The Life Cycle of Corporate Venture Capital*

Song Ma†

Abstract

This paper establishes the life cycle of Corporate Venture Capital (CVC), from the *initiation* of CVC programs, to their *operation* and the decision of *termination*, in order to better understand the economics of financing innovation. To study the *initiation* stage, I use an identification strategy that isolates firm-specific innovation shocks and show that the CVC life cycle typically follows a period of deteriorated internal innovation and when external information is valuable. At the *operation* stage, CVCs select portfolio companies with similar technological focus but that have a different knowledge base. They actively use new knowledge generated from their portfolio companies, and change their human capital to facilitate this process. CVC programs are *terminated* when internal innovation recovers and the informational benefit diminishes. Those findings are consistent with an explanation that firms strategically use CVC to acquire innovation knowledge from the entrepreneurial sector.

JEL Classification: G24 G34 O32 D83

Keywords: Corporate Venture Capital, Information Acquisition, Innovation, Entrepreneurship

*This paper is based on my dissertation submitted to Duke University. I am indebted to my dissertation committee: John Graham (co-chair), David Robinson (co-chair), Manuel Adelino, Alon Brav, Manju Puri, and Ronnie Chatterji. Sincere thanks also go to Jean-Noël Barrot (discussant), Lauren Cohen, John de Figueiredo, Joan Farre-Mensa, Simon Gervais, Philippe Gorry (discussant), Cam Harvey, Thomas Hellmann, Yael Hochberg, Hyunseob Kim, Laura Lindsey, Xiaoding Liu (discussant), William Mann (discussant), Justin Murfin, Bruce Petersen, Jillian Popadak, Adriano Rampini, Mark Schankerman, Morten Sørensen, Ming Yang, seminar participants at CKGSB, CICF (Xiamen), Copenhagen Business School, Cornell, Duke, Entrepreneurship and Innovation seminar, FIRS (Lisbon), Harvard, HKU, HKUST, Imperial College, LBS, Maryland, Michigan State, NBER Entrepreneurship Research Boot Camp, NC State, NFA (Mont Tremblant), Ninth Annual Searle Center/USPTO Conference on Innovation Economics, Rochester, Toronto, UNC, Utah, WUSTL Corporate Finance Conference, and Yale. I also benefited from discussions with several practitioners. All errors are my own. The Internet Appendix is available at: `http://faculty.som.yale.edu/songma/`.

†Yale University, song.ma@yale.edu, (203) 436-4687.

1 Introduction

Innovation is the engine of economic growth, but the pathways to successful innovation remain far from clear (Lerner, 2012). To solve this puzzle, economists examine corporate activities such as research and development, mergers and acquisitions, and strategic alliances (see, e.g., Robinson (2008), Brown et al. (2009), Manso (2011), Bena and Li (2014), Seru (2014), among others), as well as entrepreneurial finance activities particularly venture capital (Kortum and Lerner, 2000). One area that has received less attention is non-financial firm's foray into venture capital—that is, firms create Corporate Venture Capital (CVC) divisions to make systematic minority equity investments in innovative startups. CVC has become an economically significant phenomenon. According to the National Venture Capital Association (NVCA), CVC investments accounted for about 20% of Venture Capital (VC) investment in 2015, and are undertaken by firms with different sizes in a variety of industries.

Theoretically, CVCs may differ from independent venture capitalists by virtue of their ability to not only seek financial returns but also reap strategic benefits from the early relationship with innovative startups. Hellmann (2002) argue that strategic investors choose to invest in companies that have the strongest asset complementarities, Hellmann, Lindsey, and Puri (2008) provide supporting evidence using VC arms of banks by showing that investing in a company during venture stage can bring future lending business for the bank. As the CVC phenomenon emerges from all sectors particularly innovative industries, the empirical question arises as to how firms as strategic venture investors differ from independent venture capitalists who are purely for financial returns (Gompers and Lerner, 2000), and to what extent firms' venture capital investments interact with their innovation dynamics and through what channel.

Identifying how firms make strategic CVC investment to benefit their innovation is subtle. As opposed to internal R&D and M&A, in which human capital and legal property rights on the produced (acquired) innovation are obtained by the investing firms, CVC parents do not directly own innovation produced by their portfolio companies.[1] In surveys

[1] CVC parents can certainly acquire those companies later, but acquisitions made by CVC investors of their portfolio companies are rare—Benson and Ziedonis (2010) and Dimitrova (2013) show that fewer than

of corporate venture capitalists, Siegel et al. (1988) and Macmillan et al. (2008) show that to help the parent firm to acquire information on new technologies and markets is the top of the CVC wish list.[2] This suggests that the strategic benefit that CVCs bring to parents' innovation is largely in the form of information and early knowledge from the entrepreneurial sector. Theoretically, this information acquisition rationale relates to a long-held framework in the economics of innovation that dates back at least to Nelson (1982) and Telser (1982).[3] Under this theory, the innovation process is framed as a two-step process, in which firms acquire information and generate ideas (first step) before they invest in and produce innovation based on those ideas (second step), and better innovation ideas are obtained through investing in information acquisition. Following this logic, even though CVC investments do not directly produce or acquire innovation for the firm, they benefit parents' innovation by acquiring information and help generate new innovative ideas.

In this paper I examine how strategic CVC investments interact with the innovation of the parent firm, and hypothesize around its information acquisition role. Although much of the literature focuses on innovation changes following certain organizational event window, this paper take a more dynamic approach and aims to test hypotheses along the full life cycle of Corporate Venture Capital. I start by asking what innovation conditions motivate firms to initiate CVC programs in the first place, and why. I then explore various dimentions on how CVC programs are operated, and how the strategic benefits are harvested. In then end, I investigate the staying power of CVC, and how the termination decision relates to the innovation dynamics of the firm.

Answers to these questions help to establish an investment pattern, which I call the *CVC life cycle*. The CVC life cycle typically follows a period of deteriorated internal innovation and when external information is valuable. At the operation stage, CVCs select portfolio companies with similar technological focus but that have a different knowledge base. They

one-fifth of CVC investors acquired their portfolio companies. CVC units that did conduct such acquisitions acquired fewer than 5% of their portfolio companies (that is, one out of 20 investments). Such acquisitions are typically associated with more negative abnormal returns compared to other acquisitions.

[2]Startups are an important source of technological and market knowledge, as well as innovative ideas (Scherer, 1965; Acs and Audretsch, 1988; Kortum and Lerner, 2000; Zingales, 2000; Gonzalez-Uribe, 2013).

[3]See also Nelson and Winter (1982); Dosi (1988); Jovanovic and Rob (1989); Kortum (1997); Fleming and Sorenson (2004); Frydman and Papanikolaou (2015), among others.

actively use new knowledge generated from their portfolio companies, and change their human capital to facilitate this process. CVC programs are terminated when internal innovation recovers and the informational benefit diminishes. Figure 1 summarizes the CVC life cycle graphically.

[FIGURE 1 HERE]

The CVC life cycle begins with the *initiation* stage, in which a firm launches CVC investment, typically following a deterioration in internal innovation. That is, when firms experience a decline in internal innovation, and therefore can benefit from potential informational gains by connecting to highly innovative entrepreneurs, they are more likely to initiate CVC investment. Quantitatively, a two-standard-deviation decline in innovation quantity (quality) increases the probability that a firm will initiate CVC by about 52% (67%). Firms in the same industry cluster CVC activities when their sector experiences technological shocks, forming "industry CVC waves."

To mitigate the concern that innovation capability is determined by endogenous factors such as governance, which could simultaneously explain CVC activities, I identify plausibly exogenous shocks to firms' abilities to generate ideas and produce innovation. The instrumental variable *Knowledge Obsolescence* captures the evolution of usefulness of a firm's accumulated knowledge base, and varies due to exogenous technological evolution and is independent of such endogenous factors as corporate governance and product market status. The finding that CVCs are initiated following innovation deterioration holds under this identification strategy. I also submit the results to a battery of robustness checks, including subsample analyses and different sampling criteria. In addition, several potential alternative interpretations of the result, such as the effects of financial constraints, excess cash and managerial desperation, do not seem to explain this finding.

How do CVCs select portfolio companies and reap the strategic benefit for innovation? At the *operation* stage of the CVC life cycle, I find that CVCs primarily invest in startups that are innovating in technological areas that are proximate to the CVC parent firm, suggesting that CVCs prefer to acquire knowledge from companies whose technologies can be adapted to the parent firms' innovation. Interestingly, conditional on proximate technological areas, CVCs prefer startups with *less* overlaps of knowledge base defined by historical patent citations. This suggests that CVC parents aim to acquire updated and incremental knowledge. As opposed to financial return-driven traditional VCs, who exhibit local (home) bias when selecting portfolio companies in order to mitigate information asymmetry (Cumming and Dai, 2010; Hochberg and Rauh, 2012), I find that CVC investment appears to have a "reverse home bias." That is, even though CVCs are less likely to invest in geographically distant companies, they are also less likely to invest in companies in their own geographic regions, for which local innovation spillovers (Peri, 2005; Matray, 2014) substitute information acquisition using CVC.

I further explore how strategic benefits are harvested by CVC parent firms. I first hypothesize that CVC parent firms could internalize acquired knowledge through innovating based on technologies of their portfolio companies. This channel is supported by the empirical finding that CVC parents cite patents generated by their portfolio startups in an abnormally high intensity, benchmarked by the citing pattern of their industry peers. I do not find the same citation pattern before a CVC invests in a startup. Second, CVC parents capitalize on information by gaining efficiency when making information-sensitive decisions, such as external acquisitions of companies and innovations. As discussed early, those efficiency gain from acquisition activities is not driven by events when CVC parents acquire their own portfolio companies—information acquired by CVC appears to be more generic. Moreover, I show that CVC parent firms alter their human capital base by hiring additional inventors who can use knowledge newly acquired from their portfolio companies.

The CVC life cycle ends with the *termination* stage, when CVC parents stop making incremental investment in new startups. Unlike independent VCs that typically have a pre-determined fund life (median of 10 years), CVCs' staying power is closely related to the innovation dynamic of the parent firm—they are terminated when internal innovation begins to recover. The median duration of the life cycle is about four years. When CVC divisions last more than four years, firms typically hibernate CVC activities during years when internal innovation remains productive. This evidence is consistent with the information acquisition rationale, which predicts decreased CVC activity when the marginal benefit shrinks after new information is assimilated into parent firms. Interestingly, if innovation again deteriorates at the parent firm, the CVC life cycle begins anew.

This paper is related the literature that seeks to understand the strategic benefit of CVC investments (see Dushnitsky (2006), Maula (2007), and Lerner (2012) for surveys[4]). In a setting of bank-affiliated VC arms where the innovation channel is shut down intentionally, Hellmann, Lindsey, and Puri (2008) show that bank-VCs invest in startups for future lending relationships. Mathews (2006) models how the CVC-type of equity arrangement could stabilize such strategic relationship. Chemmanur, Loutskina, and Tian (2014) show that those strategic fit not only benefit the CVC investor but also the startup companies. Dushnitsky and Lenox (2005b) and Dushnitsky and Lenox (2006) show that parent firms' financial valuation and innovation improves after CVC investment, consistent with an explanation of knowledge spillovers from startups to CVC investors.

The idea that firms conduct CVC to acquire innovation knowledge was proposed by Fast (1977, 1978). This paper attempts to push forward this classic understanding with a set of new testable hypotheses, taking advantage of new datasets on CVC and innovation. On the one hand, the life-cycle scope allows me to identify how strategic considerations motivate firms to make the initial decision to enter the VC field, to invest in strategically complement startups, and to end such investment when strategic values from connecting to startups diminish—these important dynamics were largely unknown in this young literature. On the other hand, exploiting the richness of data, I empirically identify the process that a piece of information is selected and transferred from a startup to the CVC parent firm, and then integrated by the firm at the level of inventors, which more directly supports the economic reasoning than simply looking at patent counts and citations.

In broader terms, this paper connects to the literature on the role of different ways to finance and organize innovation. In their classic work, Aghion and Tirole (1994) model several cases in which, taking the research idea and informational environment as given, equity investment is optimal to provide incentive for R&D projects. On the empirical

[4]For more readings on CVC, see, e.g., Siegel, Siegel, and MacMillan (1988); Gompers and Lerner (2000); Bottazzi, Da Rin, and Hellmann (2004); Dushnitsky and Lenox (2005a, 2006); Benson and Ziedonis (2010); Basu, Phelps, and Kotha (2011); Chemmanur, Loutskina, and Tian (2014); Dimitrova (2013); Ceccagnoli, Higgins, and Kang (2015); Wadhwa, Phelps, and Kotha (2015).

side, Robinson (2008) shows that firms use strategic alliances to implement riskier projects when they are endowed with a set of exogenous ideas and are capable of assessing them. Bena and Li (2014) show that firms with stronger innovation capabilities and conditions make acquisitions targeting companies with high knowledge overlaps. Seru (2014) shows that such acquisition decisions might destroy acquirers' innovative abilities. One common framework of those papers is that they typically assume that the information structure and research ideas are exogenous, and those different organizational arrangements are used to efficiently implement those endowed ideas.

But innovation ideas are unlikely to be exogenous. The CVC setting provides us an opportunity to deviate from the above framework and revisit the innovation process modeled by Nelson (1982), Telser (1982) and Jovanovic and Rob (1989), in which firms' innovation ideas are endogenously obtained through investing into the process of search and acquiring knowledge. As a result, beyond gaining insights on CVC itself, this paper allows us to take a close look at how firms manage their sequential innovation process. Fortunately, the constructed dataset is rich enough to help link the knowledge acquisition stage with the implementation of those knowledge—I find direct evidence that CVC acquired information is integrated into corporate innovation through follow-up R&D and acquisition decisions, and firms adjust their human capital based to facilitate this process.

Though the paper is crafted in a way to highlight strategic benefits of CVC, specifically the role of acquiring knowledge for innovation, the goal is not to argue that those are the only factors motivating CVC investments. Indeed, a beauty of CVC is its ability to help firms with different blends of goals (similar to M&As and strategic alliances, which are conducted for a variety of reasons). However, it is an interesting question that remains: to what extent can the CVC life cycle help us distinguish whether CVC is more for strategic or for financial returns. While I cannot conclusively answer this question and it is likely the answer will change case-by-case, evidence along the CVC life cycle collectively suggests that CVCs differ from independent VCs that are purely financial return-driven. I find that the decision of launching CVC is largely independent to the financial condition of the deteriorating firm; the investment decision focuses on informational gain rather than controlling information asymmetry (less knowledge overlap, reverse home bias); and the decision to terminate CVC is not determined by the success (failures) of previous investment but rather by the innovation dynamics of the firm. Going forward, an alternative way to interpret the empirical contribution of the paper is the life-cycle analytical framework, which could be exploited in other CVC settings, used to identify related economic forces, employed to categorize if certain CVC is more strategic or financial. But those extensions are beyond the scope of this paper itself.

