The Life Cycle of Corporate Venture Capital*

Song Ma

This paper investigates why industrial firms conduct Corporate Venture Capital (CVC) investment in entrepreneurial companies. I test alternative views on CVC by exploiting the entry, investment, and termination decisions of CVC divisions. CVC *entry* follows deteriorations of a firm's internal innovation. At the *investment* stage, CVCs select startups with a similar technological focus but that have a non-overlapping knowledge base, and they integrate technologies generated from these ventures. CVCs are *terminated* when parent firms' innovation recovers. Overall, the desire to regain innovation after adverse shocks, rather than managerial misbehaviors or pure financial returns, motivates incumbent firms to adopt CVCs.

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Recent decades have witnessed non-financial firms' forays into venture capital. Specifically, firms create Corporate Venture Capital (CVC) divisions to make systematic minority equity investments in innovative startups.[1] CVC has become a common form of corporate investment adopted by hundreds of firms and emerged as an important source of entrepreneurial capital accounting for about 20% of VC investment (National Venture Capital Association, 2016). The question naturally arises—why do firms step out of their traditional businesses to make arm's length entrepreneurial investments in startup ventures?

Classic corporate finance theories, though not being dedicated to theorize the CVC phenomenon, provide several distinct, yet mutually non-exclusive, views to guide the exploration of CVC rationales. First, the existence of CVC could be rooted in the fundamental conflicts between shareholders and managers. A long-lasting literature shows that managers extract private utilities by expanding firm boundaries, which in turn affects their decisions on investments (Jensen, 1986; Stulz, 1990; Denis et al., 1997). CVCs, if not properly structured and monitored, can simply be reflecting managers' desire to build an empire or to enjoy managerial perks via venture investing. Hence, the *agency view* of CVC.

Alternatively, CVCs can be motivated by incumbent firms' desire to garnish financial returns from the promising entrepreneurial sector. Investing in a startup requires a comprehensive assessment of its business idea, particularly in innovation-intensive industries (Trester, 1998; Ewens, Nanda, and Rhodes-Kropf, 2017). Being affiliated with an incumbent firm thus allows a CVC to exploit its advantageous knowledge about the industry and specific technologies generated from its core business. The financial motive could be particularly strong when internal investment opportunities are poor, following the classic Q-theory argument. Hence, the *financial view* of CVC.

Finally, CVCs can be used to seek strategic benefits from connecting to startups, most noticeably to expose firms to startups' new technologies which can strengthen their own internal innovation abilities.

[1]Consider, for example, GM Ventures, the CVC unit initiated by General Motors in 2010. On behalf of General Motors, GM Ventures invested in dozens of auto-related technological startups, including automotive clean-tech and advanced materials, among other fields, through minority equity stakes.

Hellmann (2002) and Hellmann, Lindsey, and Puri (2008) shows that firms make CVC investments when there are complementarities between startups and parent firms' core businesses. Mathews (2006) theorizes that the main strategic benefits can be in the form of knowledge transfers from entrepreneurs to incumbent CVC parent firms.[2] Lerner (2012) argues that CVC is an important component in the architecture of corporate innovation. Hence, the *strategic view* of CVC.

The goal of this paper is to investigate these different views of the CVC rationale. Understanding this question is important for shareholders who need to govern and monitor adoptions of CVCs, for startups and venture capitalists who work with CVCs in entrepreneurial financing, as well as for policy makers who regulate interactions between firms and aim to stimulate innovation. To achieve this goal, I compile a comprehensive sample of CVC divisions launched by US-based public firms in the past three decades using information from both archival data and media searches. This sample is augmented by information on CVC investment history, portfolio companies, and parent firms' innovation, financials, and governance. This detailed dataset allows the empirical study to investigate each stage of the CVC life cycle—from why firms enter CVC, to how CVCs invest, to the decision of terminating CVCs. The key insight that can help us distinguish agency, financial, and strategic views is that they generate different predictions at each stage of the CVC life cycle.

The analysis starts from the CVC *entry* decisions. Under the agency view, CVCs are a sign of governance failures and should be formed more often in firms whose shareholders are unable to discipline managers. The financial view of CVC would predict firms entering the CVC business either following a period when their industry knowledge becomes more advantageous in assessing venture opportunities, or when their internal investment opportunities are poor. The strategic view, which stresses CVCs' function of acquiring innovative knowledge from the startup sector, predicts that CVCs will be started as external knowledge becomes more valuable to complement internal innovation.

[2] Surveys among CVC practitioners also indicate that CVC investments allow parent firms to acquire information on new innovation and markets (Siegel et al., 1988; Macmillan et al., 2008).

I explore the determinants of the CVC entry decision in a firm-year panel. The key finding is that CVCs typically start following deteriorations in internal innovation, captured by decreases in innovation quantity and quality. Quantitatively, a one-standard-deviation decline in innovation quantity, measured using the annual number of new patent applications, increases the probability that a firm will initiate a CVC in that year by about 26% relative to the unconditional entry probability. Similarly, a one-standard-deviation decline in innovation quality, measured using new patents' lifetime citations, increases the entry probability by 34%. This finding first supports the strategic view of CVC, which builds upon the long-held theory in the economics of innovation that dates back to Nelson (1982) and Telser (1982). It argues that exposing to new innovation knowledge is especially valuable when the ability to internally generate ideas deteriorates.[3] Meanwhile, the evidence is also consistent with the financial view, which may predict CVC entries when internal investment opportunities dry up.

In contrast, measures of corporate governance, including institutional shareholding and G-Index, do not explain CVC entry decisions. This lends little support to the agency view. However, one may worry that the aforementioned relation between innovation deteriorations and CVC entries could result from unobserved agency forces. For example, an entrenched manager can simultaneously destroy internal innovation and launch CVC as a perk. To assess this argument, I isolate variations to innovation that are plausibly unrelated to contemporaneous managerial behaviors. Specifically, I construct a variable labeled as *Knowledge Obsolescence* to track the usefulness of a firm's pre-determined knowledge accumulations by making use of detailed citation patterns. I find that knowledge obsolescence predicts an individual firm's innovation quantity and quality deteriorations, and the relation between those deteriorations and CVC launches continue to hold when exploiting these plausibly exogenous variations to innovation ability. This further rules out the agency view.

The CVC entry specification is refined to further explore whether the evidence leans more toward the financial view or the strategic view. CVCs are classified into strategic CVCs and financial CVCs based on the

[3] See also Nelson and Winter (1982); Dosi (1988); Jovanovic and Rob (1989); Kortum (1997); Fleming and Sorenson (2004); Frydman and Papanikolaou (2017), among others.

corporate announcements and media coverage at the point of entry. Strategic CVCs are the majorities, and the decline of internal innovation mostly motivates entries of strategic CVCs but not financial CVCs. In addition, under the financial view, entering CVC (better opportunities) should be accompanied by a decrease in internal investment (poor opportunities). However, I do not find evidence that CVC investment is accompanied by a shift away from internal investment. Overall, though the findings are not conclusive yet at this stage, the strategic view is more consistent with the empirical evidence at CVC entry.

The analysis moves on to the *investment* phase of the CVC life cycle with the hope to further explore the strategic vs. the financial view. In this stage, I examine the selection of portfolio companies and whether and how CVC parent firms' innovation paths are affected by their portfolio companies. I find that the technological proximity of the patent portfolios of a CVC parent firm and a startup has a positive effect on the probability of a venture relation formation. But more importantly, conditional on working in proximate technological areas, CVCs are more likely to invest in startups about which they have less information, captured by fewer mutual citations. Geographically, the prior literature demonstrates that financial return-driven IVCs exhibit a local bias when selecting portfolio companies in order to take advantage of local knowledge and facilitate monitoring (Cumming and Dai, 2010; Hochberg and Rauh, 2012). In contrast, CVCs appear to have a "reverse home bias"—that is, they are less likely to invest in companies in their own geographic regions, with which there are already strong local innovation spillovers (Peri, 2005; Matray, 2016).

I also examine whether CVC parent firms subsequently utilize the technologies of their portfolio startups. CVC parent firms are more likely to cite patents generated by their portfolio startups after making the investment. This citation pattern only happens after investments are made, and never before. This pattern does not hold for placebo-pairs constructed by pairing CVC parents' closely matched industry peers with startups. Overall, the investment pattern of CVCs differs from those of financial return-driven IVCs. CVCs invest in companies about which they do not necessarily have advantageous knowledge of, and they integrate the complementary technologies from their portfolio companies into their own organic innovation development.

This evidence lends further support to the strategic view of CVCs.

The final analysis concerns the *termination* stage of CVCs. In principle, CVCs are not constrained by the typical IVC fund life of 10 to 12 years. If CVCs are indeed used by firms as a way to invest in ventures using advantageous information or as a result of agency conflicts, CVCs should remain in business for a significant period. However, CVCs appear to be temporary divisions that have shorter and non-uniform life cycles. The median duration of the CVC life cycle is about four years, with an average of six. The CVC life cycle ends with the *termination* stage, when CVC parents stop making incremental investments in new startups. I show that a CVC's staying power is closely related to the innovation dynamic of the parent firm, and it is terminated when internal innovation begins to recover. The staying power and termination decision are not explained by exit failures of portfolio companies or by governance changes such as CEO turnover.

In summary, this paper investigates different views of CVCs using the life cycle evidence across the entry, investment, and termination stages. The findings lend the strongest support to the strategic view—CVCs are in general temporary corporate divisions for incumbent firms in response to negative innovation shocks, and help those firms to expose themselves to new technologies in order to regain their innovation edge. The agency view and the financial view, though plausible in some cases, cannot consistently explain the large-sample empirical patterns.

This paper contributes to the emerging literature on CVC. In prior literature, Hellmann, Lindsey, and Puri (2008) exploit a bank-VC setting and show that banks use their venture capital arms to build early relationships with startups that have larger future debt capacity, which complements their lending business. Dushnitsky and Lenox (2005b, 2006) show that CVC investments positively correlate with parent firms' future internal innovation rates and firm value, and Chemmanur, Loutskina, and Tian (2014) show that CVCs benefit portfolio companies. Benson and Ziedonis (2010) studies cases of CVC-led acquisitions. This paper contributes to the literature in two ways. First, it provides, to the best of my knowledge, the first empirical exploration of why and how CVC investment decisions are made, while prior studies on CVC rationales are largely confined to surveys of managerial motives (Siegel, Siegel, and MacMillan, 1988; Macmillan, Roberts, Livada, and Wang, 2008). Second, the new evidence demonstrates the life cycle pattern of CVC investments, which can serve as a base for future discussions on many CVC issues such as financing innovation, knowledge spillover, creative destruction, among others.[4]

In broader terms, this paper builds on the literature on innovation outside firm boundaries. Nelson (1982), Telser (1982), and Jovanovic and Rob (1989) show that firms endogenously obtain innovation knowledge through searching ideas and acquiring information externally. Aghion and Tirole (1994) theorize firms' trade-offs when deciding to organize innovation inside or outside the boundaries of the firm. On the empirical side, Robinson (2008) shows that firms use strategic alliances to implement riskier projects when they are endowed with a set of exogenous ideas. Bena and Li (2014) show that firms with stronger innovation capabilities acquire companies with high knowledge overlaps. This paper complements that literature in two ways: first, it provides new comprehensive evidence of the under-explored CVC block in the architecture of innovation; second, it explicitly links CVC to previously studied forms of innovation efforts by tracking granular R&D, human capital, and acquisition decisions prior and subsequent to CVC investments.

The remainder of the paper proceeds as follows. Section 1 describes sample construction and documents stylized facts. Sections 2 through 4 cover each stage of the CVC life cycle. Section 5 concludes.

