The Life Cycle of Corporate Venture Capital

Song Ma*

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Abstract

This paper establishes the life-cycle dynamics of Corporate Venture Capital (CVC) to explore the information-acquisition role of CVC investment in the process of corporate innovation. I exploit an identification strategy that allows me to isolate exogenous shocks to a firm's ability to innovate. Based on this strategy, I first find that the CVC life cycle typically begins following a period during which corporate innovation has deteriorated and external information is valuable, lending support to the hypothesis that firms conduct CVC investment to acquire information and innovation knowledge from startups. Building on this analysis, I show that CVCs acquire information by investing in companies that are technologically proximate but have a different knowledge base. Following CVC investment, parent firms internalize the acquired knowledge into internal R&D and external acquisition decisions. Human capital renewal, such as hiring additional inventors who are capable of integrating new innovation knowledge, is integral in this step. The CVC life cycle lasts about four years, terminating as innovation in the parent firms rebounds. These findings shed new light on discussions about firm boundaries, managing innovation, and corporate information choices.

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I. Introduction

In the past three decades corporations have created in-house Corporate Venture Capital (CVC) divisions to make systematic minority equity investments in early-stage entrepreneurial ventures. These CVC investments account for about 20% of VC investment,[1] and are undertaken not only by technology firms in the media spotlight (such as Google Venture and Intel Capital), but also commonly by moderate-size firms in a variety of industries. Both academicians and practitioners seek to understand CVC's potential as an innovation model for Corporate America (Macmillan et al., 2008; Lerner, 2012), yet the economic rationale behind CVC and its role in a corporation have been understudied (Chemmanur and Fulghieri, 2014).

Why do firms engage in CVC investment and connect to the entrepreneurial sector? A well-accepted yet hard-to-test view is that "acquiring information and innovative knowledge" is a primary mission of CVC (Siegel et al., 1988; Macmillan et al., 2008). To fit this argument into the context of economic theories, Nelson (1982) frames the innovation process as a two-stage sequential process, in which corporations "acquire information and generate ideas" (first stage) before investing and organizing R&D activities (second stage). In the information acquisition stage, corporations search for new innovative ideas and seek better understanding of those ideas. Including this stage in studying innovation can reconcile several important patterns in economic growth and innovation dynamics (Jovanovic and Rob, 1989; Kortum, 1997).[2] Despite the importance of acquiring information, very little empirical work has studied how firms organize their investment to actively acquire innovative knowledge to

[1] In 1999 and 2000, CVC investment peaked at almost $20 billion a year. Although the numbers throughout the VC industry fell in the 2000s, CVC growth has rebounded in recent years (69% increase in 2014, NVCA). CVC is thus an important component of the overall VC investment, and, as I show later, has a "multiplier effect" on a firm's internal and external investment and R&D. For more readings on VC, please refer to Gompers and Lerner (2000b); Kortum and Lerner (2000); Hellmann and Puri (2002); Hsu (2004); Sørensen (2007); Bottazzi et al. (2008); Da Rin et al. (2011).

[2] Existing studies have overwhelmingly focused on the second stage of the innovation process—investing and organizing innovation with an exogenous idea and pre-determined informational structure. 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; Mathews (2006) and Fulghieri and Sevilir (2009) study the problem of strategic equity investment from the industrial organization perspective, and theorize the benefits of coordinating market entry and obtaining competitive advantages; Hellmann (2002) emphasizes that asset complementarity and product market synergies lead firms to invest in synergistic entrepreneurial ventures, particularly when external financing is costly (Allen and Phillips, 2000).

generate ideas.

Testing the information acquisition view of CVC, therefore, not only allows us to understand a primary rationale of CVC investment, but also provides an empirical setting to understand how firms search and generate new ideas in the broad innovation process. This paper examines this "information acquisition" hypothesis in the context of the life-cycle dynamics of Corporate Venture Capital, using a hand-collected comprehensive CVC data set. At each stage of the CVC life cycle—*initiation*, *operation*, and *termination*—the evidence is consistent: CVC is used to acquire information and innovation knowledge from the entrepreneurial sector. Essentially, CVC serves as a transitory information-acquiring step in regaining an upward innovation trajectory, typically after a firm experiences a deterioration in internal innovation. Figure 1 summarizes the CVC life cycle.

[FIGURE 1 AROUND HERE]

The CVC life cycle begins with the *initiation* stage in which a firm launches CVC investment, typically following a deterioration in internal innovation. Quantitatively, a two-standard-deviation decline in innovation quantity (quality) increases the probability that a firm will initiate CVC by about 52% (67%). To mitigate endogeneity issues that could drive this result, I identify exogenous shocks to innovation performance. The instrumental variable, *Knowledge Obsolescence*, captures the rate of obsolescence that results from exogenous technological evolution of each firm's technology base. This instrumental variable captures the exogenous change in a firm's ability to innovate by tracking the usefulness of its accumulated knowledge. This should be independent of current CVC decisions. The empirical strategy helps to establish a causal link between innovation deterioration and CVC investment.

One explanation for the above finding is that firms with deteriorating innovation have lower productivity in generating ideas and producing innovation and thus have larger potential informational gains from connecting to highly innovative entrepreneurs.[3] Consistent with this explanation, the effect of innovation deterioration is stronger when a firm faces higher informational uncertainty in its technological areas. Several potential alternative

[3]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).

interpretations of the result, such as the effects of financial constraints, excess cash, and weak corporate governance, do not explain this finding.

When studying the *operation* stage of the CVC life cycle, I first examine how CVCs strategically choose portfolio companies to acquire information from. Specifically, how does the trade-off between complementarity and substitutability (Hellmann, 2002) shape CVC portfolio formation? I find that CVCs primarily invest in startups that are innovating in technological areas that are close to the CVC parent, suggesting that CVCs prefer to invest in companies with substitute technologies. Moreover, the portfolio companies appear to possess different knowledge (which I measure using overlaps of innovation profiles and patent citations) from the parent firms, which suggests that CVC parents aim to acquire updated knowledge in their key areas of expertise.[4] For example, an automobile CVC parent firm is likely to invest in an engine startup, particularly when this startup specializes in cutting-edge clean-tech that the firm does not possess.

I then examine how the information acquired through CVC investment benefits the parent firm. After investing in startups through CVC, firms begin to innovate more and with higher quality. Importantly, CVC parent firms appear to internalize acquired knowledge by conducting research involving more intense usage of the new information acquired from their portfolio companies. Meanwhile, the informational benefit is also capitalized through increased efficiency when making external acquisitions of companies and innovations. Moreover, human capital renewal, such as hiring additional inventors who are capable of using the newly acquired knowledge, is integral to this information acquisition and integration.

The CVC life cycle ends with the *termination* stage as CVC parents stop making incremental investment in startups, typically 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 information

[4]Interestingly, CVC investment appears to have a "reverse home bias"—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, from which they may acquire information through local innovation spillover (Peri, 2005; Matray, 2014).

is assimilated into parent firms. Interestingly, if innovation again deteriorates at the parent firm, the CVC life cycle begins anew.

By analyzing the rationale for CVC investment, this paper adds to the existing CVC literature, which has largely taken CVC activities as given.[5] Closer to this paper, Dushnitsky and Lenox (2005a) and Basu et al. (2011) study the environmental variables affecting CVC investment using small samples, with analyses tilted toward industry-level factors rather than firm-level dynamics. The CVC life cycle described herein is consistent with the rationale of information acquisition and documents the intertemporal dynamics, also contributes to existing studies of CVCs and strategic investment in broad terms (Allen and Phillips, 2000; Hellmann, 2002; Mathews, 2006; Fee et al., 2006; Fulghieri and Sevilir, 2009), which mainly build static models to examine non-informational strategic benefits.