The remainder of the paper proceeds as follows. Section 2 describes how the data are collected and constructed. Section 3 through 5 cover each stage of the CVC life cycle. Section 6 concludes.

2 Sample and Data

I construct a hand-collected sample of Corporate Venture Capital units affiliated with US-based public firms. I start with a list of CVCs identified by the VentureXpert Venture Capital Firms database (accessed through Thomson Reuters SDC Platinum), which is standard in VC studies (Chemmanur, Loutskina, and Tian, 2014). Each CVC on the list is manually matched to its unique corporate parent in Compustat by checking multiple sources (Factiva, Google, etc.). I remove VC divisions operated by financial firms, which differ from CVC arms of industrial firms (Hellmann, Lindsey, and Puri, 2008). From VentureXpert I also obtain the investment history of each CVC, including basic information about the startup companies it invests in and the timing and features of each CVC deal.

[TABLE 1 HERE]

The main sample consists of 381 CVC firms initiated between 1980 and 2006.[5] Table 1 summarizes this CVC sample by tabulating the time-series dynamic and the industry composition. Panel A presents the number of CVC division initiations and investment deals by year. CVC activities are heavily concentrated in the first half of the 1980s and the second half of the 1990s. This is consistent with existing studies on "CVC waves"

[5] I focus on CVCs initiated no later than 2006 to allow for the whole CVC life cycle (investment behaviors, follow-up innovation, and terminations) to realize after CVC initiations.

(Gompers and Lerner, 2000; Dushnitsky, 2006) and is revisited and refined in Section 3.2.3. Panel B summarizes the industry distribution of CVC parent firms, where industries are defined by the Fama-French 48 Industry Classification. The Business Services industry (including IT) was the most active sector in CVC investment, with 90 firms investing in 821 venture companies. Electronic Equipment firms initiated 46 CVC divisions that invested in 921 companies. Pharmaceutical firms launched 28 CVCs and invested in 254 deals. Other active sectors include Computers and Communications.

The CVC sample is augmented with Compustat for financial statement data and with CRSP for stock market performance. Variable constructions are described in the Appendix. All data items are pre-winsorized at the 1% and 99% levels. SDC Platinum provides organizational information on M&As and strategic alliances. For corporate governance data, I extract institutional shareholding information from the WRDS Thomson Reuters 13(f) data and obtain G-index data from Andrew Metrick's data library.[6]

Innovation is a crucial data component of this paper for three reasons. First, because innovation knowledge generated in the entrepreneurial sector has the potential to create great value for CVC parent firms (Scherer, 1965; Acs and Audretsch, 1988; Kortum and Lerner, 2000; Macmillan et al., 2008), it is an important part of the information set that CVC units intend to acquire. Second, comprehensive innovation data create a valuable setting to measure informational relationships (Bena and Li, 2014) and knowledge flows (Gomes-Casseres et al., 2006; Gonzalez-Uribe, 2013; Matray, 2014). Third, the quality of detailed innovation data maintained and updated by the United States Patent and Trademark Office (USPTO) is superior to most alternative data sources on corporate activities.

I obtain basic innovation data from the NBER Patent Data Project and from Bhaven Sampat's patent and citation data.[7] The combined database provides detailed patent-level records on more than four million patents granted by USPTO between 1976 and 2012. I link this database to Compustat using the bridge file provided by NBER. Beyond the standard database, I also introduce several data sets and cleaning procedures that are relatively new

[6]Accessed using `http://faculty.som.yale.edu/andrewmetrick/data.html`.

[7]For more information on the NBER Patent Data Project, please refer to Hall, Jaffe, and Trajtenberg (2001). The data used in this paper were downloaded from `https://sites.google.com/site/patentdataproject/`. Sampat's data can be accessed using `http://thedata.harvard.edu/dvn/dv/boffindata`.

to the literature[8]: I link the USPTO database to entrepreneurial companies in VentureXpert using a fuzzy matching method based on company name, basic identity information, and innovation profiles, similar to Gonzalez-Uribe (2013) and Bernstein, Giroud, and Townsend (2014); I also introduce the Harvard Business School inventor-level database in order to examine how firms adjust their innovative human capital as a specific channel to facilitate information acquisition and integration; and last, I introduce the Google Patent Assignment and Reassignment database, which tracks all transactions of each patent.

The combined innovation data provide three layers of innovation information that are helpful for characterizing the CVC life cycle. First, I employ two main variables to measure basic corporate innovation performance. I measure innovation *quantity* by calculating the number of patent applications, which are eventually granted, filed by a firm in each year. I use the patent's year of application instead of the year it is granted because that better captures the actual timing of innovation. I use the logarithm of one plus this variable, that is, $\ln(1 + NewPatent)$ (denoted as $\ln(NewPatent)$), to fix the skewness problem for better empirical properties. I measure the *quality* of innovation, based on the average lifetime citations of all new patents produced by a firm in each year. Similar to the logarithm transformation performed on *quantity*, I use $\ln(1 + Pat.Quality)$ (denoted as $\ln(Pat.Quality)$). Citation measures are adjusted for right-censoring as suggested by Jaffe and Trajtenberg (2002) and Lerner and Seru (2015).

The second layer of innovation data is citations firms make in their own patents. By tracking the citations a firm makes, I can measure the technological areas in which the firm works and the specific underlying technologies. Moreover, examining the citation network among firms (including both established firms and startups) allows us to construct variables capturing the technological relation between CVCs and startups and to measure dynamic information flows between firm pairs.

The third layer of innovation data concerns micro-level activities—I track inventors (engineers, scientists, etc.) who contribute to a firm's patents and their mobility, and study patent transactions taking place in the market for technologies. As shown in Gonzalez-Uribe (2013), Bernstein, Giroud, and Townsend (2014), and Brav et al. (2016), inventor-level

[8]Please refer to related sections and the Appendix for more details

information can help infer the motivation behind corporate activities from the perspective of labor adjustment. In addition, the full set of patent transactions from the Google Patent database allows to examine how firms trade off different economic forces through their activities in transacting patents and adjusting innovation portfolios (Akcigit, Celik, and Greenwood, 2016).

3 CVC Initiations: The Effect of Innovation Deterioration

Why do firms initiate Corporate Venture Capital programs? Under the information acquisition view of CVC, capacity-constrained firms trade off between acquiring information for new ideas and producing existing ideas (Nelson, 1982; Telser, 1982; Jovanovic and Rob, 1989). The allocation of capacity to information acquisition is determined by the quantity and quality of existing ideas available to the firm—the fewer (lower) the quantity (quality) of existing innovation ideas become, the more likely it is the firm will implement CVC, in search of better innovation paths. Moreover, when internal innovation deteriorates, cannibalization concern from information acquisition (Arrow, 1962)—that newly acquired ideas will replace existing ones with high adjustment cost and organizational complexity—is mitigated, strengthening the motive to initiate CVC.

Figure 2 visualizes CVC parent firms' innovation dynamics before initiating their CVC divisions. Innovation performance, measured by patenting quantity (Panel (a)) and quality (Panel (b)), is tracked for five years from $t-4$ to t (t is the year of CVC initiation). Firm-year measures are adjusted by the averages of all peer firms in the same 3-digit SIC industry in the same year to exclude the influence of industry-specific time trends.

[FIGURE 2 HERE]

Panel (a) tracks innovation quantity of CVC parent firms, measured by the logarithm of the number of new patent applications. Four years before initiating their CVC units, CVC parents were more innovative than their peers by producing around 35% more patents each year. This advantage shrinks continuously by about 25% until year t. In Panel (b), CVC parent firms' innovation enjoys 15% higher average citations compared to their industry peers in $t-4$, and this number decreases to well below 0 at the time of CVC initiation. In untabulated results, I find that the performance deterioration pattern is robust to measures of product market performance, that is, ROA and sales growth. Overall, Figure 2 presents a clear pattern at the start of the CVC life cycle—that is, CVC initiations typically follow deteriorations in parent firms' internal innovation, which is consistent with the information acquisition view of CVC.

Building on Figure 2, I first confirm the relation between innovation deterioration and CVC initiation using a simple empirical setting. I then explore an identification strategy that controls for several endogeneity concerns and sharpens the role of the information acquisition motive by analyzing several alternative explanations of the pattern. Firm-level CVC initiation decisions are then aggregated to an industry-level pattern, which presents how the information acquisition function fits into the technological evolution in each industry.

3.1 Baseline Results

To statistically identify the effect of innovation performance on CVC initiations, I estimate the following specification using a firm-year panel (sample construction described below):

$$I(CVC)_{i,t} = \alpha_{industry \times t} + \beta \times \Delta_\tau Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}, \tag{1}$$

where $I(CVC)_{i,t}$ is equal to one if firm i launches a CVC unit in year t, and zero otherwise.[9] $\Delta_\tau Innovation_{i,t-1}$ is the change of innovation over the past τ years ending in $t-1$, which naturally differences out firm-specific innovation levels. I use a three-year ($\tau = 3$) innovation shock throughout the main analysis and report robustness checks using other horizons in the Appendix. Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets),

[9]Dummy variable $I(CVC)_{i,t}$, instead of the size of CVC investment each year, is more appropriate to capture the corporate decision on CVC investment for two reasons: (1) the decision to start a CVC unit is at the executive level, whereas the size of investment in subsequent years is plausibly determined by the CVC team; and (2) the data on investment size in VentureXpert have potential sample selection issues such as CVCs strategically hiding good deals they invested in (to avoid competition from other CVCs). I report the analysis on annual CVC investment size in Section 5 Table 10.

leverage, and R&D ratio (R&D expenditures scaled by total assets). Industry-by-year fixed effects are included to absorb industry-specific time trends in CVC activities and innovation. A negative β indicates that the probability of starting a CVC increases with innovation deterioration.

3.1.1 Summary Statistics

In the regression sample, I keep observations with valid ROA, size, leverage, R&D ratio, and at least $10 million in book assets. Only "innovative firms," defined as those that filed at least one patent application that was eventually granted by the USPTO, are included. Industries (3-digit SIC level) with no CVC activities during the sample period are removed.

Table 2 presents descriptive statistics based on whether a CVC division is initiated in the firm-year, which provides a benchmark to position CVC parent firms in the universe of innovative public firms. First, CVC parents are typically large firms. On average, a CVC parent has $10.1 billion in book assets in 2007 USD (median is $2.4 billion) just before launching its CVC unit, whereas non-CVC parent firms have less than $3 billion in book assets (median is $0.2 billion). Second, CVC parent firms are innovation intensive in terms of patenting quantity, echoing the size effect. Third, corporate governance variables are comparable between the two subsamples. Overall, the basic characteristics are consistent with existing stylized facts that CVC parent firms tend to be larger corporations with more business resources (Dushnitsky and Lenox, 2005a; Basu, Phelps, and Kotha, 2011).

[TABLE 2 HERE]

Consistent with Figure 2, CVC parent firms on average experience more negative innovation shocks before starting their CVC divisions. CVC parents on average experience a -7% (-10%) change in patenting quantity (quality) three years before launching their CVC units, compared to the control firms, which experience a 12% (8%) shock. Similar to the deterioration in innovation, CVC parents appear to underperform in terms of ROA and market-to-book ratio before CVC initiations.

3.1.2 Results

[TABLE 3 HERE]

Table 3 presents the estimation results of model (1). Columns (1) and (2) focus on the effect of changes in innovation quantity. In column (1), the model is estimated using Ordinary Least Squares (OLS). The coefficient of -0.007 is negative and significant, meaning that a more severe decline in innovation quantity in the past three years is associated with a higher probability of initiating CVC investment. This estimate translates a two-standard-deviation decrease (2σ-change) in $\Delta \ln(NewPatent)$ into a 51.54% increase from the unconditional probability of launching CVC unites. Column (2) reports the model estimation from a Logit regression, and I report the marginal effect evaluated at sample mean. Column (2) delivers an almost identical message as column (1).

Columns (3) and (4) study the effect of deterioration in innovation quality and use OLS and Logit, respectively. In column (3), the coefficient of -0.004 means that a two-standard-deviation decrease in $\Delta \ln(Pat.Quality)$ increases the probability of CVC initiation by 67.09%, and this is economically comparable to that in column (1). Column (4) delivers a consistent message. Overall, Table 3 confirms the pattern in Figure 2 that CVC initiations typically follow a deterioration in innovation, lending support to the information acquisition view of CVC.

It is worth stressing the importance of incorporating industry-by-year fixed effects in model estimations. Previous studies on technological evolution and restructuring waves highlight the possibility that certain industry-specific technology shocks could be driving innovation changes and organizational activities at the same time (Mitchell and Mulherin, 1996; Harford, 2005; Rhodes-Kropf, Robinson, and Viswanathan, 2005). In Table 3, after absorbing this variation using industry-by-year fixed effects, the results are identified using the cross-sectional variation in innovation dynamics within an industry-by-year cohort.

3.2 Identification Strategy

Potential endogeneity problems arise from unobservables that are hard to control for in model (1). For instance, agency problems (such as empire-building managers) could hinder innovation and lead simultaneously to the initiation of CVC as a pet project, biasing the estimation in favor of finding a negative relation between innovation and CVC investment. On the other hand, CEOs who are more risk tolerant could improve corporate innovation (Sunder, Sunder, and Zhang, 2014) as well as encourage interactions with entrepreneurs using CVC, biasing the estimation against finding the result.

3.2.1 Instrumental Variable

To address endogeneity concerns and rule out competing interpretations, I construct a new instrumental variable by exploiting the influence of exogenous technological evolution on firm-specific innovation. The idea that technological evolution affects corporate innovation is intuitive—a firm specializing in 14-inch hard disk drives (HDD) was less likely to produce valuable innovation when 8-inch HDD technology emerged, and this happened repeatedly along the development path of HDDs (5.25-inch, 3.5-inch, 2.5-inch, Solid State Drives) (Christiansen, 1997). Indeed, "new technologies come and go, taking generations of companies with them" (Igami, 2014).

Earlier studies formalize this intuition and model the influence of technological evolution on the value of firms' knowledge accumulation. A negative shock to the value of a firm's accumulated knowledge space implies a longer distance to the knowledge frontier and a higher knowledge burden to identify valuable ideas and produce radical innovation (Jones, 2009). Firms working in a fading area benefit less from knowledge spillover (Bloom, Schankerman, and Van Reenen, 2013), which in turn dampens growth in innovation and productivity.