1. Data and Measurements

1.1. The CVC Sample

I construct a sample of Corporate Venture Capital units affiliated with US-based public firms, starting with the list of CVCs identified by the standard VentureXpert database. Each CVC on the list is manually matched to its unique corporate parent in Compustat by checking multiple sources (Factiva, Google, Lexus/Nexis,

[4]There is a broader business literature of CVC, see Dushnitsky (2006) and Maula (2007) for surveys. For more readings, see, e.g., Bottazzi, Da Rin, and Hellmann (2004); Dushnitsky and Lenox (2005a); Basu, Phelps, and Kotha (2011); Dimitrova (2013); Smith and Shah (2013); Ceccagnoli, Higgins, and Kang (2017); Wadhwa, Phelps, and Kotha (2016).

etc.). VC divisions operated by financial firms (e.g., bank affiliated or insurance company affiliated) are excluded from the sample.

[Insert Table 1 Here.]

The main sample consists of 381 CVC firms initiated between 1980 and 2006.[5] Table 1 tabulates the time-series dynamic and the industry composition of CVC activities. Panel A presents the number of CVC initiations and investment deals by year. Panel B summarizes the industry distribution of CVC parent firms, and 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.

In addition, I also collect investment deals conducted by CVC investors from VentureXpert. These data can help to characterize investment patterns of each investor, such as the time horizon of investment, number of companies invested, and stages of investment. They also allow us to observe the identity, final outcome, and demographic information of portfolio companies, which in turn can be used to link those entrepreneurial companies to other data sources like patent data, as discussed below.

1.2. Innovation Data

Basic innovation data are obtained from the NBER Patent Data Project and from Bhaven Sampat's patent and citation data.[6] The combined database provides detailed patent-level records on more than four million patents granted by the USPTO between 1976 and 2012. It provides information on the patent assignee (the entity, such as the firm, which owns the patent), the number of citations received by the patent, the technology

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

[6] 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`.

class of the patent, and the patent's application and grant year. This database is linked to Compustat using the bridge file provided by NBER. I also link this database to startups 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 (2016). Details of the matching algorithm are explained in related sections below and in Appendix B.[7]

I employ two main variables to measure corporate innovation performance. Innovation *quantity* is calculated as the number of patent applications, which are eventually granted, filed by a firm in each year. A patent's year of application is used instead of the year it is granted because the former 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. Innovation *quality* is calculated based on the average lifetime citations of all new patents produced by a firm in each year. Citation measures are adjusted for right-censoring as suggested by Jaffe and Trajtenberg (2002) and Lerner and Seru (2015). Similar to the logarithm transformation performed on *quantity*, I use $\ln(1+Pat.Quality)$ (denoted as $\ln(Pat.Quality)$).

Besides innovation performance, the data can also track citations made by firms in their own patents. For example, the data allow the observation of General Motors citing the "Internal combustion engine control for improved fuel efficiency" of Tula Technology Inc (US Patent Number 7577511, granted August 18, 2009) in its own patent "Fuel consumption based cylinder activation and deactivation control systems and methods" (US Patent Number 9341128, granted May 17, 2016). These information helps in two ways: first, in a static term, I can identify specific underlying technologies used by each firm; in a dynamic term, these information allows to construct variables capturing the technological diffusion among firms, such as from startups to incumbents.

[7] Several Appendix tables conduct analyses on patent transactions and innovative labors. USPTO Patent Reassignment Records are used to identify patent transactions conducted by firms. The Harvard Business School inventor-level database is used to track the mobility and productivity of innovative labor around CVC activities.

1.3. Firm-level Measures

For classic corporate governance measures, institutional shareholding information is extracted from the WRDS Thomson Reuters 13(f) data. I use total percentage institutional shareholding and the shareholding of top five institutional investors to capture the monitoring intensity of shareholders. I also obtain G-Index data from Andrew Metrick's data library.[8]

The sample is augmented with Compustat for financial statement data and with CRSP for stock market performance. The key financial variables include leverage (debt in current liabilities and long-term debt, scaled by book assets), ROA (the ratio of EBITDA to book assets), and R&D ratio (R&D expenses scaled by book assets). All variables are winsorized at the 1% and 99% levels.

2. The Entry of CVC

To understand why incumbent industrial firms make CVC investments, I first explore the decision of CVC entry formally defined as the establishment of the CVC division. The strategic view, which mainly argues the CVCs' function is to acquire innovative knowledge from the startup sector (Fast, 1978; Dushnitsky and Lenox, 2005b; Mathews, 2006), predicts CVCs to be started when external knowledge becomes more valuable to complement internal innovation (Hellmann, 2002). To be more specific, the theories on information acquisition and innovation model firms choosing between allocating the capacity to produce existing ideas and to acquire knowledge from outside that can strengthen internal innovation in later periods (Nelson, 1982; Telser, 1982; Jovanovic and Rob, 1989). The allocation of capacity to information acquisition, such as through CVC, is determined by the quantity and quality of existing ideas available to the firm—the smaller (lower) the quantity (quality) of existing innovation ideas becomes, the more likely the firm will implement CVC, in search of better innovation paths. Accordingly, CVCs are more likely to be launched following innovation deteriorations.

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

The root of the agency view of CVC is the long-lasting literature in corporate finance showing that managers extract private utilities by expanding firm boundaries, which in turn affects their decisions on investments (Jensen, 1986; Stulz, 1990) and on the diversification of the corporation (Denis, Denis, and Sarin, 1997). Proponents of this view argue that CVCs manifest managers' desire to enjoy managerial perks via venture investing or to build an empire, rather than to create value for the firm. Accordingly, CVCs tend to form in firms whose shareholders are unable to discipline managers.

The financial view, which builds on the VC-nature of CVCs, suggests that CVCs simply reflect incumbent firms' motivation to garnish financial returns from the promising entrepreneurial sector. This view, on the one hand, would predict firms entering the CVC business following a period when their industry knowledge becomes more advantageous in assessing venture opportunities, like when their internal operation prospers. On the other hand, following the classic Q-theory argument, the financial motive could be particularly strong when internal innovation opportunities are poor, thus external venture investment opportunities are more appealing.

2.1. Baseline Model Specification

The baseline model examines the CVC entry decision on the firm-year panel of US public firms with valid ROA, size (logarithm of total assets), leverage, R&D ratio, and at least $10 million in book assets. Only "innovative firms," defined as those that filed at least one patent application that was eventually granted by the USPTO, are included. Industries (3-digit SIC level) with no CVC activities during the whole sample period are excluded. The empirical model takes the following form:

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

where $I(CVC)_{i,t}$ is equal to one if firm i launches a CVC unit in year t, and zero otherwise.[9] $\Delta_\tau Innovation_{i,t-1}$

[9] Since the model predicts CVC launches, a CVC parent firm naturally drops out of the sample after the initiation. It re-enters

is the change of firm innovation performance (*Innovation* measurements described below) over the past τ years ending in $t-1$, which naturally differences out firm-specific innovation levels. I use a three-year ($\tau = 3$) innovation shock throughout the main analysis and report robustness checks using other horizons. *Governance* measures include institutional shareholdings and the G-Index. Firm-level controls $X_{i,t-1}$ include ROA, size, leverage, and R&D ratio. Industry-by-year fixed effects are included to absorb industry-specific time trends, and industries are defined by the Fama-French 48 Industry Classification.

[Insert Table 2 Here.]

Table 2 presents descriptive statistics of the regression sample. I show for both firm-year observations when a CVC division was initiated and those observations when a CVC was not initiated. CVC parents are typically large firms. On average, a CVC parent has $10.1 billion in book assets (median is $2.4 billion) just before launching its CVC unit, whereas non-CVC parent firms have less than $3 billion in book assets (median is $0.2 billion). CVC parent firms are innovation intensive in terms of patenting quantity, echoing the size effect. CVC parent firms experience more negative innovation shocks before starting their CVC divisions—they on average experience a -7% (-10%) change in patenting quantity (quality) within the three years prior to launching their CVC units, compared to the control firms, which experience a 12% (8%) shock. Corporate governance variables, G-Index and Institutional Shareholding, are comparable between the two subsamples.

2.2. Baseline Regression Results

Table 3 presents the Ordinary Least Squares (OLS) estimation of a linear probability model (1). Column (1) focuses on the effect of changes in innovation quantity. 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 investments. This estimate translates a two-standard-deviation decrease (2σ-

after one CVC life cycle concludes.

change) in $\Delta\ln(NewPatent)$ into a 51.54% increase from the unconditional probability of launching CVC unites.

Column (2) studies the effect of deterioration in innovation quality. 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 (3) simultaneously estimates the effects of changes in innovation quantity and quality. The estimates are largely unchanged compared to columns (1) to (2). Overall, CVC entries typically follow deteriorations in internal innovation of a firm.

[Insert Table 3 Here.]

Columns (4) to (6) study the effects of classic corporate governance measures on CVC entry. Neither institutional shareholding nor G-Index has any real influence on the CVC entry decision. In column (4), I use total institutional shareholding to measure governance intensity and find it has positive insignificant effect on CVC entry. The result is similar when we use the shareholding of only top 5 institutional shareholders. In column (5) we focus on G-Index (which unfortunately restricts the sample size significantly). G-Index also does not have explanatory power on the initiation of CVCs.

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

I conduct an array of robustness checks to confirm that the CVC initiation results are not driven by the sampling process or specifications. In Table A1, I report the analysis using alternative horizon parameters τ. In Table A2, I estimate the probability of CVC entry using a hazard model developed by Meyer (1990) and utilized in Whited (2006), which fit this paper's context due to its capability of incorporating time-varying predictors and stratified groups. I find similar results in those analyses. I also show that the results are robust to removing firms that are large or small, that are from specific industries, or that are located in specific locations (Table A3).

2.3. Assessing the Agency View of CVC Entry

Table 3 provides supporting evidence for the strategic view and the financial view of CVC, but is largely inconsistent with the agency view. However, to cleanly interpret the result that CVC entries follow internal innovation deteriorations, it is necessary to understand the variations that drive innovation changes in the first place. For example, it could still be the case that Table 3 means that an entrenched manager could hinder innovation and simultaneously lead to the initiation of CVC as a pet project. As a result, to more confidently rule out the agency interpretation of CVC entry, I need an exogenous shifter that could affect an individual firm's ability to generate innovation ideas internally (the first stage), but which is unlikely to affect CVC investments through the agency channel (the exclusion restriction).

The main idea of the empirical strategy is to exploit the influence of exogenous technological evolution on firm-specific innovation knowledge. In other words, the instrument variable will shock the individual firm's ability to generate innovation using exogenous changes to the usefulness of its accumulated knowledge. For example, the empirical strategy will exploit the cases in which a firm specializing in 14-inch hard disk drives (HHDs) becomes less able to innovate when the technology moves on to the 8-inch HDDs.[10]

To implement the idea of measuring the influence of exogenous technological evolution on an individual firm's capability to innovate, I build on the literature of bibliometrics and scientometrics, which measures the obsolescence and aging of a scientific discipline[11] using the dynamics of citations referring to the specific field. In particular, I construct a firm-year level variable, termed as *Knowledge Obsolescence* (*Obsolescence* in short), to capture the τ-year (between $t-\tau$ and t) rate of obsolescence of the knowledge possessed by a

[10] Indeed, "new technologies come and go, taking generations of companies with them" (Christiansen, 1997; Igami, 2017).

[11] The methodology has been similarly applied to evaluate the impact of specific technologies, individual research, among others.

firm as of $t-\tau$.

