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When do incumbents learn from entrepreneurial ventures? Corporate venture capital and investing firm innovation rates

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Abstract

In this paper, we focus on the potential innovative benefits to corporate venture capital (CVC), i.e. equity investments in entrepreneurial ventures by incumbent firms. We propose that corporate venture capital programs may be instrumental in harvesting innovations from entrepreneurial ventures and thus an important part of a firm's overall innovation strategy. We hypothesize that these programs are especially effective in weak intellectual property (IP) regimes and when the firm has sufficient absorptive capacity. We analyze a large panel of public firms over a 20-year period and find that increases in corporate venture capital investments are associated with subsequent increases in firm patenting.

Keywords: Technology entrepreneurship; Corporate venture capital; Innovation; Appropriability

1. Introduction

A firm's dynamic capability, i.e., its ability to develop and acquire valuable resources and capabilities, is largely related to finding knowledge external to the firm and integrating it with internal knowledge (Teece et al., 1997; Henderson and Cockburn, 1994). In this vein, scholars have examined a number of ways in which firms may source external knowledge including regional learning, university research, recruitment of high-human capital personnel, mergers and acquisition, and alliances. However, little attention has been paid to the potential innovative benefits of investing corporate venture capital (CVC). Corporate venture capital is equity investment by incumbent firms in independent entrepreneurial ventures, i.e., relatively new, not-publicly-traded companies that are seeking capital to continue operation (Gompers and Lerner, 1998).

At its peak in 2000, established firms invested more than $16 billion, or 15% of all venture capital investments, through nearly 400 CVC programs (Venture Economics, 2001). Despite a significant drop-off in corporate venture capital investment corresponding to the decline in the financial markets in 2001, a number

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of leading corporations including Intel, Microsoft, Merck and others have continued to invest in new ventures (Chesbrough, 2002). Ostensibly, these investments are aimed to generate a substantial financial return on investment through the sale of ownership stakes post initial public offering (IPO) or through eventual acquisition. However, firms often assert that one of the major motivations for investing is to gain a window onto valuable, novel technologies so as to improve firm innovative efforts. Many firms report that this is their primary motivation for investing corporate venture capital (Siegel et al., 1988).

In this paper, we explore the prospects for CVC to provide a window on technology. We investigate whether CVC investment is associated with knowledge gains to incumbent firms. Do firms that invest corporate venture capital learn about and appropriate new technologies and practices from those ventures in which they invest? Our investigation builds on two theoretical pillars. First, the knowledge necessary to generate innovations may likely reside outside the boundary of incumbent firms (Arrow, 1974; Cohen and Levinthal, 1990). Second, entrepreneurial startups may be a valuable source of such knowledge (Aghion and Tirole, 1994; Kortum and Lerner, 2000; Shane, 2001).

Placed together, these two pillars suggest that corporate venture capital programs may be an important instrument for accessing valuable knowledge from entrepreneurial ventures. We propose that corporate venture capital investments increase incumbent firm innovation rates. We expect this effect to be especially strong when firms possess the internal capabilities to leverage venture knowledge and operate in an external context that permits capitalization on that knowledge. In particular, we propose that in weak intellectual property (IP) regimes, CVC will provide privileged access to venture specific knowledge and permit greater opportunities to learn from that knowledge. Furthermore, we propose that the greater a firm's absorptive capacity, the greater the marginal impact of CVC investment on firm innovation rates.

Empirically, we analyze a large unbalanced panel of U.S. public firms during the time period 1975–1995. Of those firms in our dataset, approximately 250 firms engaged at least in some level of CVC investing during the time period. Data is pulled from VentureXpert, Compustat, and the U.S. Patent databases. Discrete choice, fixed-effect and random-effect models are adopted to establish a relationship between CVC investment and patenting. We adopt a number of controls to address possible unobserved, time-variant heterogeneity. We find that increases in CVC investment are associated with subsequent increases in future citation-weighted patenting rates. Furthermore, we find that the magnitude of this effect depends on the firm's absorptive capacity and the strength of intellectual property protection.

The paper contributes to the growing literatures on sourcing external knowledge, broadly, and investing corporate venture capital, narrowly. Unlike other knowledge sourcing arrangements, CVC investment is a capital expenditure that is easily observed and measured. The deployment of other external innovative inputs is often difficult to observe and even more challenging to determine their cost. For example, the cost of establishing personal ties with university scientists is difficult to estimate (Cohen et al., 2002). Data on the cost of maintaining R&D alliances is typically not available to researchers and may not even be calculated by alliance members. The ability to measure the dollar amount of corporate venture capital investments enables us to better capture its elasticity with respect to incumbent firm patenting output. More importantly, these investments are observed irrespective of their success or contribution to firm innovation rates.

The research presented in this paper complements the existing corporate venture capital literature in a number of ways. Previous empirical research on venture capital investments by corporations has focused primarily on the narrow, financial returns to investing in new ventures (e.g., Gompers and Lerner). While a handful of empirical studies have looked at the broader strategic benefits of venturing activity (e.g., Siegel et al., 1988; Chesbrough, 2002), none of these studies directly evaluate the effect of external corporate venture capital investment on incumbent firm innovation using patenting. Our extensive longitudinal dataset allows for more sophisticated econometric models and allows us to address issues of unobserved heterogeneity and temporal precedence.

2. Theory and hypotheses

Researchers have long postulated that incumbent firms operating in competitive markets are inclined to innovate in order to sustain profitability (Schumpeter, 1942; Arrow, 1962). Yet, despite this economic inclination to innovate, numerous researchers have highlighted the organizational limits of established firms to generate innovations internally (Henderson, 1993). The view that incumbent firms face difficulties in generating ground breaking, radical innovations is well established (Tushman and Anderson, 1986; Henderson, 1993). Innovation in large part requires the integration of diverse knowledge sets (Arrow, 1974). To the extent there are constraints on the creation and sharing of knowledge within a single organization, incumbent firms may find that they lack the knowledge necessary to innovate.

To overcome these constraints, incumbent firms may seek to exploit knowledge external to the firm (Cohen and Levinthal, 1990). This has been the focus of numerous studies that investigate the ability to create new knowledge through the recombination of knowledge across organizational boundaries (Henderson and Cockburn, 1994). Potential sources of knowledge include regional networks of employees and firms (Saxenian, 1990; Almeida and Kogut, 1999), academic and government labs (Cohen et al., 2002), and other established firms accessed either through technology alliances or mergers and acquisitions (Hagedoorn and Schakenraad, 1994; Gulati, 1995; Powell et al., 1996; Capron et al., 1998; Ahuja and Katila, 2001).

Entrepreneurial ventures may be a particularly important source of knowledge. A number of scholars have advanced the idea that entrepreneurial ventures are likely to be the source of highly valuable and innovative ideas (Kortum and Lerner, 2000; Zingales, 2000). According to this line of reasoning, star scientists/innovators will opt away from fixed salary (i.e., as an employee in a corporate R&D lab) and towards profit sharing (i.e., founding their own new venture) when they have an idea that is highly lucrative (Anton and Yao, 1995; Gans and Stern, 2003). Thus, we expect to observe the formation of new ventures only when entrepreneurs have highly innovative ideas (Aghion and Tirole, 1994). Indeed, Kortum and Lerner (2000) observe that entrepreneurial, human-capital intensive ventures generate higher levels of patenting output than established firms. Shane (2001) provides further empirical evidence that new venture formation is associated with underlying entrepreneurial inventions that are of high economic value.

Both practitioners and scholars have proposed that corporate venture capital may provide a valuable avenue to access this pool of knowledge (Chesbrough, 2003; Gans and Stern, 2003; Poser, 2003; Roberts and Berry, 1985). By investing in new ventures, incumbent firms may gain a window onto the venture's technologies and practices (Chesbrough and Tucci, 2002). Exposure to novel, pioneering technologies may in turn increase the likelihood that established firms would create breakthrough innovations (Ahuja and Lampert, 2001). Siegel et al. (1988) in a survey of 52 corporate venture programs, report that corporations rank "exposure to new technologies and markets" as the leading objective for engaging in corporate venture capital programs. Corporate venture capital may also contribute to firm innovativeness by increasing the demand for corporate innovations. Investment in ventures with complementary product and services may increase the demand for current and future corporate products and consequently encourage further corporate innovations (Brandenburger and Nalebuff, 1996).

A similar point has been made in the related technology alliances literature. Hagedoorn and Schakenraad (1994) and Ahuja (2000) indicate that knowledge from innovative alliance partners may spillover and positively affect the innovativeness of a firm. Stuart (2000) shows that firm's patenting rates increase the more technologically advanced are its alliance partners. Rothaermal (2001) argues that incumbent firms that pursue alliances improve their new product development efforts when faced with radical technological changes. To the extent that entrepreneurial startups possess valuable knowledge, corporate venture capital may provide a firm a window onto the operations of portfolio companies that can generate similar advantages to those associated with having innovative alliance partners.

2.1. CVC investment

We propose that CVC investment provides a unique opportunity to learn from new ventures. In many instances, entrepreneurs desire and actively seek corporate investment. Entrepreneurial ventures are willing to accept incumbent access to their operations in exchange for the benefits they receive from having a corporate partner. In addition to funding, incumbent firms provide substantial value added services (Block and MacMillan, 1993) as well as facilitate new ventures' access to complementary assets (Teece, 1986; Pisano, 1991), endorsements (Stuart et al., 1999), and international product markets (Acs et al., 1997). Indeed, empirical evidence indicates that CVC-backed ventures fair better than independent venture capitalist-backed ones (Gompers and Lerner, 1998; Maula and Murray, 2001).

