved using the baseline parameterization but with c_p set to 0.12, which renders $\hat{n} = \infty$. The dashed blue line plots the optimal innovation intensity of high-type incumbents with the option of CVC, solved in partial equilibrium under the baseline parameterization and the same skilled wage rate (ω_s) and creative destruction rate (τ) as in the solid black line. The associated size threshold is $\hat{n} = 6$. In the right-hand-side panel, the red dash-dot line plots the optimal innovation intensity of low-type incumbents using the baseline parameterization, while the solid black line plots the optimal innovation intensity of low-type incumbents in an economy without CVC activity, solved using the baseline parameterization but with c_p = 0.12 and $\hat{n} = \infty$.

where $\tilde{\zeta} > 0$, $\tilde{\sigma} > 0$, and $\tilde{\zeta} + \tilde{\sigma} < 1$. The baseline model corresponds to $\tilde{\zeta} = 1/\zeta = 0.5$ and $\tilde{\sigma} = 1 - 1/\zeta = 0.5$. In what follows, I maintain $\tilde{\zeta} = 0.5$ but set $\tilde{\sigma} = 0.45$. For comparison, Akcigit and Kerr (2018) work with $\tilde{\zeta} = 0.5$ and suggest that $\tilde{\zeta} + \tilde{\sigma} = 0.9$ is a good estimate for the level of decreasing returns to innovation in firm size.

Figure 3.5: Innovation Intensity Under Decreasing Returns (High-Type)



Notes: In the left-hand-side panel, the solid black line plots the optimal innovation intensity of high-type incumbents in an economy without CVC activity, which is decreasing in firm size. The dashed blue line plots the optimal innovation intensity of high-type incumbents with the option of CVC, solved under the same parameterization and the same skilled wage (ω_s) and creative destruction rate (τ) as in the black solid line. The difference between the two lines represents the partial equilibrium effect of CVC, which is plotted in the right-hand-side panel.

Under this general specification, even the problem of low-type incumbents no longer admits a closed-form solution. In particular, the innovation intensity of low-type firms will now depend on firm size. Consequently, the size distribution of low-type firms, the creative destruction rate, and the labor market clearing condition need to be adjusted accordingly, in addition to adjusting the problem of high-type incumbents to accommodate decreasing returns. Section C.2.2 of the Appendix provides detailed derivations for these modifications.

Qualitatively, the key insights from the baseline model carry over to the generalized model. I start with the firm-level results. Recall that the baseline model predicts that the option value of CVC should induce an S-shaped schedule for innovation intensity among high-type firms. Figure 3.5 confirms this pattern under decreasing RTS. In the left-hand-side panel, the solid black line plots the optimal innovation intensity of high-type incumbents in an economy without CVC activity, which is decreasing in firm size. The dashed blue line plots the optimal partial-equilibrium innovation intensity of high-type incumbents with the option of CVC, solved under the same parameterization and the same skilled wage rate (ω_s) and creative destruction rate (τ) as in the black solid line. The difference between the two lines represents the partial equilibrium effect of CVC, which is plotted in the right-hand-side panel and is roughly S-shaped. Thus, high-type firms switching to CVC experience an increase in innovation effort even before the switch. The closer a firm is to the size threshold, the stronger is the innovation incentive. In general equilibrium, increased competition and skilled wages push the dashed blue line downwards, in a similar fashion as in the baseline model.

Turning to aggregate implications, I report in Table 3.5 selected moments from the general model when I repeat the same comparative statics exercise as above. Notwithstanding the coarse calibration, the general model predicts the same qualitative relationships between the extent of CVC and aggregate outcomes as in the baseline model. Namely, higher levels of CVC are associated with higher growth rates, greater competition, and lower entry rates.

Table 3.5: Comparative Statics Under Decreasing Returns: A Decline in c_p

Variable	Data	$\hat{n} = \infty$	$\hat{n} = 15$	$\hat{n} = 5$	$\hat{n} = 3$	$\hat{n} = 1$
Growth rate (%)	2.22	3.87	3.87	3.87	3.89	3.95
Creative destruction rate (%)	n.a.	27.68	27.68	27.72	27.84	28.29
Entry rate (%)	7.35	11.1	11.1	11.07	10.98	10.87

3.4 Discussion

Thus far, I have presented a highly stylized endogenous growth model that features incumbent-entrant partnerships via CVC. In this section, I discuss the longitudinal and cross-sectional implications of the model, taking the simple structure as is. I then revisit the simplifying assumptions in the current model and outline possible directions for follow-up work.

Empirical implications The model's longitudinal implications about how CVC and innovation efforts vary over time for a firm are guided by the S-shaped schedule for innovation intensity. Specifically, when we focus on within-firm changes in innovation effort, we expect that firms engaged in CVC should on average experience an increase in innovation effort even *before* the switch. This can be interpreted as a type of competition *for* CVC among incumbents and is a direct consequence of the existence of a size threshold for CVC.

In addition, the model predicts a cross-sectional relationship between CVC activity and in-house R&D. Specifically, incumbent firms engaged in CVC should on average conduct more in-house R&D, as the capacity gain from CVC makes in-house R&D more productive.

Possible model extensions In the current model, the process of forming a CVC relationship is captured by a number of reduced-form assumptions. First, the model abstracts from a financing motive for CVC on the entrants' side. This implies that the model is likely understating the positive effect of CVC on entry, considering that CVC could help relax the financial constraint facing entrants. A related limitation of not having the financing aspect of CVC is that the current model cannot shed light on the question of whether resources spent on CVC would have yielded better outcomes (either at the firm level or economy wide) had these resources been spent on internal R&D. Second, the model abstracts from ex-ante heterogeneity on the entrants' side, and thus cannot speak to the role of positive assortative matching and selection among entrants into CVC. Third and more broadly, the model is agnostic about the underlying mechanisms through which incumbent and entrant firms form CVC relationships.

3.5 Concluding Remarks

This paper studies the aggregate implications of CVC by developing a model of endogenous firm innovation that bridges the entrepreneurial and the incumbent sectors. The model is broadly consistent with a set of micro-level patterns on U.S. CVC activity, including the double treatment effect associated with a CVC relationship on both the start-up and the investing firms, and the selection of larger, more innovative incumbents into CVC. The model could benefit from a sharper characterization of the financing motive of CVC and the determinants of selection on the entrants' side.

Through the lens of the model, CVC activity affects the macroeconomy through changes in innovation incentives among incumbent firms, the size distribution of firms, and the entry incentive of outside entrepreneurs. While incumbent firms engaged in CVC innovate more and gain market share as they benefit from the positive treatment, the rest of the incumbent firms innovate less as they face increased competition and skilled wages for employing R&D workers.

The effect of CVC on entry is twofold. On the one hand, CVC improves the prospects for outside entrepreneurs to enter as a high-type firm, encouraging entry R&D. On the other hand, CVC raises competition and skilled wages, making smaller firms more likely to exit thus discouraging entry R&D. Quantitatively, a rise in CVC activity, parameterized by a decline in the fixed cost of starting CVC incurred by the incumbents, is found to lead to higher aggregate growth, greater competition, lower entry, and a fattening of the firm size distribution at both tails.

Appendix A: Chapter 1

A.1 Further Details on Data Construction

Filters for raw extraction in VentureXpert I focus on U.S. based firms that received CVC or TVC financing during the period 1980–2018. Since VentureXpert includes both venture capital and buyout deals, the first filter is to exclude all buyout related deals during the sample period. For each venture capital deal, VentureXpert provides information about both the investing fund and the fund's management firm. To identify a CVC unit, I restrict the type of the management firm to be "Corporate PE/Venture," which includes "Corporate Subsidiary or Affiliate" and "Corporate Venture Program." I further restrict the fund type to be "Corporate PE/Venture Fund." Restricting the fund type in addition to firm type ensures that deals involving, for example, corporate evergreen funds, are excluded from the raw extraction. To identify a TVC unit, I restrict the type of the management firm to be "Private Firm Investing Own Capital" and I restrict the fund type to be "Independent Private Partnership." The restriction on fund type filters out deals that involve private partnerships of unknown nature and small business investment companies (SBICs). SBICs are privately owned investment funds that are licensed and regulated by the Small Business Administration (SBA).

The next set of filtering criteria is put on geographic locations. Specifically, I require the funded firms and the investing entities (both the funds and their management firms) to be located in the United States. Since neither the fund nor the fund's management firm is necessarily the corporate parent, I am allowing for deals involving a foreign parent who invests via a U.S. vehicle. For example, 7 Ventures, the Texas based CVC unit that invests on behalf of 7 Eleven, is ultimately held by Tokyo-based Seven & i Holdings Co Ltd. My dataset contains investments made by 7 Ventures as long as those investments go to U.S. based firms.

Finally, and following common practice in the VC literature, I restrict the stage level of a funded firm to be "Startup/Seed," "Early Stage," "Expansion," or "Later Stage." This restriction filters out deals involving bridge loans, open market purchases, private investment in public equity, and other stages of venture capital investments for more mature firms.