For each firm i in year t, this instrument is constructed in three steps, formally defined in formula (2). First, firm i's predetermined knowledge space in year $t-\tau$ is defined as all the patents cited by firm i (but not belonging to i) up to year $t-\tau$. This fixed set of patents proxies for the underlying technological knowledge that firm i managed to accumulate. I then calculate the number of external citations (made by firms other than i itself) received by this $KnowledgeSpace_{i,t-\tau}$ in $t-\tau$ and in t, respectively. Last, $Obsolescence^{\tau}_{i,t}$ is defined as the rate of change between the two, which naturally absorbs effects of the size of the firm and its knowledge space. Formally,

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

A larger *Obsolescence* means a greater decline of the value and utility of a firm's knowledge within the τ-year period, as captured by that less new innovation builds on those knowledge.

2.3.1. Knowledge *Obsolescence* and Innovation. This idea that knowledge obsolescence affects innovation (the first stage) builds upon two theoretical pillars. First, the knowledge stock of an individual or institution determines the quantity and quality of its innovation production. Jones (2009) shows that 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. Bloom, Schankerman, and Van Reenen (2013) show that firms working in a fading area benefit less from knowledge spillover, which in turn dampens growth in innovation and productivity. Second, knowledge itself ages. In the past few decades, several disciplines have developed the concept of the obsolescence of knowledge, skills, and technology. The most famous result might be, roughly speaking, that half of our knowledge today will be of little value (or even proven wrong) after a certain amount of time (i.e., half-life), and this half-life is becoming shorter and shorter (Machlup, 1962). Economists have studied the effect of obsolescence of knowledge and skills on labor and industrial organization, as well as the aggregate growth (Rosen, 1975).

Empirically, the effect of knowledge obsolescence on corporate innovation is validated in the first-stage regression, in which I instrument $\Delta_\tau Innovation_{i,t}$ with $Obsolescence^{\tau}_{i,t}$ using the following form:

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

[Insert Table 4 Here.]

Table 4 columns (1) and (3) report results where *Innovation* is measured using the quantity and quality of new patents, respectively. Results show that a faster rate of *Knowledge Obsolescence* is associated with weaker internal production of innovation. The estimate of -0.114 in column (1) translates a 10% increase in the rate of obsolescence of a firm's knowledge space into a 1.14% decrease in its patent applications; this same change is associated with a 1.28% decrease of its patent quality. The F-statistics of these first-stage regressions are both well above the conventional threshold for weak instruments (Stock and Yogo, 2005).

2.3.2. 2SLS Results. The first stage regression (3) allows us to extract variations to innovation driven by plausibly exogenous trends of knowledge obsolescence. The fitted value from this model, denoted as $\Delta\widehat{Innovation}$, is then used in the second-stage regression,

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

and columns (2) and (4) of Table 4 show the estimation results. The effect of obsolescence-driven innovation shocks $\Delta\widehat{Innovation}$ on starting a CVC unit is both economically and statistically significant. The coefficient of -0.007 in column (2) translates a σ-change in $\Delta\ln(NewPatent)$ to a 26% change in the probability of launching CVC investment. The gaps between the OLS estimates (in Table 3) and the 2SLS estimates are small. This comparison suggests that the agency-related interpretation does not seem to drive the OLS estimation initially.

In a reduced form, Table 2 also reports summary statistics for *Obsolescence*. The number of citations received by a firm's predetermined knowledge space decays by 8% in the control group, which can be interpreted as a benchmark three-year natural decay of knowledge. Firms' knowledge spaces on average decay by 29% in the three years before initiating a CVC division, which demonstrates a much more severe hit by the technological evolution. Table 4, column (5) 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 start CVC activities.

2.3.3. Discussions on the Empirical Assumptions. To further justify *Obsolescence* to be a valid source of exogenous variation to innovation that does not affect CVC investments through the agency channel, I provide additional discussions on this assumption in this section.

The first building block of the instrument is the formation of the *KnowledgeSpace*, defined as the set of patents that a firm cites in its previous patents. One potential concern is that a firm's knowledge space can signal the capability of its manager, which in turn can affect is innovation policy. I assess this concern both qualitatively and quantitatively. On the one hand, historical poor management is unlikely to affect the specific timing of current CVC launches—in other words, it is unlikely that poor innovation decisions before $t-\tau$ should lead to CVC investments in t. On the other hand, in an additional analysis, I construct the historic knowledge space of firm i based on its citation before $t-10$ and track the obsolescence of this knowledge space from $t-3$ to t.[12] The possibility that the managerial vision ten years ago still strongly affects CVC decisions today is thin, thus better disentangling firms' knowledge spaces with concurrent managerial decisions. Table 5, Panel A presents results, which are qualitatively and quantitatively similar to Table 4.

[Insert Table 5 Here.]

[12] This analysis necessarily focuses on the sample in the later period and firms that have longer patenting histories.

The second key component of the instrument is the citation dynamics regarding knowledge spaces. One might worry that the firm itself could be a main driver of the technological evolution. For example, a manager might decide to change the course of innovation areas using CVC, and this change could potentially lead to citation changes to the firm's own knowledge base (say, a diesel engine maker enters the gas engine industry and stops citing diesel engine technologies). To be on the conservative side, I have excluded patents owned by the firm from its own knowledge space and all citations made by the firm itself in the variable construction. In other words, any direct impact of a firm itself on the citation dynamic is eliminated from the measure. In addition, I conduct an empirical test in which I repeat the 2SLS analysis in subsamples of firms with high vs. low innovation impact, where innovation impact is categorized using the median of the number of patents possessed by the firm in each year. The idea is that those low-impact firms are less likely to endogenize the technological evolution. I report the result in Panel B of Table 5, and the results are both qualitatively and quantitatively similar to Table 4. The results are also robust when defining innovation impact using total patent applications in the past three years or using market valuation.

Overall, Table 5 suggests that despite potential concerns, the relation between innovation deterioration and CVC launches does not seem to be driven by the variation in agency frictions. These results, combined with the evidence that both institutional shareholding and the G-Index both lack power in explaining CVC entry, lend little support to the agency view of CVC.[13]

2.4. Assessing the Financial View of CVC Entry

What is left unclear is whether the CVC entry in response to innovation deteriorations is motivated by strategic learning or the desire to seek financial returns. Instead of attempting to rule out this financial interpretation, the goal here at the entry analysis is milder. I try to examine to what extent we can distinguish whether the relation between innovation deteriorations and CVC initiations is driven by strategic or financial considerations. Additional analyses to assess these views will be provided in later stages of the life cycle.

[13] A more detailed discussion on the *Obsolescence* variable is provided in Appendix C.

I conduct three additional analyses. The first analysis examines whether innovation deteriorations motivate financial or strategic CVCs. I categorize CVCs in the sample into financial or strategic driven by collecting information disclosed at the announcement of CVC initiations using a news search, following a similar approach as Dushnitsky and Lenox (2006). For each CVC in the sample, I search for media coverage and corporate news at its initiation using Lexis-Nexis, Factiva, and Google. Based on this compiled information, CVCs are coded as financial and strategic. When the main object of a CVC unit is difficult to be categorized, I code it as "unknown." In the end, I successfully categorized 204 CVCs.

The logic behind the analysis is straightforward: if financial return is a key driver behind the relation, the result in Table 3 and Table 4 should hold at least as strongly when focusing on the initiations of the small set of financial CVCs. I report the results in Table 6, Panel A, which shows that innovation deteriorations motivate strategic CVCs with much higher intensities, suggesting that the main effect that innovation deteriorations have on CVC decisions is mostly driven by strategic considerations. Meanwhile, financial CVCs are less responsive to internal innovation performance.

[Insert Table 6 Here.]

The second analysis is to examines whether CVC entries are accompanied by declines of internal R&D. If CVCs reflect corporate actions to seek higher financial returns when internal investment opportunities dry up, we would expect an internal R&D decrease to reflect the shift away from internal investment. In contrast, if CVCs are for strategic complementarities, one could expect R&D to be stable and to be shifted toward the technologies in portfolio startups. In Table 6, Panel B, I show that measures of innovation input (i.e., R&D) expenditures scaled by total assets or sales do not affect the CVC entry decision. Putting this result into the context of Table 3, the interpretation is that CVC is not a way for firms to shift from internal innovation to external innovation, but for them to respond to deteriorating innovative capabilities.

The third analysis examines whether the cash flow condition of an individual firm is related to the firm's CVC entry decision in response to the innovation decline. The idea is that if CVC is used to invest excess cash in external opportunities when the internal pool has poor quality, one would expect the initiation pattern to be stronger in firms with more cash flow. I test this hypothesis by repeating the initiation study using subsamples of firms that are more or less financially constrained, and the results are shown in Table 6, Panel C. In fact, the main results hold strongly in both subsamples with above-median and below-median cash flow.

Admittedly, it is difficult to dispute that financial returns are important for any corporate investment; in fact, a small set of CVCs declare themselves as financial return driven. However, the additional evidence provided in Table 6 suggests that the strategic view of CVC is the main driving force behind CVC entries.

3. The Investment of CVC

To further distinguish between the strategic and the financial view of CVC, the analysis moves on to the investment stage of the CVC life cycle. Under the strategic view, CVCs are adopted to help parent firms learn new innovative knowledge from the entrepreneurial sector and then to further implement those new technologies to complement their internal innovation. Accordingly, CVCs are expected to invest in startups that can provide newer and more useful knowledge and to integrate this new technological information with parent firms' organic R&D. Under the financial view, in contrast, CVCs are investment vehicles for incumbent firms to exploit their industry knowledge in selecting targets and to harvest financial returns. Accordingly, CVCs are expected to act like financial return-driven IVCs and to invest in companies about which they possess advantageous information about and that are easier for them to monitor.

3.1. CVC Portfolio Formation

I start by examining characteristics that lead to the formation of a CVC-startup deal, and the key test is an empirical matching model between CVCs and portfolio companies. I first build a data set of all potential CVC-startup pairs by pairing each CVC i with each entrepreneurial company j that had ever recived an investment by a VC. I remove such pairs when the active investment years of the CVC firm i (between initiation and termination) and the active financing years of company j (between the first and the last round of VC financing) do not overlap.

For each CVC-startup pair i-j, I construct two variables, *Technological Proximity* (*TechProximity*) and *Knowledge Overlap* (*Overlap*), to assess the role of technological distances on CVC-startup matching. *TechProximity* is calculated as the Cosine-similarity between the CVC's and the startup's vectors of patent weights across different technology classes (Jaffe, 1986; Bena and Li, 2014). A higher *TechProximity* indicates that the pair of firms works in closer areas in the technological space. *Overlap* is calculated as the ratio of—(1) numerator: the number of patents that receive at least one citation from CVC firm i *and* one citation from entrepreneurial company j; and (2) denominator: the number of patents that receive at least one citation from either CVC i *or* company j (or both). A higher *Overlap* means that the pair of firms shares broader common knowledge in their innovation.[14]

In addition to measuring the technological distance for each pair, I also construct two measures to capture the geographic distance. *Local* is a dummy variable indicating whether CVC firm i and company j are located in the same Commuting Zone (CZ). CZ is used as the main geographic delineation because it has been shown to be more relevant for geographic economic activities (Autor, Dorn, and Hanson, 2013; Adelino, Ma, and Robinson, 2017). I also include the natural logarithm of the distance between firm i and startup j (accurate at zip-code-level, kilometers).

The empirical test exploits a reduced-form matching model on this sample of CVC-startup pairs to predict the decision of CVC i investing in company j, in the following form,

$$\begin{aligned} I(CVC_i\text{-}Target_j) = \alpha + \beta_1 \times TechProximity_{ij} + \beta_2 \times KnowledgeOverlap_{ij} \\ + \beta_3 \times Local_{ij} + \beta_4 \times Distance_{ij} + \gamma \times X_{i,j} + \varepsilon_{i,j}, \end{aligned} \tag{5}$$

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

where the dependent variable $I(CVC_i\text{-}Target_j)$ indicates whether CVC i actually invests in company j (i.e., the realized pair). In $X_{i,j}$ I control for CVC (i)-level characteristics including number of annual patent applications and average citations of patents; I also control for those innovation characteristics at the startup (j)-level.