There are at least three channels through which corporate venture capital activity facilitates firm learning from entrepreneurial ventures. First, the due-diligence process provides the firm a unique opportunity to learn about entrepreneurial inventions even prior to committing capital. Post investment, an investor may learn about novel technologies by maintaining board seats (or board observation rights) as well as utilizing dedicated liaisons. Finally, a failing venture may also constitute a learning experience to the extent that it offers technological insights, or conversely points at market unattractiveness.

Prior to funding a venture, investors conduct thorough due diligence of the venture's operations and business plan. This generally includes a background check of the founders and key management team, discussions with key customers, and a review of the product and technology. Corporate venture capitalists often leverage corporate R&D personnel to gauge a venture's technological feasibility and consult corporate executives to determine business and market risks. Henderson and Leleux (2002) observed that a person or team from the business unit was typically involved in the due diligence process. For example, Agilent Technologies corporate venture capital group "works closely with the company's existing businesses to share information, qualify investment opportunities, and connect portfolio companies to Agilent's own initivatives" (Chesbrough, 2002:6).

As a result, a firm's business units become privy to the novel technologies that they review. In addition, the business units often gained insight into future technologies and products (Chesbrough, 2002). Consider, for example, Intel's investment in Berkeley Networks: "As Intel performed its due diligence on its investment, it began to see the outlines of a possible strategy shift . . . culminating in the Intel Internet Exchange Architecture, launched in 1999. The investment in Berkeley Networks allowed Intel to identify a promising opportunity more quickly than it might have otherwise" (Chesbrough, 2002:9).

Once the investment round has taken place, corporations employ various mechanisms to learn from their portfolio ventures. Corporate investors often secure board seats, or at least board observation rights, which provide them with knowledge of ventures' key activities and technologies. UPS actively pursued such advantages from its CVC activities: "United Parcel Service decreases the distance between business units and venture investments by requiring board observation rights for its leading business managers. Board meetings help senior UPS business managers learn about start-up operations, technologies and business models, increasing UPS's ability to capture strategic value from its venture investments (Corporate Executive Board, 2000)". A study of 91 U.S.-based ventures that operated mainly in the computer and communication industries during the late 1990's, finds that in 31% of the cases the corporate investor held a board seat and in 40% of the cases it did not have a seat but did hold observer rights (Maula, 2001). These results are echoed in a recent survey of European venture capital practices (Bottazzi et al., 2004) that reports CVC investors serve on portfolio companies' boards (68%) and conduct close monitoring and site visits (70%) almost as frequently as independent venture capitalists do (78%, 76%, respectively).

Incumbent firms also institute specific organizational routines to encourage and funnel learning from ventures at the post-investment stage. It has long been recognized that successful learning is contingent upon close interaction between firms' personnel that accommodates rich media and information flows (Arrow, 1974; Daft and Lengel, 1986). Sony Corporation created two parallel and distinct functions responsible for knowledge transfer between its portfolio companies and the corporation (International Business Forum, 2001). In addition to securing board seats to its CVC group (Sony Strategic Venture Investments), Sony's business divisions established liaisons with the ventures. These liaisons' specific goal was to learn about and source the portfolio company's technology. Motorola pursued a similar strategy as part of its own CVC activities (Corporate Executive Board, 2000).

CVC investors can derive benefits even from failed portfolio ventures when technologies remain viable after the originating venture has dissolved (Hoetker and Agarwal, 2004) and failure itself carries informational weight (McGrath, 1999). Chesbrough (2002:6) echoes this view of CVC investments: "Agilent has recently invested in a startup company making wireless radio-frequency devices, a product area Agilent plans to explore in its own business. If this investment is successful, Agilent's future business will benefit; if it fails, Agilent will get a valuable early warning about pitfalls to avoid in that business".

Through these learning structures, incumbent firms that invest in entrepreneurial ventures may increase the stock of knowledge from which they may base innovation. The larger a firm's equity investment in new ventures, the greater the stock of entrepreneurial knowledge a firm has access due to either (a) access to a greater number of new ventures (i.e., more opportunities to conduct and learn from due-diligence, as well as board observation rights and witnessing failure), or (b) greater access to their portfolio companies (i.e., greater leverage vis-à-vis the venture and hence more chances to secure board seats and deploy liaisons).

The greater the stock of entrepreneurial knowledge a firm has accessed, the greater the subsequent innovation output. This increase in a firm's innovation rate may result from at least two mechanisms (Ahuja and Katila, 2001). First, to the extent that innovation results from the novel combination of existing knowledge, the expansion of the firm's knowledge base will lead to a greater number of possible knowledge configurations (Kogut and Zander, 1992). Second, the exposure to new technologies and practices through CVC investment will increase a firm's absorptive capacity, i.e., the ability to absorb and use additional external knowledge (Cohen and Levinthal, 1990). Thus, we hypothesize:

Hypothesis 1. All else being equal, greater firm investment in entrepreneurial ventures leads to increases in the investing firm's innovation rate.

2.2. Intellectual property regime

The magnitude of the innovative impact of CVC investment is likely to vary across both industries and firms. The degree to which a firm may innovate as a result of its investment in entrepreneurial ventures likely depends on the inability of ventures to shelter their intellectual property (Anand and Galetovic, 2000; Gans and Stern, 2003). All else being equal, the marginal benefit of CVC investment should be greater the weaker the intellectual property regime, i.e., when ventures struggle to protect their innovations from imitation through legal mechanisms such as patents. The reasons for this are two-fold.

First, corporate venture capital may be a uniquely advantageous strategy for gaining a window on entrepreneurial technologies in weak IP regimes. Ventures will likely resort to secrecy as a way to appropriate the gains from innovation in industries where the intellectual property regime is weak (Cohen et al., 2001). In strong IP regimes, ventures may have the option to patent their technology and license it to prospective incumbents. For example, biotech firms often patent and license their technology to pharmaceutical firms. CVC investment in these environments is less likely to provide privileged access to external knowledge, compared with other strategies (e.g. licensing). In contrast, in weak IP regimes, the ability to conduct due-diligence, as well as the chance to participate on board meetings provide the corporation with a unique opportunity to pierce the veil of secrecy and provide an effective vehicle to learn about the venture's closely-held technologies.

Second, even when patented, a venture's innovation is more likely to be appropriated by investing firms under weak IP regimes. Defending the rights for a patent is costly (Lerner, 1995). When the intellectual property regime is weak, a cash-constraint venture may not have the means to prohibit investors from appropriating its knowledge. In weak patent regimes, ventures may find it too costly to receive and defend patents for their technology. Similarly, "survivors" of a failed venture may find it difficult to enforce patent rights on the former venture's technologies. The same technology may lead to patents for investing firms who possess the resources necessary to profit from patenting. Incumbent firms are more likely to have the resources necessary to fight lawsuits and other challenges to their patents. Furthermore, incumbents are more likely to possess complementary capabilities in research, manufacturing, and distribution, which they can leverage to their advantage.

Hypothesis 2. The weaker intellectual property regimes, the greater a firm's investment in entrepreneurial ventures will impact the firm's innovation rate.

2.3. Absorptive capacity

We do not expect the marginal effect of CVC investment on innovation rates to be uniform across all firms. Within a focal industry, the degree to which a firm may learn from its CVC investments will depend in part on the absorptive capacity of the firm. Cohen and Levinthal (1990) advance the view that internal and external sources of innovations are interdependent. In line with their absorptive capacity argument, Kleinknecht and van Reijen (1992) report that having an internal R&D department increases the likelihood of co-operative R&D with other firms. Others have also reported that firms with an expertise in a given research domain exhibit higher levels of knowledge absorption from external sources (Pisano, 1991; Veugelers, 1997).

We propose that the impact of investment in entrepreneurial ventures on firm innovation rates will be greater for those firms who have a strong base in innovation. The ability of an investing firm to transfer or create knowledge through its interaction with a venture likely requires a firm to have sufficient technical understanding to both grasp and capitalize on that knowledge. Internal research and development provides the foundation upon which firms may learn from the ventures they invest. R&D personnel are often mobilized to conduct technological due diligence, and some are later chosen to serve as liaisons between corporate business units and the ventures. Indeed, Intel's investment experience and high technological absorptive capacity allowed it to recognize, as early as the due diligence stage, the opportunity associated with Berkeley Networks' technology.

Hypothesis 3. The greater a firm's absorptive capacity, the greater a firm's investment in entrepreneurial ventures will impact the firm's innovation rate.

3. Data and method

In our analysis, we explore the relationship between corporate venture capital and incumbent firm innovation rates. Specifically, we explore the varying levels of firm CVC investment and compare their subsequent innovation rates. We adopt patent data as a measure of innovation to be consistent with recent studies on technology alliances (Baum et al., 2000; Stuart, 2000) and entrepreneurship (Ahuja and Lampert, 2001; Almeida et al., 2003). We cannot directly measure the generation of patents as a result of investment in specific ventures, because the data do not permit such attributions. Following Hausman et al. (1984), we adopt a patent production function (see methods below) to estimate the sensitivity of a firm's innovative output to various innovative-inputs in general (for a review see Griliches, 1990) and venture capital investments in particular (Kortum and Lerner, 2000).

3.1. Sample

We constructed a large, unbalanced panel of U.S. public firms during the period 1969–1999. The panel includes all public firms that invested corporate venture capital or patented during this period. The resulting dataset includes 2289 firms and 45,664 firm-year observations. The database contains information on firms' venturing activity collected from Venture Economic's VentureXpert database, patenting activity from the Hall et al. (2001) dataset derived from the U.S. Patent Office, and financial data from Standard & Poor's Compustat database.