Linking VentureXpert to Capital IQ As explained in the main text, I use Capital IQ to disambiguate the funded firms and the investing entities as well as to identify the ultimate parent of an investing entity. The linking between VentureXpert and Capital IQ is done for the entire sample period rather than annually. I first create two pooled header files using VentureXpert data: one for the funded firms and the other for the investing entities. For funded firms, the header file contains unique records defined by firm name and location information, and is supplemented with firm founding year, four-digit SIC code, and the dates of the firm's first and last financing rounds. The supplemental information is used to valid links as described below. For investing entities, the header file contains unique records defined by firm name and location, and is supplemented with the first and last dates when a firm is seen in VentureXpert to make a deal.[1]

To create the counterpart header files for Capital IQ, I focus on firms classified in Capital IQ as "Private Company", "Public Company," "Corporate Investment Arm," and "Private Investment

[1]Note that the header file for investing entities is primarily based on firm-side information rather than fund-side information. Fund information is used, however, when firm information is missing or undisclosed.

Firm." In principle, I could extract all the qualifying firms from Capital IQ; in reality, however, the download is nearly infeasible given the large number of private firms and the limit on download size. Fortunately, Capital IQ offers a set of Excel built-in functions that can circumvent the download. Specifically, there is a company lookup function that can return five company IDs when a company name is provided. These are the top five results one would get when manually searching the company name in Capital IQ's online platform. I therefore load into Excel all the firm names from the VentureXpert header files and let the company lookup function generate the most likely firm IDs. I then use the IDs to extract the associated firm names, detailed addresses, founding years, four-digit SIC codes, and information about the ultimate parents in cases of TVC and CVC units, using other Capital IQ built-in lookup functions in Excel. These firms then form the header files to be matched with VentureXpert.

The name and address matching procedure The header files from VentureXpert and Capital IQ are merged using a standard name and address matching procedure that follows Akcigit et al. (2019), Davis et al. (2014), Davis et al. (2019), and Dinlersoz et al. (2019), among others. Firm name, street address, city, state, and five-digit zip code variables are first standardized to facilitate string comparison. Record linking is then performed in a sequential manner with nine passes. Each pass uses less stringent matching criteria than the previous one, and successfully matched records are removed from the set of records to be matched in the next pass. More precisely, the first pass requires firms to have exactly the same name, street address, city, and state. The second pass requires firms to have exactly the same name, city, state, and zip code. The third pass requires firms to have exactly the same name, city, and state. In the fourth to sixth passes, I use Stata reclink2 algorithm to fuzzy match on (i) firm name and street address, (ii) firm name and zip code, and (iii) firm name, blocking on city and state. In the seventh and eighth passes, I fuzzy match on (i) firm name and zip code and (ii) firm name, blocking on state. In the nineth pass, I remove all geographic blocking variables and fuzzy match on firm name only. Matches from the last pass are kept only if they have a high enough quality score or are manually reviewed for validity. Links from the first eight passes are flagged for manual review if there are large discrepancies in founding year or SIC code between the matched pair.[2]

Tracking firm ownership changes over time At this point, the matched CVC and TVC units in VentureXpert are each linked with a firm ID in Capital IQ and a corporate parent associated with the firm ID. The parent ID, however, is based on a firm's current status; I need instead a history of the firm's ownership changes to assign deals made by the firm at different points in time to a parent.

I implement the following procedure to track firm ownership changes over time, First, I extract from Capital IQ the "Company Status" field for each linked firm ID. The field includes "Operating," "Acquired," "Operating Subsidiary," "Reorganizing," "Liquidating," "Out of Business," and "No Longer Investing." I then assign all deals made by a firm to the firm ID if (i) the firm ID is the same as the parent firm ID and the firm is neither acquired nor an operating subsidiary (most TVC firms and CVC firms that invest through an internal division fall into this category); or (ii) the firm ID is not the same as the parent firm ID, but the date of the first ownership change is post the last observed venture deal made by the firm. Likewise, I assign all deals made by a firm to the parent firm ID if (i) the firm ID is not the same as the parent firm ID, the firm type is "Corporate Investment Arm," and the firm is not acquired; or (ii) the firm ID is not the same

[2] For example, the link for a funded firm is dropped if the first financing round is prior to the founding year, up to some measurement errors in the founding year.

as the parent firm ID, and the date of the latest ownership change is before the first observed venture deal made by the firm. When the acquisition date is missing in Capital IQ, I supplement the information by searching the SDC Platinum Mergers and Acquisitions database. After this step, about 99.5% of the matched firms are assigned a single parent, referred to as the "funder" throughout the paper.

For the remaining firms, attention needs to be paid on the timing of ownership changes. Consider the example of Compaq Computer. The firm was acquired by HP in 2001 and is last seen in VentureXpert to make a deal in 2005. A question arises regarding what cutoff date to use when assigning deals made by Compaq Computer after 2001. It is not immediately clear whether the acquisition date is an appropriate choice. For one thing, staged financing implies that not all of the committed capital is necessarily released to a funded firm after an investment round, so some of the deals that Compaq Computer made after 2001 may well be follow-up investments. For the vast majority of acquired firms, I stop seeing them making any investment by the third year after the acquisition event. Therefore, I assign deals made within the next two years of an acquisition to the acquired firm. Deals made afterwards, if any at all, are assigned to the acquiring firm. This treatment does not affect the empirical results materially given the small number of cases.

Merging in exit outcomes The SDC Platinum Global New Issues database is used to identify the subset of funded firms that went public as of 2018. I first extract from the database the list of firms that issued an IPO between 1980 and 2018, using the following filtering criteria: (i) The issuer is located in the United States; (ii) The transaction status is coded as "Live"; (iii) The type of security issued is common shares, which may be labeled in a variety of ways in the database such as "Common Shares," "Ord/Common Shares," "Class A Shares," "Ordinary Shares," "Class B Shares," and "Class A Ord Shs;" and (iv) The offering is not related to real estate investment trusts, American depository receipts, closed-end funds, units, and penny stocks (with an offer price below $5). For this set of firms, I extract their firm names, detailed location information, four-digit SIC codes, and issuance dates. I then merge this set of firms with the VentureXpert-Capital IQ linked funded firms, using the same name and address matching procedure outlined above. Links are flagged for manual review if there is a large discrepancy in SIC code or the issuance date is prior to the firm's last financing round.[3] Successfully linked firms are identified as having exited via an IPO.

Exits via M&A are identified in a similar fashion. I use the SDC Platinum Mergers and Acquisitions database to extract the list of M&As involving U.S. targets between 1980 and 2018. I focus on completed as opposed to pending, tentative, unknown, or withdrawn transactions, and I restrict the transaction form to be the following: (i) merger (stock or assets), in which a combination of business takes place or 100% of the stock of a public or private company is acquired; (ii) acquisition of majority interest (stock), in which the acquiror holds less than 50% and is seeking to acquire 50% or more, but less than 100% of the target company's stock; (iii) acquisition of assets, in which the assets of a company, subsidiary, division, or branch are acquired; and (iv) acquisition of certain assets, conditional on the share owned by the acquiror after the transaction being greater than 50%.[4] For this list of transactions, I obtain the associated

[3] Occasionally, a valid link involves a firm raising financing round(s) after its IPO. I keep the link but drop the financing round(s) post the IPO date when constructing the analysis sample.

[4] The excluded transaction forms include: (i) acquisition of partial interest, in which the acquiror holds less than 50% and is seeking to acquire less than 50%, or the acquiror holds over 50% and is seeking less than 100% of the target's stock; (ii) acquisition of remaining interest, in which the acquiror holds over 50% and is seeking to acquire 100% of the target's stock; (iii) acquisition (by shareholders), in which 100% of a firm is spun off or split off; (iv) buyback, in which the firm buys back its equity securities or securities convertibles into equity, either on the open market, through privately negotiated transactions, or through a tender offer; (v) exchange offer, in which a firm

target firm names, detailed location information, four-digit SIC codes, the announcement and effective dates of the transactions, and information about the acquirors. I then merge this set of target firms with the VentureXpert-Capital IQ linked funded firms. Successfully matched firms are considered as having exited via an acquisition, dated using the announcement date of the transaction.[5] When a funded firm is linked to both an IPO and one or multiple acquisitions, the exit status is defined using the earliest event.

Merging in PatentsView The linking of PatentsView to the working dataset is done using a similar name and address matching procedure outlined above. The number of passes is reduced, however, to accommodate the fact that assignee location information is limited to city and state only.[6]

When linking assignees to funded firms, the underlying assumption is that each funded firm remains a single-unit establishment until it experiences an exit event. The linking of assignees to CVC funders is more involved given that many CVC funders are multi-unit firms and may file patents through different subsidiaries. I first merge the list of assignees to the set of CVC units and their parents identified previously. To capture additional patents the funder may file through subsidiaries other than the CVC unit(s), I augment my links for publicly listed CVC funders using the crosswalk from Autor et al. (2020). The authors develop an algorithm that leverages a web search engine to match the company name on a patent to the corresponding Compustat (parent) firm identifier; they do so for corporate patents granted by the USPTO between 1975 and March 2013.

offers to exchange new securities for its equity securities outstanding or its securities convertible into equity; and (vi) recapitalization, in which a firm undergoes a shareholders' leveraged recapitalization and issues a special one-time dividend allowing shareholders to retain an equity.

[5]I allow for hostile M&As, although none of the matched firms had hostile M&As.

[6]County information is available for a very small number of assignees.