[Insert Table 7 Here.]

Table 7 presents coefficients estimated from model (5). In column (1), a positive and significant coefficient means that the *Technological Proximity* between a CVC and an entrepreneurial company increases the likelihood of CVC deal formation. This means that a one-standard-deviation increase of *TechProximity* between a CVC parent firm and a startup doubles the probability that an investment relationship is formed. Column (2) examines *Knowledge Overlap*. The negative coefficient means that after conditioning on technological proximity, CVC parent firms prefer to invest in companies about which they have more limited knowledge. A one-standard-deviation increase of *Overlap* leads to a 40% decrease in investment probability.

In column (3), I explore whether CVCs are more or less likely to invest in geographically proximate firms. The venture capital literature, and the investment literature more broadly, has documented a "home (local) bias" phenomenon—when investing in companies that are geographically closer, financial return-driven investors can better resolve the information asymmetry problem and conduct more efficient monitoring (Da Rin, Hellmann, and Puri, 2011). In columns (3) and (4), however, I find that CVCs do not really invest in their "home" companies with and without controlling for the distance measure. The dummy variable indicating that the CVC and the startup are located in the same Commuting Zone negatively affects the probability of investment. This finding is consistent with the strategic explanation that CVC parent firms can acquire innovation knowledge from startups in the same CZ through local innovation spillover (Jaffe et al., 1993; Peri, 2005; Matray, 2016), which decreases the marginal benefit of making a CVC investment in them.

Overall, Table 7 shows that CVC investment behaviors differ greatly from the well-studied IVCs. CVCs invest in companies that possess knowledge complementary to the parent firm, rather than those over which they possess advantageous information. In addition, they invest in companies at longer distance at the expense of monitoring difficulties, in order to acquire knowledge that can otherwise be hard to obtain. Those all appear to be more consistent with the strategic view of CVCs.[15]

3.2. Identifying Integrated Strategic Complementarities

Do parent firms integrate CVC-led innovation knowledge to complement their internal innovation? This section tests whether the investment relationship between a CVC and an entrepreneurial venture leads the parent firm to adopt innovation produced by the entrepreneurial venture, which will be captured by new patent citations made by the firm to the venture.[16] An ideal setting for this test is to have similar firms and first randomly assign some of them to launch CVC divisions and some not, then randomly assign portfolio companies to those CVC units. A higher occurrence of CVCs citing their own portfolio companies would be a sign that technological knowledge flows from the invested venture to the CVC parent—that is, innovation complementarities are integrated.

Lacking such an ideal setting that exogenously generates CVC units and exogenously matches CVCs with startups, this section instead attempts to create a setup by carefully constructing a set of control firms using similar approaches as Bena and Li (2014) and Brav et al. (2017). Specifically, for each CVC-startup pair (i-j) that was formed in year t, I use a propensity score matching method and match each CVC parent firm i with five non-CVC firms in t from the same 2-digit SIC industry that has the closest propensity score estimated using firm size (the logarithm of total assets), market-to-book ratio, $\Delta Innovation$, and the total number of patents applied for by the firm up to year $t-1$. I denote those firms as i'. I also match venture j with five entrepreneurial ventures using a propensity score estimated using venture age, total number of granted patents by year $t-1$, and the same key innovation technology class. I denote those firms as j'.[17]

[15] Appendix D provides a more in-depth discussion on the investment patterns of CVCs and their differences with traditional IVCs.

[16] An existing literature uses patent citation behaviors to track knowledge spillovers (Jaffe and Trajtenberg, 2002; Gomes-Casseres et al., 2006; Gonzalez-Uribe, 2013). Alcacer and Gittelman (2006) and Gomes-Casseres et al. (2006), among others, discuss the advantages and potential pitfalls in using this approach.

[17] Since these are early-stage ventures, financial statement information is unavailable and thus cannot be incorporated in the

With those matched firms and startups, I create a set of control pairs for each realized CVC-venture pair i-j, by pairing $\{i, i'\} \times \{j, j'\}$.

The central empirical test estimates whether CVC parent firm i is more likely to make new citations to startup company j's patents after i invests in j, using the following model:

$$\begin{aligned} Cite_{ijt} = \alpha + \beta \cdot I(CVC_i\text{-}Portfolio_j) \times I(Post_{ijt}) \\ + \gamma_1 \cdot I(CVC_i\text{-}Portfolio_j) + \gamma_2 \cdot I(Post_{ijt}) + \varepsilon_{ijt}, \end{aligned} \tag{6}$$

where observations are at the i-j-t level. $I(CVC_i\text{-}Portfolio_j)$ indicates whether the pair is a realized CVC-startup pair or a constructed control pair. For each pair in $\{i, i'\} \times \{j, j'\}$, 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.[18] $I(Post_{ijt})$ 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 five-year time period.

[Insert Table 8 Here.]

The key coefficient of interest, β, captures the incremental intensity of integrating a startup's innovation knowledge into organic innovation after a CVC invests in the company. Table 8, column (1) shows the regression results. The coefficient of 0.197 means that the citing probability increases by 19.7% after establishing the link through CVC investment. In column (3), I perform an analysis similar to that in column (1) except that I look at the probability that a CVC parent firm cites not only patents owned by the startup but also patents previously cited by the startup. In other words, the potential citation now covers the broader technological knowledge that the startup works upon (similar to the definition of knowledge in defining the instrument in (2)). Column (3) extends the message conveyed in column (1)—CVC parent firms not only

matching algorithm.

[18] Essentially, a matched control firm is assumed to have the same investment history as the CVC parent firm to which it is matched to.

cite the portfolio company's own patents, but also benefit from the knowledge indirectly carried by portfolio companies, reaching to the broader knowledge behind.

Do CVC parents benefit from complementarities from financially successful startups or also from failed startups? I explore this question by modifying model (6) and separately estimate the intensity of citing knowledge possessed by companies that either exit successfully (acquired or publicly listed) or eventually 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.

Importantly, $I(CVC_i\text{-}Portfolio_j)$ is insignificant as a standalone variable, meaning that before investing in a startup through CVC, a parent firm does not cite technologies of the startup at a higher rate compared to its matched controls. This partially addresses the concern that CVC is incumbents' way of supporting startups on which they already technologically rely, as opposed to seeking new complementarities. This is also consistent with findings in Table 7 that the technological overlap of a CVC parent and its portfolio companies is small. $I(Post_{ijt})$ is insignificant, reassuring that CVC is not just riding a trend of more aggressive citing behaviors from incumbents to the entrepreneurial sector.

In sum, though the analysis is subject to the common problem of lacking identification in an exogenous shock sense (Gomes-Casseres, Hagedoorn, and Jaffe, 2006), the evidence clearly shows that CVC parents integrate the innovation complementarities obtained from entrepreneurial ventures into their internal innovation. In untabulated results, I also find that internal R&D within the five-year period after CVC initiations is higher than the benchmark level of the firm, suggesting that CVC parents actively use startups' technologies to complement organic innovation.

3.3. Additional Evidence on Channels

In the Online Appendix, I explore channels that can contribute to the active materialization of the complementarities. In Table A4, I identify one channel that CVC parents actively manage to facilitate the process: human capital renewal. Indeed, inventors, usually highly educated scientists and engineers, are key in absorbing, processing, and using information to produce innovation. Recent studies also find that firms actively reallocate innovative human resources to spur innovation and adjust the scope of innovation (Lacetera, Cockburn, and Henderson, 2004; Bernstein, 2015; Brav, Jiang, Ma, and Tian, 2017). I examine the intensity of human resource adjustment around the initiation of CVC investment and of inventor productivities during this period, and I find an abnormally high inventor turnover rate. Importantly, newly hired inventors concentrate more heavily on processing and integrating new innovation knowledge into the innovation at the parent firm.

In Table A5, I examine external acquisitions made by CVC parents. Acquiring innovation has become an 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 understanding of markets and technological trends. Complementary innovation knowledge from the CVC experience can help parent firms to form more precise expectations of acquisition deals, thereby improving efficiencies when making such decisions.[19] I show that acquisition efficiencies significantly increase after a firm initiates a CVC unit, where acquisition efficiencies are measured using cumulative abnormal returns (CAR) for M&A deals and using patent citation growth around transactions for acquisitions of specific technologies.

These new evidence mean to provide evidence that the materialization of strategic complementarities is not due to passive spillovers—instead, CVC parents actively adjust real activities to facilitate such a process. Combining these evidence with the portfolio selection and integration of strategic complementarities, this section provides further support to the view that CVCs are more likely to be used to seek strategic benefit from the entrepreneurial sector.

[19] To be clear, those acquisitions are not necessarily limited to their CVC portfolio companies and can reach a broader domain using the general innovation and industry knowledge they learn from CVC experience. In fact, CVC relations between parent firms and startups seldom involve asset consolidation (Benson and Ziedonis, 2010; Dimitrova, 2013). In general, the acquisition of portfolio companies by investing CVCs is rare—fewer than one-fifth of CVC investors acquired their portfolio companies. CVC units that did conduct such acquisitions acquired fewer than 5% of their portfolio companies (that is, one out of 20 investments).

4. The Termination of CVC

The CVC life cycle analysis concludes with the termination decision of CVCs. What is the staying power of CVC units, and at what conditions do parent firms terminate their CVC units? Under the agency view, the rationale of CVC is rooted in the fundamental and long-lasting conflicts between shareholders and managers. As a result, CVCs should remain alive for an unspecified but significant period, and the termination should likely follow turnovers of top executives. The agency view is not the only one that predicts long-lasting CVCs. The financial view argues that advantageous industrial knowledge is potentially an important source of value in CVC. This informational advantage presumably should support CVC for a long time. The strategic learning view disagrees with the above predictions, and argues that a capacity-constrained firm will allocate fewer resources to information acquisition yet more to innovation production once the internal innovation becomes more promising (Nelson, 1982; Jovanovic and Rob, 1989). This view in essence predicts that CVCs are inherently transitory organizations to help firms overcome difficulties in internal innovation (i.e., "shock therapy").

4.1. The Staying Power of CVC

I start by examining the staying power of CVC. The duration of a CVC unit is calculated as the period between the initiation and the termination dates.[20] Table 9 shows that CVC units stay for a relatively short period of time—the median duration of a CVC is four years, and a significant portion (46%) of CVCs actively invest for three years or fewer.[21] Around 27% of firms operate CVCs for a long period (more than ten 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

[20]When a clear termination date is not disclosed, I define it as the date of the investor's last investment in any portfolio company. As a result, the duration could be underestimated, particularly toward the end of the sample. To mitigate bias, I categorize a fund 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 those active investors are excluded from analysis of this variable.

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

short, the years between initiation and termination are mostly active. As the duration increases, an increasing proportion of years are under hibernation. When I examine these hibernation periods, I find a pattern of consecutive hibernating years—for example, CVCs with eight-year durations have a median of four years of consecutive hibernation. In other words, these CVCs typically have a lengthy pause in their CVC experience, bridging two shorter active periods of investment.

[Insert Table 9 Here.]

One might argue 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 Table 9, I calculate the success rate of deals invested by CVCs categorized by CVC duration. An investment deal is defined as a "success" if the entrepreneurial company was acquired or went public. I exclude cases in which the company is still active without a successful exit. Success rates of investments do not correlate with CVC duration, inconsistent with the idea of CVC incompetence.