To construct our database, we first identified the population of firms engaging in corporate venturing activity through the VentureXpert database.[1] The database contains a comprehensive coverage of investment, exit, and performance activity in the private equity industry from 1969 to 1999. We searched the population of all private equity investments for any investments by firms or their funds.[2] For these firms, we collected data on the annual amount of venturing investments (disburse-

[1] The database is offered by Venture Economics, a division of Thomson Financial. The data are collected through industry associations (European Venture Capital Association, the National Venture Capital Association, and other key associations in Asia and Australia) and the investment banking community. These data have been used in several academic studies on the venture capital industry (Bygrave, 1989; Gompers, 1995).

[2] We included the following VentureXpert categories: Non-Financial Corp Affiliate or Subsidiary Partnership, Venture/PE Subsidiary of Non-Financial Corp., Venture/PE Subsidiary of Other Companies NEC, Venture/PE Subsidiary of Service Providers, Direct Investor/Non-Financial Corp, Direct Investor/Service Provider, SBIC Affiliate with non-financial Corp. and Non-Financial Corp. Affiliate or Subsidiary. We excluded investments by corporate pension funds because these investments are distinct and unlikely to result in learning benefits.

ments). Note, these amounts represent the actual dollar value invested during a given year, and should not be confused with dollars committed to venturing activity (usually reported in the professional media), which represent the total dollar amount a fund has committed to invest over the fund's life. We believe the former measure is more appropriate given the focus of our study on the benefits of having a viable window onto innovative ventures. Similarly, we focus on CVC investment made directly in entrepreneurial ventures and exclude capital allocated to intermediaries such as traditional venture capital funds (e.g., the practice of fund-of-funds).

We augmented our CVC data with patenting data constructed by Hall et al. (2001) (hereafter HJT) that are based on the U.S. Patent Office database. We added to our sample all U.S. firms within the same industries (based on four-digit standard industrial classification, SIC, classification) as those firms in our CVC dataset over the time period 1969–1999. The HJT datasets contain detailed information on almost 3 million U.S. patents granted between 1963 and 1999, all citations made to these patents since 1974 (over 16 million), and a match of patients' assignees to Compustat. Standard & Poor's Compustat database was used to provide annual firm-level accounting and financial data thus limiting our sample to publicly traded firms. An automated, matching algorithm and hand-checking were used to link the VentureXpert data with the HJT patenting dataset and Compustat.[3] Furthermore, while the HJT patenting dataset bases the ownership structure of firms circa 1989, we manually matched up firms to U.S. Patent and Trademark Office (PTO) assignee codes to ensure we capture the patenting activity of all firms.

The resulting sample included 2289 firms and 45,664 observations. Two hundred and forty seven firms of these firms invested corporate venture capital some time during the period 1969–1999. For each of the 2289 firms, we collected annual financial data such as research expenditures and book value of assets for the years 1969–1999 from Compustat. We established the annual patent output for each firm using the HJT dataset. Approximately 80% of the public firms from the VentureXpert database were issued a patent over the 1969–1999 time frame.

3.2. Measures

We capture the rate of innovation within firms using a firm's citation-weighted count of patents (*Citations*). There are a number of measures of a firm's innovativeness adopted in the empirical literature (see Hagedoorn and Cloodt, 2003, for a recent review). Some studies employ R&D expenditures as a proxy of a firm's innovation competencies (Henderson and Cockburn, 1994) while others employ surveys of new product announcements (Acs and Auretsch, 1988). Patents (Griliches, 1990) and patent citations (Trajtenberg, 1990; Harhoff et al., 1999) are perhaps the most popular measures of innovative performance. Based on an analysis of 1200 companies in high-tech industries, Hagedoorn and Cloodt (2003: 1375) conclude "the overlap between each of these four indicators is that great ... that in high-tech sectors any of these four indicators could be taken as a measure of innovative performance in the broad sense".[4]

We opt to capture the rate of innovation within a firm as the count of forward (future) citations to patents applied for in a given year by a firm (*Citations*).[5] In doing so, we build on previous studies that have found patent citations is a good indicator of the value of the invention (Trajtenberg, 1990; Harhoff et al., 1999). Previous studies have employed patents and citation-weighted patents to gauge innovative output in the chemical (Ahuja, 2000), pharmaceuticals (Henderson and Cockburn, 1994), information (Stuart, 2000) and devices (Brockhoff et al., 1999) sectors, among others.

[3] The HJT database provides not only the name of the company to which the patent was assigned but also the ultimate (parent) firm name. Therefore, a firm with a single entry in Compustat can have multiple assignee-names in the HJT database. Since the knowledge gained through a venturing activity can be put to use in different divisions and subsidiaries of the corporation, we consider every assignee-name associated with a corporation, as long as it holds more than 50% of the original assignee.

[4] We believe their conclusion applies to our study: Hagedoorn and Cloodt's (2003) sample and our sample share many characteristics. Specifically, they studied companies operating in four high-tech industries (aerospace and defense, computer and office machinery, pharmaceuticals, electronics and communications), over the period 1992–1998. Their results hold for the sub-sample of U.S. firms (which constituted about 70% of their all sample).

[5] To increase confidence in our findings, we also ran each of our models with unweighted patent counts as well. We discuss these alternative specifications in the results.

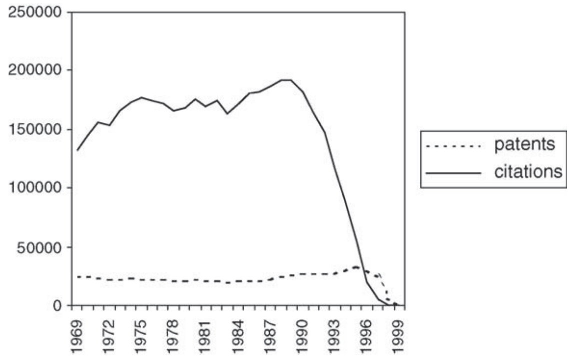

Fig. 1. Total patents and citations in our sample (1969–1999).

Only patent applications that were later granted are included in our dataset. We chose to use application year rather than grant year, because our main interest is to record changes to the focal firm's knowledge base rather than its ability and timing of appropriating rents. Hall et al. (2001) report that the distribution of forward lag in citation (i.e., the number of years between patent's application date and later citing-patents application date) is about 3–4 years. Thus, our citation-weighted patents variable is truncated on the right. Patents granted in recent years have not been available long enough to be cited by future patents (see Fig. 1). Variation in citing behavior across technological fields and along years may also bias our citation-weighted patents variable (Hall et al., 2001). We address these potential biases in our methods discussion below.[6]

Our primary independent variable is annual CVC investments in millions of dollars (CVC). This variable is calculated as the sum of all investments via all venturing funds by a firm in a year. Control variables include annual firm research expenditures in millions of dollars (*Research*) and firm size measured as total firm assets in millions of dollars (*Assets*). We would expect that larger in-house research expenditures would lead to greater patenting output (Henderson and Cockburn, 1996). Similarly, larger firms possess greater resources for investing in research and thus are more likely to patent more (Schumpeter, 1942; Cohen and Levinthal, 1990). All three variables are adjusted to 1999 dollars using the Consumer Price Index.

In most models, we include a measure to capture the technological opportunities available per industry. We define (*Industry Citations*) as the average number of citation-weighted patents applied to by firms in a given year in a given industry defined by each four-digit standard industrial classification. This measure helps control for time-variant, differences across industries, such as citation 'inflation' in certain industries, that may be driving an apparent relationship between CVC investment and patenting. More importantly, by controlling for *Industry Citations*, we attempt to address the fact that some industries at some points in time may experience greater technological ferment that may drive both the opportunities to invest in new ventures and the opportunities to innovate internally (Klevorick et al., 1995). We further address this potential confounding, alternative hypothesis by performing a separate analysis for individual industry segments.

As an additional control, we include a measure of the stock of patents a firm has been granted (*Patent Stock*). Since we analyze a relatively long period of time, it is possible that unobserved, time-variant firm-level characteristics such as alliance activity or mergers and acquisitions affect patenting activity. Following Blundell et al. (1995), we calculate this measure by calculating the depreciated sum of all patents applied from 1963 to the current year.[7]

$$\text{Patent Stock}_{it} = \ln(\text{Patents}_{it} + (1-\delta)\,\text{Patent Stock}_{it-1})$$

We include this measure to partially control for possible firm-level unobserved heterogeneity that is not fixed throughout time. Previous studies examining patenting rates have used similar measures (Ahuja and Katila, 2001).

To test our hypothesis concerning the moderating effect of intellectual property protection, we create a measure derived from the Carnegie Mellon Survey (CMS) of Research and Development (Cohen et al., 2001).

[6] We also followed the 'citation-fixed-effects' approach of Hall et al. (2001) and rescaled our dependent variable by dividing the absolute number of citations made to a given patent, by the average number of citations made to all patents in the same technological group and application year. Our results are robust to this specification. See Hall et al. (2001) for a complete discussion.

[7] We adopted a depreciation rate of 30% as in Blundell et al. (1995). We experimented with other values (e.g., 0%) and received consistent results. At a depreciating rate of 30%, patents granted prior to 1963 have little impact on 1969 *Patent Stock* especially given the 1–4 year lag between patent application and granting.