Mapping I-O commodities to SIC industries The BEA's Input-Output Account in its original form is defined at the commodity level. Specifically, the "make" table shows each commodity's usage in producing other commodities while the "use" table shows the consumption of each commodity by other commodities. I first combine the "make" and "use" tables to determine the flows from an upstream commodity to a downstream commodity. I then crosswalk from BEA commodities to four-digit SIC industries using the concordance provided by the BEA. For manufacturing industries that do not map one-to-one with a commodity, I follow Acemoglu et al. (2016) and allocate the flows proportionately on the basis of shipments and materials usages measured in the NBER-CES data. For non-manufacturing industries, shipments and materials usage data are not available, so an allocation procedure is not possible. I follow Acemoglu et al. (2016) again and aggregate certain non-manufacturing industries to ensure that each resulting industry is mapped to non-overlapping commodities.

Mapping patent technology classes to SIC industries Each patent in my dataset is assigned a four-digit technology class by the USPTO based on the Cooperative Patent Classification (CPC) system. The CPC is a joint effort between the USPTO and the European Patent Office to develop a common, internationally compatible technology classification system. Since January 2015, the USPTO completely switched to using the CPC system and stopped classifying new utility patents using the old United States Patent Classification (USPC) system. CPC technology classes have been retrospectively applied to older utility patents. Goldschlag et al. (2019) use the Algorithmic Links with Probabilities (ALP) approach and provide concordances that translate CPC technology codes into multiple vintages of the North American Industrial Classification System (NAICS) and other industry classification systems excluding the SIC.[7] I use one of their

[7]The ALP methodology is an automated approach that relies on the text mining of patent abstracts and keywords

concordances that associates a four-digit CPC technology class to a six-digit NAICS industry (1997 vintage) with a probability weight. I then crosswalk from 1997 NAICS codes to 1987 SIC codes using the employment-weighted concordance developed by Acemoglu et al. (2016).

List of high-tech industries High-tech industries used in Figure 1.2 are defined as in Hecker (2005) and Haltiwanger et al. (2014) and listed in the table below. These industries are chosen on the basis of the intensity of science, engineering, and technician employment. Specifically, a set of technology-oriented occupations are first identified. Next, 14 "Level-1" industries that contain the highest concentrations of technology-oriented workers are chosen. These high-tech industries are defined by the 2002 NAICS codes. I crosswalk the 2002 NAICS codes to the 1987 SIC codes using the employment-weighted concordance from the replication files of Acemoglu et al. (2016).[8]

Table A.1: List of High-Tech Industries

NAICS Code	Industry
Information and Communications Technology (ICT) High-Tech	
3341	Computer and peripheral equipment manufacturing
3342	Communications equipment manufacturing
3344	Semiconductor and other electronic component manufacturing
3345	Navigation, measuring, electromedical, and control instruments manufacturing
5112	Software publishers
5161	Internet publishing and broadcasting
5179	Other telecommunications
5181	Internet service providers and Web search portals
5182	Data processing, hosting, and related services
5415	Computer systems design and related services
Miscellaneous High-Tech	
3254	Pharmaceutical and medicine manufacturing
3364	Aerospace product and parts manufacturing
5413	Architectural, engineering, and related services
5417	Scientific research-and-development services

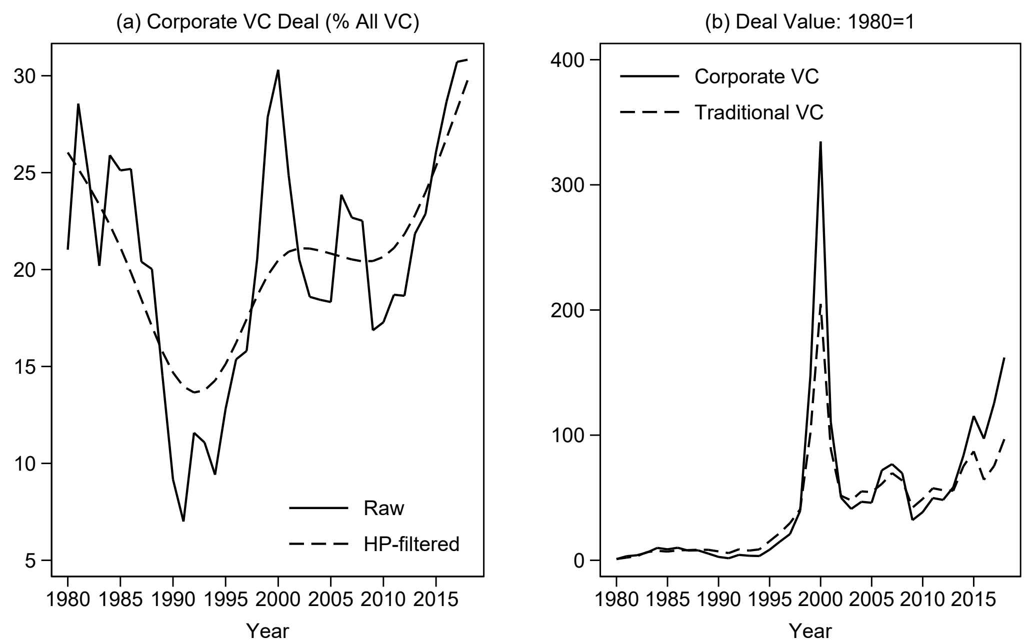
extracted from industry classification descriptions.

[8]Accessible at `https://www.journals.uchicago.edu/doi/suppl/10.1086/682384`.

A.2 Additional Figures and Tables

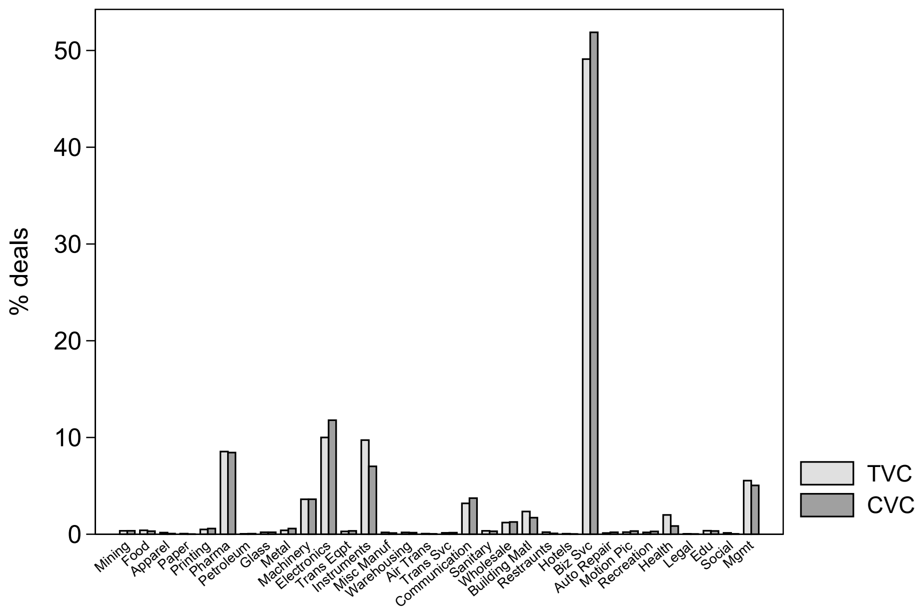
FIGURES

Figure A.1: Size of the CVC Market, 1980–2018



Notes: VC data are obtained VentureXpert. Deals are restricted to those (i) made between US-based corporate or traditional VC funders and US-based businesses and (ii) coded in VentureXpert as being "Startup/Seed", "Early Stage", "Expansion", or "Later Stage." Deal values are deflated to 2015 U.S. dollars using the GDP deflator and winsorized at the 1st and 99th percentiles. Because VentureXpert does not report the funding contribution by each investing entity for syndicated deals, corporate VC value is computed as the total funding amount of the deals that involve corporate VC funders.

Figure A.2: Industry Distribution of TVC Deals versus CVC Deals



Notes: Industries at defined at the two-digit SIC level as in Figure 1.3.

Table A.2: Characteristics of Funded Firms, 1980–2018

	Syndicated [N=4,183] (1)	TVC-alone [N=15,850] (2)	CVC-alone [N=658] (3)	P-val on diff (1)-(3)	P-val on diff (2)-(3)
Age at 1st round	1.8	2.8	3.8	0.000	0.000
Total years of funding	3.8	2.0	0.5	0.000	0.000
Total rounds	4.2	2.7	1.4	0.000	0.000
Total funding (mln $)	55.1	23.6	12.2	0.000	0.000
% in CA, NY, MA	70.1	57.5	59.1	0.000	0.439
% High-tech	81.8	74.5	73.4	0.000	0.531
# Patents at first round	0.7	0.6	1.2	0.149	0.000

Notes: Table reports statistics from a t-test of equality in means. Firm age is winsorized at the 1st and 99th percentiles; funding amount is deflated to 2015 U.S. dollars using the GDP deflator and winsorized at the 1st and 99th percentiles; high-tech sectors are defined as by Hecker (2005) and Haltiwanger et al. (2014); CA, NY, MA represent the three top destination states of VC investments; patent counts are winsorized at the 99th percentile.

Table A.3: Characteristics of Funders, 1980–2018

	CVC [N=712]	TVC [N=2,595]	P-val on diff
Lifespan (years)	6.1	7.4	0.000
Investment duration with a firm			
- years	0.6	0.9	0.000
- rounds	1.4	1.7	0.000
When first invests a firm, at			
- what age	3.5	3.6	0.289
- which round	2.3	1.8	0.000
Four-digit SICs invested per funder	4.5	7.4	0.000
MSAs invested per funder	4.5	6.4	0.000

Notes: Table reports statistics from a t-test of equality in means. CVC funders are restricted to those in the non-farm business sectors as defined in the main text. Firm age is winsorized at the 1st and 99th percentiles.