4.2. Innovation Improvements and CVC Termination

I exploit a hazard model to statistically correlate innovation improvement and governance with an individual firm's decision to terminate its CVC. A CVC parent firm enters the sample in the year of CVC initiation. The key variable of interest is $\Delta Innovation$, which measures the difference between innovation level in year t and that of the initiation year. The coefficients estimated from the model are shown in columns (1) and (2) of Table 10, and the hazard ratio is reported at the bottom of the columns ($exp(\beta)$). The positive and significant coefficients (hazard ratio > 1) mean that larger improvements of innovation from the initiation year motivate parent firms to terminate CVC investment. In columns (3) to (5), I focus on corporate governance related measures. Institutional shareholding, G-Index, and the event of CEO turnover do not have any explanatory power on the CVC termination decision.

[Insert Table 10 Here.]

The staying power and termination analyses reveal the transitory nature of CVC, and the termination of CVCs is driven by the fulfillment of the temporary strategic learning goal in the innovation process. In contrast, and again, it is unlikely that CVCs are driven by the agency conflicts between shareholders or the intention to utilize advantageous information to make venture investment.

5. Concluding Remarks

This paper establishes the life cycle of Corporate Venture Capital to understand the economic rationale behind these activities. I find that firms initiate CVC programs following deteriorations in internal innovation in order to seek innovation complementarities generated from the entrepreneurial sector. I further characterize the investment stages of the CVC life cycle, in which CVC parent firms strategically select portfolio companies working in proximate technological areas, but in which they also possess complementary knowledge and actively integrate newly acquired technological knowledge into corporate innovation and broader decisions. CVCs are terminated when internal innovation recovers in parent firms. Alternative views on CVC, such as that CVC is just a type of managerial perk project or that CVC is mainly for financial returns from venture investment, do not seem to explain the rise of CVC.

There are several questions that are of interests but which are not addressed in this paper due to limited data availabilities: How can we calculate the return of CVC investments by correctly incorporating strategic benefits? How do CVCs and traditional IVCs resolve conflicts of interests in syndicated deals given that they have different motivations? What is the optimal compensation scheme for CVC executives? These questions are left for future explorations.

Key Variable Definitions

Variable	Definition and Construction
	a. Innovation 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.
New Patents	Number of patent applications filed by a firm in a given year. The natural logarithm of this variable plus one is used in the paper, i.e., $\ln(NewPatent) \equiv \ln(New\ Patent + 1)$.
Patent Quality	Average citations received by the patents applied by a firms in a given year. The natural logarithm of this variable plus one is used in the paper, i.e., $\ln(Pat.Quality) \equiv \ln(Patent\ Quality + 1)$.
	b. CVC-Startup Relationship
Technological Proximity	Degree of similarity between the distribution of two firms' (i and j) patent portfolios across two-digit technological classes using the same technique as in Jaffe (1986) and Bena and Li (2014). Formally, $$TechnologicalProximity = \frac{S_i S_j'}{\sqrt{S_i S_i'}\sqrt{S_j S_j'}},$$ where the vector $S = (S_1, S_2, \cdots, S_K)$ captures the distribution of the innovative activities, and each component S_k is the percentage of patents in technological class k in the patent portfolio.
Knowledge Overlap	Firm i's knowledge in year t, $K_{i,t}$ is constructed as the patents that received at least one citation from firm i up to year t, and similar for firm j's knowledge $K_{j,t}$. *Knowledge Overlap* is calculated as the ratio of—(1) numerator: the cardinality (size) of the set of patents that receive at least one citation from CVC firm i and one citation from entrepreneurial company j; and (2) denominator: the cardinality of the set of patents that receive at least one citation from either CVC i or company j (or both). That is, $$KnowledgeOverlap_{ij,t} = \frac{Card(K_{i,t} \cap K_{j,t})}{Card(K_{i,t} \cup K_{j,t})}$$
Local	Dummy indicating whether CVC firm i and entrepreneurial company j are located in the same Commuting Zone (CZ). When the CVC and the firm headquarter are located in different areas, I use the location that is closer to the startup.
$\ln(Distance)$	Natural logarithm of the kilometer distance between firm i and entrepreneurial company j (accurate at Zipcode level). When the CVC and the firm headquarter are located in different areas, I use the location that is closer to the startup.
	c. Firm Characteristics
Size (Log of Assets)	The natural logarithm of total assets in millions, adjusted to 2007 US dollars.
Firm ROA	Earnings before interest, taxes, depreciation, and amortization scaled by total assets.
M/B	The market value of common equity scaled by the book value of the common equity.
Leverage	Book debt value scaled by total assets.

Cash Flow	(Income before extraordinary items + depreciation and amortization) scaled by total assets.
Firm R&D	Research and development expenses scaled by total assets.
Institutional Shareholding	Total shares (in %) held by the top five institutional shareholders in the firm.
G-Index	Governance index constructed in Gompers, Ishii, and Metrick (2003), which classifies and counts governance provisions that restrict shareholder rights.
CEO Turnover	Dummy variable indicating whether the firm overcomes a CEO turnover event in the year, data extracted from ExecuComp.

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Table 1
CVC Entries and Investment Deals By Year and Industry

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

Panel A: CVC Activities by Year

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

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

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

Table 2
Summary Statistics of the Sample

This table summarizes firm characteristics at the firm-year level. CVC observations ($I(CVC)_{i,t} = 1$) are those when firm i launched a CVC division in year t (and those firms are categorized as non-CVC observations in other years). The CVC sample is defined in Table 1. *Obsolescence* is constructed as the changes in the number of citations received by a firm's predetermined knowledge space, formally defined in Section 2.2.3 in the paper. *New Patents* is the number of patent applications filed by a firm in a given year. The natural logarithm of this variable plus one is used in the paper, i.e., $\ln(NewPatent) \equiv \ln(New\ Patent + 1)$. *Patent Citations* is the average citations received by the patents applied by a firms in a given year. The natural logarithm of this variable plus one is used in the paper, i.e., $\ln(Pat.Quality) \equiv \ln(Patent\ Quality + 1)$. $\Delta\ln(NewPatent)$ and $\Delta\ln(Pat.Quality)$ are three-year change of the innovation variables. *Total Assets* is reported in millions, adjusted to 2007 US dollars. *Firm R&D* is defined as research and development expenses scaled by total assets. *Firm ROA* is calculated as earnings before interest, taxes, depreciation, and amortization scaled by total assets. *M/B* is the market-to-book ratio, defined as market value of common equity scaled by the book value of the common equity. *Leverage* is the book debt value scaled by total assets. *Cash Flow* is defined as (Income before extraordinary items + depreciation and amortization) scaled by total assets. Observations are required to have valid ROA, total assets, leverage, firm R&D , 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. Detailed variable definitions are provided in the Appendix.

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

Table 3
Determinants of CVC Entry

This table examines the determinants of Corporate Venture Capital entry decisions. The analysis is performed using the following specification:

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

The panel sample is described in Table 2. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t, and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average life-time citations per new patent in each firm-year plus one). *Governance* measures include institutional shareholdings and the G-Index. 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). Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation, and industries are defined by the Fama-French 48 Industry Classification. T-statistics are shown in parentheses and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Economic significance estimates are reported at the bottom of the table, and are calculated as changes of the probability of CVC initiations from a two standard deviations change of $\Delta Innovation$, divided by the unconditional initiation probability.

	(1)	(2)	(3)	(4)	(5)	(6)
	$I(CVC) = 1$					
$\Delta\ln(NewPatent)$	-0.007***		-0.006***			
	(-6.227)		(-4.705)			
$\Delta\ln(Pat.Quality)$		-0.004***	-0.004***			
		(-4.459)	(-3.775)			
Institutional Shareholding				0.001		-0.002
				(0.578)		(-0.154)
G-Index					0.001	0.001
					(0.903)	(0.729)
Size (Log of Assets)	0.003***	0.003***	0.003***	0.004***	0.007***	0.008***
	(11.090)	(11.034)	(10.741)	(10.929)	(3.872)	(3.837)
Leverage	-0.005**	-0.004**	-0.005**	-0.004*	-0.033**	-0.034**
	(-2.371)	(-2.051)	(-2.356)	(-1.777)	(-2.193)	(-2.190)
Firm R&D	0.015***	0.011***	0.014***	0.017***	0.076*	0.081*
	(3.439)	(3.093)	(3.319)	(4.215)	(1.862)	(1.893)
Firm ROA	-0.003	-0.003	-0.003	0.000	-0.012	-0.016
	(-1.275)	(-1.567)	(-1.332)	(0.051)	(-0.497)	(-0.577)
Observations	25,976	25,976	25,976	25,976	5,061	5,061
Pseudo R-squared	0.122	0.121	0.122	0.063	0.227	0.208
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4
Innovation Deterioration and CVC Initiation—Exogenous Variations to Innovation

This table examines the relation between innovation deterioration and the initiation of Corporate Venture Capital using the following Two-Stage Least Squares (2SLS) specification:

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

The panel sample is described in Table 2. Columns (1) and (3) report the first-stage regressions, which regress the three-year change in innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average life-time citations per new patent in each firm-year plus one) on the three-year *Obsolescence*. Columns (2) and (4) 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). Column (5) reports the reduced-form regression, which predicts the decision to initiate CVC using *Obsolescence*. 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) First Stage	(2) 2SLS	(3) First Stage	(4) 2SLS	(5) Reduced Form
Obsolescence	-0.114***		-0.128***		0.001**
	(-12.165)		(-17.064)		(2.171)
$\Delta \ln(NewPatent)$		-0.007***			
		(-3.597)			
$\Delta \ln(Pat.Quality)$				-0.004***	
				(-2.577)	
Firm ROA	0.090***	-0.003	0.070***	-0.003	-0.000
	(4.711)	(-1.289)	(4.170)	(-1.600)	(-0.071)
Size (Log of Assets)	0.028***	0.003***	0.031***	0.003***	0.003***
	(12.664)	(11.401)	(16.106)	(11.238)	(6.353)
Leverage	-0.103***	-0.005**	-0.091***	-0.004**	0.002
	(-5.155)	(-2.484)	(-5.179)	(-2.095)	(0.921)
Firm R&D	0.489***	0.015***	0.420***	0.011***	0.006*
	(11.931)	(3.476)	(11.423)	(3.157)	(1.794)
F-Statistic	147.99		291.18		
Observations	25,976	25,976	25,976	25,976	25,976
R^2	0.398	0.118	0.370	0.109	0.315
Industry × Year FE	Yes	Yes	Yes	Yes	Yes

Table 5
Assessing the Validity of the *Obsolescence* Instrument

This table presents analysis to access the validity of the *Obsolescence* instrument. The baseline model is adopted from Table 4, in the form of the following Two-Stage Least Squares (2SLS) specification:

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

In Panel A, the analysis is performed using an *Obsolescence* instrument constructed by tracking the citation dynamics of knowledge spaces defined ten years ago (as opposed to three years ago in Table 4), using equation (2). Columns (1) and (3) report the first-stage regression, which regress the three-year change in innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average life-time citations per new patent in each firm-year plus one) on the $Obsolescence$. Columns (2) and (4) 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 Panel B, the 2SLS analysis is performed on subsamples of firms with higher vs. lower innovation impact, where innovation impact is categorized using the median of the number of patents possessed by the firm in each year. Columns (1) and (2) focus on the subsample of firms with higher innovation impact, and columns (3) and (4) focus on the subsample of firms with lower innovation impact.

In all regressions, 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.