The questionnaire was administered in 1994 to a random sample of U.S. manufacturing R&D labs drawn from the Directory of American Research and Technology. Overall, 1478 R&D unit managers answered about mechanisms they use in order to protect profits due to inventions in their focal industry. These included a variety of mechanisms such as patents and secrecy. *IP Protection* reflects the relative importance of patenting as a way to protect intellectual property. *IP Protection* was measured as the mean percentage of innovations for which patenting was considered effective. The higher the value of *IP Protection*, the greater the value of patenting. Note, by construction, this variable varies across industry but is time-invariant.

To test Hypothesis 3, we capture the absorptive capacity of the firm in a number of ways. It is a common practice to capture firm absorptive capacity with its contemporaneous R&D expenditure (Cohen and Levinthal, 1990). Unfortunately, this may simply add noise to our results since CVC funds and R&D labs likely compete for corporate resources implying a countervailing substitution effect. To avoid concerns over potential substitution between contemporaneous levels of CVC and R&D, we use historical level of R&D. In particular, *Past R&D* measures the 3-year sum of past research and development outlays. That is, our first proxy for firm absorptive capacity is the sum of R&D in year $t-2$ to year $t-4$.

As an alternative measure for absorptive capacity, we employ firm stock of prior patents (described above) as a proxy for absorptive capacity. On a theoretical level, we believe *Patent Stock* may be an attractive construct for firm absorptive capacity. Each dollar spent on internal R&D may not generate the same amount of knowledge stock. According to Hall et al. (2001), patents should be a good proxy for knowledge capital because it represents the success of an R&D program not just its input.

Absorptive capacity, as originally conceived, is not a state variable rather it is domain specific. A firm may possess an absorptive capacity in one domain of knowledge but lack absorptive capacity in another domain. To address the domain specific nature of absorptive capacity, we adopt a third measure based on the technological proximity between an investing firm's domain of expertise and the domain of expertise of the firm's portfolio ventures. In particular, we follow Jaffe (1986) and examine the extent of an overlap between CVC and portfolio companies technological portfolios. Each firm's technological portfolio is determined by measuring the distribution across patent classifications of the patents associated with its businesses, using Silverman's (1996) concordance between SIC codes (i.e., line of business) and patent classes (i.e., domain of expertise). We believe this measure is more appropriate than the cross-citation measure of technological overlap (Mowery et al., 1996) for the purpose of measuring a firm's absorptive capacity.[8]

Generating the *Venture Proximity* measure involves a number of steps. First, we identify the technological portfolio that is associated with each corporate investor based on its businesses (Silverman, 1996). Next, for each venture within an investing firm's portfolio, we identify the venture's domain of expertise using the same methodology. Since these ventures are not yet publicly traded companies, they are not typically associated with a SIC code. Rather, we only know their Venture Economics Industry Classification (VEIC)—a Venture Economics proprietary industry classification scheme. We manually assign a SIC to each venture using a manual two-step process.[9] Third, the overlap in technological portfolios (i.e., activity in the same patent classes) is then calculated for each CVC firm-portfolio venture pair. Finally, for each CVC investor, *Venture Proximity* is defined as the average proximity across all of its portfolio companies.

[8] The measure proposed by Mowery et al. (1996) is a strong indicator of a technological bond between two firms. However, it may underplay information about the similarities of firms that do not cite each other (a likely event given that entrepreneurial ventures have not been around for a long period of time). The extent to which similar patent classes are use by the two firms, irrespectively of whether or not they cite each other, is consistent with the conceptual construct of firm's absorptive capacity.

[9] Coding each venture involved the following steps: (1) identify all ventures in Venture Economics (VE) that ever pursued a public offering (IPO); (2) record their VEIC code as available through VE; (3) identify them through Compustat and record their SIC code; (4) generate an initial mapping of VEIC-to-SIC. (5) for a given VEIC code, identify all IPOed ventures and their SIC codes; (6) review relevant information about them from VE database. This includes the following VE fields: company business description, company competitors, company customers, company internet tech group, company primary customer type, company product keywords; (7) for each of the non-IPOed ventures, review the same VE fields and assign an appropriate SIC code; (8) triangulate venture's line of business through other databases (e.g., Dun and Bradstreet, Lexis-Nexis).

3.3. Method

Our dependent variable (*Citations*) is a count of patent citations for patents applied for by a firm in a given year and as such is bounded at zero and assumes only integer values. We address the discrete nature of *Citations* by adopting a negative binomial model. The negative binomial model is commonly used in the patenting literature for over dispersed count data like ours (Griliches et al., 1987). The negative binomial model is a generalized form of a Poisson model where an individual, unobserved effect is introduced in the conditional mean (Greene, 2000). We do not adopt a Poisson model because the assumption of constant dispersion appears violated, i.e. the mean and variance of the event count are not proportional. A Lagrange multiplier test of overdispersion proposed by Cameron and Trivedi (1998) was used to test this assumption.[10]

In general, we assume a 1-year lag between our regressors and dependent variables. In other words, we examine the association between last year's value of our independent variables and this year's patenting levels. In the case of *Research*, previous research looking at the relationship between research expenditures and firm patenting have found high within firm correlation of R&D over time thus supporting the use of a one-year lag (Hall and Zedonis, 2001). However, absent prior research on the impact of corporate venture capital on patenting output, we take a cautious approach and employ a distributed lag analysis for CVC (Ahuja and Katila, 2001). There is likely to be a lag between investment in new ventures and changes in innovative output for the investing firm. While the learning benefits from due-diligence may be immediate, more substantive learning is likely to take place only after ties have been established and trust is built. Furthermore, the learning that may derive from board seats and technical liaisons may transpire over a longer period of time as a venture's technology matures. Similarly, learning from a venture's mistakes and failures takes time as well.

Thus, we expect that the positive effect of CVC investment on firm innovativeness will likely transpire for years after the investment activity. In this spirit, we consider both unrestricted and a geometric models of a distributed lag between CVC investment and innovative output. In the unrestricted case, we consider the effect CVC investment has on patenting output from one to six years later: CVC_{t-k} where $k = 1–6$. We use a χ^2 test to test the joint hypothesis that the impact of all six lags is significantly different from zero in combination. For the geometric distributed lag model, we assume that the joint impact of CVC activity over time has the following standard functional form:

$$\text{CVC}_{\text{distributed lag}} = \Sigma_j (1-\lambda)\lambda^j (\text{CVC})_{t-j}.$$

The geometric lag has the appealing attribute of having one coefficient to capture the impact of CVC activity.

Since our sample traces multiple industries over a long period of time, our findings might be biased due to unobservable heterogeneity related to macroeconomic factors, industry attributes, or firm characteristics. In our analysis, we adopt a number of strategies to address possible unobserved heterogeneity in addition to the use of *Industry Citations* and *Patent Stock*. First, year fixed-effects are included to control for macroeconomic trends such as economic downturns and periods of general technological ferment that may ultimately affect overall patenting levels. Year fixed-effects also control for yearly variations in patent citation rates as a result of right truncation of the data. To further address biases from the truncation of citation-weighted patents, we restrict our sample to the period 1975–1995.[11] By excluding the most recent year's data, we also remove any bias introduced by the internet bubble economy of the late 1990s. By excluding the years prior to 1975, we improve the accuracy of the HJT matching of firms to patents.[12]

Second, we include firm-effects to address possible firm-specific unobserved heterogeneity. Firm-effects are a common practice in panel data analysis and serve as a control for unobserved, time-invariant firm-level characteristics that may in part be driving patent activity within the firm. We employ both firm fixed-effects

[10] The LM test was operationalized using a likelihood ratio test in Stata version 7.0. A significant χ^2 statistic is interpreted as a rejection of the base hypothesis of constant dispersion. To increase confidence in our results, we also ran our various models using a Poisson specification and found consistent results. The Poisson models may be provided by the authors upon request.

[11] While the number of firms in the sample remains unchanged (2289), limiting the time-period reduces the number of firm-year observations to 31,876.

[12] We estimated our models over a number of different time periods and found consistent results. Estimations based on the full 1969–1999 panel improved our results. Tables for these estimations may be provided by the authors upon request.

and firm random-effects. In the negative binomial context, firm fixed-effects are estimated using a conditional maximum likelihood estimator. The random-effects specification assumes that the regressors and the firm-specific effects are uncorrelated. As explained in the analysis below, each of the methods has strengths and weaknesses and the literature does not have a strong preference for one method. We also include sector dummies to control for possible fixed industry effects that are not captured by the firm-effects.

In summary, we adopt a negative binomial specification with firm, sector, and year fixed and random effects and lagged independent variables. The expected number of citation-weighted patents given a set of independent variables may be given for the random-effects specification by,

$$E[Citations_{it}|X_{it-1}] = \lambda_{it} = \exp(\beta' X_{it-1} + \varepsilon_{it} + \nu_i)$$

where β is the coefficient vector, X_{it-1} represents our set of time-variant firm characteristics including CVC, and ν_i and ε_{it} are independent random variables.

4. Analysis and results

Fig. 2 (Panel A) presents a summary of total annual investment in new ventures during the period 1969–2003 (in 2003 dollars). We observe that corporate venturing activity has gone through three waves during the last 30 years that closely parallel the investment patterns of independent VC funds. The first wave peaked in the early seventies. Activity declined until approximately 1978, when changes in legislation led to an increase in venturing investments by independent venture capitalists as well as established firms. This second wave peaked around 1986 with total annual investment at approximately \$250 million per year (in original dollars). Investments declined sharply after the stock crash of 1987 to a level of \$25 million in 1993. The third wave began with the rise of the Internet in the mid-1990s. By 2000, the total amount of rounds in which established firms participated reached a record level of nearly \$16 billion (in original dollars).