This paper also provides an opportunity to revisit classic issues at the intersection of information economics and corporate finance. Firms search, process, and use information to guide their information-sensitive decisions, such as investment and innovation.[6] Identifying firms' information choices and their direct effects has been difficult due to data limitations (Van Nieuwerburgh and Veldkamp, 2010; Gargano et al., 2014): When do firms actively acquire information and how? What information do firms pursue? How do firms use acquired information? As discussed above, the CVC life cycle is a promising setting in which to answer those questions: Firms actively acquire information during innovation downturns; information acquisition often focuses on updated knowledge in core business areas; the acquired information is used for both internal operation and external acquisitions; and information acquisition activities slow down when the marginal informational gain shrinks.

This paper also naturally connects to the literature on financing and managing innovation and the boundaries of the firm, and contributes to this agenda in two ways. First, I highlight the informational motivation behind organizing innovation, complementing existing studies that typically assume that the information structure is predetermined (Aghion and Tirole,

[5]See, e.g., Siegel, Siegel, and MacMillan (1988); Gompers and Lerner (2000a); Bottazzi, Da Rin, and Hellmann (2004); Dushnitsky and Lenox (2006); Benson and Ziedonis (2010); Chemmanur, Loutskina, and Tian (2013); Dimitrova (2013); Ceccagnoli, Higgins, and Kang (2015); Wadhwa, Phelps, and Kotha (2015). For more background readings on CVC, please refer to Dushnitsky (2006); Maula (2007); Macmillan, Roberts, Livada, and Wang (2008); Lerner (2012).

[6]See, for example, Dow and Gorton (1997); Chen, Goldstein, and Jiang (2007); Bond, Edmans, and Goldstein (2012); Yang (2013).

1994; Robinson, 2008; Bena and Li, 2014; Seru, 2014). Second, rather than studying CVC alone, I explicitly identify the process of integrating CVC-acquired knowledge into R&D and acquisition decisions. Ideally, these analyses can be viewed as stepping stones toward understanding the whole system of financing and organizing innovation, in which different organizational structures interact with each other.

The remainder of the paper proceeds as follows. Section II describes the data. Section III presents how information acquisition motivates CVC initiation following innovation deterioration. Section IV examines how CVCs operate to acquire and use information. Section V describes the staying power and exit dynamics of CVCs. Section VI discusses the findings in the context of the literatures on the boundaries of the firm, information economics, and entrepreneurship.

II. Sample and Data

I exploit a hand-collected sample of Corporate Venture Capitals affiliated with US-based public firms. To identify CVC investors, 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, 2013). For each CVC on the list, I manually match it to its unique corporate parent in Compustat by checking multiple sources (Factiva, Google, etc.). I remove VC divisions operated by financial firms, which are different from CVC arms of industrial firms (Hellmann, Lindsey, and Puri, 2008). From VentureXpert I obtain the investment history of each CVC, including basic information about the startup company, and the timing and characteristics of each CVC deal.

[TABLE I AROUND HERE]

The main sample consists of 381 CVC firms initiated between 1980 and 2006.[7] Table I 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

[7]I focus on CVCs initiated no later than 2006 to allow for investment behaviors to realize (after 2006) and to ensure the quality of the innovation database, as will be described later.

half of the 1990s. This is consistent with existing studies on "CVC waves" (Gompers and Lerner, 2000a; Dushnitsky, 2006). 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 mergers and acquisitions 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.[8]

Innovation is a crucial data component of this paper for three reasons. First, innovation knowledge generate from the entrepreneurial sector could create great value for CVC parent firms (Macmillan et al., 2008), therefore it is an important part of the information acquisition motive. Second, the system of citation network creates a valuable setting to measure informational relationship and knowledge flows (Gonzalez-Uribe, 2013). 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 the basic innovation database from the NBER Patent Data Project and from Bhaven Sampat's patent and citation data.[9] The combined database provides detailed patent-level records on more than 3 million patents granted by USPTO between 1976 and 2012. I link this database to Compustat using the bridge file provided by NBER.

I employ two main variables to measure corporate innovation performance. First, 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

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

[9]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`.

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. Second, 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 $\ln(Pat.Quality)$).

I preview three additional steps in constructing innovation data.[10] First, 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). This step allows me to construct variables capturing the technological relation between CVCs and startups and to create a dynamic citation network. Second, I 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. Third, I construct a full set of patent transactions from the Google Patent database, which allows me to examine how information acquisition improves the efficiency of acquiring external innovation.

III. CVC Initiations: The Effect of Innovation Deterioration

Why do firms initiate CVC programs? Indeed, the cost of investing in CVC is not negligible—when doing so, firms devote capital, time, and such intangible resources as industry knowledge and marketing channels (Lerner, 2012; Chemmanur, Loutskina, and Tian, 2013), which could otherwise be used for R&D, acquisitions, or other corporate activities.[11] The entrepreneurs they support, meanwhile, could potentially grow to be strong competitors that are detrimental to the CVC parent firms themselves in the long run.

Is CVC just another example of pet-project that allows managers to act as venture capitalists, or a conscious corporate decision on firm boundaries in the pursuit of long-term growth opportunities? If the latter, are firms more likely to engage in CVC investment under

[10] These steps are detailed in related sections and the Appendix.

[11] These requirements for capital and other resources explain why CVC parents tend to possess stronger cummulated technological and marketing resources than their peers (Dushnitsky and Lenox, 2006; Basu, Phelps, and Kotha, 2011).

certain situations than others? Siegel, Siegel, and MacMillan (1988), Chesbrough (2002), and Macmillan et al. (2008) argue that CVC serves as a window to new technology, new ideas, and industry trends generated in the entrepreneurial sector.[12] This learning process, moreover, is structured to be flexible and with lower adjustment cost (Lerner, 2012). Under this information acquisition hypothesis, CVC investment should be more appealing when acquiring information could more significantly improve the firm's performance of a firm. One such occasion is when a firm experiences a negative innovation shock and exhausts innovative ideas internally, thereby benefiting more through learning from startups.

A. A Graphical Illustration

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 AROUND 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 significantly more innovative than their peers and on average doubled their peers' patent production. 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.

[12] CVC parents could learn new knowledge from entrepreneurial companies through due diligence (Henderson and Leleux, 2002), through obtaining board seats in startups (Maula et al., 2001; Bottazzi, Da Rin, and Hellmann, 2004), and through creating communication platforms for inventors in both the parent firm and entrepreneurial ventures (Dushnitsky and Lenox, 2005b).

B. *Empirical Strategies and Baseline Results*

To statistically identify the effect of innovation performance on CVC initiations, I start by estimating the following specification using a panel data of firm-year observations:

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

where $I(CVC)_{i,t}$ is equal to one if firm i launches a CVC unit in year t, and zero otherwise.[13] $\Delta_\tau Innovation_{i,t-1}$ is the change of innovation over the past τ years ending in $t-1$. 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), 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.

B.1. Summary Statistics

Table II presents descriptive statistics based on whether a CVC division is initiated in the firm-year. Only observations with valid ROA, size, leverage, R&D ratio, and at least $10 million in book assets are kept in the sample. Only "innovative firms," defined as those that filed at least one patent application that was eventually granted by the USPTO, are included in the panel sample. Industries (3-digit SIC level) with no CVC activities during the sample period are removed.

Table II provides a benchmark to position CVC parent firms in the Compustat universe of publicly traded corporations. 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, while non-CVC parent firms have less than $3 billion in book

[13]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 of investment size in VentureXpert has 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 as an important result in Section V.