Table A.4: First-Stage Regressions

	No Industry Controls		With Industry Controls	
	$\ln(CVC)$	$\ln(TVC)$	$\ln(CVC)$	$\ln(TVC)$
(A) Leave-one-out instruments				
$\ln(\widehat{CVC}) - IV1$	0.312***	0.178***	0.312***	0.162***
	(0.017)	(0.024)	(0.017)	(0.021)
$\ln(\widehat{TVC}) - IV1$	-0.012	0.277***	-0.015	0.229***
	(0.013)	(0.028)	(0.013)	(0.026)
R-squared	0.861	0.850	0.861	0.875
(B) Purging instruments				
$\ln(\widehat{CVC}) - IV2$	0.603***	0.361***	0.601***	0.338***
	(0.036)	(0.045)	(0.036)	(0.041)
$\ln(\widehat{TVC}) - IV2$	0.017	0.586***	0.010	0.471***
	(0.031)	(0.061)	(0.032)	(0.057)
R-squared	0.861	0.850	0.862	0.875
Observations	1,527	1,527	1,527	1,527
Four-digit industry effects	y	y	y	y
Two-digit industry-by-period effects	y	y	y	y

Notes: The table reports first-stage regressions in estimating Equation (1.14) using a 2SLS procedure. CVC and TVC are measured respectively by the number of deals. IV 1 refers to the leave-one-out approach to constructing the funder supply shifts as given by Equation (1.16), excluding the broad two-digit SIC industry; IV 2 refers to the purging approach as given by Equation (1.18). Industry-level controls include the average age of funded firms at the first funding event. Robust standard errors are clustered at the four-digit SIC level. *** p<0.01; ** p<0.05; * p<0.1.

Table A.5: Robustness: The Causal Effects of CVC and TVC on Patenting Outcomes

$\ln(PAT)$	(1) OLS Counts	(2) 2SLS IV 1 Counts	(3) 2SLS IV 2 Counts	(4) 2SLS IV 2 Citation-wgt	(5) 2SLS IV 2 Citation-wgt
(A) Short sample					
$\ln(CVC)$	0.271***	0.366***	0.341**	0.366**	0.404**
	(0.065)	(0.122)	(0.132)	(0.165)	(0.177)
$\ln(TVC)$	0.500***	0.532***	0.454***	0.533***	0.458**
	(0.051)	(0.137)	(0.148)	(0.189)	(0.226)
P-val on diff	0.025**	0.475	0.665	0.609	0.887
Observations	1,186	1,186	1,186	1,186	1,186
R-squared	0.844	0.224	0.227	0.182	0.186
Kleibergen-Paap F stat	n/a	33.770	25.670	25.670	18.863
(B) Pooled purging regression					
$\ln(CVC)$	0.313***	0.402***	0.344***	0.326**	0.356**
	(0.059)	(0.112)	(0.114)	(0.142)	(0.142)
$\ln(TVC)$	0.432***	0.468***	0.448***	0.555***	0.477***
	(0.044)	(0.100)	(0.109)	(0.125)	(0.153)
P-val on diff	0.188	0.725	0.602	0.321	0.637
Observations	1,527	1,527	1,527	1,527	1,527
R-squared	0.827	0.211	0.215	0.168	0.177
Kleibergen-Paap F stat	n/a	60.301	51.122	51.122	36.753
(C) Weighted purging regression					
$\ln(CVC)$	0.313***	0.402***	0.348**	0.325*	0.354**
	(0.059)	(0.112)	(0.135)	(0.170)	(0.174)
$\ln(TVC)$	0.432***	0.468***	0.481***	0.663***	0.603***
	(0.044)	(0.100)	(0.145)	(0.177)	(0.208)
P-val on diff	0.188	0.725	0.601	0.281	0.472
Observations	1,527	1,527	1,527	1,527	1,527
R-squared	0.827	0.211	0.221	0.163	0.173
Kleibergen-Paap F stat	n/a	60.301	25.607	25.607	21.763
Four-digit industry effects	y	y	y	y	y
Two-digit industry-by-period effects	y	y	y	y	y
Industry controls	n	n	n	n	y

Notes: The table examines robustness of Table 1.6. Panel (A) uses the short sample ending in 2009. Panel (B) pools both CVC and TVC funders when running the purging regression in Equation (1.17). Panel (C) weights the purging regression in Equation (1.17) by each funder's base period investments in industry i. The dependent variable is (log) patent counts or citation-weighted patent counts. CVC and TVC are measured by the number of deals. Patents are restricted to those applied for within a five-year window after the first funding event in Panel (A) and a four-year window in panel (B) and (C). Citations are restricted to a three-year window after the application date and scaled by the technology field-by-year means. Self-citations are excluded. Industry controls include the average age of funded firms at the first funding event. Column (2) uses the leave-one-out instrument as given by Equation (1.16), excluding the broad two-digit SIC industry. Columns (3)-(5) use the purging instrument as given by Equation (1.18). Robust standard errors are clustered at the four-digit SIC level. *** p<0.01; ** p<0.05; * p<0.1.

Table A.6: Robustness: The Causal Effects of CVC and TVC on Successful Exits

	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
		IV 1	IV 2	IV 2	IV 2
$\ln(Exits)$	IPO+M&A	IPO+M&A	IPO+M&A	IPO	M&A
(A) Short sample					
$\ln(CVC)$	0.224***	0.238***	0.240***	0.101**	0.219***
	(0.036)	(0.062)	(0.067)	(0.051)	(0.068)
$\ln(TVC)$	0.268***	0.179**	0.193**	0.011	0.205***
	(0.028)	(0.071)	(0.080)	(0.058)	(0.078)
P-val on diff	0.392	0.622	0.730	0.378	0.920
Observations	1,186	1,186	1,186	1,186	1,186
R-squared	0.896	0.342	0.347	0.047	0.321
Kleibergen-Paap F stat	n/a	26.635	18.863	18.863	18.863
(B) Pooled purging regression					
$\ln(CVC)$	0.220***	0.181***	0.180***	0.069**	0.128***
	(0.037)	(0.049)	(0.046)	(0.035)	(0.044)
$\ln(TVC)$	0.178***	0.096*	0.090*	0.002	0.115**
	(0.022)	(0.050)	(0.054)	(0.040)	(0.049)
P-val on diff	0.340	0.328	0.304	0.326	0.866
Observations	1,527	1,527	1,527	1,527	1,527
R-squared	0.844	0.218	0.214	0.018	0.202
Kleibergen-Paap F stat	n/a	48.301	36.753	36.753	36.753
(C) Weighted purging regression					
$\ln(CVC)$	0.220***	0.181***	0.160***	0.012	0.148***
	(0.037)	(0.049)	(0.059)	(0.042)	(0.055)
$\ln(TVC)$	0.178***	0.096*	0.132	0.073	0.108
	(0.022)	(0.050)	(0.080)	(0.055)	(0.071)
P-val on diff	0.340	0.328	0.831	0.499	0.734
Observations	1,527	1,527	1,527	1,527	1,527
R-squared	0.844	0.218	0.226	0.040	0.206
Kleibergen-Paap F stat	n/a	48.301	21.763	21.763	21.763
Four-digit industry effects	y	y	y	y	y
Two-digit industry by period effects	y	y	y	y	y
Industry controls	y	y	y	y	y

Notes: The table examines robustness of Table 1.7. Panel (A) uses the short sample ending in 2009. Panel (B) pools both CVC and TVC funders when running the purging regression in Equation (1.17). Panel (C) weights the purging regression by each funder's base period investments in industry i. The dependent variable is (log) number of successful exits. Successful exits are restricted to a nine-year window since the first funding event in Panel (A) and a four-year window in Panel (B) and (C). CVC and TVC are measured by the number of deals. All specifications control for four-digit SIC industry fixed effects, two-digit SIC industry-by-period fixed effects, and industry-level controls that include the average age of funded firms at the first funding event. Column (2) uses the leave-one-out instrument as given by Equation (1.16), excluding the broad two-digit SIC industry. Columns (3) to (5) use the purging instrument as given by Equation (1.18). Robust standard errors are clustered at the four-digit SIC level. *** p<0.01; ** p<0.05; * p<0.1.