To implement the idea and measure the influence of exogenous technological evolution on each firm's capability to innovate, I build on the literature of bibliometrics and scientometrics, which measure the obsolescence and aging of a discipline or technology using the dynamics of citations that refer to the discipline or technology. The instrument, termed as *Knowledge Obsolescence* (*Obsolescence* hereafter), attempts to capture the τ-year (between $t-\tau$ and t) rate of obsolescence of the knowledge possessed by a firm as of $t-\tau$. For each firm i in year t, this instrument is constructed in three steps (formally defined in formula (2)). First, firm i's predetermined knowledge space in year $t-\tau$ is defined as all the patents cited by firm i (but not belonging to i) up to year $t-\tau$. I then calculate the number of citations received by this $KnowledgeSpace_{i,t-\tau}$ in $t-\tau$ and in t, respectively. Last, $Obsolescence^{\tau}_{i,t}$ is defined as the change between the two. A larger *Obsolescence* means a greater decline of the value and utility of a firm's knowledge, as capture by that less new innovation builds on those knowledge.

$$Obsolescence^{\tau}_{i,t} = -[\ln(Cit_t(KnowledgeSpace_{i,t-\tau})) - \ln(Cit_{t-\tau}(KnowledgeSpace_{i,t-\tau}))]. \tag{2}$$

The validity of the exclusion restriction first rests on the assumption that, controlling for industry-specific technological trends and firm-specific characteristics, the technological evolution regarding a firm's knowledge space, which is predetermined and accumulated along its path, is orthogonal to its current decision on CVC other than through affecting innovation performance and needs for new knowledge. For example, one might worry that a firm's knowledge space could be determined by the type and capability of its managers, which could simultaneously affect CVC decisions.

This concern is mitigated by using a predetermined knowledge space formed along the corporate history (up to the year when $\Delta Innovation$ is calculated, i.e., $t-3$ in the main analysis) rather than the concurrent one. To further confirm that this concern is not driving the result, I construct the knowledge space of a firm i in year t based on its innovation profile in $t-10$. The possibility that managerial vision ten years ago still strongly affects CVC decisions today is thin. Using this instrument construction that better disentangles firms' knowledge spaces with concurrent decisions, the result still holds (presented in the Internet Appendix).

One might also worry that the firm itself could be a main driver of the technological evolution measured by citation dynamics. This concern is addressed first by excluding patents owned by the firm from its own knowledge space and then by excluding all citations made by the firm itself in the variable construction. It is mitigated further by a robustness check on a subsample of medium and small firms, which are less likely to endogenize technological evolution.

In Table 2, I report summary statistics for *Obsolescence*. The number of citations received by a firm's predetermined knowledge space decays by 8% in the control group, which can be interpreted as a mild three-year natural decay of knowledge. The knowledge space on average decays by 29% in the three years before a parent firm initiates its CVC arm, which demonstrate a much more severe hit by the technological evolution.

3.2.2 Empirical Strategy and Results

I exploit the instrument in a standard 2SLS framework. In the first stage, I instrument the change in innovation with $Obsolescence^{\tau}_{i,t}$ using the following form:

$$\Delta_{\tau}\widehat{Innovation}_{i,t-1} = \pi'_{0,industry\times t} + \pi'_{1} \times Obsolescence^{\tau}_{i,t-1} + \pi'_{2} \times X_{i,t-1} + \eta_{i,t-1}. \qquad (3)$$

The predicted change in innovation is then used in the second stage to deliver a consistent estimator, that is,

$$I(CVC)_{i,t} = \alpha_{industry\times t} + \beta \times \Delta_{\tau}\widehat{Innovation}_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}. \qquad (4)$$

Table 4 presents the estimation results of models (3) and (4). Column (1) reports a reduced-form regression in which *Obsolescence* is used to explain the decision to launch a CVC program. The positive coefficient 0.001 indicates that firms experiencing larger technological decays are more likely to initiate CVC activities.

Columns (2) and (4) report first-stage regressions where $\Delta Innovation$ (*Innovation* measured by the quantity and quality of new patents) is predicted using *Obsolescence*, and a larger *Obsolescence* (faster rate of technological decaying) is associated with poorer innovation performance. The estimate of -0.114 in column (2) translates a 10% increase in the rate of obsolescence of a firm's knowledge space into a 1.14% decrease in its patent applications; this same change is associated with a 1.28% decrease of its patent quality as measured by lifetime citations. The F-statistics of these first-stage regressions are both well above the conventional threshold for weak instruments (Stock and Yogo, 2005).

[TABLE 4 HERE]

Columns (3) and (5) show the second-stage estimation results. The key explanatory variables are now fitted innovation changes predicted from the first stage. The causal effect of innovation shocks on starting a CVC unit is both economically and statistically significant. The coefficient of -0.007 in column (2) translates a 2σ-change in $\Delta \ln(NewPatent)$ to a 52% change in the probability of launching CVC investment.

The gaps between the OLS estimates (in Table 3) and the 2SLS estimates are small. This comparison suggests that endogeneity issues are not biasing the OLS estimation in any clear direction on net. This does not mean, however, that no endogeneity issues are involved—as discussed above, competing endogenous forces could drive the OLS bias in either direction, mitigating the net effect. The Appendix shows that the result is robust to several sampling criteria, such as excluding the IT and Pharmaceutical sectors, excluding California-based firms, and excluding very big or very small firms.

3.2.3 Industry CVC Waves

In previous analyses that focus on firm-level evidence, I control for industry-by-year fixed effects to absorb potential confounding industry-specific time-variant trends. In this section, I look into this part of the variation by examining the industry-by-year pattern of CVC investment and how it speaks to the information acquisition view of CVC.

Existing CVC research documents that CVC investment clusters as waves and shows strong cyclicality (Gompers, 2002; Dushnitsky, 2006; Lerner, 2012). Figure 3 plots the time series of the instances of 381 CVCs studied in the sample. Both the number of launches of new CVC units and the number of deals invested are plotted. The graph highlights two waves—most CVC units were launched in either the early to mid-1980s or the later 1990s. More than 20 firms began CVC investments in each year from 1983 to 1986, and 72 firms started CVC units in 1999. CVC deals occurred in two similar waves: in the first wave, from 1983 to 1986, CVC units invested in 50 deals each year on average; this number was reached again 10 years later, in 1996, at the beginning of the second CVC wave.

[FIGURE 3 HERE]

Explanations for these waves emphasize macro-level factors (tax change, market condition, etc.) that do not directly speak to one important aspect that attracts less attention—CVC waves do not happen uniformly in each industry. That is, some industries waved in only one of the two periods, with little activity in the other. In Figure 4, the sample is broken down to produce a by-industry CVC investment graph. Four industries are presented—machinery, printing and publishing, business services (including IT), and pharmaceuticals. Two observations can be gleaned from these figures. First, CVC investments cluster not only at the aggregate level (as in Figure 3) but also at the industry level, and this industry-level clustering is what can be termed an "industry CVC wave." Second, and more important, different industries waved at different times.

[FIGURE 4 HERE]

To be more specific, most CVC investments in the machinery industry were made in the 1980s, but the industry was not heavily involved in the second aggregate CVC wave in the 1990s. In contrast, printing and publishing firms were relatively silent during the 1980s CVC wave but rode the second wave in the later 1990s. Even IT firms, the overall most active group in the CVC field, were relatively uninvolved in the first aggregate wave but invested aggressively in the second wave. The pharmaceutical industry, another highly active industry in CVC investments, was almost equally active during the two aggregate waves, and this industry continued investing even outside the waves (in contrast to most other industries). Table 5 Panel A compiles industry CVC wave periods, jointly defined using the clustering of CVC initiations and investment. I limit each wave period to at most four years. In general, most industries experience at least one wave period and more than 50% of the CVC investments were made during that short window.

[TABLE 5 HERE]

Despite that firm-level innovation deteriorations motivate individual firms to initiate CVC, those activities cluster while the industry experience an expansion of innovation knowledge. Table 5 Panel B presents that median quantity and quality of innovation improves before the emerge of CVCs. Combining this analysis with firm-level results shown in Table 3 and Table 4—CVC is more intensely used by those firms that are negatively shocked during a period when their own industry is experiencing a technological improvement and expansion.[10]

3.3 Additional Economic Forces and Robustness

Table 3 and Table 4 test the information acquisition view of CVC by examining the relation between CVC initiation decisions and the productivity of corporate innovation performance. An advantage of this analytical framework is its flexibility to be extended to study additional economic forces behind the innovation process, and this is the goal of this subsection.

Financial Returns. What is the role of financial condition in firms' decision to operate a CVC? On the one hand, anecdotal cases (e.g., Google, Intel) give us the impression that CVC is an investment channel for cash-rich firms to make equity investments in the startup market. In contrast, the structure and features of CVC investments could lead to the hypothesis that CVC could be poor-man's innovation, that is, declining firms are more financially constrained and cannot conduct internal R&D or M&As, which are on average more costly than CVC. In Table A.I of the Appendix, I show that the main result is robust on the subsample of firms whose KZ-index is below the industry median or whose cash-flow ratio is above the industry median (less financially constrained).

Managerial Desperation and "Gambling". Early research shows that desperate managers, after experiencing a negative shock, might aggressively seek outside solutions to the deterioration. In the CVC context, one could reasonably worry that the result simply documents that desperate managers are more likely to conduct CVC investment as a way to gamble for a quick recovery. Higgins and Rodriguez (2006) shows that this type

[10] In Internet Appendix, Table A.VI compiles a list of underlying technological and market shocks.

of “gambling” activities typically lead to unsuccessful outcomes. Following this logic, I investigate this issue by studying the success rate of portfolio companies invested by CVCs categorized by the severity of innovation declines at initiation. If the concern is indeed the case, we would expect CVC parents that experienced the largest hit before initiating to have lower performance because they likely made the decision out of desperation. In Table A.II, I find that those CVCs whose parents' performance decline the most actually score a similar, if not higher success rate compared to other CVCs.

More Robustness. To confirm that the results are not driven by the sampling process or specifications, I conduct an array of robustness checks. In the Appendix, I show that: the result is not sensitive to the length used to capture innovation changes ($\tau = 3$ in the paper); the result is robust to removing firms that are large/small, that are from specific industries (such as IT or pharmaceuticals), or that are located in specific locations (in California); and that the result also holds for deteriorations of product market performance such as ROA and growth rate in sales.

4 CVC Operations: Select, Acquire, and Integrate Information

Section 3 presents evidence consistent with the view that the information acquisition motive drives the initiation of the CVC life cycle, and discusses the role of other economic considerations in this decision. This section extends the exploration by focusing on the operation stage of the CVC life cycle—how CVCs select which portfolio companies to acquire valuable information from, and how they harvest the information spillover from those startups to benefit parent firms.

4.1 CVC Portfolio Formation

I start by examining how the selection of portfolio companies reflects the CVC information acquisition rationale. Selecting portfolio companies involves trading off multiple factors that determine the efficiency of information acquisition. The first consideration is the technological proximity between the parent firm and a startup. The conceptual idea is that investing in technologically proximate companies facilitates the process of absorbing and integrating information, therefore creating greater informational benefit (Cohen and Levinthal, 1990; Dushnitsky and Lenox, 2005b). The second factor is incremental informational value through investment. Indeed, investing in companies with very similar knowledge sets adds little marginal informational benefit, although it could be efficient for creating synergies (Bena and Li, 2014). The third determinant is the availability of alternative information acquisition channels. The working hypothesis is that CVC investors should pursue information that would be difficult to acquire without the CVC channel, that is, we should expect CVC investment to concentrate on companies with little informational communication otherwise.

4.1.1 Empirical Setting

To empirically analyze how these informational mechanisms affects CVC parents' portfolio company selection, I build a data set by pairing each CVC i with each entrepreneurial company j that was ever invested by a VC. I remove cases when the active investment years (between initiation and termination) of CVC firm i and the active financing years of company j (between the first and the last round of VC financing) do not overlap.

For each CVC-startup pair i-j, I construct three variables, *TechProximity*, *Overlap*, and *SameCZ*, which capture the informational relation between the two, echoing the three potential portfolio determinants outlined above.[11] I then estimate a probability model on this sample to predict the decision of CVC i investing in company j, that is,

$$\begin{aligned} I(CVC_i\text{-}Target_j) = \alpha &+ \beta_1 \times TechProximity_{ij} + \beta_2 \times Overlap_{ij} \\ &+ \beta_3 \times SameCZ_{ij} + \gamma \times X_{i,j} + \varepsilon_{ij}, \end{aligned} \tag{5}$$

where the dependent variable, $I(CVC_i\text{-}Target_j)$, indicates whether CVC i actually invests in company j.

The first measure, *Technological Proximity* (*TechProximity*), is calculated as the Cosine-

[11] The Appendix describes the methodology identifying innovation activities of entrepreneurs through merging patent data sets with VentureXpert and defines those variables more formally.

similarity between the CVC's and the startup's vectors of patent weights across different technology classes (Jaffe, 1986; Bena and Li, 2014). A higher *Technologial Proximity* indicates that the pair of firms works in closer areas in the technological space.

The second measure, *Knowledge Overlap* (*Overlap*), is calculated as the ratio of—(1) numerator: the number of patents that receive at least one citation from CVC firm *i and* one citation from entrepreneurial company *j*; and (2) denominator: the number of patents that receive at least one citation from either CVC *i or* company *j* (or both). A higher *Knowledge Overlap* means that the pair of firms shares broader common knowledge in their innovation.

To provide a clean interpretation of the estimation, both *Technological Proximity* and *Knowledge Overlap* are measured as of the last year before CVC *i* and company *j* both enter the VC-startup community. For example, if firm *i* initiates the CVC in 1995 but company *j* obtained its first round of financing in 1998, the measure is constructed using the patent profiles in 1997. The rationale for this criterion is to mitigate the potential interactions between CVCs and startups before investment.

To construct a proxy for the availability of alternative information acquisition channels, I rely on recent studies showing that geographic proximity influences the intensity of knowledge spillover between firms (Jaffe et al., 1993; Peri, 2005). The main variable is a dummy indicating whether CVC firm *i* and company *j* are located in the same Commuting Zone (CZ). I use CZ as the geographic delineation because it has been shown that CZ is more relevant for geographic economic activities (Autor, Dorn, and Hanson, 2013; Adelino, Ma, and Robinson, 2016) and innovation spillover (Matray, 2014). Projecting the information acquisition hypothesis on this context, we should expect that CVCs invest less in companies that are in the same geographic location, from which they could learn through the more inexpensive mechanism of local knowledge spillover.

4.1.2 Results

Table 6 presents coefficients estimated from model (5). In column (1), a positive and significant coefficient means that the *Technological Proximity* between a CVC and an entrepreneurial company increases the likelihood of CVC deal formation. This result is consistent with the interpretation that CVCs select companies from which they are more capable of absorbing knowledge for their core business.

[TABLE 6 HERE]

Column (2) examines the effect of *Knowledge Overlap*. The negative coefficient means that after conditioning on the technological proximity, CVC parent firms prefer to invest in companies with lower overlap in knowledge bases. In other words, CVCs select portfolio companies through which they are exposed to more new innovation knowledge. Importantly, this result could potentially distinguish the information acquisition rationale for CVC with the alternative rationale that CVC is conducted for product market synergies and asset complementarity. Under non-informational strategic concerns, firms favor targets with both close technological proximity and high knowledge overlap in order to achieve economic synergies (Bena and Li, 2014).