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 II AROUND 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. Consistent with the deterioration in innovation, CVC parents appear to underperform in terms of ROA and market-to-book ratio before CVC initiations.

B.2. Baseline Results

[TABLE III AROUND HERE]

Table III 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 CVCs. 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.

It is worth stressing the importance of incorporating industry-by-year fixed effects in the estimation. 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). However, after absorbing this variation using industry-by-year fixed effects, the results in Table III are identified using the cross-sectional variation within an industry-by-year cell. In the Appendix, I present a separate analysis on the industry-by-year trends of CVC activities.[14]

Overall, Table III confirms the pattern in Figure 2 that CVC initiations typically follow innovation deterioration. This finding supports the information acquisition hypothesis for the CVC rationale, because the informational motive becomes larger as internal innovation becomes increasingly unproductive, making external knowledge more valuable. To strengthen this interpretation, I tackle two hurdles using the analyses that follow. The first hurdle is to resolve the identification problem arising from endogenous factors that simultaneously affect both innovation and CVC decisions. The second hurdle is to present further evidence that CVC investment following innovation deterioration is due primarily to the response to informational motives.

C. Identification: Endogeneity and Instrumental Variables

Potential endogeneity problems arise from unobservables that are hard to control for in model (1). Particularly important is the concern that agency problems (such as empire-building managers) could hinder innovation and lead simultaneously to CVC as a pet project, biasing the estimation in favor of finding a negative relation between innovation and CVC investment. On the other direction, 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.

[14]The main finding is that industrial CVC activities cluster in time to form “industry CVC waves.” This finding is further refined by connecting CVC waves to industry-level shocks.

C.1. Instrumental Variable and Empirical Strategy

To address the endogeneity concern 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 firms' innovation is intuitive—a firm specializing in 14-inch hard disk drive (HHD) was less likely to produce valuable innovation when 8-inch HHD technology came, and this happened repeatedly along the development of HHDs (5.25-inch, 3.5-inch, 2.5-inch, Solid State Drives). Indeed, "new technologies come and go, taking generations of companies with them" (Igami, 2014). Earlier studies formalize this intuition and identify several mechanisms that technological evolution affects firms' ability to innovate. 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 will benefit less from knowledge spillover (Bloom, Schankerman, and Van Reenen, 2013), which in turn dampens growth in innovation and productivity.[15]

To implement the idea and measure the influence of exogenous technological evolution on each firm, I build on bibliometrics and scientometrics literature, which measure obsolescence and aging of a discipline/technology using the dynamics of citations referring to the discipline/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. 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, and a

[15]One concern is that when a firm's knowledge space becomes hotter, product market competition becomes more severe, which in turn could disincentivize innovation and imply that emerging knowledge value could lead to lower innovation performance. This concern, however, is shown to be secondary by Bloom, Schankerman, and Van Reenen (2013), and is further resolved by the first-stage regression in Table IV.

larger *Obsolescence* means a larger decline of the value and usefulness of a firm's 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 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. One might worry that a firm's knowledge space could be affected by the type and capability of its managers, but this concern should be minimized by using a predetermined knowledge space formed along the corporate history rather than the concurrent one. One might also worry that the firm itself could be the main driver of the technological evolution. This concern is addressed first by excluding patents owned by the firm from its own knowledge space and 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 II, I report summary statistics for *Obsolescence*. The activeness of a firm's predetermined knowledge space decays by 8% in the control group, which can be interpreted as a very 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 is a much more severe hit by the technological evolution.

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:

$$\Delta_\tau \widehat{Innovation}_{i,t-1} = \pi'_{0,industry\times t} + \pi'_1 \times Obsolescence^{\tau}_{i,t-1} + \pi'_2 \times X_{i,t-1} + \eta_{i,t-1}. \tag{3}$$

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

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

C.2. 2SLS Results

Table IV 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 in the quality 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 IV AROUND 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 III) and the 2SLS estimates are very 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 there are no endogeneity issues involved—as discussed earlier, competing endogenous forces could drive the OLS bias in either direction and the net effect is therefore mitigated. 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.

D. Interpretation: Uncertainty of Informational Environment

Table IV overcomes the identification hurdle in establishing causality between innovation deterioration and CVC initiations. This subsection attempts to strengthen the interpretation of this relation, that is, innovation deterioration affects CVC investment through the mechanism of changing the information acquisition motive. Specifically, I explore heterogeneous effects of innovation deteriorations on CVC initiations across uncertainty levels that firms face in their informational environment. The working hypothesis is that the impact of innovation deterioration should be stronger when the uncertainty level is higher, that is, identifying valuable innovation opportunities and methods becomes more difficult and information is therefore more valuable.

I estimate an extended model based on the OLS model (1) and 2SLS models (3) and (4). The sample is categorized into two subgroups by the median of uncertainty levels of firms' informational environment, indicated by $I_{uncertainty}$. I then introduce $I_{uncertainty}$ and its interaction with $\Delta Innovation$ into the model. Formally, the model is extended to

$$\begin{aligned} I(CVC)_{i,t} = \alpha_{industry \times t} &+ \beta \times \Delta_\tau Innovation_{i,t-1} \\ &+ \beta' \times \Delta_\tau Innovation_{i,t-1} \times I_{uncertainty,it} \\ &+ \gamma' \times I_{uncertainty,it} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}. \end{aligned} \tag{5}$$

The interaction term β' can be interpreted as the "additional responsiveness" to innovation changes of firms that are under a more uncertain environment. The coefficient γ' is the standalone effect of uncertainty. When estimating using 2SLS, I instrument $\Delta_\tau Innovation_{i,t-1}$ with $Obsolescence$, and the interaction term is instrumented by the interaction of $Obsolescence$ and $I_{uncertainty,it}$.

For the purpose of interpretation, the uncertainty measure needs to capture the difficulty of identifying valuable innovative ideas and promising innovation trajectories. To fulfill this criterion, I construct a spread-based variable to measure the quality dispersion of new innovation opportunities that a firm exposes to, in the same spirit as many existing uncertainty proxies (Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012; Jurado, Ludvigson, and Ng, 2013).

The measure, referred to as *Innovation Uncertainty*, is calculated as follows: in the first step, for each technology class c categorized by USPTO, I calculate its patent quality dispersion in year t as the standard deviation of lifetime citations of all patents applied under class c in year t, and I further standardize this standard deviation by the mean of their lifetime citations to make it comparable across technology classes. A higher quality dispersion captures the content that there are various innovation routes at the time that eventually lead to very different outcomes. In the second step, I calculate each firm i's exposure to different classes in year t, ω_{ict} as the number of i's patents in c divided by the number of its total patents, as of year t. In the last step, I calculate the firm-year level uncertainty measure by weighting the class-year uncertainties in step one using the firm-year weights in step two.

[TABLE V AROUND HERE]

Table V reports the results. Columns (1) and (4) report the first-stage results, columns (2) and (5) report the OLS results, and columns (3) and (6) report the 2SLS estimations. In column (2), the unconditional responsiveness of CVC initiation on innovation quantity shock is -0.006. If the firm faces higher uncertainty in its informational environment, therefore having stronger needs to acquire information on new technology and market trends to resolve uncertainty (as categorized by $I_{uncertainty}$), the responsiveness increases by 50% to -0.009 (-0.006−-0.003). The magnitude is even more striking in column (3), where the responsiveness on innovation quality doubles when the firm is uncertain about future technology trends (from -0.005 to -0.010). The coefficient associated with $I_{uncertinty}$ is positive, suggesting that uncertain environments motivate firms to undertake CVC investment.