Table 1 presents a summary of the investment activity of the 20 largest venturing firms in our sample in terms of total cumulative dollars invested. Intel leads the list with total investments approaching \$1.5 billion since 1992. The top 20 is dominated by the largest electronics and computer concerns such as Microsoft, Sony, Motorola, AOL, and Dell. Johnson & Johnson is the first pharmaceutical firm to appear in the top 20 at the 13th position with cumulative investments approximating \$196 million. The relatively lower investment levels by pharmaceutical firms may simply capture the well documented inclination of these firms towards other forms of inter-organizational arrangements (Pisano, 1991; Baum et al., 2000; Rothaermal, 2001). For example, the 'relative incidence' of licensing, in comparison to other channels for external knowledge acquisition, may be particularly high in the pharmaceutical industry (Anand and Khanna, 2000).[13] A majority of the top 20 firms have started their corporate venturing funds after 1993. A few have been engaged in corporate venturing since the sixties including Xerox, Johnson & Johnson, and Motorola. A handful of firms including Intel, Sony and Xerox have numerous funds with which to distribute funds.

Fig. 2 (Panel B) also presents a summary of total annual corporate venture capital activity by sectors during the period 1969–1997.[14] We exclude data from 1998 and 1999 in the graphs since investment levels in these years were orders of magnitude greater for a number of sectors (in particular, the information technology sector comprised of semiconductors, computers and telecommunications). Consistent with Table 1, we observe that firms in the information and devices sectors, and to some extent the pharmaceutical industry, actively engage in corporate venture capital. The chemical industry and the metals industry had lively CVC investment during the 1980's that was not matched during the following wave of general CVC activity in the 1990's. We may speculate that much of the run up in CVC investment in the late 1990's was driven by the Internet. For example, the publishing industries surge in CVC investment starting in 1995 was a result of established media moguls such as News Corp. investing in internet start-ups that provided news and other information on-line.

[13] Anand and Khanna (2000:126) "Pharmaceutical patents, in particular, can be made very strong . . .. Hence, both the aggregate incidence of licensing, as well as the ratio of licenses to joint ventures (i.e., the relative incidence), is likely to be greater when property rights over technologies are strong, ceteris paribus". The implications for firm's innovation rates are discussed in the results.

[14] Sectors were defined by SIC code as follows: chemicals (28** excluding 2834 and 2836, 29**, 3080), pharmaceuticals (2834, 2836), devices (38**), and information (357*, 367*, 48**, 3663).

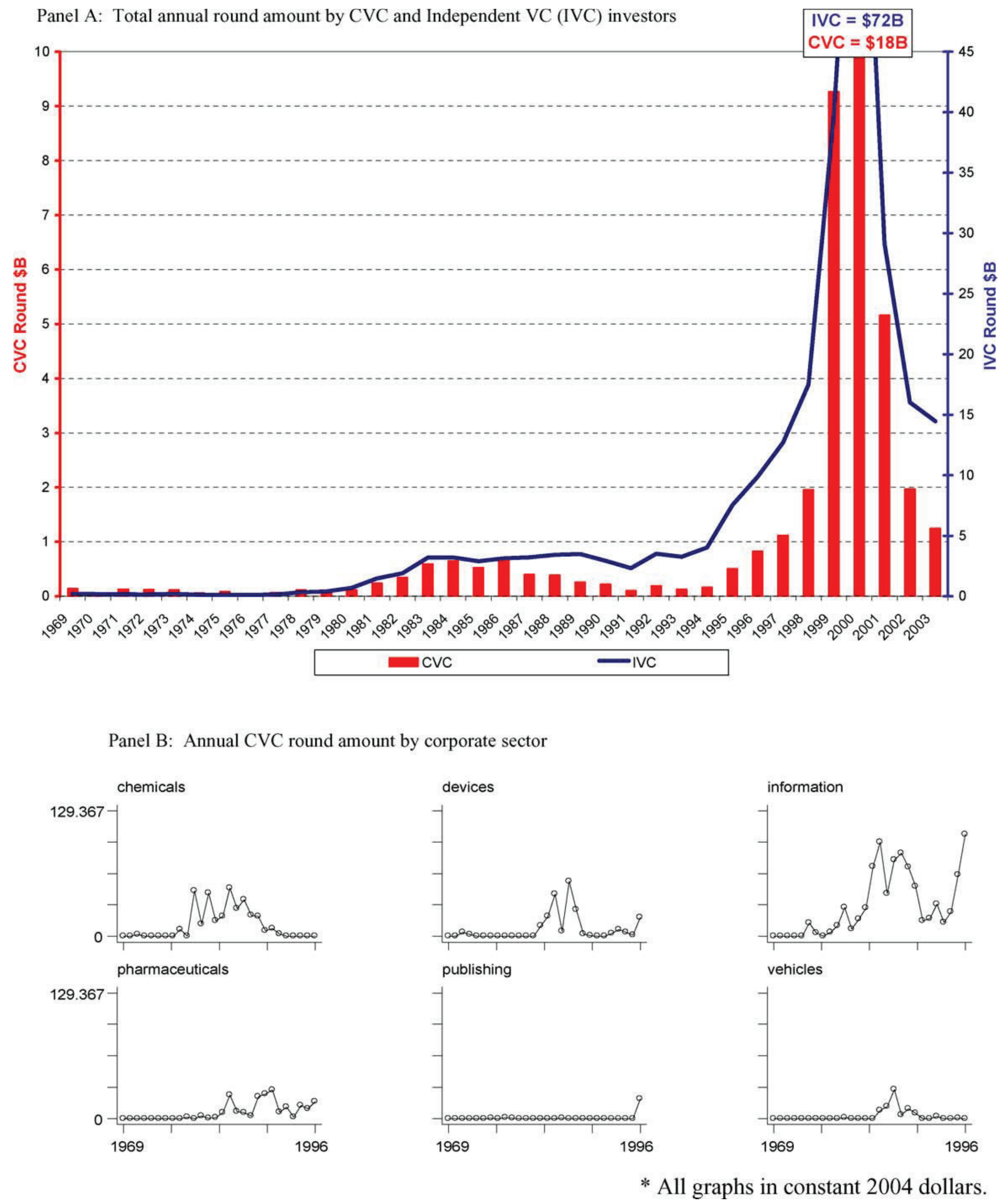

Fig. 2. Annual corporate venture capital investments (total and by sector). Panel A: total annual round amount by CVC and independent VC (IVC) investors. Panel B: annual CVC round amount by corporate sector.

Table 1
Activity summary of 20 largest venturing firms (1969–1999)

Firm	Year began investing	Maximum annual ventures	Total dollars invested[a]	Maximum annual invested[a]	Average annual rounds	Total venture funds
Intel	1992	179	1486	771	57	5
Cisco	1995	55	1056	730	19	1
Microsoft	1983	29	713	436	7	1
Comdisco	1992	70	554	334	24	2
Dell	1995	48	502	395	26	1
MCI Worldcom	1996	11	495	410	8	1
AOL	1993	39	333	169	10	2
Motorola	1963	33	315	177	11	1
Sony	1984	30	313	169	7	6
Qualcomm	1999	5	262	207	5	1
Safeguard	1983	21	231	118	6	3
Sun Micro	1999	31	204	180	19	1
J & J	1961	21	196	80	5	2
Global-Tech	1999	13	188	122	11	1
Yahoo	1997	5	186	163	3	1
Xerox	1960	30	184	24	13	6
Compaq	1992	21	182	113	5	3
Citigroup	1999	11	156	93	9	1
Ford Motor	1951	22	146	125	8	4
Comcast	1996	16	144	84	11	1

[a] In millions of dollars.

Table 2 presents definitions, descriptive statistics, and the correlation matrix for the variables in our patent count model. We use the natural log of each of our primary independent variables. We observe that firms, on average, are granted 13.5 patents per year and receive approximately seven citations per patent. However, the relatively few firms who patent in great numbers skew these numbers. The main independent variable, CVC, varies from \$0 to \$52.5 M in absolute terms. The correlations between independents variables were not deemed high enough to warrant series concern of multicollinearity. To allay fears of multicollinearity between firm size and CVC, we estimated each of our models using intensities and found consistent results.

Table 3 presents estimates from various specifications of our model. In Model 1, we present a base specification where CVC is not included as an independent variable. We estimate a firm fixed-effect, negative binomial specification with *Citations* as our dependent variable using a conditional maximum likelihood (CML) estimator.[15] For simplicity, we do not present the coefficient estimates for the year and sector dummies. We find not surprisingly that larger firms (*Assets*) who engage in more research (*Research*) have higher citation-weighted patenting rates in the next year.

In Model 2, we introduce *Patent Stock* and *Industry Citations* as controls for time-variant unobserved heterogeneity. Recall that *Patent Stock* helps control for firm-specific heterogeneity such as the underlying innovativeness of the firm at different points in time. *Industry Citations* proxies for the technological opportunities present in the industry at a particular time. We find that both *Patent Stock* and *Industry Citations* have a significant, positive effect on future patent levels. In contrast with Model 1, we find that large firms are *less* likely to generate citation-weighted patents. This result indicates the importance of controlling for time-variant unobserved heterogeneity when studying a sample that covers a long period of time. In essence, the results suggests that the marginal output of quality patents is lower for larger firms, once we control for fluctuation in industry innovativeness (i.e., *Industry Citations*) and the intrinsic – and most importantly time-variant, or evolving – innovativeness of each firm (i.e., *Patent Stock*).

[15] Our overdispersion test statistic is presented in Models 4 through 8 of Table 3. The significance of these estimates indicates a rejection of the hypothesis of constant dispersion and a preference for negative binomial over Poisson.