Table A.7: Robustness: The Effects of CVC and TVC using Count Data Models

	(1) OLS	(2) IV 1 Reduced-form	(3) IV 2 Reduced-form	(4) IV 2 Reduced-form
(A) Patents				
$\ln(CVC)$	0.032	0.244***	0.464***	0.472***
	(0.108)	(0.075)	(0.149)	(0.152)
$\ln(TVC)$	0.752***	0.421***	0.885***	0.804**
	(0.105)	(0.124)	(0.279)	(0.314)
P-val on diff	0.000***	0.186	0.134	0.261
(B) Successful Exits				
$\ln(CVC)$	0.104*	0.206***	0.500***	0.481***
	(0.054)	(0.043)	(0.085)	(0.087)
$\ln(TVC)$	0.823***	0.204**	0.634***	0.527**
	(0.063)	(0.089)	(0.225)	(0.228)
P-val on diff	0.000***	0.982	0.583	0.853
Observations	971	971	971	971
Four-digit IO industry effects	y	y	y	y
Two-digit IO industry by period effects	y	y	y	y
Industry controls	n	n	n	y

Notes: The table reports Poisson pseudo-maximum likelihood estimates of Equation (1.14) using the baseline sample ending in 2014. The dependent variable is patent counts in Panel (A) and the number of successful IPOs and acquisitions in Panel (B). Patents and exits are restricted to a four-year window after the first funding event. CVC and TVC are measured by the number of deals. Column (2) uses the leave-one-out instrument as given by Equation (1.16), excluding the broad two-digit SIC industry. Columns (3) and (4) use the purging instrument as given by Equation (1.18). Industry controls include the average age of funded firms at the first funding event. Robust standard errors are clustered at the four-digit SIC industry level. *** p<0.01; ** p<0.05; * p<0.1.

Table A.8: Robustness: The Channels of CVC with Unweighted Linkage Measures

$\ln(PAT)$	(1) IV 2 Reduced-form Counts	(2) IV 2 Reduced-form Counts	(3) IV 2 Reduced-form Counts	(4) IV 2 Reduced-form Counts	(5) IV 2 Reduced-form Counts	(6) IV 2 Reduced-form Citation-wgt
$\ln(CVC)$	0.381***	0.394***	0.340***	0.323***	0.394***	0.455***
	(0.064)	(0.075)	(0.060)	(0.066)	(0.062)	(0.088)
$\ln(TVC)$	0.155**	0.157**	0.168**	0.172**	0.149**	0.146*
	(0.074)	(0.073)	(0.077)	(0.077)	(0.074)	(0.082)
$\ln(CVC) \times \Omega^{IO-NetDown}$	0.164***				0.158***	0.182***
	(0.044)				(0.045)	(0.061)
$\ln(CVC) \times \Omega^{IO-Down}$		0.149***				
		(0.047)				
$\ln(CVC) \times \Omega^{IO-Up}$		-0.173***				
		(0.064)				
$\ln(CVC) \times \Omega^{Tech-NetUp}$			0.087***		0.089***	0.122***
			(0.019)		(0.018)	(0.021)
$\ln(CVC) \times \Omega^{Tech-Up}$				0.090***		
				(0.027)		
$\ln(CVC) \times \Omega^{Tech-Down}$				-0.086***		
				(0.019)		
Observations	932	932	932	932	932	932
R-squared	0.835	0.835	0.831	0.831	0.837	0.807
Four-digit IO industry effects	y	y	y	y	y	y
Two-digit IO industry-by-period effects	y	y	y	y	y	y
Industry controls	y	y	y	y	y	y

Notes: The table reports reduced-form IV estimates of Equation (1.19), using the baseline sample and unweighted linkage measures. The dependent variable is (log) patent counts or citation-weighted patent counts. Patents are restricted to those applied for within a four-year window after the first funding event. Citations are restricted to a three-year window after the application date and scaled by technology field-by-year means. Self-citations are excluded. The instruments for CVC and TVC are constructed using the purging approach as defined by Equation (1.18). Industry controls include the main effects of the linkage terms and the average age of funded firms at the first funding event. See Appendix A.1 for details on mapping SIC industries and patent technology classes to I-O industries. Robust standard errors are clustered at the four-digit I-O industry level. *** p<0.01; ** p<0.05; * p<0.1.

A.3 Theory Appendix

Value of a variety First substitute the inverse demand function (1.2) back into the CES aggregator (1.1), replacing p_j with $\frac{\epsilon}{\epsilon-1}w_u$:

$$Y^{\frac{\epsilon-1}{\epsilon}} = \int_{\mathcal{N}} \varphi_j^{\frac{1}{\epsilon}} \left(Y\varphi_j \left(\frac{\epsilon}{\epsilon-1} w_u \right)^{-\epsilon} \right)^{\frac{\epsilon-1}{\epsilon}} d_j. \tag{A.1}$$

Manipulate to obtain:

$$w_u = \frac{\epsilon-1}{\epsilon}\Phi, \tag{A.2}$$

where Φ is the aggregate appeal index defined as:

$$\Phi = \left[\int_{\mathcal{N}} \varphi_j dj \right]^{\frac{1}{\epsilon-1}}. \tag{A.3}$$

Without loss of generality, suppose that there is a unit mass of production workers who supply their labor inelastically. The labor market clearing condition for production workers therefore requires:

$$\int_{\mathcal{N}} y_j dj = 1, \tag{A.4}$$

where I have used the condition that $y_j = l_j$ as in Equation (1.3). Substitute the inverse demand function Equation (1.2) into Equation (A.4) and manipulate to get:

$$Y = \Phi. \tag{A.5}$$

Entrepreneur profits in Equation (1.4) can then be rewritten as:

$$\Pi(\varphi_j) = \frac{1}{\epsilon}\Phi^{2-\epsilon}\varphi_j. \tag{A.6}$$

Now conjecture that the value in (1.5) takes a closed-form $V = A\Phi^{2-\epsilon}$. Substitute the guess into Equation (1.5):

$$rA\Phi^{2-\epsilon} - (2-\epsilon)g_\Phi A\Phi^{2-\epsilon} = \frac{1}{\epsilon}\Phi^{2-\epsilon}\varphi_j, \tag{A.7}$$

where $g_\Phi \equiv \partial\Phi/\partial t$. Collect terms and rearrange to obtain:

$$A = \frac{\frac{1}{\epsilon}\varphi_j}{r-(2-\epsilon)g_\Phi}. \tag{A.8}$$

Using notation in the main text, we get $\nu = \frac{1/\epsilon}{r-(2-\epsilon)g_\Phi}\Phi^{2-\epsilon}$.

Appendix B: Chapter 2

B.1 Data Appendix

Identifying CVC units in VentureXpert Since VentureXpert includes both venture capital and buyout deals, the first filtering criteria is to exclude all buyout related deals during the period 1980–2018. For each venture capital deal, VentureXpert provides information on both the investing fund and the fund's management firm. To identify a CVC unit, I restrict the type of the management firm to be "Corporate PE/Venture," which includes "Corporate Subsidiary or Affiliate" and "Corporate Venture Program." I further restrict the fund type to be "Corporate PE/Venture Fund," which contains the following categories: "Non-Financial Corp Affiliate or Subsidiary Partnership," "SBIC Affiliated with Non-Financial Corp," "Venture PE/Subsidiary of Non-Financial Corp," "Venture PE/Subsidiary of Other Companies NEC," "Venture PE/Subsidiary of Service Providers," "Direct Investor/Non-Financial Corp," and "Direct Investor/Service Provider." Restricting the fund type in addition to firm type ensures that deals involving, for example, corporate evergreen funds, are excluded from the raw extraction. Next, I restrict the management firms and their funded firms to be located in the United States. Finally, and following common practice in the venture capital literature, I restrict the stage level of a funded firm to be "Startup/Seed," "Early Stage," "Expansion," or "Later Stage." This restriction filters out deals involving bridge loans, open market purchases, private investment in public equity, and other stages of venture capital investments in more mature firms.

Name and address matching procedure Since neither the investing fund or the fund's management firm is necessarily the corporate parent, a key step in the construction of the dataset involves identifying the corporate parent of a CVC unit. I draw on Capital IQ for firm ownership information. CVC units in VentureXpert are therefore first merged with firms in Capital IQ to identify their corporate parents, using a name and address matching procedure. Linked parent firms that are publicly traded are then merged with Compustat to obtain their financial data, using the Capital IQ-Compustat firm identifier crosswalk maintained by Standard & Poor's.

The linking between VentureXpert and Capital IQ is done for the entire sample period rather than annually. I first create a CVC header file that pools all CVC units over the sample period. The header file contains unique records defined by firm name and location, and is supplemented with the first and last dates when a firm is seen in VentureXpert to make a deal.[1]

To create the counterpart header files for Capital IQ, I focus on firms classified in Capital IQ as "Private Company", "Public Company," and "Corporate Investment Arm." In principle, I could download all the qualifying firms from Capital IQ; in practice, however, the large number of private firms and the limit on download size make the download difficult. Instead, I use Capital IQ's built-in functions in Excel to circumvent the download. Specifically, one of the Excel built-in functions can return five company IDs when a company name is provided. The five IDs correspond to the top five results one would get when manually searching the company name in Capital IQ's online platform. I therefore load into Excel all the firm names from the VentureXpert header files and let the company lookup function generate the most likely firm IDs.

[1]Note that the header file is primarily based on firm-side information rather than fund-side information. Fund information is used instead when firm information is missing or undisclosed.

I then use the IDs to extract the associated firm names, detailed addresses, founding years, four-digit SIC codes, and information about the ultimate parents. These firms then form the Capital IQ header files to be matched with VentureXpert.