Overall, Table V shows that the causal relation between deterioration in innovation and the decision to engage in CVC investment is stronger when there is higher demand to acquire information on new technologies and new markets, which favors the informational rationale behind CVC. This result cannot be explained by the interpretation that firms make CVC investments before acquiring a new technology, as a way to wait for the uncertainty to resolve. Indeed, CVC investment seldom evolves acquisition of the portfolio company. Recent studies examine acquisition cases when CVC investors acquire portfolio companies in which they invested (Benson and Ziedonis, 2010; Dimitrova, 2013). In general, acquiring portfolio companies is rare—fewer than one-fifth of CVC investors acquired their portfolio companies. CVCs that did conduct such acquisitions acquired fewer than 5% of their portfolio companies (that is, one out of 20 investments).

In the Online Appendix, I explore several alternative CVC rationale which could be consistent with the finding that innovation deterioration leads to CVC investment, such as financial constraints and managerial desperation (Higgins and Rodriguez, 2006), and these factors cannot explain the finding.

IV. CVC Operations: Select, Acquire, and Integrate Information

Section III presents evidence on how the information acquisition motive drives the initiation of the CVC life cycle. To further bolsters the information acquisition hypothesis, this section moves to examine how firms operate CVC and its role within the boundaries of the firm. Specifically, I study two important activities in CVC *operation*—selecting information sources (portfolio companies) and harvesting informational benefit.

A. CVC Portfolio Formation

I start by examining how CVCs select portfolio companies and how this process reflects the 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 the 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 the incremental informational value through investment. Indeed, investing in companies with very similar knowledge sets contributes little marginal informational benefit, although it could be efficient for strategic reasons such as synergy (Bena and Li, 2014). The third determinant is the availability of alternative information acquisition channels. The working hypothesis here 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.

To empirically analyze how CVC parent firms balance these economic forces in selecting portfolio companies, I construct 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 active financing years of company j (between the first and the last round of VC financing) do not overlap. I estimate a probability model on this sample to predict the decision of CVC i investing in company j, that is,

$$\begin{aligned} I(CVC_i\text{-}Target_j) = \alpha + \beta_1 \times TechProximity_{ij} + \beta_2 \times Overlap_{ij} \\ + \beta_3 \times SameCZ_{ij} + \gamma \times X_{i,j} + \varepsilon_{ij}, \end{aligned} \tag{6}$$

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

A.1. Measurements

The key variables of interest in model (6) are *TechProximity*, *Overlap*, and *SameCZ*, which capture the informational relation between a CVC parent firm i and an entrepreneurial company j, echoing the three potential portfolio determinants outlined above.[16]

The first measure, *Technological Proximity* (*TechProximity*), is calculated as the *Cosine*-similarity between the CVC's and 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 work in closer areas in the technological space.

The second measure, *Knowledge Overlap* (*Overlap*), is calculated as the ratio of—(1) numerator: the cardinality of the set of patents that receive at least one citation from CVC firm i *and* one citation from entrepreneurial company j; (2) denominator: the cardinality of the set 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 share broader common knowledge in their innovation.

In order to provide a clean interpretation of the estimation, both *Technological Proximity*

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

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 while company 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 (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, 2014) 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.

A.2. Results

Table VI presents coefficients estimated from model (6). In column (1), a positive and significant coefficient means that the *Technological Proximity* between a CVC and an entrepreneurial company increases the likelihood of a 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 VI AROUND 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 different 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, knowledge spillover specifically, on CVC's portfolio selection. The literature on VCs, 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 VI 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.

B. Internalizing Acquired Information into R&D

The rationale of information acquisition for CVC investment is convincing only if CVC parents can use newly gathered information to improve their operations. In this subsection, I study how CVC parent firms internalize acquired information into organic R&D.

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 own 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 (2000a) suggest that the efficiency of CVC is constrained by the incentive problem embedded in its organizational and compensation structure. Additionally, 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.

B.1. Internal Innovation during CVC

To set the stage, I first examine how CVC investment influences internal innovation. Under the information acquisition hypothesis, parent firms should be able to harvest the informational benefit, particularly through improvements in information-sensitive activities such as innovation; moreover, newly gathered information should be reflected in those activities.

I assess this idea by characterizing the innovation dynamic of CVC parents around their CVC investment across several dimensions. The first set of measurements is simply innovation quantity and quality as employed in Section III. The second set of variables is *New Cite Ratio* and *Explorativeness*, which measure the proportion of new knowledge used in innovation. New knowledge is identified using patent citations referring to patents that never previously cited by the firm. Specifically, I first define firm i's existing knowledge in year t as all patents that are owned by i or that were cited by firm i's patents filed up to t; other patents are considered new knowledge to the firm. *New Cite Ratio* of a patent is calculated as the ratio between citations made to new knowledge and the total number of citations made by the patent. Based on this measure, a patent is flagged as *Explorative* if at least 80% of its citations are based on new knowledge (*New Cite Ratio*$\geq$ 80%). I transform these patent-level measures to firm-year level by averaging across all patents produced by firm i in year t.[17] Higher *New Cite Ratio* and *Explorativeness* suggest an innovation scheme focusing on exploring new ideas using new knowledge.

To construct a proper control group for CVC parents, I use a propensity score matching method and match each CVC parent firm that launches its CVC unit in year t with two non-CVC firms from the same year t and 2-digit SIC industry that have the closest propensity score

[17] This measure is motivated by theoretical work on motivating innovation (e.g., Manso (2011)), and recently implemented in empirical studies (Almeida, Hsu, and Li, 2013; Custódio, Ferreira, and Matos, 2013; Brav, Jiang, Ma, and Tian, 2015).

estimated using firm size (the logarithm of total assets), market-to-book ratio, $\Delta Innovation$, and patent stock,[18] similar to the sample construction strategy in Bena and Li (2014). The CVC launching year for a CVC parent firm is also the "pseudo-CVC" year for its matched firms, and I include firm data beginning five years before the (pseudo-) event year through five years after the event.

I characterize corporate innovation dynamics around CVC investment under a standard difference-in-differences (DiD) framework:

$$\begin{aligned} y_{i,t} = \alpha_{FE} &+ \beta \cdot I(CVCParent)_i \times I(Post)_{i,t} \\ &+ \beta' \cdot I(CVCParent)_i + \beta'' \cdot I(Post)_{i,t} + \gamma \times X_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where dependent variables $y_{i,t}$ are innovation quantity, quality, new cite ratio, and explorativeness. $I(CVCParent)_i$ is a dummy variable indicating whether firm i is a CVC parent 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. The model includes industry-by-year fixed-effects $\alpha_{industry \times t}$ to absorb industry-specific technological trends.[19] The coefficient of interest β measures the incremental changes in innovation benchmarked by those of the matched firms.

[TABLE VII AROUND HERE]

Table VII reports the results. Columns (1) to (4) study the dynamics of patent quantity and quality. The β-coefficients associated with the difference-in-differences term are positive and significant across all columns, meaning that CVC parent firms' innovation performance improves following CVC investment. The coefficients should be interpreted in semi-elasticity terms. Following CVC investment, parent firms' innovation quantity increase is 23.9% larger than the matched firms (column (1)), and these new innovations collect on average 21.7% more lifetime citations (column (3)) compared to the level before CVC investment.

Columns (5) and (6) study the ratio of new knowledge used in innovation. After CVC initiations, firms conduct innovation that involves more intense use of knowledge that they

[18]Patent stock is constructed as the total number of patents applied for by the firm up to year $t-1$.
[19]The result is robust to controlling for firm fixed effects and year fixed effects.

have not used before—the estimate of 0.097 in column (5) can be interpreted as a 9.7% increase in using new information (that is, one out of ten citations). Similarly, in columns (7) and (8), the proportion of explorative patents that are mainly ($\geq$ 80%) produced based on new knowledge increases by around 4%.[20]

B.2. Direct Spillover from Portfolio Companies to CVC Parents

Is this information integrated into organic innovation acquired through the CVC channel? I answer this question by further identifying the specific information flow from portfolio companies to CVC parent firms, attributing innovation changes to knowledge acquired through CVCs.