In column (3), I study the effect of alternative information acquisition channels, specifically knowledge spillover, on CVC portfolio selection. The literature on VC, and on investment more broadly, has documented a "home (local) bias" phenomenon—when investing in companies that are geographically closer, investors can better resolve the information asymmetry problem and conduct more efficient monitoring (Da Rin, Hellmann, and Puri, 2011). In column (3), however, I find that CVCs do not really invest in their "home" companies. The dummy variable indicating that the CVC and the startup are located in the same Commuting Zone negatively affects the probability of investment, which is consistent with the explanation that CVC parent firms can acquire information from startups in the same CZ through local innovation spillover (Matray, 2014), which decreases the marginal benefit of making a CVC investment in them.

Overall, Table 6 shows that CVCs strategically select information sources and invest in companies from which they could acquire beneficial information. They invest in companies that work in similar technological areas and possess knowledge new to the parent firm. They are less likely to invest in companies located in the same geographic areas from which they could gain information through inexpensive local knowledge spillover.

4.2 Internalizing Acquired Information

The rationale of information acquisition for CVC investment is convincing only if CVC parents can use newly gathered information to improve their operations. Several economic frictions could hinder CVCs from gathering and integrating information from startups, challenging the information acquisition rationale. Hellmann (2002) theoretically shows that entrepreneurs could intentionally avoid CVC investment to protect their innovation. Dushnitsky and Lenox (2005b) and Kim, Gopal, and Hoberg (2013) argue that the absorptive ability (Cohen and Levinthal, 1990) of CVC parent firms imposes a limit on the knowledge transferred through the relationship. Gompers and Lerner (2000) suggest that the efficiency of CVC is constrained by the incentive problem embedded in its organizational and compensation structure. In addition, high adjustment costs of R&D investment (Hall, Griliches, and Hausman, 1986; Lach and Schankerman, 1989) can decrease the speed and intensity of the integration of new knowledge acquired through CVC.

Showing how information is incorporated into corporate decisions can be challenging due to the invisible nature of information. Following the literature that uses patent citations as a measure of knowledge spillover, I study how CVC parent firms internalize acquired information into organic R&D by tracking patent citations made to their portfolio companies (Jaffe and Trajtenberg, 2002; Gomes-Casseres et al., 2006; Gonzalez-Uribe, 2013).[12] Empirically, I estimate whether CVC parent firm i makes new citations to startup company j's own patents (or possessed knowledge) after the CVC invests in the startup, using the following model:

$$\begin{aligned} Cite_{ijt} = \alpha + \beta \cdot I(CVCParent) \times I(Post) \times I(Portfolio) \\ + \Phi[I(CVCParent), I(Post), I(Portfolio)] + \varepsilon_{ijt}. \end{aligned} \tag{6}$$

To control for observed characteristics of CVC parents that could influence their behaviors in citing entrepreneurial companies, I construct a tighter control group for those firms.

[12] Alcacer and Gittelman (2006) and Gomes-Casseres et al. (2006), among others, discuss the advantages and potential pitfalls in using this approach.

I use a propensity score matching method and match each CVC parent firm i that launches its CVC unit with a non-CVC firms from its CVC launch year and 2-digit SIC industry that has the closest propensity score estimated using firm size (the logarithm of total assets), market-to-book ratio, $\Delta Innovation$, and the total number of patents applied for by the firm up to year $t-1$, similar to the sample construction strategy in Bena and Li (2014).

Observations are at the i-j-t level. The full set of i-j pairs then denotes the potential information flow that could happen between a CVC parent firm (or a matched firm) and a startup, captured by patent citations. $I(CVCParent)$ is a dummy variable indicating whether firm i is a CVC parent or a matched control firm. $I(Portfolio)$ indicates whether company j is in the CVC portfolio of firm i. For each i-j pair, two observations are constructed, one for the five-year window before firm i invests in company j, and one for the five-year window after the investment.[13] $I(Post)$ indicates whether the observation is within the five-year post-investment window. The dependent variable, $Cite_{ijt}$, indicates whether firm i makes new citations to company j's innovation knowledge during the corresponding time period.

[TABLE 7 HERE]

The key variable of interest, $I(CVCParent) \times I(Post) \times I(Portfolio)$, captures the incremental intensity of integrating a portfolio company's innovation knowledge into organic innovation after a CVC invests in the company. Table 7 column (1) shows the regression results. The coefficient of 0.173, means that the citing probability increases by 17.3% after establishing the link through CVC investment.

I further explore the depth of information acquisition from portfolio companies. Specifically, in column (3), I perform an analysis similar to that in column (1) except that I look at the probability that a CVC parent firm cites not only patents owned by the startup but also patents previously cited by the startup. In other words, the potential citation now covers the broader technological knowledge that the startup works upon (similar to the definition of knowledge in defining the instrument in (2)). Column (3) extends the message conveyed

[13] A matched control firm is assumed to have the same investment history as the CVC parent firm to which it is matched to.

in column (1)—CVC parent firms not only cite the portfolio company's own patents, but also benefit from the knowledge indirectly carried by portfolio companies, reaching to the broader knowledge behind.

Does information acquisition concentrate only on successful investment? I explore this question by modifying model (6) and separately estimate the intensity of citing knowledge possessed by companies that either exit successfully (acquired or publicly listed) or fail at last. The result is reported in columns (2) and (4), and it appears that CVC parents acquire knowledge from both successful and failed ventures.

Estimated coefficients of other terms in model (6) are useful for understanding several important patterns in the economic relationship. $I(CVCParent) \times I(Portfolio)$ is insignificant, meaning that before investing in a startup through CVC, a parent firm does not cite technologies of the startup at a higher rate compared to their matched controls, addressing the concern that CVC is incumbents' way of supporting startups that they already technologically rely on as opposed to acquiring information. This is also consistent with findings in Table 6 that the technological overlap of a CVC parent and its portfolio companies is small. $I(CVCParent) \times I(Post)$ is positive, suggesting that CVC parents in general move to an innovation strategy in which they incorporate more new knowledge in internal innovation, indirectly supporting the information acquisition rationale of CVC. But this magnitude is only 30% of the intensity of direct information acquisition from startups in their CVC portfolio.

4.3 Human Capital Renewal and CVC Information Acquisition

Evidence thus far suggests that CVC parent firms devote effort to integrating and using information acquired from the entrepreneurial sector. In this section, I identify one important channel that CVC parents actively manage to facilitate the information acquisition process: human capital renewal. Indeed, inventors, usually highly educated scientists and engineers, are key in absorbing, processing, and using information to produce innovation. Recent studies also find that firms actively reallocate innovative human resources to spur innovation and adjust the scope of innovation (Lacetera, Cockburn, and Henderson, 2004;

Bernstein, 2015; Brav, Jiang, Ma, and Tian, 2016).

I rely on the Harvard Business School patenting database for inventor-level information.[14] This database includes unique inventor identifiers that are constructed based on a refined disambiguation algorithm employing multiple characteristics (Lai, D'Amour, and Fleming, 2009). After matching inventors to employer firms, I track the employment history and annual patenting activities of each inventor.[15] Using a criterion similar to that in Bernstein (2015) and Brav et al. (2016), I identify inventors who leave the firm, stay in the firm, and newly hired in the firm. I also link each inventor to her/his history of patenting.

[TABLE 8 HERE]

I start by examining the intensity of human resource adjustment around the years of initiating CVC investment. The analysis is performed on the same firm-year panel of CVC firms and their propensity score-matched controls. In Table 8 Panel A, I study the number of inventors leaving the firm (columns (1) and (2)) and the number of inventors newly hired by the firm (columns (3) and (4)). The coefficient, 0.119 in column (1), can be interpreted as showing that CVC parent firms have 11.9% more inventors leaving the firm (leavers) than in the period before CVC investment. The vacancies created by leavers are filled by newly hired inventors; the 0.110 estimated in column (3) means that CVC parents hire about 11% more new inventors compared to the years before CVC investment, benchmarked by their industry peers.

Is those new blood crucial for the firm? In columns (5) and (6), I examine the proportion of patents mainly contributed by inventors new to the firm. A patent is considered as "mainly contributed by new inventors" if at least half of the patent's inventor team have three or fewer years of patenting experience in the firm as of the patent application year. The positive coefficient of 17.1% in column (5) means that CVC parent firms rely more

[14] Available at: `http://dvn.iq.harvard.edu/dvn/dv/patent`.

[15] One limitation of this analysis is that inventor mobility is detected conditional on new patent filings; the observed mobility is thus associated with inventors who patent more frequently. But at any rate, these people should be those who are economically more important to the firm. See Bernstein (2015) for a detailed discussion of the limitations associated with this database.

heavily on new inventors when operating a CVC, consistent with the proposition that firms hire new inventors to process new information and produce innovation.

Table 8 Panel B presents new inventors' intensity of incorporating new knowledge. The patent-level sample consists of all the patents produced by CVC parent firms and their matched control firms from five years before the event to five years after it. Beyond the standard terms $I(CVCParents)_i$ and $I(Post)_{i,t}$, I introduce an indicator variable $I_{\text{New Inventor's Pat}}$ that equals one if new inventors contribute at least half of the patent and zero otherwise. The unconditional effect of $I_{\text{New Inventor's Pat}}$ is positive, meaning that patents produced by firms' new inventors typically incorporate more knowledge new to the firm. Meanwhile, the interaction term $I(CVCParents) \times I(Post)$ is associated with higher *New Cite Ratio*, suggesting that CVC parents are able to increase their use of new knowledge in innovation in general. A key result in this table is the positive coefficient associated with the triple difference $I_{\text{New Inventors' Pat}} \times I(CVCParent) \times I(Post)$, which implies that new inventors in CVC parent firms concentrate more heavily on processing and integrating new information and innovation knowledge. In column (2), I focus on the cross-sectional sample of all patents produced by CVC parent firms during the five-year window after CVC initiation (that is, $I(CVCParents) = I(Post) = 1$) and find that newly hired inventors are more likely to use knowledge acquired from CVC portfolio companies in their new innovation.

5 CVC Terminations: Staying Power and Investment Dynamics

In a frictionless world, CVC parents would want to keep investing in CVC to acquire information from entrepreneurs. With frictions, however, CVC could become less appealing as the parent firm's internal innovation recovers. For example, a capacity-constrained firm will allocate less resources to information acquisition yet more to innovation production once the internal innovation becomes more premising (Nelson, 1982; Jovanovic and Rob, 1989). In addition, the cannibalization concern (Arrow, 1962) will disincentivize innovative incumbents to search for newer ideas that will replace the existing ones, and this effect could be particularly large, with high adjustment cost and organizational complexity. Overall, as firms assimilate information into their innovation decisions and begin to have an upward innovation trajectory, the benefit of keeping a standalone CVC unit shrinks. In this scenario, CVC investment may fade out as internal innovation recovers and firms devote more resources to this regained innovation path. This section examines this implication of the information acquisition hypothesis by focusing on the termination stage of the CVC life cycle.

Importantly, looking at the termination stage provides further opportunities to distinguish the dominating strategic motivation behind CVC investment.[16] Under other possible CVC rationales, CVC remains advantageous in organizing innovation due to its superior ability to obtain asset complementarity (Hellmann, 2002), motivate entrepreneurs (Aghion and Tirole, 1994; Chemmanur, Loutskina, and Tian, 2014), and obtain competitive advantages (Mathews, 2006; Fulghieri and Sevilir, 2009). Even though these studies focus primarily on static trade-offs and do not concern intertemporal dynamics, they implicitly imply that firms might invest persistently in CVCs for long periods of time.

5.1 The Staying Power of Corporate Venture Capital

I start by examining the staying power of Corporate Venture Capital. To do so, it is necessary to define the date of terminating each CVC unit, which is not widely disclosed. When this termination date is not available, I define it as the date of the CVC's last investment in a portfolio company. As a result, the staying power analysis could underestimate the duration of CVCs, particularly toward the end of the sample. To mitigate bias, I categorize a CVC unit as "active" if its last investment happened after 2012 (as of March 2015) and VentureXpert codes its investment status as "Actively seeking new investments," and I exclude those active CVCs from the analysis. The duration of a CVC cycle is calculated as the period between the initiation and termination of the division.

[TABLE 9 HERE]

[16]This is in the same spirit as Kaplan (1991), where the staying power is powerful to examine the economic motivation behind leveraged buyouts.

Table 9 tabulates the duration of CVC divisions. The median duration of a CVC is four years, and a significant portion (46%) of CVCs actively invest for three years or less,[17] lending support to the argument that the benefit from CVC investment shrinks as information is assimilated. Around 27% of firms operate CVCs for a long period (more than 10 years). To understand why this is so, I report the median number of total and longest consecutive years that a CVC is put into hibernation, defined as a year when no incremental investment was made. When the CVC duration is short, the years between initiation and termination are mostly active. As their duration increases, an increasing proportion of years are under hibernation. When I examine these hibernation periods, I find a pattern of consecutive hibernating years—for example, CVCs with eight-year durations have a median of four years of consecutive hibernation. In other words, these CVCs typically have a lengthy pause in their CVC experience, bridging two shorter active periods of investment.

One might conclude that the short average CVC life cycle indicates that some CVC parent firms are incompetent in the VC business and thus terminate their CVC divisions too quickly. To rule out this concern, in the last column of Table 9, I calculate the success rate of deals invested by CVCs categorized by CVC durations. An investment deal is defined as a "success" if the entrepreneurial company was acquired or went public (I exclude cases when the company is still alive without a successful exit). Success rates of investments do not correlate with CVC duration, inconsistent with the idea of CVC incompetence.

5.2 Innovation Improvements and CVC Termination

What determines the termination and hibernation of CVCs? To echo Table 3, which shows that innovation deterioration motivates CVC initiations, I conclude my analysis of the CVC life cycle by examining corporate innovation at termination. Table 10 Panel A performs simple statistical tests that compare innovation levels at the initiation and termination of the CVC life cycle. The analysis is performed on all CVCs that can be

[17] They certainly could interact with their portfolio companies for longer periods of time after terminating incremental investment.

assigned a termination date (upper panel) and on the subgroup that stayed in business for at least five years. When examining the industry-year adjusted innovation measures, we observe statistically significant improvements at the CVC termination point compared to the initiation stage.

[TABLE 10 HERE]

I exploit a hazard model to statistically relate innovation improvements and the decision to terminate a CVC. A CVC parent firm enters the sample in the year of CVC initiation. The key variable of interest is $\Delta Innovation$, which measures the difference between innovation level in year t and that of the initiation year. The coefficients estimated from the model are shown in columns (1) and (2) of Table 10 Panel B. The positive and significant coefficients mean that larger improvements of innovation from the initiation year motivate parent firms to terminate CVC investment. The hazard ratio, calculated as the exponential of the estimated coefficients, are also presented in a separate row.