The two header files are merged using a standard name and address matching procedure that follows Akcigit et al. (2019), Davis et al. (2014), Davis et al. (2019), and Dinlersoz et al. (2019), among others. Firm name, street address, city, state, and five-digit zip code variables are first standardized to facilitate string comparison. Record linking is then performed in a sequential manner with nine passes. Each pass uses less stringent matching criteria than the previous one, and successfully matched records are removed from the set of records to be matched in the next pass. More precisely, the first pass requires firms to have exactly the same name, street address, city, and state. The second pass requires firms to have exactly the same name, city, state, and zip code. The third pass requires firms to have exactly the same name, city, and state. In the fourth to sixth passes, I use Stata reclink2 algorithm to fuzzy match on (i) firm name and street address, (ii) firm name and zip code, and (iii) firm name, blocking on city and state. In the seventh and eighth passes, I fuzzy match on (i) firm name and zip code and (ii) firm name, blocking on state. In the nineth pass, I remove all geographic blocking variables and fuzzy match on firm name only. Matches from the last pass are kept only if they have a high enough quality score or are manually reviewed for validity. Links from the first eight passes are flagged for manual review if there are large discrepancies in founding year or SIC code between the matched pair.

Tracking ownership changes over time At this point, the matched CVC units in VentureXpert are each linked with a firm ID in Capital IQ and a corporate parent associated with the firm ID. The parent ID, however, is based on a firm's current status; I need instead a history of the firm's ownership changes to assign deals made by the firm at different points in time to the parent firm.

I implement the following procedure to track firm ownership changes over time, First, I extract from Capital IQ the "Company Status" field for each linked firm ID. The field includes "Operating," "Acquired," "Operating Subsidiary," "Reorganizing," "Liquidating," "Out of Business," and "No Longer Investing." I then assign all deals made by a firm to the firm ID if (i) the firm ID is the same as the parent firm ID and the firm is neither acquired nor an operating subsidiary (most CVC firms that invest through an internal division fall into this category); or (ii) the firm ID is not the same as the parent firm ID, but the date of the first ownership change is post the last observed venture deal made by the firm. Likewise, I assign all deals made by a firm to the parent firm ID if (i) the firm ID is not the same as the parent firm ID, the firm type is "Corporate Investment Arm," and the firm is not acquired; or (ii) the firm ID is not the same as the parent firm ID, and the date of the latest ownership change is before the first observed venture deal made by the firm. When the acquisition date is missing in Capital IQ, I supplement the information by searching the SDC Platinum Mergers and Acquisitions database. After this step, about 99.5% of the matched firms are assigned a single parent, referred to as the "funder" throughout the paper.

For the remaining firms, attention needs to be paid on the timing of ownership changes. In rare cases, a firm keeps making CVC investments after it experiences a change in ownership. For example, Compaq Computer Corp, which used to be publicly traded, was acquired by HP Inc in 2001. Meanwhile, Compaq is last seen to make an investment in VentureXpert in 2005. A question is what fraction of the investments made by Compaq post 2001 was on behalf of HP. The answer is not immediately clear given the nature of staged financing in venture capital activity. Since not all of the committed capital is necessarily released to the funded firm after an investment round, some of the deals made by Compaq after 2001 may be follow-up investments. For the vast majority of acquired firms, I stop seeing them making any investment by the third year after the acquisition event. I therefore assign deals made within the next two years of an acquisition to the acquired firm. Deals made afterwards, if any at all, are assigned to the acquiring firm. This treatment does not affect the empirical results materially given the small number of cases.

B.2 Coarsened Exact Matching

As described in the main text, the selection within public firms into CVC is likely not random. Specifically, CVC funders are on average larger, older, disproportionately represented in manufacturing and services sectors, and hold large patent portfolios. Without balancing these differences, a simple difference-in-differences or event study approach would yield biased estimates of the treatment effects of CVC on funders' innovation outcomes. To mitigate the selection bias, I match each CVC funder in the sample with observationally similar non-CVC firms using a coarsened exact matching procedure. More precisely, each funder that started CVC in a given year (the event year) between 1980 and 2012 is sorted (as of the event year) into cells defined by the full cross product of ten firm size categories, five age categories, 239 industries at the three-digit SIC level, and four categories for patent growth rates in the two years prior to the event year (two categories for each year). I then identify from the same year all non-CVC firms that fall into the same cell as a given funder. These firms are then taken to be the control units for the funder in that cell.

For firm size categories, I use deciles in log assets deflated to 2015 U.S. dollars. The firm age categories are: 0–5 years, 6–10, 11–15, 16–20, and 21 or more years. The patent growth categories between year t and $t-1$ are given by two equally spaced bins in the DHS growth rate of patent stock. The patent growth categories between year $t-1$ and $t-2$ are defined analogously.[2] Following the literature as summarized by Hall et al. (2010), patent stock is calculated using a perpetual inventory method with a depreciation rate of 15%. Specifically, $PatentStock_{it} = NewPatents_{it} + (1-\delta)PatentStock_{it-1}$, where $NewPatents_{it}$ is the number of patents applied by firm i in year t (conditional on being granted by March 2013), and δ is the depreciation rate. The initial patent stock for a given firm is calculated as the average number of patents applied by the firm during 1980 and 1985.

Since the above procedure is performed for each year, a non-CVC firm may be matched with multiple CVC firms. To ensure that a single trajectory is followed for the non-CVC firm, its latest match is kept. After this elimination, 99 CVC firms are matched with 245 non-CVC firms that form the control group.

[2] Note that the DHS measure is bounded between -2 (exit) and 2 (entry). Results are broadly robust to using finer bins for patent growth, matching additionally on patent growth between year $t-2$ and $t-3$, or not matching on pre-trends in patenting at all.

Appendix C: Chapter 3

C.1 Proof of Propositions

Proof of Proposition 3.1 Conjecture that $V_n^L = n\nu_L Y$. Substitute this guess into the original value function:

$$rn\nu_L Y - gn\nu_L Y = \max_{z_n^L \geq 0} \; n\pi Y - \frac{(z_n^L)^\zeta n w_s}{\theta_L} + n z_n^L \nu_L Y - n\tau\nu_L Y. \tag{C.1}$$

Note that both n and Y can be canceled out from each side of Equation (C.1). Therefore, $z_n^L = z^L$ $\forall n$. Rearrange:

$$\nu_L = \frac{\pi}{\rho + \tau} + \frac{1}{(\rho + \tau)} \max_{z^L \geq 0} \left\{ -\frac{(z^L)^\zeta \omega_s}{\theta_L} + z^L \nu_L \right\}, \tag{C.2}$$

where $\omega_s \equiv w_s/Y$ denotes the normalized skilled wage and I have used the Euler condition $r - g = \rho$. Expression (C.2) states that the per-product franchise value, ν_L, is composed of a production value (first term on the right-hand side) and an innovation option value (as represented by the maximization operator). It follows that the first-order condition is:

$$z^L = \left[\frac{\theta_L \nu_L}{\zeta \omega_s} \right]^{\frac{1}{\zeta - 1}}. \tag{C.3}$$

Substituting Equation (C.3) back into Equation (C.2) yields the expression for ν_L in the main text.

Proof of Proposition 3.2 Conjecture that $V_n^H = \nu_n^H Y$. Note that by abuse of notation, ν_n^H represents a function of both firm type and firm size. Substitute this guess into the original value function:

$$\begin{aligned} rv_n^H Y - gv_n^H Y = n\pi Y \quad &+ \quad \max \left\{ \begin{array}{l} \max_{z_n^H \geq 0} \{ -(z_n^H)^\zeta n w_s/\theta_H + n z_n^H \left(v_{n+1}^H - v_n^H \right) Y \}; \\ \max_{z_n^H \geq 0} \{ -(z_n^H)^\zeta n w_s/(\kappa\theta_H) - c_p Y + n z_n^H \left(v_{n+1}^H - v_n^H \right) Y \} \end{array} \right\} \\ &+ \quad n\tau \left(v_{n-1}^H - v_n^H \right) Y. \end{aligned} \tag{C.4}$$

Cancel Y from both sides of Equation (C.4) and rearrange:

$$\begin{aligned} \rho v_n^H Y = \; n\pi \quad &+ \quad \max \left\{ \begin{array}{l} \max_{z_n^H \geq 0} \{ -(z_n^H)^\zeta n \omega_s/\theta_H + n z_n^H \left(v_{n+1}^H - v_n^H \right) \}; \\ \max_{z_n^H \geq 0} \{ -(z_n^H)^\zeta n \omega_s/(\kappa\theta_H) - c_p + n z_n^H \left(v_{n+1}^H - v_n^H \right) \} \end{array} \right\} \\ &+ \quad n\tau \left(v_{n-1}^H - v_n^H \right), \end{aligned} \tag{C.5}$$

where ω_s denotes the normalized skilled wage and I have used the Euler condition $r - g = \rho$.