Empirically, I study whether CVC parent firms more intensely cite innovation knowledge possessed by their portfolio companies. 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. These data further allow me to determine whether firm i makes a new citation, which it never cited before, to a patent that is possessed by company j.

The analysis estimates whether CVC parent firm i makes new citations to company j's patents or knowledge after the CVC invests in the portfolio company, using the following model:

$$\begin{aligned} Cite_{ijt} = \alpha + \beta \cdot I(CVCParent) \times I(Post) \times I(Portfolio) \\ + \Phi[I(CVCParent), I(Post), I(Portfolio)] + \varepsilon_{ijt}. \end{aligned} \tag{8}$$

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

[20]Some might worry that this result merely means that CVC parent firms start to diversify and thus innovate in areas that they had not explored before. In unreported results, I find that the increase in using new information concentrates on technological areas closer to the firm's core expertise, which is inconsistent with the "*diversification*" story.

after the investment.[21] $I(Post)$ 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 VIII AROUND 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 VIII column (1) shows the regression results. The coefficient of 0.159, means that the citing probability increases by 15.9% after establishing the link through CVC investment.

I further explore the depth of information acquisition from portfolio companies. Specifically, 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 a broader technological area that the startup works in. Column (3) extends the message conveyed 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 (8) 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.

C. Using Information through External Acquisitions

After presenting how firms integrate acquired innovation knowledge into internal R&D, in this section, I explore an alternative channel through which firms could benefit from CVC-acquired information—acquiring external innovation. Acquiring innovation has become an

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

important component of corporate innovation (Bena and Li, 2014; Seru, 2014), and identifying promising acquisition targets (companies or innovation) requires a valuable information set, such as great understandings on markets and technological trends. Under the information acquisition hypothesis, CVC-acquired information allows parent firms to form more precise expectations on acquisition deals, thereby improving efficiencies when making acquisition decisions.[22]

C.1. Efficiency of Acquiring Companies

I first study how efficiently CVC parent firms conduct acquisitions of companies. Following the literature, acquisition efficiency is measured using three-day, five-day, and seven-day cumulative abnormal returns (CAR) of an acquisition deal centered on the acquisition announcement day. The analysis is performed on a cross section of mergers and acquisitions deals conducted by CVCs and their matched control firms between five years before and five years after (pseudo-) CVC initiations, and the unit of observation is an acquisition deal. The key variable of interest is the difference-in-differences variable $I(CVCParent)_i \times I(Post)_{i,t}$ indicating whether the acquirer i is within five years after launching its CVC division. If firms could conduct more efficient external acquisitions based on the information gathered from CVC investment, one would expect the abnormal announcement returns to be higher for these deals.

[TABLE IX AROUND HERE]

Table IX Panel A presents the result. Columns (1) to (3) examine three-day, five-day and seven-day CAR (in *basis points, bps*), respectively. The positive and significant coefficients across all three columns confirm that firms conduct more successful external acquisitions as they internalize the information acquired through their CVC investment. Quantitatively, compared to their industry peers, acquisitions made by CVC parent firms experience a 65 bps improvement in the three-day abnormal return from one-day before the announcement to one-day after the announcement, and a greater than 130 bps increase in abnormal return during the $[-3, 3]$ window.

[22] Those acquisitions are not necessarily limited to their CVC portfolio companies, and can reach to a broader domain using the general innovation and industry knowledge they learn from CVC experience.

C.2. Acquisition of External Innovation

To study how CVC-acquired information is capitalized through acquisitions of innovation, I compile a detailed data set on firms' acquisition of patents (either "company and patents" or "patents only"). The database on patent transactions is based on USPTO patent assignment files, hosted by Google Patents. This database provides useful information for identifying patent transactions: the assignment date; the participating parties, including the assignee—the "buyer" in a transaction—and the assignor—the "seller" in a transaction; and comments on the reason for the assignment. To gather additional information on the original assignee and patent technology classes, I merge the raw assignment data with the USPTO patent databases, and with the HBS inventor database. I then follow a procedure, based on Serrano (2010) and Akcigit, Celik, and Greenwood (2013), in which I separate patent transactions from all patent reassignment records, that is, I remove reassignments associated with cases such as a patent transfer from the employee inventor to the employer firm, or a patent transfer between different subsidiaries of a firm. A more detailed description of the data and methodology is provided in the Appendix.

I perform the analysis on the sample of patent purchases conducted by CVC parent firms and their control firms, and the unit of observation is a patent transaction.[23] The dependent variable is calculated as the citation growth from the n-year ($n = 1, 2, 3$) period before the patent transaction to the same length after the transaction.[24] This variable intends to capture whether the purchased patents better fit the buyer than the seller, thereby signaling a more efficient transaction. As in Panel A, the key variable of interest is the difference-in-differences term $I(CVCParent)_i \times I(Post)_{i,t}$, indicating whether the patent buyer i is within five years after launching its CVC division. If firms could capitalize the information learned from CVC by conducting more efficient patent purchases, one would expect a positive coefficient to be associated with the difference-in-differences term.

In Panel B of Table IX, I report the citation growth around patent transactions. The

[23]To be clear, some patents are transacted under one "deal," and I necessarily treat each of them as one individual observation.

[24]For example, when $n = 3$, $\Delta Citation[-3, +3]$ is calculated as total citations received by the transacted patent from one year to three years after the transaction *minus* total citations received from 3 years to one year before the transaction.

positive coefficient in column (1), 0.200, means that after benchmarked by patent transactions conducted by their matched control firms and pre-CVC transactions, patents purchased by CVC parent firms receive on average 0.2 more citations during the first year under the new owner than the last year under the old owner. Column (2) uses a two-year horizon to calculate citation increases, and the economic magnitude increases to 0.607. Column (3) shows an amplified result due to a three-year horizon.

It is worth discussing the economic interpretation behind this spike in citations after CVC firms' patent transactions. In principle, a spike in citations indicates that the underlying patent becomes increasingly visible and popular, plausibly because it better fits the overall innovation profile of the new owner or is commercialized more successfully after the transaction. Specifically in our context, this particularly strong increase in citations is consistent with the interpretation that CVC parent firms acquire innovation that is in turn better commercialized and made visible to the industry.

D. Human Capital Renewal and Information Acquisition

Evidence thus far suggests that CVC parent firms devote effort to integrating and utilizing information acquired from the entrepreneurial sector. Identifying, processing, and integrating new information is difficult, how do CVC parents accomplish this task? I identify one important channel that CVC parents actively manage: human capital renewal. Indeed, inventors, usually highly educated scientists and engineers, are key in absorbing, processing, and using information to produce new 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, 2015). In this section, I explore the role of inventors in facilitating knowledge gathering and use.

I rely on Harvard Business School patenting database for inventor-level information.[25] 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

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

annual patenting activities of each inventor.[26] Using a similar criterion as in Bernstein (2015) and Brav et al. (2015), I identify the number of inventors who leaves the company and the number of inventors who are newly hired in each year.

[TABLE X AROUND 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 control firms as in Table VII, using model (7). In Table X 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 the period before CVC investment. The vacancies created by leavers are filled by inventors newly hired by the firm; 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.

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 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 X 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.

[26] One limitation of this analysis is that we detect inventor mobility 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.