To capture how innovation improvements affect the decision to put CVC into hibernation, I investigate the intensive margin of CVC investment—the number of portfolio companies a CVC invests in each year and the key variables of interests, $\Delta Innovation$, are defined as above. Columns (3) and (4) present the results, and the findings are consistent with columns (1) and (2)—innovation improvements are associated with a lower level of CVC activities.

Overall, Table 10 matches the finding at the initiation stage, and is consistent with the information acquisition hypothesis, which predicts that when firms regain their upward trajectory in corporate innovation, the marginal informational benefit of CVC shrinks, which in turn leads to the termination or hibernation of the CVC unit.

6 Concluding Remarks

How do corporations finance and manage their innovation process in the pursuit of long-term growth? This paper sheds light on this fundamental question by studying an emerging economic phenomenon, Corporate Venture Capital (CVC). Armed with an identification strategy that allows me to isolate firm-specific innovation shocks, I find that firms initiate CVC programs following a deterioration in innovation, and their main motivation is to acquire information and innovation knowledge from the entrepreneurial sector. This information acquisition rationale leads me to further characterize the operation and termination stages of the CVC life cycle, in which CVC parent firms strategically select information sources (portfolio companies), actively integrate newly acquired information into corporate decisions, and terminate CVCs when the informational benefit diminishes.

Beyond establishing the CVC life cycle and the information acquisition rationale behind, the paper is a stepping stone toward understanding several broad economic questions.

Organizing Innovation. This paper joins the endeavor to understand the architecture of innovation and contributes to this literature by suggesting three areas for future work. First, more research should be done to achieve a better understanding of details in CVC operations. Second, the information acquisition motive behind organizing innovation, which I highlight in this paper, has been largely overlooked in the literature (Tirole, 2010) but is worth further exploration. Third, the interaction between CVC investment and alternative organizational forms considered here calls for future studies that could consider the system of organizing innovation as a whole by seriously incorporating the interactions among different organizational structures and a dynamic intertemporal scope.

Information Economics. Information is important in all areas of finance, yet information choices have been hard to study both theoretically and empirically. Empirical work on corporate decisions regarding information management is especially limited by the unobservability of related behaviors. By examining the CVC life cycle and innovation process, this paper obtains several results regarding information acquisition and use that are hard to show under alternative settings. Future work could explore the CVC setting to answer more questions at the intersection of information economics and corporate finance.

Creative Destruction. In broader terms, this paper provides new evidence concerning the co-movement of entrepreneurship, creative destruction, and economic growth. Entrepreneurial companies and incumbent firms differ in their ability to develop radical and disruptive innovation and to capture new investment opportunities (Hall, 1993; Henderson, 1993; Jensen, 1993; Adelino, Ma, and Robinson, 2016; Acemoglu and Cao, 2015), and this difference generates the creative destruction momentum. By highlighting CVC as an effective incumbent-entrepreneur bridge, this paper essentially suggests that the two seemingly disentangled sectors could be closely intertwined, which in turn affects both micro-level corporate behaviors and the aggregate process of creative destruction.

References

Acemoglu, Daron, and Dan Cao, 2015, Innovation by entrants and incumbents, *Journal of Economic Theory* 157, 255–294.

Acs, Zoltan J., and David B. Audretsch, 1988, Innovation in large and small firms: an empirical analysis, *American Economic Review* 678–690.

Adelino, Manuel, Song Ma, and David T. Robinson, 2016, Firm age, investment opportunities, and job creation, *Journal of Finance* Forthcoming.

Aghion, Philippe, and Jean Tirole, 1994, The management of innovation, *Quarterly Journal of Economics* 109, 1185–1209.

Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood, 2016, Buy, keep, or sell: Economic growth and the market for ideas, *Econometrica* 84, 943–984.

Alcacer, Juan, and Michelle Gittelman, 2006, Patent citations as a measure of knowledge flows: The influence of examiner citations, *Review of Economics and Statistics* 88, 774–779.

Arrow, Kenneth, 1962, Economic welfare and the allocation of resources for invention, in *The rate and direction of inventive activity: Economic and social factors*, 609–626 (Princeton University Press: Princeton, NJ).

Autor, David H, David Dorn, and Gordon H. Hanson, 2013, The china syndrome: Local labor market effects of import competition in the united states, *American Economic Review* 103, 2121–2168.

Basu, Sandip, Corey Phelps, and Suresh Kotha, 2011, Towards understanding who makes corporate venture capital investments and why, *Journal of Business Venturing* 26, 153–171.

Bena, Jan, and Kai Li, 2014, Corporate innovations and mergers and acquisitions, *Journal of Finance* 69, 1923–1960.

Benson, David, and Rosemarie H. Ziedonis, 2010, Corporate venture capital and the returns to acquiring portfolio companies, *Journal of Financial Economics* 98, 478–499.

Bernstein, Shai, 2015, Does going public affect innovation?, *Journal of Finance* 70, 1365–1403.

Bernstein, Shai, Xavier Giroud, and Richard R. Townsend, 2014, The impact of venture capital monitoring: Evidence from a natural experiment, *Rock Center for Corporate Governance at Stanford University Working Paper* .

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, 2013, Identifying technology spillovers and product market rivalry, *Econometrica* 81, 1347–1393.

Bottazzi, Laura, Marco Da Rin, and Thomas Hellmann, 2004, The changing face of the european venture capital industry: Facts and analysis, *Journal of Private Equity* 7, 26–53.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, 2016, How does hedge fund activism reshape corporate innovation, *Available at SSRN 2409404* .

Brown, James R, Steven M Fazzari, and Bruce C Petersen, 2009, Financing innovation and growth: Cash flow, external equity, and the 1990s r&d boom, *Journal of Finance* 64, 151–185.

Ceccagnoli, Marco, Matthew J Higgins, and Hyunsung D Kang, 2015, Corporate venture capital as a real option in the markets for technology .

Chemmanur, Thomas J, Elena Loutskina, and Xuan Tian, 2014, Corporate venture capital, value creation, and innovation, *Review of Financial Studies* 27, 2434–2473.

Christiansen, Clayton, 1997, The innovator's dilemma, *Harvard Business School Press, Boston* .

Cohen, Wesley M., and Daniel A. Levinthal, 1990, Absorptive capacity: a new perspective on learning and innovation, *Administrative science quarterly* 128–152.

Cumming, Douglas, and Na Dai, 2010, Local bias in venture capital investments, *Journal of Empirical Finance* 17, 362–380.

Da Rin, Marco, Thomas F Hellmann, and Manju Puri, 2011, A survey of venture capital research .

Dimitrova, Lora, 2013, Strategic acquisitions by corporate venture capital investors .

Dosi, Giovanni, 1988, Sources, procedures, and microeconomic effects of innovation, *Journal of Economic Literature* 1120–1171.

Dushnitsky, Gary, 2006, *Corporate venture capital: past evidence and future directions* (Oxford University Press: Oxford, UK).

Dushnitsky, Gary, and Michael J. Lenox, 2005a, When do firms undertake r&d by investing in new ventures?, *Strategic Management Journal* 26, 947–965.

Dushnitsky, Gary, and Michael J. Lenox, 2005b, When do incumbents learn from entrepreneurial ventures?: Corporate venture capital and investing firm innovation rates, *Research Policy* 34, 615–639.

Dushnitsky, Gary, and Michael J. Lenox, 2006, When does corporate venture capital investment create firm value?, *Journal of Business Venturing* 21, 753–772.

Fast, Norman D, 1978, *The rise and fall of corporate new venture divisions*, volume 977 (UMI Research Press Ann Arbor, MI).

Fast, Norman David, 1977, *The evolution of corporate new venture divisions*, Ph.D. thesis, Harvard University.

Fleming, Lee, and Olav Sorenson, 2004, Science as a map in technological search, *Strategic Management Journal* 25, 909–928.

Frydman, Carola, and Dimitris Papanikolaou, 2015, In search of ideas: Technological innovation and executive pay inequality .

Fulghieri, Paolo, and Merih Sevilir, 2009, Organization and financing of innovation, and the choice between corporate and independent venture capital, *Journal of Financial and Quantitative Analysis* 44, 1291.

Gomes-Casseres, Benjamin, John Hagedoorn, and Adam B. Jaffe, 2006, Do alliances promote knowledge flows?, *Journal of Financial Economics* 80, 5–33.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate governance and equity prices, *The Quarterly Journal of Economics* 107–155.

Gompers, Paul, and Josh Lerner, 2000, *The determinants of corporate venture capital success: Organizational structure, incentives, and complementarities*, 17–54 (University of Chicago Press).

Gompers, Paul A., 2002, Corporations and the financing of innovation: the corporate venturing experience, *Economic Review–Federal Reserve Bank of Atlanta* 87, 1–18.

Gonzalez-Uribe, Juanita, 2013, *Venture Capital and Innovation*, Ph.D. thesis, Columbia University.

Hall, Bronwyn H, 1993, The stock market's valuation of r&d investment during the 1980's, *American Economic Review* 259–264.

Hall, Bronwyn H., Zvi Griliches, and Jerry A. Hausman, 1986, Patents and r&d: Is there a lag?, *International Economic Review* 265–283.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The nber patent citation data file: Lessons, insights and methodological tools .

Harford, Jarrad, 2005, What drives merger waves?, *Journal of Financial Economics* 77, 529–560.

Hellmann, Thomas, 2002, A theory of strategic venture investing, *Journal of Financial Economics* 64, 285–314.

Hellmann, Thomas, Laura Lindsey, and Manju Puri, 2008, Building relationships early: Banks in venture capital, *Review of Financial Studies* 21, 513–541.

Henderson, Rebecca, 1993, Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry, *RAND Journal of Economics* 248–270.

Higgins, Matthew J, and Daniel Rodriguez, 2006, The outsourcing of r&d through acquisitions in the pharmaceutical industry, *Journal of Financial Economics* 80, 351–383.

Hochberg, Yael V, and Joshua D Rauh, 2012, Local overweighting and underperformance: evidence from limited partner private equity investments, *Review of Financial Studies* hhs128.

Igami, Mitsuru, 2014, Estimating the innovator's dilemma: Structural analysis of creative destruction in the hard disk drive industry, *Available at SSRN 1733174* .

Jaffe, Adam B., 1986, Technological opportunity and spillovers of r & d: Evidence from firms' patents, profits, and market value, *American Economic Review* 984–1001.

Jaffe, Adam B., and Manuel Trajtenberg, 2002, *Patents, citations, and innovations: A window on the knowledge economy* (MIT Press: Cambridge, MA).

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson, 1993, Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics* 577–598.

Jensen, Michael C., 1993, The modern industrial revolution, exit, and the failure of internal control systems, *Journal of Finance* 48, 831–880.

Jones, Benjamin F, 2009, The burden of knowledge and the death of the renaissance man: is innovation getting harder?, *Review of Economic Studies* 76, 283–317.

Jovanovic, Boyan, and Rafael Rob, 1989, The growth and diffusion of knowledge, *Review of Economic Studies* 56, 569–582.

Kaplan, Steven N, 1991, The staying power of leveraged buyouts, *Journal of Financial Economics* 29, 287–313.

Kim, Keongtae, Anandasivam Gopal, and Gerard Hoberg, 2013, Product market competition and corporate venture capital investment in the it industry: An empirical analysis, *Available at SSRN 2259967* .

Kortum, Samuel, and Josh Lerner, 2000, Assessing the contribution of venture capital to innovation, *RAND Journal of Economics* 674–692.

Kortum, Samuel S, 1997, Research, patenting, and technological change, *Econometrica* 1389–1419.

Lacetera, Nicola, Iain M Cockburn, and Rebecca Henderson, 2004, Do firms change capabilities by hiring new people? a study of the adoption of science-based drug discovery, *Advances in strategic management* 21, 133–160.

Lach, Saul, and Mark Schankerman, 1989, Dynamics of r & d and investment in the scientific sector, *Journal of Political Economy* 880–904.

Lai, Ronald, Alexander D'Amour, and Lee Fleming, 2009, The careers and co-authorship networks of us patent-holders since 1975 .

Lerner, Josh, 2012, *The architecture of innovation: The economics of creative organizations* (Harvard Business Press).

Lerner, Josh, and Amit Seru, 2015, The use and misuse of patent data: Issues for corporate finance and beyond, *Booth/Harvard Business School Working Paper* .

Macmillan, Ian, E Roberts, V Livada, and A Wang, 2008, Corporate venture capital (cvc) seeking innovation and strategic growth. recent patterns in cvc mission, structure, and investment, *NIST GCR* 08–96.

Manso, Gustavo, 2011, Motivating innovation, *Journal of Finance* 66, 1823–1860.

Mathews, Richmond D., 2006, Strategic alliances, equity stakes, and entry deterrence, *Journal of Financial Economics* 80, 35–79.

Matray, Adrien, 2014, *Essays in Empirical Corporate Finance*, Ph.D. thesis, Jouy-en Josas, HEC.

Maula, Markku VJ, 2007, 15 corporate venture capital as a strategic tool for corporations, *Handbook of research on venture capital* 371.

Mitchell, Mark L., and Harold J. Mulherin, 1996, The impact of industry shocks on takeover and restructuring activity, *Journal of Financial Economics* 41, 193–229.

Nelson, Richard R, 1982, The role of knowledge in r&d efficiency, *Quarterly Journal of Economics* 453–470.

Nelson, Richard R, and Sidney G Winter, 1982, *An evolutionary theory of economic change* (Harvard University Press: Cambridge, MA).

Peri, Giovanni, 2005, Determinants of knowledge flows and their effect on innovation, *Review of Economics and Statistics* 87, 308–322.

Rhodes-Kropf, Matthew, David T. Robinson, and S. Viswanathan, 2005, Valuation waves and merger activity: The empirical evidence, *Journal of Financial Economics* 77, 561–603.

Robinson, David T., 2008, Strategic alliances and the boundaries of the firm, *Review of Financial Studies* 21, 649–681.

Scherer, Frederic M., 1965, Firm size, market structure, opportunity, and the output of patented inventions, *American Economic Review* 1097–1125.

Seru, Amit, 2014, Firm boundaries matter: Evidence from conglomerates and r&d activity, *Journal of Financial Economics* 111, 381–405.

Siegel, Robin, Eric Siegel, and Ian C. MacMillan, 1988, Corporate venture capitalists: Autonomy, obstacles, and performance, *Journal of Business Venturing* 3, 233–247.

Stock, James H, and Motohiro Yogo, 2005, Testing for weak instruments in linear iv regression, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* 80.

Sunder, Jayanthi, Shyam V. Sunder, and Jingjing Zhang, 2014, Ceo sensation seeking and corporate innovation, *Available at SSRN 2474909* .

Telser, Lester G, 1982, A theory of innovation and its effects, *The Bell Journal of Economics* 69–92.

Tirole, Jean, 2010, *The theory of corporate finance* (Princeton University Press: Princeton, NJ).

Wadhwa, Anu, Corey Phelps, and Suresh Kotha, 2015, Corporate venture capital portfolios and firm innovation, *Journal of Business Venturing, Forthcoming* .