Now, suppose that the solution to the outer maximization is given by an integer, $\hat{n}$, such that:

$$\begin{aligned} \rho v_n^H = \; n\pi \quad &+ \quad \left\{ \begin{array}{ll} \max_{z_n^H \geq 0} \{ -(z_n^H)^\zeta n \omega_s/\theta_H + n z_n^H \left(v_{n+1}^H - v_n^H \right) \} & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \{ -(z_n^H)^\zeta n \omega_s/(\kappa\theta_H) - c_p + n z_n^H \left(v_{n+1}^H - v_n^H \right) \} & \text{for } n \geq \hat{n} \end{array} \right\} \\ &+ \quad n\tau \left(v_{n-1}^H - v_n^H \right). \end{aligned} \tag{C.6}$$

We can rewrite v_n^H as:

$$v_n^H = n \times \begin{cases} \max_{z_n^H \geq 0} \frac{\pi - (z_n^H)^\zeta \omega_s/\theta_H + z_n^H v_{n+1}^H + \tau v_{n-1}^H}{\rho + n z_n^H + n\tau} & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \frac{\pi - (z_n^H)^\zeta \omega_s/(\kappa\theta_H) - c_p + z_n^H v_{n+1}^H + \tau v_{n-1}^H}{\rho + n z_n^H + n\tau} & \text{for } n \geq \hat{n}. \end{cases} \tag{C.7}$$

It follows that:

$$b(n) \equiv \frac{v_n^H}{n} = \begin{cases} \max_{z_n^H \geq 0} \left\{ h(n, z_n^H) + \frac{z_n^H(n+1)}{\rho + (z_n^H + \tau)n} b(n+1) + \frac{\tau(n-1)}{\rho + (z_n^H + \tau)n} b(n-1) \right\} & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \left\{ \hat{h}(n, z_n^H) + \frac{z_n^H(n+1)}{\rho + (z_n^H + \tau)n} b(n+1) + \frac{\tau(n-1)}{\rho + (z_n^H + \tau)n} b(n-1) \right\} & \text{for } n \geq \hat{n}, \end{cases} \tag{C.8}$$

where $h(n, z_n^H) = \frac{\pi - \frac{(z_n^H)^\zeta \omega_s}{\theta_H}}{\rho + (z_n^H + \tau)n}$ and $\hat{h}(n, z_n^H) = \frac{\pi - \frac{(z_n^H)^\zeta \omega_s}{\theta_H} - \frac{c_p}{n}}{\rho + (z_n^H + \tau)n}$.

I next show that the function $b(n)$ satisfies Blackwell's sufficient conditions for a contraction, given a size threshold $\hat{n}$. Define the operator T by:

$$Tf(n) = \begin{cases} \max_{z_n^H \geq 0} \left\{ h(n, z_n^H) + \frac{z_n^H(n+1)}{\rho + (z_n^H + \tau)n} f(n+1) + \frac{\tau(n-1)}{\rho + (z_n^H + \tau)n} f(n-1) \right\} & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \left\{ \hat{h}(n, z_n^H) + \frac{z_n^H(n+1)}{\rho + (z_n^H + \tau)n} f(n+1) + \frac{\tau(n-1)}{\rho + (z_n^H + \tau)n} f(n-1) \right\} & \text{for } n \geq \hat{n}. \end{cases} \tag{C.9}$$

First note that $h(n, z_n^H)$ and $\hat{h}(n, z_n^H)$ are bounded functions. Therefore, T maps the space of continuous, bounded functions into itself (Berge's Maximum Theorem). In addition, for any continuous, bounded functions f and g with $f(n) \leq g(n)$, and for all $n \in \mathbb{Z}^{++}$, we have:

$$Tf(n) = \begin{cases} \max_{z_n^H \geq 0} \left\{ h(n, z_n^H) + \frac{z_n^H(n+1)}{\rho + (z_n^H + \tau)n} f(n+1) + \frac{\tau(n-1)}{\rho + (z_n^H + \tau)n} f(n-1) \right\} & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \left\{ \hat{h}(n, z_n^H) + \frac{z_n^H(n+1)}{\rho + (z_n^H + \tau)n} f(n+1) + \frac{\tau(n-1)}{\rho + (z_n^H + \tau)n} f(n-1) \right\} & \text{for } n \geq \hat{n} \end{cases}$$

$$
\begin{aligned}
&\leq \begin{cases} \max_{z_n^H \geq 0} \left\{ h(n, z_n^H) + \frac{z_n^H (n+1)}{\rho + (z_n^H + \tau) n} g(n+1) + \frac{\tau (n-1)}{\rho + (z_n^H + \tau) n} g(n-1) \right\} & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \left\{ \hat{h}(n, z_n^H) + \frac{z_n^H (n+1)}{\rho + (z_n^H + \tau) n} g(n+1) + \frac{\tau (n-1)}{\rho + (z_n^H + \tau) n} g(n-1) \right\} & \text{for } n \geq \hat{n} \end{cases} \\
&= (Tg)(n). \qquad \text{(C.10)}
\end{aligned}
$$

Therefore, the monotonicity condition is satisfied. Lastly, to see that the operator T satisfies the discounting condition, we have for any continuous, bounded function f and $a \geq 0$:

$$
\begin{aligned}
(T[f+a])(n) &= \begin{cases} \max_{z_n^H \geq 0} \left\{ h(n, z_n^H) + \frac{z_n^H (n+1)}{\rho + (z_n^H + \tau) n} [f(n+1) + a] + \frac{\tau (n-1)}{\rho + (z_n^H + \tau) n} [f(n-1) + a] \right\} & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \left\{ \hat{h}(n, z_n^H) + \frac{z_n^H (n+1)}{\rho + (z_n^H + \tau) n} [f(n+1) + a] + \frac{\tau (n-1)}{\rho + (z_n^H + \tau) n} [f(n-1) + a] \right\} & \text{for } n \geq \hat{n} \end{cases} \\
&\leq \begin{cases} \max_{z_n^H \geq 0} \left\{ h(n, z_n^H) + \frac{z_n^H (n+1)}{\rho + (z_n^H + \tau) n} f(n+1) + \frac{\tau (n-1)}{\rho + (z_n^H + \tau) n} f(n-1) \right\} + \Omega a & \text{for } n < \hat{n} \\ \max_{z_n^H \geq 0} \left\{ \hat{h}(n, z_n^H) + \frac{z_n^H (n+1)}{\rho + (z_n^H + \tau) n} f(n+1) + \frac{\tau (n-1)}{\rho + (z_n^H + \tau) n} f(n-1) \right\} + \Omega a & \text{for } n \geq \hat{n} \end{cases} \\
&= (Tf)(n) + \Omega a, \qquad \text{(C.11)}
\end{aligned}
$$

where

$$
\Omega \equiv \max_{z_n^H} \left\{ \frac{(z_n^H + \tau) n}{\rho + (z_n^H + \tau) n} + \frac{z_n^H - \tau}{\rho + (z_n^H + \tau) n} \right\} < 1. \qquad \text{(C.12)}
$$

Thus, T is a contraction mapping and possess a unique fixed point, b, such that $(Tb)(n) = b(n)$ (Stokey et al., 1989).

Proof of Proposition 3.3 Using the flow equations for low-type firms in Section 3.2.6, we have:

$$
\begin{aligned}
\mu_1^L &= \frac{z_e(1-A)}{F^L \tau} \\
2\mu_2^L &= \frac{z_e(1-A) z^L}{F^L \tau^2} = \mu_1^L \left(\frac{z^L}{\tau} \right) \\
3\mu_3^L &= \frac{z_e(1-A)(z^L)^2}{F^L \tau^3} = \mu_1^L \left(\frac{z^L}{\tau} \right)^2 \\
&\ldots
\end{aligned}
$$

$$n\mu_n^L = \frac{(1-A)(z^L)^{n-1}}{F^L\tau^n} = \mu_1^L\left(\frac{z^L}{\tau}\right)^{n-1} \tag{C.13}$$

By $1 = \sum_{n=1}^{\infty}\mu_n^L$:

$$\begin{aligned} 1 &= \mu_1^L + \sum_{n=2}^{\infty}\mu_n^L \\ &= \mu_1^L\left(\frac{\tau}{z^L}\right)\sum_{n=1}^{\infty}\frac{1}{n}\left(\frac{z^L}{\tau}\right)^n \\ &= \mu_1^L\left(\frac{\tau}{z^L}\right)\ln\left(\frac{\tau}{\tau - z^L}\right) \end{aligned} \tag{C.14}$$

Therefore,

$$\mu_1^L = \frac{z^L/\tau}{\ln\left(\frac{\tau}{\tau-z^L}\right)}, \quad \text{and} \quad \mu_n^L = \frac{\frac{1}{n}\left(\frac{z^L}{\tau}\right)^n}{\ln\left(\frac{\tau}{\tau-z^L}\right)} \tag{C.15}$$

Similarly, using the flow equations for high-type firms, we have:

$$\begin{aligned} \mu_1^H &= \frac{z_e A}{F^H\tau} \\ 2\mu_2^H &= \frac{z_e A z_1^H}{F^H\tau^2} = \mu_1^H\left(\frac{z_1^H}{\tau}\right) \\ 3\mu_3^H &= \frac{z_e A z_1^H z_2^H}{F^H\tau^3} = \mu_1^H\left(\frac{z_1^H z_2^H}{\tau^2}\right) \\ &\dots \\ n\mu_n^L &= \frac{z_e A z_1^H z_2^H \cdots z_{n-1}^H}{F^H\tau^n} = \mu_1^H\prod_{j=1}^{n-1}\left(\frac{z_j^H}{\tau}\right) \end{aligned} \tag{C.16}$$

By $1 = \sum_{n=1}^{\infty}\mu_n^H$:

$$\begin{aligned} 1 &= \mu_1^H + \sum_{n=2}^{\infty}\mu_n^H \\ &= \mu_1^H\sum_{n=1}^{\infty}\frac{1}{n}\frac{\tau}{z_n^H}\prod_{j=1}^{n}\left(\frac{z_j^H}{\tau}\right) \end{aligned} \tag{C.17}$$

It follows that:

$$\mu_1^H = \frac{1}{\sum_{n=1}^{\infty} \frac{1}{n} \frac{\tau}{z_n^H} \prod_{j=1}^{n} \left(\frac{z_j^H}{\tau} \right)}, \quad \text{and} \quad \mu_n^H = \frac{\frac{1}{n} \prod_{j=1}^{n-1} \left(\frac{z_j^H}{\tau} \right)}{\sum_{n=1}^{\infty} \frac{1}{n} \frac{\tau}{z_n^H} \prod_{j=1}^{n} \left(\frac{z_j^H}{\tau} \right)} \tag{C.18}$$

This completes the proof.