Table 2
Descriptive statistics for patenting models

Variable	Description	Mean	Standard Deviation	Min	Max	1	2	3	4	5	6	7	8	9
1. Patents	Count of new patents applied for by a firm in each year	13.544	62.107	0	2405	1.00								
2. Citations	Citation-weighted new patents applied for by a firm in each year	93.310	458.381	0	12795	0.89*	1.00							
3. ln(CVC)	Log of total annual CVC dollars invested ($M)	0.019	0.187	0	3.98	0.12*	0.13*	1.00						
4. ln(Research)	Log of total annual research expenditures ($M)	1.677	1.814	0	9.45	0.45*	0.43*	0.16*	1.00					
5. ln(Assets)	Log of total assets of firm ($M)	5.650	2.010	0.14	12.61	0.34*	0.31*	0.13*	0.53*	1.00				
6. Patent Stock	Log of the depreciated count of patents issued to a firm	41.318	181.321	0	5358	0.98*	0.88*	0.12*	0.46*	0.35*	1.00			
7. Industry Citations	Average citations within a four-digit SIC classification in each year	88.377	185.538	0	3304	0.38*	0.42*	0.09*	0.35*	0.22*	0.38*	1.00		
8. IP Protection	Relative effectiveness of patenting within each industry	0.418	0.075	0.233	0.520	0.01	0.01	0.02	0.06*	−0.12*	0.00	0.01*	1.00	
9. Venture Proximity	Average technological proximity between a firm and its ventures	0.530	0.379	0.061	1.000	−0.26*	−0.30*	−0.13*	−0.16*	−0.53*	−0.34*	−0.09	−0.01	1.00

$n = 31,876$ except for IP Protection where $n = 10,469$ and Venture Proximity where $n = 1941$.
* $p < 0.01$.

Table 3
Firm patent citation levels across all industries (1975–1995)

Specification sample model	Firm fixed-effects negative binomial				Firm random-effects negative binomial	
	Full sample[a], 1	Full sample[a], 2	Full sample[a], 3	Full sample[a], 4	Full sample, 5	CVC Investors[b], 6
$\ln(\mathrm{CVC})_{t-i}$						
w/geometric lag				0.065^{***} (0.011)	0.066^{***} (0.010)	0.043^{***} (0.011)
w/joint χ^2 test			81.73^{***}			
$\ln(\mathrm{CVC})_{t-1}$			0.040^{**}(0.013)			
$\ln(\mathrm{CVC})_{t-2}$			0.047^{***} (0.013)			
$\ln(\mathrm{CVC})_{t-3}$			0.047^{***} (0.013)			
$\ln(\mathrm{CVC})_{t-4}$			0.039^{**}(0.013)			
$\ln(\mathrm{CVC})_{t-5}$			0.028^{*}(0.013)			
$\ln(\mathrm{CVC})_{t-6}$			0.021(0.014)			
$\ln(\mathrm{Research})_{t-1}$	0.328^{***} (0.008)	0.069^{***} (0.008)	0.067^{***} (0.008)	0.067^{***} (0.007)	0.077^{***} (0.007)	0.131^{***} (0.018)
$\ln(\mathrm{Assets})_{t-1}$	0.058^{***} (0.007)	-0.034^{***} (0.007)	-0.033^{***} (0.007)	-0.033^{***} (0.007)	-0.059^{***} (0.006)	-0.067^{***} (0.019)
Patent Stock_{t-1}		0.755^{***} (0.008)	0.759^{***} (0.008)	0.757^{***} (0.008)	0.868^{***} (0.007)	0.904^{***} (0.014)
Industry $\mathrm{Citations}_{t-1}$		0.0003^{***} (0.000)	0.0003^{***} (0.000)	0.0003^{***} (0.000)	0.0002^{***} (0.000)	0.0001^{***} (0.000)
Year fixed effects	Included	Included	Included	Included	Included	Included
Sector fixed effects	Included[c]	Included[c]	Included[c]	Included[c]	Included	Included
Observations	28321[a]	28321[a]	28321[a]	28321[a]	31876	4473[b]
Firms	1916	1916	1916	1916	2275	247
Wald χ^2	5607^{***}	20758^{***}	20848^{***}	20877^{***}	36814^{***}	10155^{***}
Overdispersion test					5010^{***}	655^{***}

Standard errors are in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
[a] Firms who never patent are removed from the sample due to the fixed-effects negative-binomial specification.
[b] Sample is reduced to only those firms who make CVC investments.
[c] The negative-binomial specification does not have firm-level dummies, thus sector fixed effects are possible.

In Model 3, we add CVC investments into our model using the unrestricted distributed lagged structure. Consistent with Hypothesis 1, we find evidence that CVC investment impacts firm's patenting output. The coefficients of CVC are highly significant for five out of the six lagged variables individually, and our joint χ^2 test suggests that the total effect of CVC investments across the 6 years is statistically significant. Looking at the coefficients, we see the impact of CVC investment on quality patenting levels being greatest 2–3 years out. Over time, the impact of a given CVC investment declines until eventually it has no further effect. We estimated longer lag structures and found consistently that after 5 years there was no discernable impact of CVC investment on patenting rates.

In Model 4, we substitute our geometric distributed lag for the unrestricted distributed lag structure of Model 3. The coefficient for the geometric distributed lag is positive and statistically significant. As was mentioned above, this variable proxies for the joint impact of CVC activity over time on firm innovation rates. Similar to previous models, the coefficient estimates for ln(Research), Patent Stock, and Industry Citations are positive and highly significant and ln(Assets) is negative and significant.

One of the tradeoffs in using the CML fixed-effects, negative binomial specification is that firms who never patented over the time period are removed from the sample including a number of firms who engage in CVC but did not patent in the 1975–1995 time frame. The exclusion of firms who engage in CVC but never patent may bias our results. To address this potential bias, we adopt a random-effects specification of our negative binomial model. The random-effects specification has the advantage that we may use the full sample in our estimation. By adopting a random-effects specification, we assume that the regressors and the firm-specific effects are uncorrelated. The literature exhibits no strong preference for random-effects or fixed-effects

Table 4
Variable means and standard deviations by major sectors (1975–1995)

Sector	Chemicals	Devices	Information	Pharma	Vehicles
$\ln(\text{CVC})_{t-i}$					
w/geometric lag ($\lambda = 0.6$)	0.037 (0.290)	0.022 (0.197)	0.069 (0.379)	0.081 (0.354)	0.021 (0.182)
ln(Research)	2.291 (1.947)	2.016 (1.520)	2.406 (1.932)	3.718 (1.995)	2.304 (2.220)
ln(Assets)	6.299 (2.156)	4.542 (1.778)	5.340 (2.106)	6.189 (2.166)	6.086 (2.116)
Patent Stock	2.331 (2.009)	1.963 (1.557)	1.511 (1.743)	2.851 (2.029)	2.269 (1.829)
Industry Citations	143.323 (144.092)	106.672 (177.973)	179.630 (309.438)	169.966 (76.189)	127.805 (152.943)
IP Protection	0.345 (0.047)	0.324 (0.107)	0.248 0.087)	0.432 (0.000)	0.326 (0.031)
Observations	2817	2815	4607	969	1830
Firms	198	216	337	63	135

Standard deviations in parentheses.

in limited dependent variable models such as the negative binomial (Greene, 2000).

In Model 5, we estimate our model using *Citations* as the dependent variable and a random-effects specification. We find positive, significant coefficients for the geometric lag calculation of ln(CVC), as well as for ln(Research), Patent Stock, and Industry Citations. The coefficient for ln(Assets) remains negative and significant. Our results for the larger sample are consistent with the reduced sample from the fixed-effects specification. This gives us greater confidence in our results given that we now include firms who never patented throughout their life.

One possible driver of our results is that firms are self-selecting to invest CVC based on the attributes of the industry sector they operate in as well as various firm-level factors. In the presence of self-selection, our coefficient estimates may be overstating the direct impact of CVC investment and reflecting underlying differences between firms who invest and those who do not. In Models 3–5, we control for stable firm differences with a firm-effect specification and control for time-variant differences by the inclusion of *Patent Stock*. However, there might be additional time-variant factors that affect the desire to pursue CVC investment and the desire to increase patenting resulting in self-selection bias of our estimates. A more stringent test of the impact of firm's CVC on its innovative output should explore whether increases in the levels of quality patenting are driven by prior increases in firm's corporate venture capital.