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* and *Explorativeness*, consistent with Table VII. A key result in this table is the positive coefficient in front of 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 (3), I focus on the 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 new inventors are more likely to use knowledge acquired from CVC portfolio companies in their new innovation.

V. CVC Terminations: Staying Power and Investment Dynamics

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.

The analysis provides further opportunities to distinguish the important strategic motivation behind CVC investment. Under alternative 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, 2013), and obtain competitive advantages (Mathews, 2006; Fulghieri and Sevilir, 2009). Even though these studies focuses primarily on static trade-offs and does not concern intertemporal dynamics, it implicitly implies that firms might invest persistently in CVCs long periods of time.

A. *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 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 is calculated as the period between the initiation and termination of the division.

[TABLE XI AROUND HERE]

Table XI 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,[27] lending support to the argument that the benefit from CVC investment shrinks as information is assimilated. However, a large number of firms (27%) 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 length 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 quickly. To rule out this concern, in the last column of Table XI, I calculate the success rate of deals invested by CVCs categorized by CVC durations. An investment deal is defined

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

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.

B. Innovation Improvements and CVC Termination

What determines the termination and hibernation of CVCs? To echo Table III, which shows that innovation deterioration motivates CVC initiations, I conclude my analysis of the CVC life cycle by examining corporate innovation at termination. Table XII 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 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 XII AROUND 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 result is shown in columns (1) and (2) of Table XII Panel B. The positive and significant coefficients mean that larger improvements of innovation from the initiation year motivate parent firms to terminate CVC investment.

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 XII 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 CVC.

VI. Conclusion and Literature Revisited

How do corporations manage their boundaries of the firm in the pursuit of long-term growth? This paper shed new light on this ultimate question at the intersection of organizational economics and corporate finance by studying an emerging economic phenomenon, Corporate Venture Capital (CVC), which is VC investment systematically made by established corporations and bridges the corporate sector with the entrepreneurial sector. Is CVC a pet-project for empire-building managers, or a conscious corporate decision? Armed with an identification strategy that allows me to isolate firm-specific innovation shocks, I find that firms launch CVC programs following innovation deterioration, and the main motivation is to acquire information and innovation knowledge from the entrepreneurial sector. This information acquisition rationale leads me to further characterize the life-cycle dynamics of CVC—evolving through *initiation*, *operation*, and *termination* stage—in which CVC parent firms strategically select information sources (portfolio companies), actively integrate newly acquired information into corporate decisions, and terminate CVCs when informational benefit shrinks.

Beyond establishing the CVC life cycle and the information acquisition rationale behind these activities, I view this paper as 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 work should be done to achieve a better understanding of details in CVC operations. Second, this paper highlights the information acquisition motive behind organizing innovation, which has been largely overlooked in the literature (Tirole, 2010) but is worth future exploration. Third, this paper explicitly considers the interaction between CVC investment and alternative organizational forms, calling 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 in asset pricing and in corporate finance, either theoretically or empirically (Van Nieuwerburgh and Veldkamp, 2010). Empirical work on corporate decisions regarding information management is particularly limited by the unobservability of related behaviors. By examining the CVC life cycle, we obtain several results regarding information acquisition and utilization that would be 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, 2014; 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.

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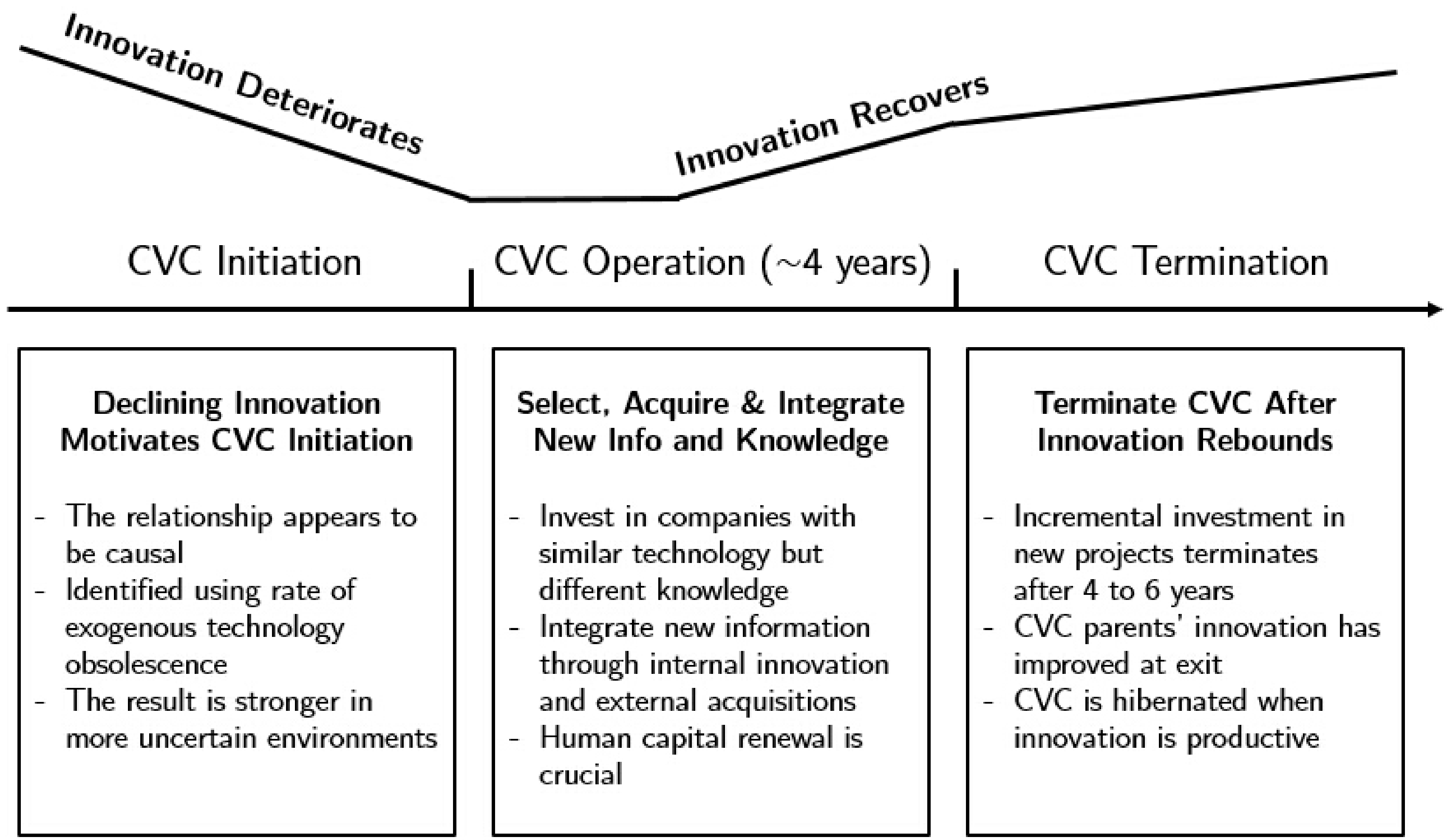
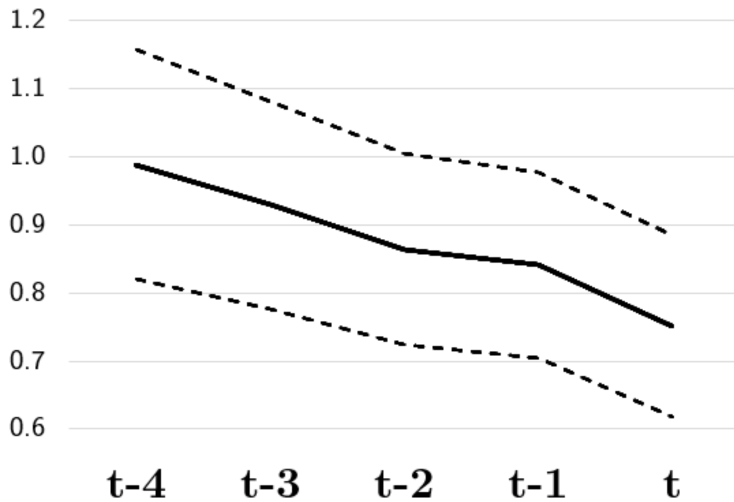
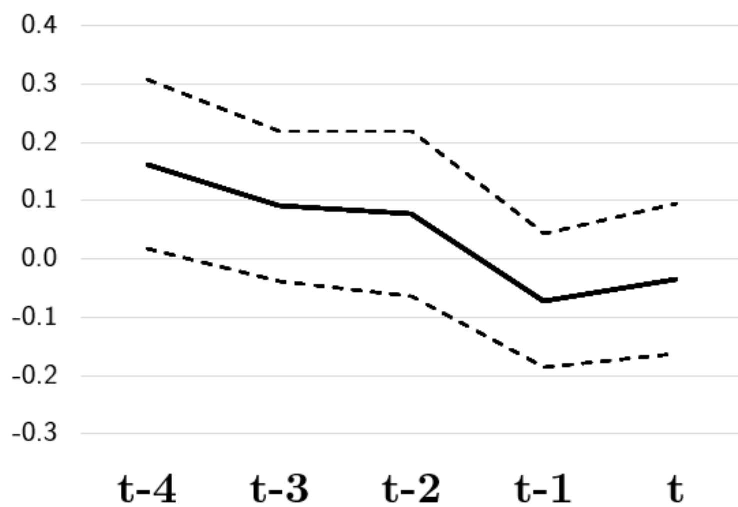