Proof of Proposition 3.4 Rearrange the final good production function:

$$\begin{aligned} \ln Y(t) &= \int_0^1 \ln y_j(t) dj \\ &= \int_0^1 \ln q_j(t) dj + \int_0^1 \ln l_j(t) dj \\ &= \int_0^1 \ln q_j(t) dj + \ln \left(\frac{1}{\gamma \omega} \right). \end{aligned} \tag{C.19}$$

Define $Q(t) = \exp\left(\int_0^1 \ln q_j(t) dj \right)$. Then, the aggregate growth rate is equal to:

$$g = \frac{\dot{Y}}{Y} = \frac{\dot{C}}{C} = \frac{\dot{Q}}{Q}. \tag{C.20}$$

Now, express $\ln Q(t)$ after a small time interval Δt as:

$$\begin{aligned} \ln Q(t + \Delta t) &= \int_0^1 \left[\tau_t \Delta t \ln(\gamma q_j(t)) + (1 - \tau_t \Delta t) \ln q_j(t) \right] dj \\ &= \tau_t \Delta t \ln(\gamma) + \ln Q(t), \end{aligned} \tag{C.21}$$

where second and higher order terms in Δt are omitted. It follows that:

$$g(t) = \frac{\dot{Q}(t)}{Q(t)} = \lim_{\Delta t \to 0} \frac{\ln Q(t + \Delta t) - \ln Q(t)}{\Delta t} = \tau_t \ln \gamma. \tag{C.22}$$

Therefore, in a stationary equilibrium, we have $g = \tau \ln \gamma$.

C.2 Omitted Derivations

C.2.1 Baseline Model

Firm employment For a firm with n products, its demand for unskilled labor is:

$$nl_j = n\frac{y_j}{q_j} = n\frac{Y}{p_j q_j} = n\frac{Y}{\frac{w_u}{q_{-j}}q_j} = \frac{n}{\omega_u \gamma}, \tag{C.23}$$

where ω_u denotes normalized unskilled wage (by Y). The firm's demand for skilled labor is:

$$\frac{z(n,\theta)^{\zeta}\omega_s}{\theta}n, \tag{C.24}$$

where ω_s denotes normalized skilled wage (by Y), and $z(n,\theta)$ is given by Proposition 3.1 and 3.2. Therefore, firm employment is proportional to firm size.

Partial derivatives For simplicity, the following derivations are made under the baseline parameterization of $\zeta = 2$. Substitute $\zeta = 2$ into Proposition 3.1:

$$4\omega_s(\rho+\tau)\nu_L = 4\omega_s\pi + \theta_L\nu_L^2 \tag{C.25}$$

$$z^L = \frac{\theta_L\nu_L}{2\omega_s} \tag{C.26}$$

Differentiate both sides of Equation (C.25) with respect to τ, holding ω_s fixed:

$$4\omega_s\nu_L + 4\omega_s(\rho+\tau)\frac{\partial\nu_L}{\partial\tau} = 2\theta_L\nu_L\frac{\partial\nu_L}{\partial\tau}. \tag{C.27}$$

Rearrange:

$$[2\theta_L\nu_L - 4\omega_s(\rho+\tau)]\frac{\partial\nu_L}{\partial\tau} = 4\omega_s\nu_L. \tag{C.28}$$

Substitute Equation (C.26) into the left-hand side of the above equation and cancel terms:

$$\underbrace{\left[z^L - (\rho+\tau)\right]}_{<0}\frac{\partial\nu_L}{\partial\tau} = \underbrace{\nu_L}_{>0}, \tag{C.29}$$

where $z^L - (\rho+\tau) < 0$ follows from $z^L < \tau$. Hence, $\partial\nu_L/\partial\tau < 0$. It follows immediately that $\partial z^L/\partial\tau < 0$ (holding ω_s fixed), by differentiating Equation (C.26) with respect to τ and making use of $\partial\nu_L/\partial\tau < 0$.

Analogously, Differentiate both sides of Equation (C.25) with respect to ω_s, holding τ fixed:

$$4(\rho+\tau)\nu_L + 4\omega_s(\rho+\tau)\frac{\partial\nu_L}{\partial\omega_s} = 4\pi + 2\theta_L\nu_L\frac{\partial\nu_L}{\partial\omega_s}. \tag{C.30}$$

Rearrange:

$$\underbrace{[2\theta_L\nu_L - 4\omega_s(\rho+\tau)]}_{<0}\frac{\partial\nu_L}{\partial\omega_s} = 4\underbrace{[(\rho+\tau)\nu_L - \pi]}_{>0}, \tag{C.31}$$

where $2\theta_L\nu_L - 4\omega_s(\rho+\tau) < 0$ was shown earlier and $(\rho+\tau)\nu_L - \pi > 0$ follows from rearranging Equation (C.25) to get $(\rho+\tau)\nu_L - \pi = \theta_L\nu_L^2/(4\omega_s)$. Finally, differentiate Equation (C.26) with respect to ω_s, holding τ fixed:

$$\frac{\partial z^L}{\partial \omega_s} = \underbrace{-\frac{\theta_L \nu_L}{2\omega_s^2}}_{<0} + \frac{\theta_L}{2\omega_s} \underbrace{\frac{\partial \nu_L}{\partial \omega_s}}_{<0} < 0. \tag{C.32}$$

C.2.2 Generalized Model

Under the generalized innovation production function, the associated cost function becomes:

$$\tilde{C}(z, n, \theta) = \frac{z^\zeta n^\sigma w_s}{\theta}, \tag{C.33}$$

where $\zeta = 1/\tilde{\zeta}$ and $\sigma = (1 - \tilde{\sigma})/\tilde{\zeta}$.

The value function of low-type incumbents becomes:

$$\begin{aligned} rV_n^L - \dot{V}_n^L = \max_{z_n^L \geq 0} \quad & \Bigg\{ \quad n\pi Y - \frac{(z_n^L)^\zeta n^\sigma w_s}{\theta_L} \\ & + \quad n z_n^L \left(V_{n+1}^L - V_n^L\right) + n\tau \left(V_{n-1}^L - V_n^L\right) \Bigg\}. \end{aligned} \tag{C.34}$$

Guess $V_n^L = v_n^L Y$. Substitute the guess into the above value function, cancel terms, and rearrange:

$$\begin{aligned} \rho v_n^L = \max_{z_n^L \geq 0} \quad & \Bigg\{ \quad n\pi - \frac{(z_n^L)^\zeta n^\sigma \omega_s}{\theta_L} \\ & + \quad n z_n^L \left(v_{n+1}^L - v_n^L\right) + n\tau \left(v_{n-1}^L - v_n^L\right) \Bigg\}. \end{aligned} \tag{C.35}$$

There is no closed-form solution to this problem, and I use the uniformization method to solve the normalized value (v_n^L) and the optimal innovation intensity (z_n^L) in the computer. Note that the intensity (z_n^L) is now a function of firm size.

The problem of high-type incumbents is solved in a similar fashion as in the baseline model. One just needs to modify the curvature of the flow cost function to allow for decreasing returns.

For the size distribution of low-type firms, we need to replace z^L with z_n^L in the flow equations in Section 3.2.6, since now the innovation intensity of low-type firms is a function of firm size. The flow equations can then be solved recursively following the proof for Proposition 3.3. In fact, the invariant distribution of low-type firms now takes a similar form as that of high-type firms:

$$\mu_n^L = \frac{\frac{1}{n}\prod_{j=1}^{n-1}\left(\frac{z_j^L}{\tau}\right)}{\sum_{n=1}^{\infty}\frac{1}{n}\frac{\tau}{z_n^L}\prod_{j=1}^{n}\left(\frac{z_j^L}{\tau}\right)}. \tag{C.36}$$

The invariant size distribution of high-type firms is characterized by the same expression in Proposition 3.3.

Finally, we need to modify the creative destruction rate and the (skilled) labor market clearing condition to be consistent with the fact that now the innovation intensity of low-type firms is a function of firm size:

$$\tau = F^L\sum_{n=1}^{\infty} n z_n^L \mu_n^L + F^H \sum_{n=1}^{\infty} n z_n^H \mu_n^H + z_e, \tag{C.37}$$

and

$$\begin{aligned} L_S = \quad & F^L \quad \sum_{n=1}^{\infty}\frac{1}{\theta_L}(z_n^L)^{\zeta} n\mu_n^L + F^H\sum_{n=1}^{\hat{n}-1}\frac{1}{\theta_H}(z_n^H)^{\zeta} n\mu_n^H \\ + \quad & F^H\sum_{n=\hat{n}}^{\infty}\frac{1}{\kappa\theta_H}(z_n^H)^{\zeta} n\mu_n^H + \frac{z_e^{\zeta}}{\theta_e}. \end{aligned} \tag{C.38}$$

These are all the changes in the generalized model relative to the baseline model.

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