In Model 6, we follow this reasoning and limit our sample to only those firms that invest corporate venture capital during the 20-year time period 1975–1995. Here we directly estimate the impact greater CVC investment has on quality patenting, given that a firm chose to make CVC investments. We once again control for firm size, R&D expenditures, patent stock and industry citations and estimate a random-effect, negative binomial specification using *Citations* as our dependent variable. We find a positive, significant coefficient estimate for ln(CVC). In other words, among those firms who invest corporate venture capital, we find that greater CVC investment increases the future output of quality patents. Thus, a firm's output of quality patenting is associated not only with the existence of CVC investment effort, but also with the magnitude of the investment.[16]

As a further analysis, we split the sample by sectors and for each sub-sample we estimate a specification similar to the one in Model 5 in Table 3. Analyzing the sector sub-samples allows us to further address any potential industry-level confounding effects not captured by *Industry Citations* and our sector dummies. We separately analyzed a negative binomial random-effects specification, using *Citations* as the dependent variable, for the five highest CVC investing sectors:

[16] We have also addressed the self-selection issue more explicitly by adopting a two-stage specification (2SLS). In the first stage, we estimate the magnitude of CVC investments. The model is based on Dushnitsky and Lenox (2003) who explore not only the propensity to invest CVC, but also the magnitude of those investments. The main independent variables in the first stage are firm's cash flow, firm's history of innovation, and industry-level measure of technological ferment. Our estimates in the second stage are consistent with previous models; once again we find a significant, positive relationship between CVC investment and firm quality patenting. The results are not included for parsimony sake.

chemicals, devices, information, pharmaceuticals, and vehicles.[17] Table 4 contains the summary statistics for our primary independent variables broken down by sector. Because the means and standard deviations are reported for all firms within each sector (i.e., investing as well as non-investing firms), the reader should interpret the values of ln(CVC) with care.[18]

Consistent with previous models, our results for Models 7 through 11 in Table 5 show that within each of the sectors, firms who engage in more research (*Research*) and have been innovative in the past (*Patent Stock*) have higher citation-weighted patenting output. We find that the coefficient of (*Industry Citations*) is statistically insignificant in most models. This is not surprising since the information contribution of this variable decreases once we split the sample by industry sector: the cross-sector variance does not enter the subsamples and within sector temporal effects are mainly absorbed by the year effects. More importantly, we find that the coefficient for the geometric lag of ln(CVC) is positive and highly statistically significant within the information and devices sectors, but insignificant within chemicals, pharmaceuticals, and vehicles. Furthermore, for the Information and devices sectors, the return to CVC investment is similar to R&D expenditures.

What may explain these findings across sectors? Earlier, we hypothesized that the intellectual property regimes may drive cross-industry heterogeneity. Referring to Table 4, we observe that the two sectors with the weakest IP protection are information and devices followed by vehicles, chemicals, and finally pharmaceuticals. Thus, we find that the impact of investment in entrepreneurial ventures on firm innovation rates is significant only in those sectors where the intellectual property regime is weak.

To explore this result further, we estimate a model using our intellectual property protection measure. Recall that this measure is only available for a subset of our industries thus reducing our sample size. In Model 12, we add *IP Protection* and interact it with CVC investment. Not surprisingly, we find that firms in industries with strong IP regimes, patent more. In addition, we find as hypothesized that the effect of CVC investment on innovation is reduced the stronger intellectual property protection. Given the coefficients of Model 12, we estimate that only for sectors where *IP Protection* is low will we expect to see a positive relationship between CVC and innovation.

This raises an interesting question, if CVC investment has positive innovative benefits only in industries with weak IP regimes, why do firms in industries with strong IP regimes invest corporate venture capital? Previous work has found that firms invest in new ventures for a number of reasons. While many firms are interested in CVC as a window on novel technology, others are interested in CVC purely as a financial investment or as a complement to other knowledge acquisition strategies (Arora and Gambardella, 1990). Interviews with CVC fund managers at pharmaceutical firms reveal that these firms often pursue CVC as a vehicle for identifying future alliance partners and takeover targets. Indeed, a recent study finds that a pharmaceutical firm's patenting-output increases in the firm's R&D contracts, licenses, and acquisitions activity, but is insignificantly associated with the firm's minority-equity investments (Nicholls-Nixon and Woo, 2003).[19] In addition, firms may fund ventures that develop complementary product or services, irrespective of the IP regime, as a strategy to increase the demand for corporate innovations (Brandenburger and Nalebuff, 1996; Dushnitsky, 2004).

Next, we raise the possibility that the impact of CVC investment on firm innovative output is moderated by firm level capabilities, in particular, a firm's absorptive capacity. Table 6 analyzes the effect of a firm's absorptive capacity on the innovation benefits due to CVC activity (Hypothesis 3). We study only those sectors where CVC is associated with subsequent patenting

[17] We did not include additional sectors for parsimony sake. The results across these industry sectors and may be provided by the authors upon request.

[18] The highest mean value for $\ln(\mathrm{CVC}_{\text{distributed lag}})$ is reported for the pharmaceutical sector, which may be misleading. Overall CVC levels are higher in the information and devices sectors (see Fig. 1). However, the number of firms in the pharmaceutical sector is lower. Because the mean is calculated across all firms within a sector, the denominator in the case of the pharmaceutical sector is lower. Consequently, the average CVC level across investing and non-investing firms is highest for that industry.

[19] Nicholls-Nixon and Woo (2003) report significant and high correlations between pharmaceutical firm's investment and its R&D contracts and acquisition activity. This is consistent with the view of CVC as a precursor to future alliance or takeover activity.

Table 5
Firm patent citation levels by sector (1975–1995)

Sector, model	Chemicals, 7	Devices, 8	Information, 9	Pharma, 10	Vehicles, 11	All Sectors, 12
$\ln(\text{CVC})_{t-i}$						
w/geometric lag ($\lambda = 0.6$)	0.032 (0.026)	0.091*** (0.024)	0.061** (0.022)	0.018 (0.040)	0.141 (0.082)	0.362* (0.176)
CVC × IP Protection						−0.756* (0.411)
IP Protection						2.424*** (0.301)
$\ln(\text{Research})_{t-1}$	0.142*** (0.023)	0.085* (0.034)	0.117*** (0.021)	0.244*** (0.048)	0.086*** (0.024)	0.223*** (0.016)
$\ln(\text{Assets})_{t-1}$	−0.077*** (0.019)	−0.024 (0.030)	−0.089*** (0.020)	−0.233*** (0.043)	−0.006 (0.024)	−0.089*** (0.015)
Patent Stock_{t-1}	0.860*** (0.019)	0.800*** (0.022)	0.861*** (0.019)	0.839*** (0.032)	0.849*** (0.022)	0.001*** (0.000)
Industry Citations_{t-1}	0.0005*** (0.000)	−0.0002 (0.000)	0.0001*** (0.000)	0.0008 (0.001)	0.0001 (0.000)	0.001** (0.000)
Year fixed effects	Included	Included	Included	Included	Included	Included
Sector fixed effects						Included
Observations	2817	2815	4607	969	1830	10469
Firms	198	216	337	63	135	749
Wald χ^2	5512***	2807***	5255***	1850***	3348***	2872***
Overdispersion test	667***	505***	610***	234***	71***	5217***

A random-effects negative binomial specification is adopted in all models. Standard errors in parentheses.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

output, i.e., the information and devices sectors (we pool the sectors together and introduce sector dummies). In Model 13, we see that for this reduced sample, we continue to find a positive, significant coefficient for a geometric lag specification of CVC investment.

As a first test of Hypothesis 3, we split our sample based on the median level of our first proxy for absorptive capacity (AC)—*Past R&D*. We observe that those firms above the median level of *Past R&D* differ considerably from those below the median level. High absorptive capacity firms engage in more R&D on average ($118M versus $1.8M) and generate greater citation-weighted patents on average (204 versus 7.2). This is driven in part by differences in firm size ($2593M versus $1198M in assets on average). Average CVC activity is substantially greater for high AC firms versus low AC firms (ln(CVC) = 0.063 versus 0.023).

Estimating our model, we find that for those firms with low absorptive capacity (i.e. below the industry median) we are not confident that the marginal effect of CVC is greater than zero (Model 14). In contrast, for firms with greater than industry median absorptive capacity, we find a significant, positive relationship between CVC and quality patenting (Model 15). These results allude to an interaction effect between CVC and a firm's absorptive capacity, consistent with Hypothesis 3. To see why, recall that each sub-sample includes CVC-investing firms as well as non-investing firms. We find that the patenting output of low absorptive capacity CVC-firms is no better than that of their non-CVC, low absorptive capacity peers (Model 14). However, high absorptive capacity CVC-firms experience significantly higher innovation rates compared to similar companies of high absorptive capacity that do not pursue corporate venture capital (Model 15).

As a more direct test, we pooled these two subsamples together and interacted CVC investment with dummy variables indicating whether a firm has high absorptive capacity or low absorptive capacity (using *Past R&D* once again). We find once again a significant, positive coefficient on CVC investment for only firms with high absorptive capacity (Model 16).

As a robustness test, we substituted *Patent Stock* for *Past R&D* as our measure of absorptive capacity. Splitting the sample into high and low patent stock using the four-digit SIC industry median, we find a significant positive effect only in the high AC sample.[20] In Model 17, we present the estimates from pooling high and low patent stock firms. We find, once again, that only high absorptive capacity firms realize innovative gains from CVC investment.

[20] We do not present these two models for parsimony sake.