Panel A: 10-Year Historic Knowledge *Obsolescence*				
	(1)	(2)	(3)	(4)
	First Stage	2SLS	First Stage	2SLS
Obsolescence	-0.052***		-0.053***	
	(-9.619)		(-9.648)	
$\Delta \ln(NewPatent)$		-0.008**		
		(-2.335)		
$\Delta \ln(Pat.Quality)$				-0.003*
				(-1.802)
F-Statistic	92.53		93.08	
Observations	20,145	20,145	20,145	20,145
R^2	0.294	0.102	0.215	0.098
Industry × Year FE	Yes	Yes	Yes	Yes

Panel B: Heterogeneity of Innovation Impact of a Firm				
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
$\Delta \ln(NewPatent)$	-0.010**		-0.003**	
	(-2.649)		(-2.535)	
$\Delta \ln(Pat.Quality)$		-0.004*		-0.001***
		(-1.989)		(-4.395)
Subsample	High Innovation Impact		Low Innovation Impact	
Observations	14,563	14,563	11,413	11,413
R^2	0.389	0.175	0.506	0.23 6
Industry × Year FE	Yes	Yes	Yes	Yes

Table 6
The Financial View at the CVC Entry Stage

This table presents evidence to access the validity of the *Obsolescence* instrument. In Panel A, I examine whether innovation deteriorations motivate financial or strategic CVCs using the same specification as in Table 4, except that the dependent variable distinguishes financial and strategic CVCs. I categorize CVCs in the sample into financial or strategic driven by collecting information disclosed at the announcement of CVC initiations using a news search, following a similar approach as Dushnitsky and Lenox (2006). For each CVC in the sample, I search for media coverage and corporate news at its initiation using Lexis-Nexis, Factiva, and Google. Based on this compiled information, CVCs are coded as financial and strategic. In columns (1) and (2), the dependent variable is a dummy that takes value one if the firm launches a CVC in that year and indicates that the CVC is for strategic purposes; in columns (3) and (4) the dependent variable is a dummy that takes value one if the firm launches a CVC in that year and indicates that the CVC is mainly financial return driven.

Panel B examines whether CVC entries are accompanied by declines of internal R&D. The empirical model correlates innovation input and the entry of CVCs, where innovation input is measured using R&D expenditures scaled by total assets (columns (1) and (3)) or scaled by sales (columns (2) and (4)).

In Panel C, the 2SLS analysis is performed on subsamples of firms with higher vs. lower cash flow ratio, categorized using the median of the sum of income before extraordinary items and depreciation and amortization scaled by total assets. Columns (1) and (2) focus on the subsample of firms with higher cash flow ratio, and columns (3) and (4) focus on the subsample of firms with lower cash flow ratio.

In all regressions, 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.

Panel A: Strategic vs. Financial CVCs				
	I(Strategic CVC)		I(Financial CVC)	
	(1)	(2)	(3)	(4)
$\Delta \ln(NewPatent)$	-0.013***		-0.002	
	(-3.722)		(-1.414)	
$\Delta \ln(Pat.Quality)$		-0.007**		-0.001
		(-2.318)		(-1.528)
Observations	25,976	25,976	25,976	25,976
R^2	0.199	0.193	0.083	0.077
Industry × Year FE	Yes	Yes	Yes	Yes

Panel B: Innovation Input and CVC Entries				
	$I(CVC)$		$I(CVC)$	
	(1)	(2)	(3)	(4)
$\Delta R\&D/Assets$	0.005*		0.001	
	(1.957)		(0.234)	
$\Delta R\&D/Sales$		0.001		-0.004
		(0.229)		(-0.730)
$\Delta \ln(NewPatent)$			-0.008***	-0.009***
			(-5.394)	(-5.155)
$\Delta \ln(Pat.Quality)$			-0.002***	-0.003***
			(-3.096)	(-3.649)
Observations	25,976	25,976	25,976	25,976
Pseudo R-squared	0.064	0.092	0.132	0.135
Industry × Year FE	Yes	Yes	Yes	Yes

Panel B: Heterogeneity of Cash Flow				
	$I(CVC)$		$I(CVC)$	
	(1)	(2)	(3)	(4)
$\Delta \ln(NewPatent)$	-0.005***		-0.009**	
	(-2.903)		(-2.119)	
$\Delta \ln(Pat.Quality)$		-0.003**		-0.006*
		(-2.394)		(-1.729)
Subsample	High Cash Flow		Low Cash Flow	
Observations	14,982	14,982	10,994	10,994
R^2	0.404	0.351	0.349	0.328
Industry × Year FE	Yes	Yes	Yes	Yes

Table 7
Corporate Venture Capital's Selection of 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 had ever received investment from a VC. 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:

$$I(CVC_i\text{-}Target_j) = \alpha + \beta_1 \times TechProximity_{ij} + \beta_2 \times KnowledgeOverlap_{ij} + \beta_3 \times Local_{ij} + \beta_4 \times Distance_{ij} + \gamma \times X_{i,j} + \varepsilon_{i,j},$$

where the dependent variable, $I(CVC_i\text{-}Target_j)$, is equal to one if CVC i actually invests in company j, and zero otherwise. *Technological Proximity* is calculated as the Cosine-similarity between the CVC's and startup's vectors of patent weighting across different technological classes (Jaffe, 1986; Bena and Li, 2014). *Knowledge Overlap* is calculated as the ratio of the cardinality (size) of the set of patents that receive at least one citation from CVC firm i and one citation from the entrepreneurial company j, and the cardinality of the set of patents that receive at least one citation from either CVC i or company j (or both). Geographical distance is measured using a dummy variable if the CVC firm i and company j are located in the same Commuting Zone (CZ), *Local*. $\ln(Distance)$ is the natural logarithm of the kilometer distance between i and j. The Appendix defines those variables more formally. CVC (i)-level characteristics include number of annual patent applications, average citations of patents; I also control for those innovation characteristics at the startup (j)-level. 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.

	$I(CVC_i\text{-}Target_j)$			
	(1)	(2)	(3)	(4)
Technological Proximity	0.031**	0.034**	0.035**	0.035**
	(2.264)	(2.135)	(2.073)	(2.291)
Knowledge Overlap		-0.020**	-0.019**	-0.019**
		(-2.001)	(-2.107)	(-1.998)
Local			-0.010***	-0.011***
			(-2.935)	(-2.767)
$\ln(Distance)$				-0.010***
				(-4.924)
Observations	868,323	868,323	847,102	847,102
R^2	0.127	0.127	0.130	0.130
CVC-level Controls	Yes	Yes	Yes	Yes
Startup-level Controls	Yes	Yes	Yes	Yes

Table 8
Integrating Innovation Complementarities from CVC Investments

This table studies how CVC parents incorporate their portfolio companies' technological knowledge in their own internal R&D. For each CVC-startup pair (i-j) that were formed in year t, I use a propensity score matching method and match each CVC parent firm i with five non-CVC firms in t from the same 2-digit SIC industry that has the closest propensity score estimated using firm size (the logarithm of total assets), market-to-book ratio, $\Delta Innovation$, and the total number of patents applied for by the firm up to year $t-1$—denote those firms as i'. I also match venture j with five entrepreneurial ventures using a propensity score estimated using venture age, total number of granted patents by year $t-1$, and the same key innovation technology class—denote those firms as j'. With those matched firms and startups, I created a set of control pairs for each realized CVC-venture pair i-j, by pairing $\{i,i'\} \times \{j,j'\}$. The analysis is performed using the following framework,

$$\begin{aligned} Cite_{ijt} = {} & \alpha + \beta \cdot I(CVC_i\text{-}Portfolio_j) \times I(Post_{ijt}) \\ & + \gamma_1 \cdot I(CVC_i\text{-}Portfolio_j) + \gamma_2 \cdot I(Post_{ijt}) + \varepsilon_{ijt}, \end{aligned}$$

where observations are at the i-j-t level. $I(CVC_i\text{-}Portfolio_j)$ indicates whether the pair is a realized CVC-startup pair or a constructed control pair. For each pair in $\{i,i'\} \times \{j,j'\}$, 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. $I(Post_{ijt})$ 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 five-year time period.

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 CVC (i)-level characteristics including number of annual patent applications, average citations of patents, and controls for those innovation characteristics at the startup (j)-level. T-statistics are shown in parentheses, and standard errors are clustered by firm. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Citing a Startup's Patents		Citing a Startup's Knowledge	
$I(CVC\text{-}Portfolio) \times I(Post)$	0.197***		0.361***	
	(4.538)		(8.196)	
$\times Successful$		0.252***		0.395***
		(7.819)		(9.956)
$\times Failed$		0.129***		0.294***
		(3.152)		(5.200)
$I(CVC\text{-}Portfolio)$	0.013		0.028	
	(1.104)		(1.344)	
$I(Post)$	0.025		0.039	
	(1.235)		(1.187)	
Firm-level Controls	Yes		Yes	
Startup-level Controls	Yes		Yes	
Observations	71,305		71,305	
R^2	0.264		0.231	

Table 9
The Staying Power of Corporate Venture Capital

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

Duration	Number	%	Cum. Prob.	Years in Hiber (Median)	Consecutive Hiber (Median)	Success Rate
≤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%
≥10	88	26.75%	100.00%	6	5	57%
Total	329					
Still Active	52					

Table 10
Innovation Improvement and the Termination of CVC Life Cycle

This table studies the decision to terminate Corporate Venture Capital. The regressions are performed on the panel of CVCs in their active years. The dependent variable is a CVC termination dummy, and the specification is estimated using a Hazard model. The key variable $\Delta Innovation_{i,t}$ is defined as the difference of innovation between year t and the year of initiation. In columns (3) to (5) the key variable of interests are governance-related proxies including institutional shareholding, G-Index, and an event dummy of CEO turnover. 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.

	(1)	(2)	(3)	(4)	(5)
	CVC Exit				
$\Delta\ln(NewPatent)$	0.355***				
	(5.585)				
$\Delta\ln(Pat.Quality)$		0.276***			
		(6.277)			
Institutional Shareholding			0.063		
			(0.163)		
G-Index				0.049	
				(0.663)	
CEO Turnover					0.022
					(0.518)
$exp(\beta)$	1.426	1.318	Not Significant		
Controls	Yes	Yes	Yes	Yes	Yes
Observations	2,489	2,489	2,489	1,167	1,822

Appendix

A. Supplementary Results

Table A1
Innovation Deterioration and CVC Initiation: $\Delta Innovation$ Horizon

This table presents 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 3 in the paper. $I(CVC)_{i,t}$ 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 four years (that is, the innovation change from $t-5$ to $t-1$) in columns (1) and (2), and over the past two years (that is, the innovation change from $t-3$ to $t-1$) in columns (3) and (4). 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 (3) and innovation quality (the natural logarithm of average citations per new patent in each firm-year plus one), shown in columns (2) and (4). The model is estimated using Two-stage Least Squares, and $\Delta Innovation$ is instrumented using knowledge $Obsolescence$ during the same period as in $\Delta Innovation$. 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 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)	(2)	(3)	(4)
	4-Year $\Delta Innovation$		2-Year $\Delta Innovation$	
$\Delta \ln(NewPatent)$	-0.006***		-0.005*	
	(-3.058)		(-1.727)	
$\Delta \ln(Pat.Quality)$		-0.003*		-0.004***
		(-1.827)		(-4.532)
Firm ROA	-0.003	-0.002	-0.003	-0.003*
	(-1.315)	(-1.485)	(-1.500)	(-1.747)
Size (Log of Assets)	0.003***	0.003***	0.003***	0.003***
	(11.486)	(11.442)	(11.300)	(11.042)
Leverage	-0.005**	-0.003**	-0.005**	-0.004**
	(-2.449)	(-2.089)	(-2.307)	(-2.251)
Firm R&D	0.014***	0.011***	0.014***	0.012***
	(3.521)	(3.258)	(3.128)	(3.123)
Observations	25,976	25,976	25,976	25,976
Pseudo R-squared	0.114	0.111	0.110	0.107
Industry × Year FE	Yes	Yes	Yes	Yes

Table A2
Determinants of CVC Entry—Hazard Model

This table examines the determinants of Corporate Venture Capital entry decisions. The analysis is performed using the following specification:

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

The panel sample is described in Table 2. $I(CVC)_{i,t}$ is equal to one if firm i launches a Corporate Venture Capital unit in year t, and zero otherwise. $\Delta Innovation_{i,t-1}$ is the innovation change over the past three years (i.e., the innovation change from $t-4$ to $t-1$). Innovation is measured using innovation quantity (the natural logarithm of the number of new patents in each firm-year plus one) and innovation quality (the natural logarithm of average life-time citations per new patent in each firm-year plus one). *Governance* measures include institutional shareholdings and the G-Index. 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 Hazard Model. Industry-by-year dummies are included in the model to absorb industry-specific time trends in CVC activities and innovation, and industries are defined by the Fama-French 48 Industry Classification. 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)
	$I(CVC) = 1$			
$\Delta\ln(NewPatent)$	-0.896***			
	(-4.702)			
$\Delta\ln(Pat.Quality)$		-0.354***		
		(-3.268)		
Institutional Shareholding			0.158	
			(0.744)	
G-Index				-0.075
				(-0.139)
$exp(\beta)$	0.408	0.702	Not Significant	
Controls	Yes	Yes	Yes	Yes
Observations	25,976	25,976	25,976	5,061
Industry $\times$ Year FE	Yes	Yes	Yes	Yes

Table A3
Innovation Deteriorations and CVC Initiations—Different Sampling Criterion

This table documents the relation between innovation deterioration and the initiation of Corporate Venture Capital under different sampling criterion. 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 original panel sample is described in Table 3 in the paper. $I(CVC)_{i,t}$ 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), (3), (5), and (7), and innovation quality (the natural logarithm of average citations per new patent in each firm-year plus one), shown in columns (2), (4), (6), and (8). The model is estimated using Two-stage Least Squares, and $\Delta Innovation$ is instrumented using knowledge *Obsolescence* during the same period as in $\Delta Innovation$. In columns (1) and (2), firms with total assets above industry median are dropped. In columns (3) and (4), firms with total assets below industry median are dropped. In columns (5) and (6), firms headquartered in California are dropped. In columns (7) and (8), firms in the Business Services industry (categorized using Fama-French 48 industry categorization) are dropped. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Drop Large Firms		Drop Small Firms		Drop Californian Firms		Drop IT Firms	
$\Delta \ln(NewPatent)$	-0.003**		-0.010**		-0.006***		-0.005***	
	(-2.535)		(-2.649)		(-4.348)		(-4.150)	
$\Delta \ln(Pat.Quality)$		-0.001***		-0.004*		-0.002***		-0.002**
		(-4.395)		(-1.989)		(-2.954)		(-2.392)
Firm ROA	-0.002	-0.002	-0.005	0.000	-0.002	-0.001	-0.003*	-0.003***
	(-0.444)	(-0.873)	(-1.418)	(0.001)	(-1.152)	(-1.138)	(-1.917)	(-3.253)
Size (Log of Assets)	0.012***	0.012***	0.005***	0.005***	0.003***	0.002***	0.003***	0.002***
	(9.533)	(10.128)	(6.384)	(6.166)	(9.186)	(11.682)	(11.568)	(13.169)
Leverage	0.009***	0.008***	-0.008*	-0.008	-0.003	-0.003	-0.003*	-0.003**
	(2.842)	(4.402)	(-1.870)	(-1.641)	(-1.071)	(-1.189)	(-1.925)	(-2.233)
Firm R&D	0.006	0.005	0.023***	0.030***	0.010***	0.009***	0.009***	0.009***
	(1.441)	(1.283)	(3.254)	(4.612)	(3.253)	(3.114)	(3.566)	(3.512)
Observations	11,413	11,413	14,563	14,563	21,338	21,338	16,616	16,616
Pseudo R-squared	0.156	0.126	0.139	0.125	0.130	0.130	0.120	0.089
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A4
Integrating Complementarities through Inventor Adjustment

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

Panel A: Inventor Mobility during CVC Operation

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

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

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

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

Panel B: New Inventors and New Information

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

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

Table A5
Integrating Complementarities 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 consists of CVCs and their propensity score-matched firms. 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

B. Merging VentureXpert with Patent Databases

In this section, I describe the process to merge entrepreneurial companies in VentrueXpert database with USPTO patent databases, through matching company names in VentureXpert with assignee names in the USPTO patent database. To minimize potential problems introduced by the minor discrepancy between different versions of the USPTO database, I use both NBER and Harvard Business School (HBS) patent databases to provide patent assignee information. After this step, each company in VentureXpert will have its original name, standardized name and a stem name; similar for USPTO assignees.

B.1. Name Standardization

I begin by standardizing company names in VentureXpert and assignee names from NBER and HBS patent database, using the name standardization algorithm developed by the NBER Patent Data Project. This algorithm standardizes common company prefixes and suffixes, strips names of punctuation and capitalization; it also isolates a company's stem name (the main body of the company name) excluding these prefixes and suffixes.

B.2. The Matching Procedure

With these standardized and stem company (assignee) names and demographic information provided by both VentureXpert and USPTO, I merge the databases following the matching procedures below:

1. Each standardized VentureXpert company name is matched with standardized names from the NBER data and HBS data.
    (a) If an exact match is identified, I consider this as a "*successful match*." The company is removed from the set of names waiting to be matched on both sides.
    (b) Otherwise, next step.

2. Each stem VentreXpert company name is matched with stem names from the NBER data and HBS data.

    (a) If an exact match of stem names if identified, and the two companies are located in the same city and state OR the two comapnies are located in the same state and the earliest patenting year in NBER and HBS databases is later than the founding year in VentureXpert, I consider this as a "*successful match*." The company is removed from the set of names waiting to be matched on both sides.

    (b) If an exact match of stem names is identified, but the two companies do not satisfy the location and chronology criterions above, I consider this as a "*potential match*." The company is moved to a pool of firms waiting for manual checks.

    (c) Otherwise, next step.

3. For the remaining companies, each stem VentureXpert company name is matched with up to 3 close stem names from the USPTO data using a fuzzy-matching method based on the Levenshtein edit distance.[22] The criterion is based on the length of the strings and the Levenshtein distance, and the threshold is determined through a random sampling procedure.

    (a) If the fuzzy-matched pair is located in the same city and state OR the two comapnies are located in the same state and the earliest patenting year in NBER and HBS databases is later than the founding year in VentureXpert, I consider this as a "*potential match*."

    (b) Otherwise, the companies are categorized as "*failed to match*."

4. The "*potential matches*" set identified in the procedures above are reviewed by hand, incorporating information from both data sources, including full patent abstracts, and company business descriptions.

[22] The Levenshtein edit distance measures the degree of proximity between two strings, and corresponds to the number of substitutions, deletions or insertions needed to transform one string into the other one (and vice versa).

(a) Pairs confirmed as successful matches through the manual check are moved to the "$\boxed{\textit{successful match}}$" set.

C. Detailed Descriptions of *Obsolescence*

This appendix provides more discussions on the variable *Knowledge Obsolescence* (or *Obsolescence* in short), which is used in the paper as an exogenous variation to firms' capability of innovating.

C.1. The Conceptual Idea and Its Roots

The proposition that knowledge obsolescence affects innovation has its roots in four basic observations.

First, knowledge begets knowledge. Isaac Newton said, "If I have seen further it is by standing on the shoulders of Giants." Indeed, the knowledge stock of an innovative individual or institution determines the quantity and quality of their innovation and knowledge production. This observation has been formalized and discussed in several strands of literature (see Jones (2009) and the papers cited therein).

Second, knowledge ages. Since the 1950s, several disciplines have developed the concept of the obsolescence of knowledge/skills/technology. The most famous result might be, roughly speaking, that half of our knowledge today will be of little value (or even proven wrong) after a certain amount of time (i.e., half-life), and this half-life is becoming shorter and shorter (Machlup, 1962). In economics, people have studied the effect of obsolescence of knowledge and skills on labor, industrial organization as well as the aggregate growth (Rosen, 1975).

Third, predicting knowledge trends is difficult, if not impossible. Even though mathematicians and bibliometricians have been developing mathematical models to fit the half-life dynamics of the overall knowledge stock, predicting the trend for each specific stock has not been successful. Indeed, it is this "impossibility" that creates the possibility of creative destruction and the fading of generations of firms.

Fourth, knowledge absorption can be difficult and slow. For any individual and institution, knowledge can be identified, absorbed, and managed at a limited rate. Even for firms, which have the option to replace human capital (innovators), the adjustment costs and uncertainty associated with the matching process limits their ability to do so.

Based on these observations, *Knowledge Obsolescence* proxies for a shock to the value and usefulness of knowledge possessed by each firm, which in turn affects innovation performance of the firm. Following Newton's storyline, when a firm is already on the shoulder of a standing Giant, the measure captures a shock to the height of the Giant (to make the Giant sit or jump, for example), and this shock exogenously determines how far the firm can see.

C.2. Variable Construction

Obsolescence attempts to capture an exogenous technological variation that is independent of a firm's recent operations but influences the firm's innovation performance. For each firm i in year t, this instrument is constructed in three steps. First, I define firm i's predetermined knowledge space in year $t-\tau$ as all the patents cited by firm i (but not belonging to i) up to year $t-\tau$. Then, I calculate the number of citations received by this $KnowledgeSpace_{i,t-\tau}$ in $t-\tau$ and in t, respectively. Last, $Obsolescence_{i,t}^{\tau}$ is defined as the change between the two, and a more negative *Obsolescence* means a larger decline of the value of a firm's knowledge:

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

Simply put, this instrument first defines the knowledge space of a firm by incorporating detailed information on the firm's innovation profile and citation history ("tree") and then measures the rate of obsolescence using exogenous citation dynamics to this knowledge space.

It is worth discussing the validity of the exclusion restriction for using this instrument in the CVC study. Generally speaking, the validity of this approach rests on the assumption that, controlling for industry-specific technological trends and firm-specific characteristics, the measured obsolescence of a firm's knowledge space predetermined years ago is orthogonal to its current CVC strategy other than through affecting current innovation performance. More discussions and validating analyses are provided in the paper.

C.3. A Simple Illustrative Example Using the Instrument

To illustrate how the instrumental variable can correct the estimation bias raising from the endogeneity problem, I describe the following simple example.[23] Assume that a firm's probability of launching a CVC unit is determined by an unconditional probability and a incremental probability determined by $\Delta Innovation$ realized in the near past, formulated as $P_{CVC} + q \cdot \Delta Innovation$. P_{CVC} stands for the unconditional probability of CVC initiations, and $\Delta Innovation$ is a dummy indicating whether the firm experienced an innovation increase ($\Delta Innovation = 1$) or an innovation deterioration ($\Delta Innovation = -1$). I make $\Delta Innovation$ a binary dummy to simplify the illustration.

Suppose that the unconditional probability of launching a CVC is heterogeneous and is correlated with $\Delta Innovation$ in some endogenous way (e.g., manager type could be driving both at the same time). Specifically, assume that there are three types of firms based on their ability to innovate: *High*-type firms are on a upward trajectory innovation ($\Delta Innovation = 1$ unconditionally) and have an unconditional probability of launching CVC $P_{CVC} = p_H$. *Sensitive*-type firms are sensitive to technological evolution and will have $\Delta Innovation = 1$ (-1) if the technology trend works in favor of (against) them, and these firms have a type-specific CVC probability of $P_{CVC} = p_M$. *Low*-type firms are in a struggling situation ($\Delta Innovation = -1$ unconditionally) and $P_{CVC} = p_L$. For simplicity, assume that the knowledge obsolescence will be either *favorable* or *disruptive* to the firm each with probability 50%, and each firm type is with probability 1/3. In the table below, we can summarize the probability of initiating a CVC unit in the six possible cases:

[23] This example is based on Bennedsen, Pérez-González, and Wolfenzon (2010) and Bernstein (2015).