Zingales, Luigi, 2000, In search of new foundations, *Journal of Finance* 55, 1623–1653.

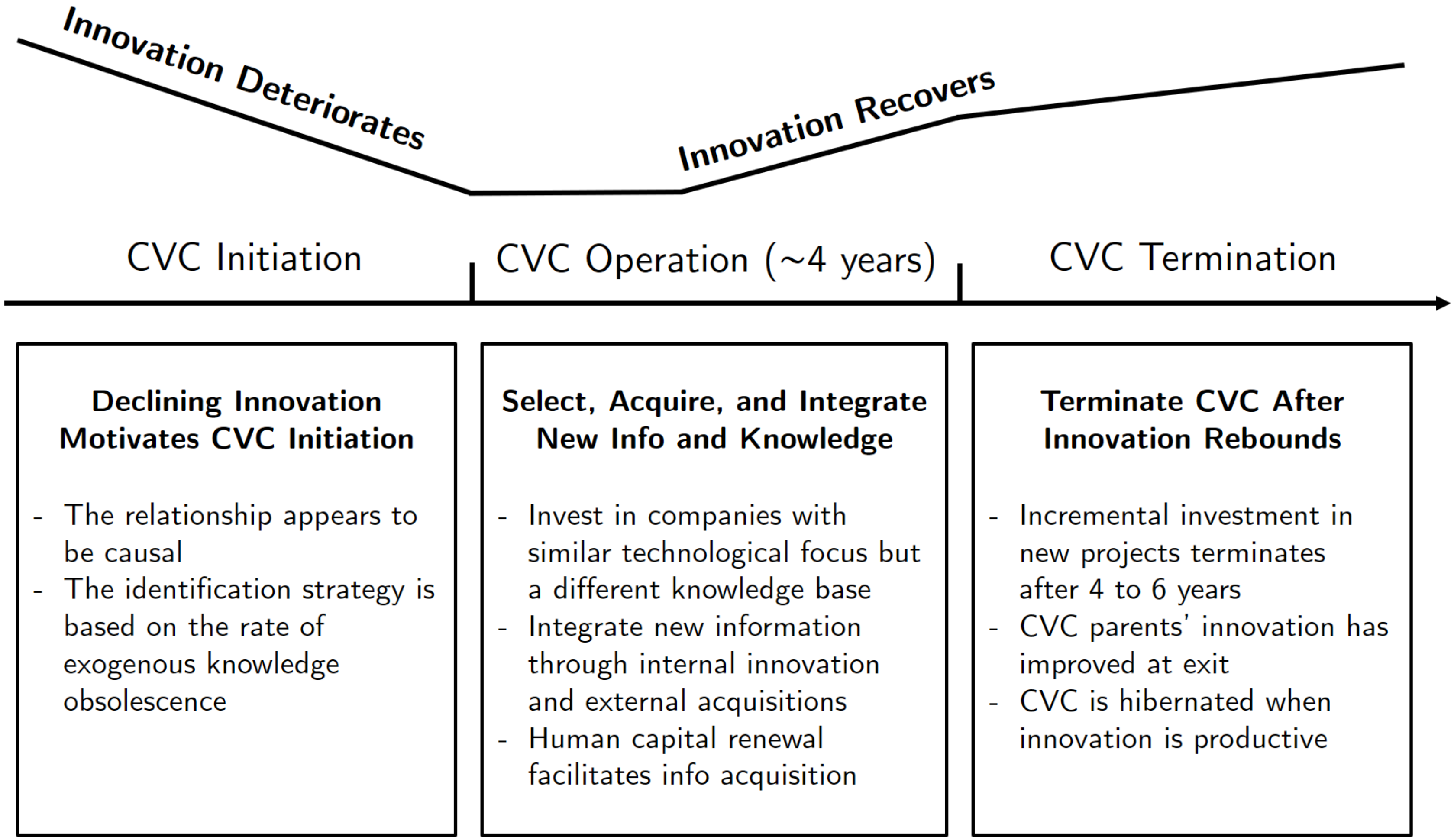
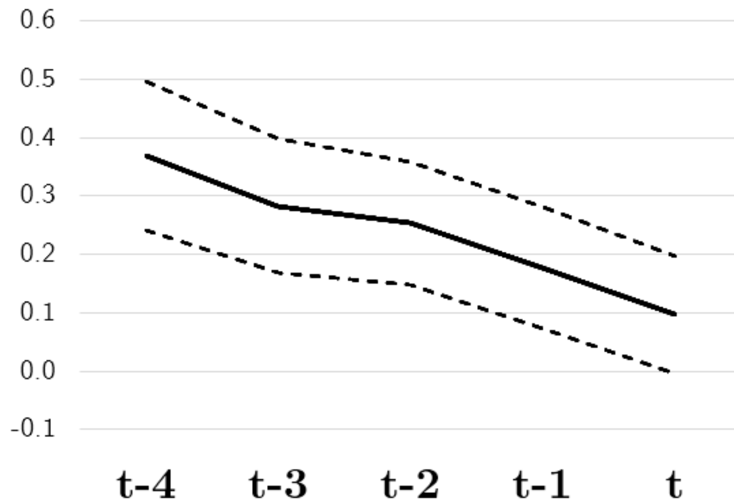
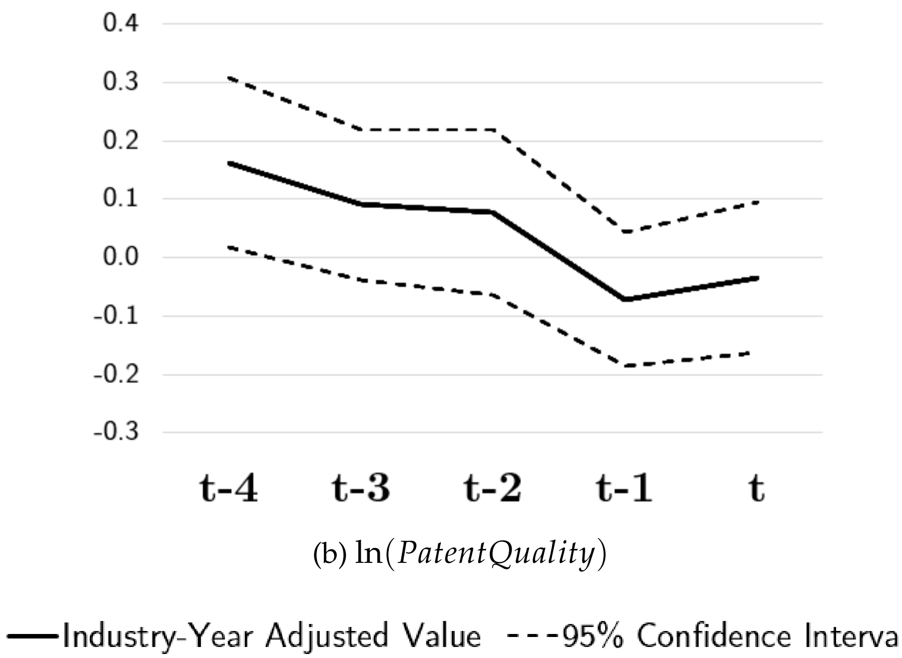


Figure 1: The Life Cycle of Corporate Venture Capital



(a) $\ln(NewPatents)$



(b) $\ln(PatentQuality)$

Figure 2: Corporate Innovation before CVC Initiations

This figure tracks corporate innovation dynamics of CVC parents before the initiation of their CVC units. $\ln(NewPatent)$ is the logarithm of the number of new patents applied by a firm in each year plus one. $\ln(PatentQuality)$ is the logarithm of average lifetime citations of new patents plus one. Each measure is adjusted by the mean of firms in the same year and industry (3-digit SIC level). The graph starts from four years before a CVC parent firm launches its CVC unit (i.e., $t-4$) and ends in the year of launching (t). 95% confidence intervals are plotted in dotted lines.

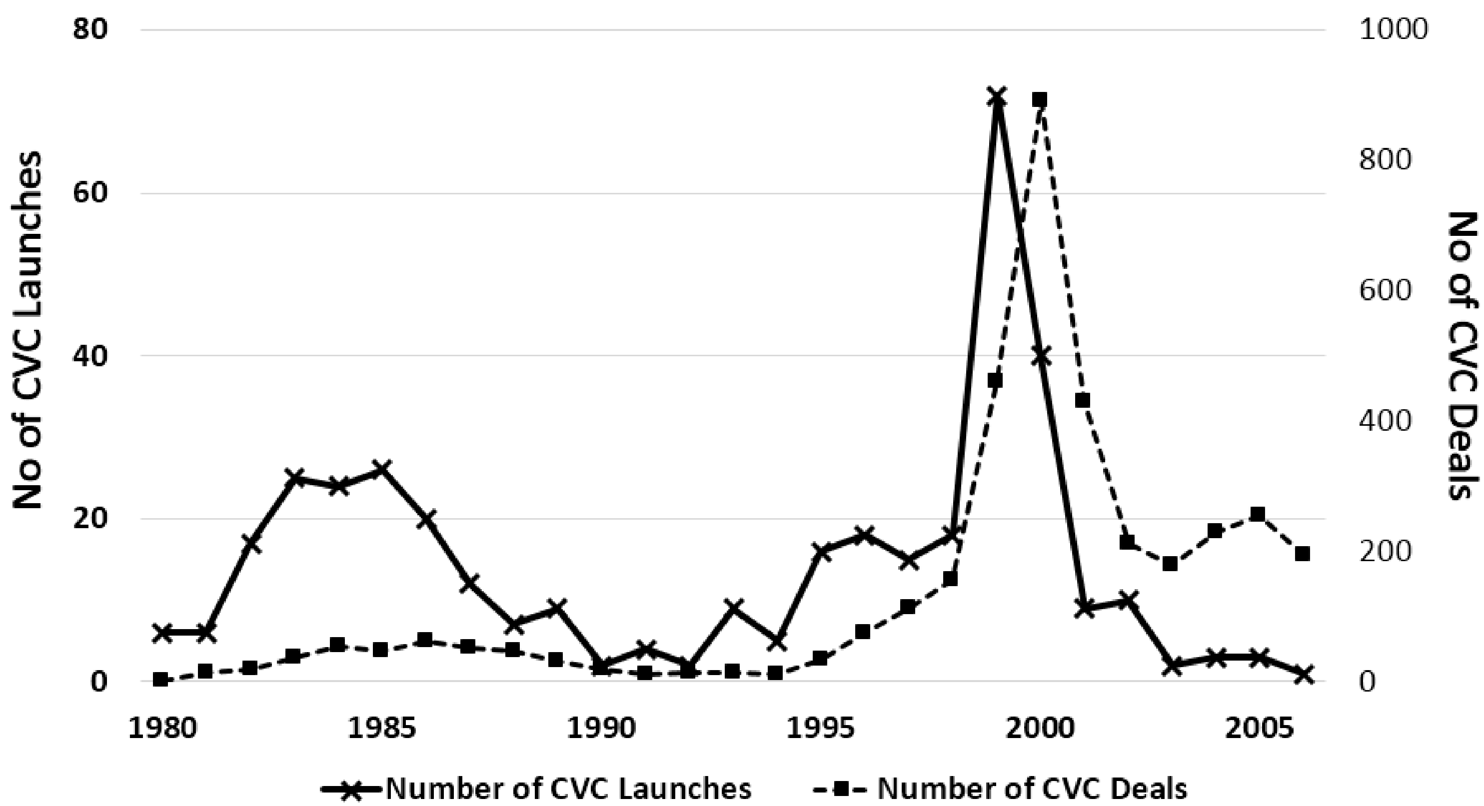
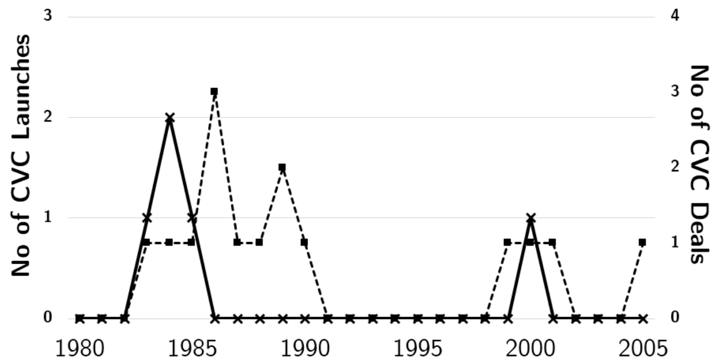
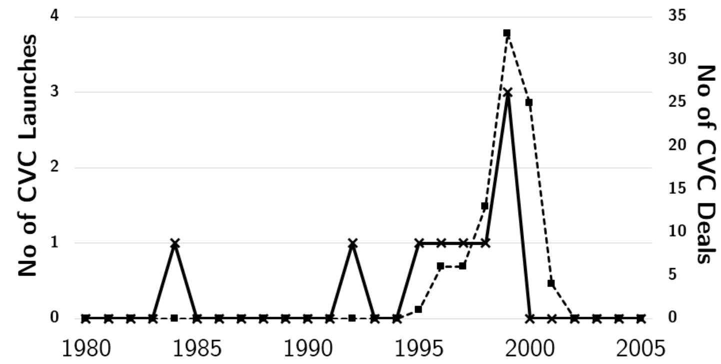


Figure 3: Time Series of CVC Investment

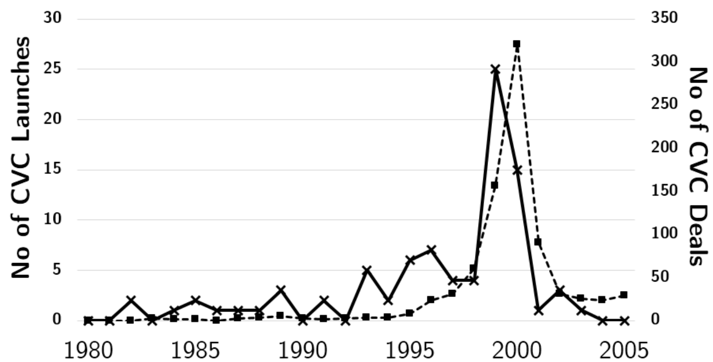
This figure plots the time series of CVC investments covered in the sample. These are CVCs affiliated to US public non-financial firms that were started between 1980 and 2006. The CVC data are from the VentureXpert Venture Capital Firm Database, accessed through Thomson Reuters SDC Platinum. CVC investment is measured as the launch of new CVC units (left axis) and the number of deals invested in (right axis). CVC deals include only the first investment that a CVC invest in a portfolio company.