Figure 1: The Life Cycle of Corporate Venture Capital



(a) ln($NewPatents$)



(b) ln($Pat.Quality$)

—Industry-Year Adjusted Value - - -95% Confidence Interval

Figure 2: Corporate Innovation before CVC Initiations

This figure tracks corporate innovation performance 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. ln($Pat.Quality$) is the logarithm of average citations of new patents. 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 firm launches its CVC unit ($t-4$) and ends in the year of launching (t). 95% confidence intervals are plotted in dotted lines.

Table I: 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 the 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 II: Summary Statistics of the Regression Sample

This table summarizes firm characteristics at the firm-year level from 1980 to 2006. 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 I. 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
Scaled Citations of New Patents	1.31	1.03	1.25	1.16	1.01	1.11
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
KZ Index	0.39	0.52	1.93	0.72	0.72	1.99
G-Index	9.09	9.00	2.74	9.13	9.00	2.39
Inst. Shareholding	0.24	0.23	0.16	0.26	0.25	0.13
Innovation Uncertainty	0.62	0.16	1.50	0.73	0.25	1.57

Table III: 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 II. $I(CVC)_{i,t}$ 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 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 is calculated by changing two standard deviations of the $\Delta Innovation$ and is reported below the estimation results.

	(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 IV: 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 II. 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 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 $I(CVC)_{i,t}$ 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 V: Innovation Deterioration and CVC Initiation—The Role of Uncertainty

This table documents the causal relation between innovation deterioration and CVC initiations across firms with heterogeneous informational environment. The analysis is performed using extended specifications based on Table III and Table IV:

$$
\begin{aligned}
I(CVC)_{i,t} = \alpha_{industry \times t} &+ \beta \times \Delta Innovation_{i,t-1} \\
&+ \beta' \times \Delta Innovation_{i,t-1} \times I_{uncertainty,it} \\
&+ \gamma' \times I_{uncertainty,it} + \gamma \times X_{i,t-1} + \varepsilon_{i,t}.
\end{aligned}
$$

The panel sample is described in Table II. Observations are categorized into two subgroups by the median of uncertainty level of the firm's informational environment, indicated by $I_{uncertainty}$, which is measured using the average dispersion of patent quality in a technology class weighted by the technological distribution of the firm's portfolio over technology classes. When estimating using 2SLS, I instrument $\Delta Innovation_{i,t-1}$ with $Obsolescence$, and the interaction term is instrumented by the interaction of $Obsolescence$ with $I_{uncertainty,it}$. Columns (1) and (4) report the first-stage regression, which regresses 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 citations per new patent in each firm-year plus one) on the three-year knowledge obsolescence as defined in (2) in the paper. Columns (2) and (5) report the OLS regression results, where $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t, and zero otherwise. Columns (3) and (6) report the second-stage regression. 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 specification 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) First Stage	(2) OLS	(3) 2SLS	(4) First Stage	(5) OLS	(6) 2SLS
$Obsolescence$	-0.115***			-0.074***		
	(-11.778)			(-15.239)		
$\Delta \ln(NewPatent)$		-0.006***	-0.005**			
		(-4.160)	(-2.045)			
$\Delta \ln(NewPatent) \times I_{uncertainty}$		-0.003**	-0.005*			
		(-2.185)	(-1.901)			
$\Delta \ln(Pat.Quality)$					-0.004**	-0.003*
					(-2.459)	(-1.730)
$\Delta \ln(Pat.Quality) \times I_{uncertainty}$					-0.002**	-0.003
					(-2.155)	(-1.625)
$I_{uncertainty}$	-0.039***	0.002	0.001	-0.028	0.008*	0.005
	(-3.093)	(1.213)	(0.669)	(-0.494)	(1.780)	(0.457)
Firm ROA	0.091***	-0.003	-0.003	-0.301	0.014	0.014
	(4.739)	(-1.259)	(-1.270)	(-1.367)	(1.401)	(1.250)
Size (Log of Assets)	0.028***	0.003***	0.003***	-0.120***	0.005***	0.003
	(12.710)	(11.108)	(11.389)	(-9.129)	(6.034)	(1.614)
Leverage	-0.101***	-0.005**	-0.005**	0.133	-0.013*	-0.005
	(-5.058)	(-2.272)	(-2.347)	(0.798)	(-1.660)	(-0.437)
Firm R&D	0.476***	0.013***	0.013***	-1.289***	0.060***	0.048**
	(11.592)	(3.254)	(3.248)	(-3.096)	(3.716)	(2.202)
F-Statistic	138.72			232.23		
Observations	25,976	25,976	25,976	25,976	25,976	25,976
R-squared	0.398	0.122	0.122	0.338	0.132	0.118
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table VI: 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 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 Closeness			
Technological Proximity	0.029**	0.039**	0.035**
	(2.020)	(1.969)	(2.358)
Knowledge Overlap		-0.018*	-0.014**
		(-1.756)	(-2.169)
Geographical Closeness			
$I(SameCZ)$			-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 VII: Characteristics of Internal Innovation around CVC Investment

This table studies levels and characteristic of innovation around the start of CVC investment. The analysis is based on the following standard difference-in-differences (DiD) framework:

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

To construct a proper control group for CVC parent firms, I employ the propensity score matching method and match each CVC parent firm that launches CVC in year t with two non-CVC firms from the same year and 2-digit SIC industry, that has the closest propensity score estimated using size (logarithm of total assets), market-to-book ratio, $\Delta Innovation$, and patent stock. The CVC launching year for a CVC parent firm is also the "pseudo-CVC" year for its matched firms, and I include firm data beginning five years before the (pseudo-) event year through five years afterward. The dependent variables $y_{i,t}$ are innovation quantity (columns (1) and (2)), quality (columns (3) and (4)), new cite ratio (columns (5) and (6)) and explorativeness (columns (7) and (8)). $I(CVCParent)_i$ is a dummy variable indicating whether firm i is a CVC parent 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. The model 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln($NewPatent$)		ln($Pat.Quality$)		*New Cite Ratio*		*Explorativeness*	
$I(CVCParent) \times I(Post)$	0.239***	0.227***	0.217***	0.170***	0.097***	0.104***	0.041**	0.039***
	(2.933)	(4.443)	(2.618)	(2.733)	(5.968)	(8.169)	(2.338)	(2.852)
$I(CVCParent)$	0.135		0.036		-0.012		0.009	
	(1.190)		(0.383)		(-0.721)		(0.543)	
$I(Post)$	0.038	0.005	0.084*	0.044	-0.006	-0.007	0.010	0.011
	(0.773)	(0.253)	(1.753)	(1.181)	(-0.519)	(-0.693)	(0.901)	(1.022)
Observations	10,289	10,289	10,289	10,289	4,834	4,834	4,834	4,834
R-squared	0.511	0.931	0.355	0.733	0.342	0.649	0.325	0.590
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes

Table VIII: Direct Information Acquisition from Portfolio Companies

This table studies the direct information acquisition of CVC parent firms from their portfolio companies by investigating how investing in an entrepreneurial company affects the CVC parent firm's possibility of innovating based on the entrepreneurial company's innovation. 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. These data further allow me to determine whether firm i makes a new citation, which it never cited before, to a patent that is possessed by 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 Company's Patents		Citing a Company's Knowledge	
$I(CVCParent) \times I(Post) \times I(Portfolio)$	0.159***		0.297***	
	(74.13)		(86.54)	
$\times Successful$		0.184***		0.354***
		(63.90)		(73.94)
$\times Failed$		0.128***		0.239***
		(39.83)		(48.70)
$I(CVCParent) \times I(Post)$	0.018***		0.049***	
	(205.12)		(382.49)	
$I(CVCParent) \times I(Portfolio)$	0.003		0.057*	
	(1.60)		(1.75)	
$I(CVCParent)$	0.003***		0.019***	
	(38.95)		(146.12)	
$I(Post)$	0.002***		0.002***	
	(38.04)		(26.08)	
Observations	1,406,734		1,406,734	
R-squared	0.01		0.02	
Industry × CVC Year FE	Yes		Yes	

Table IX: Integration of CVC-Acquired Information through External Acquisitions

This table studies the efficiency of acquiring companies or innovation around the start of 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 acquisition deals (Panel A) and patent purchases (Panel B) conducted by CVCs and their matched control firms during five years before CVC initiations and five years after CVC initiations, and the unit of observation is an acquisition deal (Panel A) and a patent purchase (Panel B). The sample of CVCs and matched firms are as described in Table VII. The dependent variables $y_{i,t}$ are cumulative abnormal returns (CARs) for acquisition of companies (Panel A) and annual citation growth for purchases of patents (Panel B). $I(CVCParent)_i$ is a dummy variable indicating whether firm i is a CVC parent 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. The model includes industry-by-year fixed effects $\alpha_{industry \times t}$. 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.

Panel A: Abnormal Returns when Acquiring Companies (in *basis points*)			
	(1)	(2)	(3)
	$CAR[-1,+1]$	$CAR[-2,+2]$	$CAR[-3,+3]$
$I(CVCParent) \times I(Post)$	65.811*	131.378**	135.693*
	(1.697)	(2.164)	(1.765)
$I(CVCParent)$	-55.009	-46.766	-185.444
	(-0.575)	(-0.385)	(-1.510)
$I(Post)$	11.615	23.546	16.984
	(0.120)	(0.208)	(0.134)
Observations	1,502	1,502	1,502
R-squared	0.272	0.275	0.281
Controls	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes

Panel B: Citation Growth after Purchasing Patents			
	(1)	(2)	(3)
	$\Delta Citation[-1,+1]$	$\Delta Citation[-2,+2]$	$\Delta Citation[-3,+3]$
$I(CVCParent) \times I(Post)$	0.200***	0.607***	1.358***
	(3.112)	(3.805)	(6.121)
$I(CVCParent)$	-0.023	-0.097	-0.095
	(-0.177)	(-1.081)	(-1.007)
$I(Post)$	0.015	0.040	0.108
	(0.375)	(0.395)	(0.764)
Observations	43,874	39,167	32,254
R-squared	0.045	0.093	0.082
Controls	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes

Table X: Inventor Adjustment and Information Acquisition

This table studies the role of inventor adjustment in information acquisition for CVC parent firms. The Harvard Business School Patent Database provides inventor-level information, which allows me to identify inventor mobility and characteristics of the inventor team for each patent. In Panel A, 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 is as described in Table VII. 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 as least half of the inventor team are have 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. Panel B studies the characteristics of patents produced by new inventors. The sample consists all the innovation produced by CVC parents and matched control firms from five years before the event to five years after the event. $I_{\text{New Inventor's Pat}}$ equals one if new inventors contribute at least half of the patent. *New Cite Ratio* and *Explorativeness* are defined in the Appendix. All specifications include 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.

Panel A: Inventor Mobility during CVC Operation

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln(1+Leavers)$		$\ln(1+NewHires)$		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	10,289	10,289	10,289	10,289	4,834	4,834
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

	(1) *New Cite Ratio*	(2) *Explorativeness*	(3) *Citing Portfolio*
$I_{\text{New Inventors' Pat}} \times I(CVCParent) \times I(Post)$	0.031**	0.038**	
	(2.364)	(2.218)	
$I_{\text{New Inventors' Pat}} \times I(CVCParent)$	0.007	0.005	
	(0.368)	(0.215)	
$I_{\text{New Inventors' Pat}} \times I(Post)$	-0.009	-0.013	
	(-0.753)	(-0.762)	
$I_{\text{New Inventors' Pat}}$	0.050***	0.068***	0.005***
	(4.621)	(5.080)	(2.671)
$I(CVCParent) \times I(Post)$	0.069***	0.044***	
	(2.656)	(2.854)	
$I(CVCParent)$	-0.041	-0.060	
	(-1.570)	(-0.703)	
$I(Post)$	-0.015	-0.022	
	(-0.888)	(-0.911)	
Observations	132,407	132,407	43,236
R-squared	0.151	0.124	0.010
Controls	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	–

Table XI: 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 that are between CVC initiation and termination yet 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 or 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 XII: 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 XI). Innovation performance is measured using innovation quantity and quality, and both are adjusted using the 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 CVC sample 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)
	Hazard of 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)
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

Appendix A. 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., $\ln(NewPatent) = \ln(New\ Patent + 1)$.
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., $\ln(Pat.Quality) = \ln(Patent\ Quality + 1)$.
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.
Explorative	Percentage of explorative patents filed in a given year by the firm; a patent is classified as explorative if at least 80% of its citations are not based on existing knowledge.
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
SameCZ	Dummy indicating whether CVC firm i and entrepreneurial company j are located in the same Commuting Zone (CZ). In cases when the CVC and the firm headquarter are located in different areas, I use whichever is closer to the startup.
$\ln(Distance)$	Natural logarithm of the mile distance between firm i and entrepreneurial company j (accurate at Zipcode-level). In cases when the CVC and the firm headquarter are located in different areas, I use whichever is closer to the startup.

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 of the set of patents that receive at least one citation from CVC firm i and one citation from entrepreneurial company j; (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, $$KnowledgeOverlap_{ij,t} = \frac{Card(K_{i,t} \cap K_{j,t})}{Card(K_{i,t} \cup K_{j,t})}$$
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.