Firm Type	*Obsolescence* Favorable	Disruptive
High	$\Delta Innovation = 1$ $p_H + q$	$\Delta Innovation = 1$ $p_H + q$
Sensitive	$\Delta Innovation = 1$ $p_M + q$	$\Delta Innovation = -1$ $p_M - q$
Low	$\Delta Innovation = -1$ $p_L - q$	$\Delta Innovation = -1$ $p_L - q$

The OLS estimates essentially compare firms that experience an innovation increase ($\Delta Innovation = 1$, the upper left triangle) with the firms that experience an innovation deterioration ($\Delta Innovation = -1$, the bottom right triangle), and the result reflects both the "treatment effect" and the selection bias (from the heterogeneity of P_{CVC}):

$$\begin{aligned}\beta_{OLS} &= \frac{1}{1-(-1)} \times \{E[Y|\Delta Innovation = 1] - E[Y|\Delta Innovation = -1]\} \\ &= q + \frac{1}{3} \times (p_H - p_L).\end{aligned} \tag{A1}$$

The bias term, $(1/3) \times (p_H - p_L)$, could be either positive or negative based on the assumption on the order of $\{p_H, p_M, p_L\}$. On the one hand, if we assume that bad governance could be driving both innovation decline and CVC initiation, then $p_L > p_H$ and β_{OLS} is more negative than the true effect q. On the other hand, if we assume that forward-looking managers could be driving both innovation improvements and CVC business, then $p_L < p_H$ and β_{OLS} is more positive than q. The true size of the bias is hard to ascertain under this framework.

The IV approach uses the exogenous variation in *Obsolescence*, which affects $\Delta Innovation$, to help back out the true q. The "first-stage" regression captures the effect of *Obsolescence* on $\Delta Innovation$:

$$\frac{1}{1-(-1)} \times \{E[\Delta Innovation|Favorable] - E[\Delta Innovation|Disruptive]\} = \frac{1}{3}. \tag{A2}$$

The reduced-form estimates the effect of *Obsolescence* on CVC activities, in the form of:

$$\frac{1}{1-(-1)} \times \{E[Y|Favorable] - E[Y|Disruptive]\} = \frac{1}{3}q. \tag{A3}$$

The IV estimate is the ratio between the reduced-form and the first-stage estimates, that is,

$$\beta_{IV} = \frac{E[Y|Favorable] - E[Y|Disruptive]}{E[\Delta Innovation|Favorable] - E[\Delta Innovation|Disruptive]} = q. \tag{A4}$$

To conclude this example, I wish to highlight two points. First, as shown in the derivation, the IV approach essentially uses only the "*Sensitive*" group to estimate the true q, or, in technical terms, the estimation relies on the "Local Average Treatment Effect (LATE)" based on the "compliers" (the observations that are responsive to the instrument). Second, both $\Delta Innovation$ and $Obsolescence$ take binary values in this example for simplicity. Obviously, those two variables both take continuous value in the data—the example's derivation can be extended to this case by weighting-average the estimates along the support of the instrument.

D. Comparing Investment Patterns of CVC and IVC

In this appendix I document three stylized facts on CVC investment patterns that complement main empirical explorations in Section 2 to 4. In specific, I contrast CVCs with traditional IVCs among various investment dimensions. The interested variables and their definitions are provided below.

Variable	**Definition and Construction**
A. Investor-specific Features	
Duration	The duration of a fund, calculated as the period between the initiation and the termination dates.[24]
Active Years of Investment	The number of years in which the investor made investment in a new venture.
Number of Companies Invested	The number of companies the investor invested through its life cycle.
B. Investor-startup-pair Level Information	
Innovative Startup	A dummy variable indicating whether the startup in the deal owned at least one patent at the time of investment, identified using the merged VentureXpert and USPTO data.
Age at Initial Investment	The age of the portfolio company at the time that the investor made its first investment.
Round of Initial Investment	The round number in which the investor made its first investment in the specific company.
Round 1, 2, ..., 5 and Above	A set of dummies that equal to one if the first time that the investor participated was the company's first, second, third, fourth, or fifth and above round, and zero otherwise.
# of Syndicating VCs	The total number of venture capital firms that syndicated in the round(s) in which the investor participated.
Geographic Distance	The distance, in kilometers, between the entrepreneurial venture and the investor location.

[24] When a clear termination date is not disclosed, I define it as the date of the investor's last investment in any portfolio company. As a result, the duration could be underestimated, particularly toward the end of the sample. To mitigate bias, I categorize a fund 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 those active investors are excluded from analysis of this variable.

Local Startup	A dummy variable that takes value one if the investor and the startup are in the same Commuting Zone (CZ).
IPO	A dummy variable that takes the value of one if the venture went public, zero otherwise, calculated for companies that were at least six years old as of March 2015.
Acquisition	A dummy variable that takes the value of one if the venture was acquired, zero otherwise, calculated for companies that were at least six years old as of March 2015.

In the table below I present investment patterns of the whole sample (including both CVCs and IVCs), the two types separately, as well as tests for the statistical significance of the differences in means across the CVC sample and the IVC sample. In Panel A, the unit of analysis is a VC fund. In Panel B, the unit of analysis is a unique pair of an investor and a startup.

Stylized Fact 1: The CVC Life Cycle. *CVCs on average are temporary corporate divisions, staying through nonuniform life cycles that are shorter that IVCs.*

I start by examining the staying power and investment time horizons of CVCs. As opposed to IVCs which typically follow a standard contractual horizon of 10 to 12 years (Barrot, 2016), or internal R&D units which are structured as a perpetual component, CVCs appear to be temporary corporate divisions that have a short investment horizons. In specific, the median duration of a CVC is four years, and the average is around six years, more than 30% shorter than IVCs. I also examine the number of years that an investor makes new investments in new startup, i.e., active years, which is 3.92 (3) years at the mean (median), only about half of IVCs' active years.

The short life cycle is not likely to be explained by the potential concern that CVCs make poor investments therefore fail to survive the venture business. When comparing the ratio of going public or being acquired across startups that are backed by CVCs and IVCs, I find that CVC-backed companies do slightly better in these successful exit dimensions, i.e., 14.09% vs. 12.57% for IPO, 36.89% vs. 34.37% for acquisitions. In earlier studies, both Gompers and Lerner (2000) and Chemmanur, Loutskina, and Tian (2014) show that CVC-backed companies perform at least as well as those backed by IVCs based on future exit outcomes.[25] The result is also unlikely to be affected by the natural attrition rates of parent firms—when restricting the CVC sample to parents that survive for at least three years beyond their CVC terminations, the pattern holds strongly.

Stylized Fact 2: Innovation-oriented. *CVCs disproportionately invest in entrepreneurial ventures that are innovation-intensive.*

What kind of companies do CVCs invest in? One striking observation is that CVCs disproportionately invest in innovation-intensive startups. Compared to a proportion of 18.49% in IVC's portfolios, more than half of CVCs' portfolio companies have patented at least once at the time of investment. The limitation of using "patenting" to capture "innovativeness" is that it misses startups conducting unpatentable invention. However, Farre-Mensa, Hegde, and Ljungqvist (2017) show that patents are crucial in determining startup innovation value and subsequent growth, and thereby are arguably the most important intellectual properties of the startup. Overall, this fact suggests that CVCs value innovation-related strategic benefits.

Stylized Fact 3: Distinct Investment Patterns. *CVCs invest in earlier stages, syndicate more, and show weaker home bias.*

CVCs tend to invest in slightly younger companies in earlier rounds. On average, CVCs make their first investment in a startup when the startup is 3.2 years old, while IVCs start to invest when a venture is around 4.1 years old. In terms of financing rounds, CVCs start to invest in the middle of the third and the fourth financing round, while IVCs on average make their initial investment closer to the fourth round. After breaking down each round, it appears that CVCs concentrate their investments in the second and third rounds, and they are less likely to invest in very early round (round 1 or seed) or later rounds (round 5 and above). Geographically, the average distance between CVC investors and their portfolio ventures is longer

[25] Admittedly, using exit outcomes such as IPO or acquisitions cannot fully reflect investment returns, which is a common data limitation. Lerner (2012) provides a in-depth discussion on cases of CVCs not making profitable investments.

compared to IVCs and their portfolio companies, and they are less likely to invest at home (startups in the same Commuting Zone). CVCs are also more likely to form syndication with other VCs.

Descriptive Investment Patterns of CVC vs. IVC

This table presents investment patterns of CVCs and traditional independent venture capitals (IVCs). Summary statistics are provided for the whole sample (including both CVCs and IVCs), the two types separately, as well as tests for the statistical significance of the differences in means across the CVC and the IVC sample.

In Panel A, the unit of analysis is a VC fund. *Duration* is the duration of a fund's investment horizon, calculated as the period between the initiation and the termination date. *Active Years of Investment* is the number of years in which the investor made investment in a new venture. *Number of Companies Invested* is the number of companies the investor invested through its life cycle.

In Panel B, the unit of analysis is a unique matching between a venture investor and a startup company. *Innovative Startup* is a dummy variable indicating whether the startup in the deal owned at least one patent at the time of investment, identified using the merged VentureXpert and USPTO data. *Age at Initial Investment* is the age of the portfolio company at the time that the investor made its first investment. *Round of Initial Investment* is the round number in which the investor made its first investment in the specific company. *Round 1, 2, ..., 5 and Above* is a set of dummies that equal to one if the first time that the investor participated was the company's first, second, third, fourth, or fifth and above round, and zero otherwise. *# of Syndicating VCs* is the total number of venture capital firms that syndicated in the round(s) in which the investor participated. *Geographic Distance* is the distance, in kilometers, between the entrepreneurial venture and the investor location. *Local Startup* is a dummy variable that takes value 1 if the investor and the startup are in the same Commuting Zone (CZ). *IPO* is a dummy variable that takes the value of one if the venture went public, zero otherwise, calculated for companies that were at least six years old as of March 2015. *Acquisition* is a dummy variable that takes the value of one if the venture was acquired, zero otherwise, calculated for companies that were at least six years old as of March 2015.

	Whole Sample		CVC		IVC		T-test (CVC vs. IVC)
	Mean	Median	Mean	Median	Mean	Median	*p*-value
			Panel A: Fund Level Statistics				
Duration (years)	8.59	9	6.22	4	9.27	10	0.00***
Active years of investment	6.42	6	3.92	3	7.14	6	0.00***
Number of companies invested	16.61	5	13.14	4	17.61	5	0.00***
			Panel B: Investment Level Statistics				
Innovative Startup	25.47%	0%	51.93%	100%	18.49%	0%	0.00***
Age at initial investment	3.95	3.6	3.26	3.2	4.13	3.8	0.00***
Round of initial investment	3.81	3	3.59	3	3.87	3	0.03**
Round 1	18.53%	0.00%	14.99%	0.00%	19.46%	0.00%	0.00***
Round 2	19.62%	0.00%	22.66%	0.00%	18.82%	0.00%	0.00***
Round 3	17.18%	0.00%	19.43%	0.00%	16.59%	0.00%	0.00***
Round 4	13.68%	0.00%	15.17%	0.00%	13.29%	0.00%	0.06*
Round 5 and above	30.99%	0.00%	27.75%	0.00%	31.84%	0.00%	0.00***
# of syndicating VCs	5.47	4	6.83	6	5.11	4	0.00***
Geographical Distance	1,429.51	535.23	1,662.49	1,134.34	1,368.03	514.75	0.04**
Local Startup	23.79%	0	21.23%	0	24.47%	0	0.02**
IPO	12.89%	0	14.09%	0	12.57%	0	0.04**
Acquisition	34.90%	0	36.89%	0	34.37%	0	0.07*