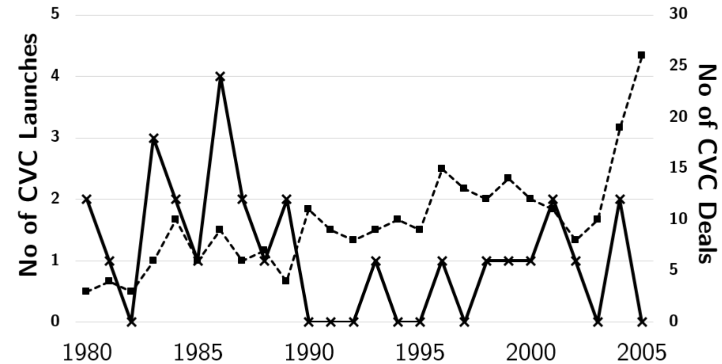
(a) Machinery Industry



(b) Printing and Publishing Industry



(c) IT Industry



(d) Pharmaceutical Industry

Number of CVC Launches — Number of CVC Deals

Figure 4: Time Series of CVC Investment—By Industry

This figure plots the by-industry time series of CVC investments covered in the sample. These are CVCs affiliated to US public non-financial firms that were started between 1980 and 2006. The CVC data are from the VentureXpert Venture Capital Firm Database, accessed through Thomson Reuters SDC Platinum. CVC investment is measured as the launch of new CVC units (left axis) and the number of deals invested in (right axis). CVC deals include only the first investment that a CVC invested in a portfolio company. Industries are classified by the Fama-French 48 Industry Classfications, based on the main SIC code of a firm reported in Compustat.

Table 1: Summary Statistics of the CVC Sample

This table provides descriptive statistics on Corporate Venture Capital activities by year (Panel A) and by industry (Panel B). CVCs are identified from the VentureXpert Venture Capital Firm Database, accessed through Thomson Reuters SDC Platinum, and are hand-matched to their unique corporate parent firms. CVC parent firms in the sample are US-based public non-financial firms. Panel A reports the annual number of CVC initiations and investment (deals) between 1980 and 2006. Panel B reports the industry distribution of CVC activities, where industries are defined by the Fama-French 48 Industry Classification.

Panel A: CVC Activities by Year

Year	No. of Launches	No. of Deals	Year	No. of Launches	No. of Deals	Year	No. of Launches	No. of Deals
1980	6	2	1989	9	32	1998	18	155
1981	6	14	1990	2	18	1999	72	460
1982	17	18	1991	4	11	2000	40	891
1983	25	37	1992	2	14	2001	9	430
1984	24	54	1993	9	14	2002	10	211
1985	26	46	1994	5	11	2003	2	179
1986	20	63	1995	16	33	2004	3	229
1987	12	51	1996	18	74	2005	3	255
1988	7	46	1997	15	112	2006	1	194

Panel B: CVC Activities by Industry (Fama-French 48 Industry Classification)

Industry	**No. of CVCs**	**No. of Deals**	**Industry**	**No. of CVCs**	**No. of Deals**
Agriculture	2	21	Shipbuilding, Railroad Equipment	1	5
Food Products	2	4	Defense	1	11
Tobacco Products	1	6	Non-Metallic and Industrial Metal Minin	1	6
Entertainment	2	114	Coal	1	4
Printing and Publishing	9	88	Petroleum and Natural Gas	8	10
Consumer Goods	4	48	Utilities	9	48
Healthcare	4	28	Communication	40	120
Medical Equipment	7	109	Business Services	90	821
Pharmaceutical Products	28	254	Computers	44	617
Chemicals	11	48	Electronic Equipment	46	921
Rubber and Plastic Products	2	7	Measuring and Control Equipment	4	32
Textiles	1	2	Business Supplies	2	10
Construction Materials	4	7	Shipping Containers	1	2
Steel Works Etc.	3	15	Transportation	3	9
Machinery	5	15	Wholesale	10	87
Electrical Equipment	9	44	Retail	14	79
Automobiles and Trucks	6	42	Restaurants, Hotels, Motels	4	13
Aircraft	2	7			

Table 2: Summary Statistics of the Regression Sample

This table summarizes firm characteristics at the firm-year level. CVC observations ($I(CVC)_{i,t} = 1$) are those when firm i launched a CVC division in year t (and those firms are categorized as non-CVC observations in other years). The CVC sample is defined in Table 1. Observations are required to have valid ROA, size (logarithm of total assets), leverage, R&D ratio (R&D expenditures scaled by total assets), and with at least $10 million in book assets, and variables are winsorized at the 1% and 99% levels to remove influential outliers. A firm is included in the panel sample only after it filed a patent application that was eventually granted by the USPTO. Industries (3-digit SIC) that did not involve any CVC activities during the sample period are removed. For each variable, mean, median, and standard deviation are reported. Variable definitions are provided in the Appendix.

	$I(CVC)_{i,t} = 0$			$I(CVC)_{i,t} = 1$		
	Mean	Median	S.D.	Mean	Median	S.D.
$\Delta \ln(NewPatent)$	0.12	0.07	0.52	-0.07	-0.05	0.61
$\Delta \ln(Pat.Quality)$	0.08	0.13	1.25	-0.10	-0.11	1.14
Obsolescence	0.08	0.00	0.41	0.29	0.21	0.54
New Patents	20.15	1.00	70.58	50.35	1.00	128.27
Patent Citations	21.03	7.26	29.80	15.46	2.64	32.81
Firm R&D	0.09	0.05	0.11	0.07	0.06	0.07
Firm ROA	0.06	0.10	0.24	0.03	0.08	0.21
Total Assets (Million)	2884.93	195.27	9325.25	10177.02	2430.89	17049.50
M/B	2.87	1.94	2.33	2.68	1.83	2.58
Leverage	0.19	0.15	0.18	0.20	0.17	0.19
Cash Flow	0.11	0.09	0.10	0.12	0.11	0.15
G-Index	9.09	9.00	2.74	9.13	9.00	2.39
Institutional Shareholding	0.24	0.23	0.16	0.26	0.25	0.13

Table 3: Innovation Deterioration and CVC Initiation

This table documents the relation between innovation deterioration and the initiation of Corporate Venture Capital. The analysis is performed using the following specification:

$$I(CVC)_{i,t} = \alpha_{industry \times t} + \beta \times \Delta Innovation_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t},$$

The panel sample is described in Table 2. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t, and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one), shown in columns (1) and (2) and innovation quality (the natural logarithm of average life-time citations per new patent in each firm-year plus one), shown in columns (3) and (4). Firm-level controls $X_{i,t-1}$ include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). The model is estimated using Ordinary Least Squares (OLS) and Logit, respectively. Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation. T-statistics are shown in parentheses and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Economic significance estimates are calculated by changing two standard deviations of $\Delta Innovation$ and are reported at the bottom of the table.

	(1) OLS	(2) Logit	(3) OLS	(4) Logit
$\Delta \ln(NewPatent)$	-0.007***	-0.004***		
	(-6.227)	(-3.057)		
$\Delta \ln(Pat.Quality)$			-0.004***	-0.003**
			(-4.459)	(-2.263)
Firm ROA	-0.003	0.000	-0.003	0.000
	(-1.275)	(0.703)	(-1.567)	(0.935)
Size (Log of Assets)	0.003***	0.001***	0.003***	0.001***
	(11.090)	(10.584)	(11.034)	(8.832)
Leverage	-0.005**	-0.003***	-0.004**	-0.003***
	(-2.371)	(-3.006)	(-2.051)	(-2.908)
Firm R&D	0.015***	0.005	0.011***	0.004
	(3.439)	(1.637)	(3.093)	(1.356)
Observations	25,976	25,976	25,976	25,976
Pseudo R-squared	0.126	0.261	0.125	0.268
Industry × Year FE	Yes	Yes	Yes	Yes
	Economic Significance—2σ-change			
$\Delta \ln(NewPatent)$	51.54%	29.45%		
$\Delta \ln(Pat.Quality)$			67.09%	50.32%

Table 4: Innovation Deterioration and CVC Initiation—Causality

This table documents the causal relationship between innovation deterioration and the initiation of Corporate Venture Capital. The analysis is performed using the following Two-Stage Least Squares (2SLS) specification:

$$\Delta \widehat{Innovation}_{i,t-1} = \pi'_{0,industry\times t} + \pi'_1 \times Obsolescence_{i,t-1} + \pi'_2 \times X_{i,t-1} + \eta_{i,t-1},$$
$$I(CVC)_{i,t} = \alpha_{industry\times t} + \beta \times \Delta \widehat{Innovation}_{i,t-1} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}.$$

The panel sample is described in Table 2. Column (1) reports the reduced-form regression, which predicts the decision to initiate CVC using *Obsolescence* as defined in (2) in the paper. Columns (2) and (4) report the first-stage regression, which regress the three-year change in innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average life-time citations per new patent in each firm-year plus one) on the three-year *Obsolescence*. Columns (3) and (5) report the second-stage regression, where $I(\widehat{CVC})_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t, and zero otherwise. $\Delta \widehat{Innovation}_{i,t-1}$ is the fitted innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). In the 2SLS framework, firm-level controls $X_{i,t-1}$ include the ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation. T-statistics are shown in parentheses and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Reduced Form	(2) First Stage	(3) 2SLS	(4) First Stage	(5) 2SLS
Obsolescence	0.001**	-0.114***		-0.128***	
	(2.171)	(-12.165)		(-17.064)	
$\Delta \ln(NewPatent)$			-0.007***		
			(-3.597)		
$\Delta \ln(Pat.Quality)$					-0.004***
					(-2.577)
Firm ROA	-0.000	0.090***	-0.003	0.070***	-0.003
	(-0.071)	(4.711)	(-1.289)	(4.170)	(-1.600)
Size (Log of Assets)	0.003***	0.028***	0.003***	0.031***	0.003***
	(6.353)	(12.664)	(11.401)	(16.106)	(11.238)
Leverage	0.002	-0.103***	-0.005**	-0.091***	-0.004**
	(0.921)	(-5.155)	(-2.484)	(-5.179)	(-2.095)
Firm R&D	0.006*	0.489***	0.015***	0.420***	0.011***
	(1.794)	(11.931)	(3.476)	(11.423)	(3.157)
F-Statistic		147.99		291.18	
Observations	25,976	25,976	25,976	25,976	25,976
R-squared	0.315	0.398	0.122	0.370	0.117
Industry × Year FE	Yes	Yes	Yes	Yes	Yes

Table 5: Industry CVC Waves

Panel A: Industry CVC Waves (1980 to 2006)

This table studies the industry clustering in CVC investment on the sample of Corporate Venture Capital (CVC) which are affiliated to US public non-financial firms between 1980 and 2006. The CVC data are from VentureXpert Venture Capital Firm Database, accessed through Thomson Reuters SDC Platinum. Panel A compiles a list of industry CVC wave periods, jointly defined using the clustering of launches of CVC units and investment deals made by CVCs. Each wave period is limited to at most four years. Industries are defined using the Fama-French 48 Industry Classification.

Industry	Wave Years	Total CVC Launches	CVC Launches in Waves	Total CVC Deals	Deals in Waves
Bus Svc (incl/ IT)	1998 to 2000	90	43	821	536
Electronic Equipment	1984 to 1986, 1998 to 2000	46	25	921	389
Computers	1984 to 1986, 1998 to 2001	44	22	617	428
Communications	1998 to 2000	40	19	120	66
Pharmaceutical	1984 to 1987, 1999 to 2001	28	10	254	65
Chemicals	1983 to 1985	11	8	48	22
Printing and Publishing	1997 to 1999	9	6	88	71
Electrical Equipment	1982 to 1983, 1996 to 1998	9	7	44	22
Utility	1997 to 2000	9	5	48	37
Petroleum	1980 to 1982	8	4	10	7
Automobile	1984 to 1985, 2000	6	3	42	29
Machinery	1983 to 1985	5	4	15	3
Healthcare	1983 to 1985	4	3	28	11
Measuring and Control Equipment	1998 to 2000	4	3	32	15

Panel B: Understanding Determinants of CVC Waves

Panel B studies the relation between industry innovation expansion and industry-level CVC investment. The dependent variables are the number of CVC units launched (columns (1) and (2)) and deals invested (columns (3) and (4)) in an industry in each year. The explanatory variables of interests are industry-level innovation growth, calculated as the 1-year growth of industry median innovation quantity and quality. The regressions control for industry characteristics and fixed effects at both industry and year dimension. Industry characteristics include industry ROA, sales growth, and R&D ratio, and are defined as the median at the industry-year. Poisson regression is used for the analysis. T-statistics are shown in parenthesis and standard errors are clustered by industry. *, **, *** denote statistical significance at the 10, 5, and 1% levels, respectively. Industries are categorized by the Fama-French 48 Industry Classification.

	(1)	(2)	(3)	(4)
	Number of CVC Initiations		Number of CVC Deals	
$\Delta\overline{\ln(NewPatent)}$	0.029		0.038**	
	(1.555)		(2.268)	
$\Delta\overline{\ln(Pat.Quality)}$		0.024**		0.017
		(2.221)		(1.281)
Observations	945	945	945	945
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 6: The Selection of CVC Portfolio Companies

This table studies how CVCs strategically select portfolio companies. I construct a cross-sectional data set by pairing each CVC i with each entrepreneurial company j that was ever invested by a Venture Capital investor. I remove cases when the active investment years of CVC firm i (between initiation and termination) and active financing years of company j (between the first and the last round of VC financing) do not overlap. The analysis is performed using the following specification:

$$I(CVC_i\text{-}Target_j) = \alpha + \beta_1 \cdot TechProximity_{ij} + \beta_2 \cdot Overlap_{ij} + \beta_3 \cdot SameCZ_{ij} + \gamma \times X + \varepsilon_{ij},$$

where the dependent variable, $I(CVC_i\text{-}Target_j)$, is equal to one if CVC i actually invests in company j, and zero otherwise. *Technological Proximity* is calculated as the Cosine-similarity between the CVC's and startup's vectors of patent weighting across different technological classes (Jaffe, 1986; Bena and Li, 2014). *Knowledge Overlap* is calculated as the ratio of the cardinality (size) of the set of patents that receive at least one citation from CVC firm i and one citation from the entrepreneurial company j, and the cardinality of the set of patents that receive at least one citation from either CVC i or company j (or both). Geographical distance is measured using a dummy variable if the CVC firm i and company j are located in the same Commuting Zone (CZ), $I(SameCZ)$. The Appendix defines those variables more formally. In order to provide a clean interpretation of the estimation, both *Technological Similarity* and *Knowledge Overlap* are measured as of the last year before CVC i and company j both enter the VC-startup community, and the goal is to mitigate the potential interaction between them in the VC-startup community. Fixed effects at CVC firm and entrepreneurial company level are included. T-statistics are shown in parentheses, and standard errors are clustered by CVC firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	$I(CVC_i\text{-}Target_j)$		
Technological Proximity	0.029**	0.039**	0.035**
	(2.020)	(1.969)	(2.358)
Knowledge Overlap		-0.018*	-0.014**
		(-1.756)	(-2.169)
$I(SameCZ)$			-0.008***
			(-2.818)
Observations	868,323	868,323	847,102
R-squared	0.129	0.129	0.130
CVC FE	Yes	Yes	Yes
Portfolio Company FE	Yes	Yes	Yes

Table 7: Direct Information Acquisition from Portfolio Companies

This table studies the direct information acquisition of CVC parent firms from their portfolio companies by investigating how CVC parents incorporate their portfolio companies' technological knowledge in their own internal R&D. I construct a control group for CVC parent firms using a propensity score matching method. I match each CVC parent firm i that launches its CVC unit with a non-CVC firms from its CVC launch year and 2-digit SIC industry that has the closest propensity score estimated using firm size (the logarithm of total assets), market-to-book ratio, $\Delta Innovation$, and the total number of patents applied for by the firm up to year $t-1$. In this sample I first identify all the patents applied by a CVC parent firm (or a matched control firm) i, and all the patents cited by those patents. I then identify all the patents applied by an entrepreneurial company j. The analysis is performed based on the following framework:

$$\begin{aligned} Cite_{ijt} = \alpha &+ \beta \cdot I(CVCParent) \times I(Post) \times I(Portfolio) \\ &+ \Phi[I(CVCParent), I(Post), I(Portfolio)] + \varepsilon_{ijt}. \end{aligned}$$

The sample is at the i-j-t level. The full set of i-j pairs then denotes the potential information flow that could happen between a CVC parent firm (or a matched firm) and a startup, captured by patent citations. $I(CVCParent)$ is a dummy variable indicating whether firm i is a CVC parent or a matched control firm. $I(Portfolio)$ indicates whether company j is in the CVC portfolio of firm i. For each i-j pair, two observations are constructed, one for the five-year window before firm i invests in company j, and one for the five-year window after the investment. $I(Post)$ indicates whether the observation is within the five-year post-investment window. The dependent variable, $Cite_{ijt}$, indicates whether firm i makes new citations to company j's innovation knowledge during the corresponding time period. The key variable of interest, $I(CVCParent) \times I(Post) \times I(Portfolio)$, captures the incremental intensity of integrating a portfolio company's innovation knowledge into organic innovation after a CVC invests in the company. Column (1) reports the result. Column (3) performs an analysis similar to that in column (1) except that it estimates the probability that a CVC parent firm cites not only patents owned by the startup but also patents previously cited by the startup. In other words, the potential citation now covers a broader technological area that the startup works in. Columns (2) and (4) separately estimate the intensity of citing knowledge possessed by companies that either exit successfully (acquired or publicly listed) or fail at last. All specifications include fixed effects imposing analysis across firms in the same industry and same year of (pseudo-) launching their CVC programs to absorb time-variant industrial technological trends. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Citing a Startup's Patents		Citing a Startup's Knowledge	
$I(CVCParent) \times I(Post) \times I(Portfolio)$	0.173***		0.322***	
	(5.61)		(7.33)	
$\times Successful$		0.215***		0.387***
		(7.93)		(9.52)
$\times Failed$		0.152***		0.262***
		(3.77)		(4.99)
$I(CVCParent) \times I(Portfolio)$	0.002		0.006	
	(0.71)		(1.15)	
$I(CVCParent) \times I(Post)$	0.056**		0.077**	
	(2.05)		(2.18)	
$I(CVCParent)$	0.011		0.018	
	(1.08)		(1.22)	
$I(Post)$	0.022		0.019	
	(1.04)		(0.94)	
Observations	71,305		71,305	
R-squared	0.152		0.127	
Industry $\times$ CVC Year FE	Yes		Yes	

Table 8: Inventor Adjustment and Information Acquisition

This table studies the role of human capital renewal in CVC parent firms' information acquisition process. The Harvard Business School Patent Database provides inventor-level information, which allows me to identify inventor mobility, characteristics of the inventor team for each patent, and the specific technologies used by each inventor in her/his innovation.

Panel A: Inventor Mobility during CVC Operation

Panel A studies inventor mobility accompanying CVC investment. The analysis is based on the following standard difference-in-differences (DiD) framework:

$$y_{i,t} = \alpha_{FE} + \beta \cdot I(CVCParent)_i \times I(Post)_{i,t} + \beta' \cdot I(CVCParent)_i + \beta'' \cdot I(Post)_{i,t} + \gamma \times X_{i,t} + \varepsilon_{i,t}.$$

The sample consists of CVCs and their propensity score-matched control firms. The dependent variables $y_{i,t}$ are the logarithm of inventor leavers (columns (1) and (2)), the logarithm of newly hired inventors (columns (3) and (4)), and the proportion of patents mainly contributed by new inventors (columns (5) and (6)). A patent is considered as mainly contributed by new inventors if at least half of the inventor team has three or fewer years' experience in the firm in the patenting year. $I(CVCParent)_i$ is a dummy variable indicating whether firm i is a CVC parent firm or a matched control firm. $I(Post)_{i,t}$ indicates whether the firm-year observation is within the $[t+1, t+5]$ window after (pseudo-) CVC initiations. All specifications include industry-by-year fixed effects $\alpha_{industry \times t}$ to absorb time-variant industrial technological trends, or firm and year fixed effects. Firm-level control variables include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(1 + Leavers)$		$\ln(1 + NewHires)$		Ratio of New Inventors' Pat	
$I(CVCParent) \times I(Post)$	0.119***	0.078*	0.110***	0.086**	0.171**	0.154*
	(3.478)	(1.896)	(2.791)	(2.142)	(2.402)	(1.948)
$I(CVCParent)$	0.015		0.019		-0.073	
	(1.217)		(1.380)		(-0.240)	
$I(Post)$	0.023	0.052*	0.003	0.037**	0.069	-0.024
	(1.297)	(1.921)	(0.149)	(2.360)	(0.774)	(-0.385)
Observations	6,859	6,859	6,859	6,859	3,223	3,223
R-squared	0.220	0.633	0.235	0.659	0.275	0.440
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	No	Yes	No	Yes	No
Year FE	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Panel B: New Inventors and New Information

Panel B studies the intensity of using newly acquired knowledge by new inventors in internal innovation. In column (1), the sample consists all the patents produced by CVC parents and matched control firms from five years before the event to five years after the event. The unit of observation is one patent. $I(CVCParent)$ is a dummy variable indicating whether the patent is filed by a CVC parent firm or a matched control firm. $I(Post)$ indicates whether the patent is filed within the $[t+1, t+5]$ window after (pseudo-) CVC initiations. $I_{\text{New Inventor's Pat}}$ equals one if new inventors contribute at least half of the patent. The dependent variable, *New Cite Ratio*, is calculated as the ratio of citations made by the patents that the producing firm never cited before. Column (2) studies who implement more knowledge directly acquired from invested startups in CVC parents. The analysis therefore focuses on the cross-sectional sample of patents produced by CVC parent firms during the five-year window after CVC initiation, and the dependent variable is an indicator of whether the patent cites the CVC's portfolio companies' patents. Column (1) includes industry-by-year fixed effects $\alpha_{industry \times t}$ to absorb time-variant industrial technological trends. Firm-level control variables include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) *New Cite Ratio*	(2) *Citing Portfolio*
$I_{\text{New Inventors' Pat}} \times I(CVCParent) \times I(Post)$	0.031**	
	(2.364)	
$I_{\text{New Inventors' Pat}} \times I(CVCParent)$	0.007	
	(0.368)	
$I_{\text{New Inventors' Pat}} \times I(Post)$	-0.009	
	(-0.753)	
$I_{\text{New Inventors' Pat}}$	0.050***	0.121***
	(4.621)	(4.354)
$I(CVCParent) \times I(Post)$	0.069***	
	(2.656)	
$I(CVCParent)$	-0.041	
	(-1.570)	
$I(Post)$	-0.015	
	(-0.888)	
Observations	132,407	41,397
R-squared	0.151	0.126
Controls	Yes	Yes
Industry × Year FE	Yes	–

Table 9: The Staying Power of Corporate Venture Capital

This table documents the staying power of Corporate Venture Capital by summarizing the durations of CVCs and investment characteristics sorted by duration. When the date of CVC termination is not available, I define it as the date of last CVC investment on portfolio companies. I categorize a CVC as "active" if its last investment happened after 2012 (as of March 2015) and VentureXpert categorizes the CVC's investment status as "Actively seeking new investments." *Duration* is calculated as the period between the initiation and termination of CVC investment. *Hibernation* (*Hiber*) is calculated as the number of years between CVC initiation and termination without any investment in entrepreneurial companies. Consecutive hibernation years are calculated as years of the CVC's longest consecutive hibernation. An investment deal is defined as a success if the entrepreneurial company was acquired or went public (I exclude cases when the company has neither gone public nor been acquired but is still alive).

Duration	Number	%	Cum. Prob.	Years in Hiber (Median)	Consecutive Hiber (Median)	Success Rate
$\leq$3	151	45.90%	45.90%	1	0	57%
4	21	6.38%	52.28%	1	1	54%
5	21	6.38%	58.66%	2	1	69%
6	10	3.04%	61.70%	2	1	59%
7	13	3.95%	65.65%	4	2	47%
8	13	3.95%	69.60%	4	4	56%
9	12	3.65%	73.25%	5	3	57%
$\geq$10	88	26.75%	100.00%	6	5	57%
Total	329					
Still Active	52					

Table 10: Innovation Improvement and the Termination of CVC Life Cycle

This table studies the decision to terminate Corporate Venture Capital. Panel A examines average innovation improvement through the CVC life cycle by comparing innovation performance at CVC initiation and CVC termination (definition as in Table 9). Innovation performance is measured using innovation quantity and quality, and both are adjusted using industry (3-digit SIC level) peers in the same year. I also report the t-statistics for the differences in means between the two time points. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The analysis is performed on all CVCs with a disclosed or defined termination date and the subgroup that lasts for at least five years.

Panel B studies the effect of innovation improvement on CVC termination and investment decisions. The regressions are performed on the panel of CVCs in their active years. The key variable $\Delta Innovation_{i,t}$ is defined as the difference of innovation between year t and the year of initiation. In columns (1) and (2), the dependent variable is a CVC termination dummy, and the specification is estimated using a Hazard model. In columns (3) and (4), the dependent variable is the annual number of investments in portfolio companies, and the model is estimated using Ordinary Least Squares (OLS). Firm-level control variables include ROA, size (logarithm of total assets), leverage, and R&D ratio (R&D expenditures scaled by total assets). *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Innovation at CVC Initiation and Termination

All	Initiation-Mean	Exit-Mean	Difference	T-Stat
Adjusted $\ln(NewPatent)$	0.75	0.91	0.16	2.18**
Adjusted $\ln(Pat.Quality)$	-0.03	0.23	0.26	1.90*

Duration $\geq$ 5	Initiation-Mean	Exit-Mean	Difference	T-Stat
Adjusted $\ln(NewPatent)$	0.79	1.03	0.24	2.43**
Adjusted $\ln(Pat.Quality)$	-0.05	0.43	0.48	2.57**

Panel B: Innovation CVC Exit and Investment

	(1)	(2)	(3)	(4)
	Termination		Number of New CVC Deals	
$\Delta\ln(NewPatent)$	0.355***		-2.291***	
	(5.585)		(-2.647)	
$\Delta\ln(Pat.Quality)$		0.276***		-0.591*
		(6.277)		(-1.776)
$exp(\beta)$	1.426	1.318		
Controls	Yes	Yes	Yes	Yes
Observations	2,489	2,489	2,489	2,489
Log-likelihood	-697.86	-363.88		
R-squared			0.127	0.128

Appendix

.1 Key Variable Definitions

Variable	Definition and Construction
	a. Instrumental Variables
Obsolescence	The variable is constructed as the changes in the number of citations received by a firm's predetermined knowledge space. Formally defined by formula (2) in the paper.
	b. Innovation Variables
New Patents	Number of patent applications filed by a firm in a given year. The natural logarithm of this variable plus one is used in the paper, i.e., $\ln(NewPatent) \equiv \ln(New\ Patent + 1)$.
Patent Quality	Average citations received by the patents applied by a firms in a given year. The natural logarithm of this variable plus one is used in the paper, i.e., $\ln(Pat.Quality) \equiv \ln(Patent\ Quality + 1)$.
New Cite Ratio	The ratio of citations made to patents not belonging to a firm's existing knowledge, divided by the number of total citations made by the patent. Transformed to firm-year level by averaging across all patents produced in the firm in each year.
Inventor Leavers	An inventor is defined as a leaver of firm i in year t, if he or she generates at least one patent in firm i between $[t-3, t-1]$ and generates at least one patent in a different firm between $[t+1, t+3]$. Identified from the Harvard Business School patenting database.
Inventor New Hires	An inventor is defined as a new hire of firm i in year t, if he or she generates at least one patent in another firm between $[t-3, t-1]$ and generates at least one patent in firm i between $[t+1, t+3]$. Identified from the Harvard Business School patenting database.
New Inventors' Pat	Proportion of patents to which new inventors of a firm contribute at least 50%.
	c. CVC-Startup Relationship
Technological Proximity	Degree of similarity between the distribution of two firms' (i and j) patent portfolios across two-digit technological classes using the same technique as in Jaffe (1986) and Bena and Li (2014). Formally, $$TechnologicalProximity = \frac{S_i S_j'}{\sqrt{S_i S_i'}\sqrt{S_j S_j'}},$$ where the vector $S = (S_1, S_2, \cdots, S_K)$ captures the distribution of the innovative activities, and each component S_k is the percentage of patents in technological class k in the patent portfolio.

Knowledge Overlap	Firm i's knowledge in year t, $K_{i,t}$ is constructed as the patents that received at least one citation from firm i up to year t, and similar for firm j's knowledge $K_{j,t}$. *Knowledge Overlap* is calculated as the ratio of—(1) numerator: the cardinality (size) of the set of patents that receive at least one citation from CVC firm i and one citation from entrepreneurial company j; and (2) denominator: the cardinality of the set of patents that receive at least one citation from either CVC i or company j (or both). That is, $$KnowledgeOverlap_{ij,t} = \frac{Card(K_{i,t} \cap K_{j,t})}{Card(K_{i,t} \cup K_{j,t})}$$
SameCZ	Dummy indicating whether CVC firm i and entrepreneurial company j are located in the same Commuting Zone (CZ). When the CVC and the firm headquarter are located in different areas, I use the location that is closer to the startup.
	d. Firm Characteristics
Size (Log of Assets)	The natural logarithm of total assets in millions, adjusted to 2007 US dollars.
Firm ROA	Earnings before interest, taxes, depreciation, and amortization scaled by total assets.
M/B	The market value of common equity scaled by the book value of the common equity.
Leverage	Book debt value scaled by total assets.
Cash Flow	(Income before extraordinary items + depreciation and amortization) scaled by total assets.
Firm R&D	Research and development expenses scaled by total assets.
Institutional Shareholding	Total shares (in %) held by the top five institutional shareholders in the firm.
G-Index	Governance index constructed in Gompers, Ishii, and Metrick (2003), which classifies and counts governance provisions that restrict shareholder rights.