Table 6
Firm patent citation levels by absorptive capacity (AC) level for the information & device sectors (1975–1995)

AC measure, sample, model	All firms, 13	Past R&D		Past R&D, all firms, 16	Patent Stock, all firms, 17	Past R&D, CVC-firms, 18	Venture proximity	
		Low AC firms, 14	High AC firms, 15				CVC-firms, 19	CVC-firms, 20
$\ln(\mathrm{CVC})_{t-i}$								
w/geometric lag ($\lambda = 0.6$)	0.081^{***} (0.016)	0.257 (0.306)	0.078^{***} (0.017)					
CVC × High AC				0.081^{***} (0.016)	0.084^{***} (0.015)	0.067^{***} (0.017)	0.015 (0.042)	
CVC × Low AC				0.131 (0.247)	−0.284 (0.206)	0.305 (0.246)	0.088^{***} (0.018)	
CVC × AC								0.573^{***} (0.167)
CVC × AC^2								-0.561^{**} (0.214)
CVC × unknown AC							−0.023 (0.056)	−0.036 (0.026)
$\ln(\mathrm{Research})_{t-1}$	0.118^{***} (0.018)	0.273^{***} (0.067)	0.073^{***} (0.022)	0.118^{***} (0.018)	0.119^{***} (0.018)	0.180^{***} (0.035)	0.168^{***} (0.034)	0.175^{***} (0.034)
$\ln(\mathrm{Assets})_{t-1}$	-0.078^{***} (0.016)	0.018 (0.031)	-0.085^{***} (0.020)	-0.079^{***} (0.016)	-0.078^{***} (0.016)	-0.114^{***} (0.036)	-0.104^{**} (0.035)	-0.107^{**} (0.035)
Patent Stock_{t-1}	0.825^{***} (0.013)	1.075^{***} (0.041)	0.809^{***} (0.015)	0.825^{***} (0.013)	0.823^{***} (0.014)	0.911^{***} (0.022)	0.915^{***} (0.022)	0.914^{***} (0.022)
Industry $\mathrm{Citations}_{t-1}$	0.001^{***} (0.000)	−0.0001 (0.000)	0.0001^{***} (0.000)	0.001^{***} (0.000)	0.0001^{***} (0.000)	0.0001 (0.000)	0.0001 (0.000)	0.0001 (0.000)
Year fixed effects	Included	Included	included	included	Included	included	included	included
Sector fixed effects	Included	Included	included	included	Included	included	included	included
Observations	7422	2217	5205	7422	7422	1941	1941	1941
Firms	553	175	378	553	553	113	113	113
Wald χ^2	8306^{***}	1001^{***}	6189^{***}	8307^{***}	8350^{***}	4402^{***}	4474^{***}	4406^{***}
Overdispersion test	1294^{***}	20.23^{***}	1217^{***}	1294^{***}	1288^{***}	237^{***}	241^{***}	239^{***}

A random-effects negative binomial specification is adopted in all models. Standard errors in parentheses. $^{*}p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Finally, we adopt our measure of venture proximity as our measure of absorptive capacity. Because *Venture Proximity* is missing for non-investing firms (who, by definition, have no ventures), we limit our sample solely to CVC-investing firms in the subsequent analyses. For comparison, in Model 18 we replicate Model 16 for the limited sample of 113 CVC-investing firms. We find once again a significant, positive coefficient on CVC investment for only firms with high absorptive capacity (using the *Past R&D* measure). The sign and significance of ln(*Assets*), ln(*Research*), *Patent Stock* and *Industry Citations* coefficients remain unchanged.

In Model 19, we present estimates splitting the sample based on those with high venture proximity and low venture proximity using the median venture proximity for a given four-digit SIC industry.[21] Surprisingly, we find that those firms who invest in technologically different ventures experience greater increases in quality patents than those who invest in technologically similar ventures. Further inquiry revealed a concave relationship between *Venture Proximity* and *Citations*. [22] In Model 20, we estimate the interaction effect between CVC investment and *Venture Proximity* and *Venture Proximity* squared. We find a positive, significant coefficient for the interaction with the primary term and a negative, significant coefficient for the interaction with the squared term. The similar absolute magnitude of the coefficients suggests a concave relationship between zero and one with approximately a 0.5 *Venture Proximity* score having the largest marginal effect of CVC investment.

This concave relationship is consistent with two potential explanations: substitution and competition. Both suggest that little learning occurs when firms' knowledge bases are diverse due to a lack of absorptive capacity, but offer different reasons for lack of learning when knowledge bases overlap. The first view suggests that as two agents become closely aligned in their knowledge sets, their knowledge becomes redundant, and thus very little learning occurs (Mowery et al., 1998; Ahuja and Katila, 2001; Lenox and King, 2004). In the context of CVC, ventures and investing firms who are well-aligned in their technological knowledge, have little to learn from one another. As the divergence between knowledge sets grows, investing firms will be able to learn novel insights from their ventures. Eventually, however, this learning will diminish as the investing firm's knowledge is so divergent from the venture's knowledge space that the investing firm fails to assimilate knowledge from the venture.

The second explanation assumes that CVC investors are interested in learning but have little opportunities to do so given the actions of ventures.[23] While the greatest learning potential may exist when two agents become closely aligned, competitive pressures may lead highly innovative entrepreneurs to avoid CVC investors: "A small high-technology company might be reluctant to approach IBM or Sony directly for funding. Therefore, the very companies in which these corporations wanted to invest were usually the ones that never made it to their doorsteps" (Gompers, 2002:1). Based on a large sample analysis, Dushnitsky (2004) concludes that ventures are most likely to be driven away from corporate investors when the two operate within the same industry.[24] Consequently, CVC investors will not be exposed to novel technologies in their primary domain of expertise or will be privy only to lower quality entrepreneurial inventions.

The results presented in Tables 3, 5 and 6 are robust to a variety of specifications. To test the sensitivity of our results to construct measurement, we estimated all the models specified above using simple patent counts rather than citation-weighted patent counts. Our coefficient estimates were consistent though often slightly less significant. In addition, we explored alternative

[21] Due to data limitations, we were not able to calculate *Venture Proximity* for all the firms in the Information & Devices sectors. To maintain comparable samples, we created a dummy variable *Unknown AC* to control for those firms for which we could not calculate *Venture Proximity*.

[22] While *R&D Expenditures* and *Patent Stock* are concerned with the overall *magnitude* of an investing-firm's knowledge base, *Venture Proximity* gauges the specific *overlap* in knowledge bases vis-à-vis portfolio companies. The former measures should exhibit a positive relationship with firm patenting output: the greater firm's knowledge base, the more it is able to learn from CVC. However, the latter measure should exhibit an inverted U-shape relationship, where a moderate level of overlap is associated with highest firm patenting.

[23] To the extent that entrepreneurial startups may be a valuable source of innovations (Aghion and Tirole, 1994; Kortum and Lerner, 2000; Shane, 2001), CVC investors may be interested in learning from them. Moreover, the corporation may be particularly interested in learning from ventures that operate in the same technological domain. These ventures are likely to possess the cutting edge technology within that technological field.

[24] Dushnitsky (2004) also reports that competitive pressures diminish as the level of complementarity between the two increases.

measures of corporate venture capital investment including the intensity of CVC spending and the number of ventures invested. Once again, our results were consistent with the specifications presented. Finally, we tested alternative specifications using negative binomial fixed-effect and Poisson fixed-effect estimators and found consistent results. The authors may provide these results upon request.

5. Discussion

Consistent with Hypothesis 1, we find strong evidence that increased corporate venture capital investment is associated with higher future patent citation levels. Consistent with Hypothesis 2, we present evidence that the relationship between CVC and patenting is driven by CVC investments in industries where patent effectiveness is low. Consistent with Hypothesis 3, we find that the marginal contribution of CVC investment to patenting is greater for firms with greater absorptive capacity. However, we present evidence that when ventures and investing firms overlap in their technological knowledge sets, the learning benefits of CVC investments may be limited.

Our findings echo recent work on inter-industry differences in appropriability regimes (Cohen et al., 2001). We find evidence that corporate venture capital serves as a window on technology only in the information and devices sectors. These two sectors are characterized by relatively weak intellectual property regimes. We do not find evidence that firms in the chemicals, vehicles, and pharmaceuticals sector (where the IP regime is stronger) receive an innovation benefit from CVC investment. We speculate that firms in these sectors are pursuing CVC primarily for identification of future partners or direct financial returns. However, we should be careful not to infer too much from the lack of statistical finding in these industries.

Our findings are also consistent with recent work on absorptive capacity. To the extent that absorptive capacity is domain specific, we expect to observe a non-monotonic relationship between absorptive capacity and learning. On one hand, a firm will learn little if it lacks expertise related to the knowledge the firm wishes to acquire (Cohen and Levinthal, 1990). On the other hand, to the extent the desired knowledge overlaps with the firm's existing knowledge base, countervailing substitution and competitive effects kick-in (Lenox and King, 2004). In particular, firm's may find that the have little to learn from ventures with similar technological expertise. In addition, ventures may have strong incentives to either avoid or at the very least keep at arm's lengths, CVC investors whose knowledge (and likely whose products) greatly overlap their own (Dushnitsky, 2004).

Our results are robust to a number of controls and model specifications. We adopt a lagged specification, examining the association between previous year's values of our independent variables and this year's patenting levels, in an effort to mitigate concerns of reverse causality. Year fixed-effects, annual industry citation levels, and sector dummies help alleviate concerns that technological ferment is driving our findings. The inclusion of firm size, research expenditures, previous innovation rates, and firm-effects help control for the possibility that firms who pursue CVC are more innovative than those who do not.

Furthermore, our findings are robust to inter-industry heterogeneity. The analysis includes a group of industry peers – all non-CVC firms who operate in the same industry – that do not exhibit the same increases in patenting output as CVC firms do. This supports our view that it is the practice of corporate venture capital, rather than industry attributes, that is associated with enhancement in firm innovativeness. Moreover, our inter-industry findings are conservative. If industry technological opportunity or firm innovativeness were driving our results, we would expect the relationship between a firm's CVC investment level and its innovative output to disappear in weak IP regimes. All else being equal, more innovative firms with greater innovative opportunities will patent less in weak IP environments. While we find that firm citation-weighted patenting declines as patent effectiveness decreases, we report a positive and significant relationship between CVC and innovation within the segment of the population characterized by weak patent effectiveness.

While we can never completely rule out the possibility of some unobserved time-variant factor driving our results, any potential confound to the observed relationship would have to vary contemporaneously with CVC investment. For example, their remains the possibility that firms simultaneously increase their CVC investments as they pursue new technology alliances or university research consortia. However, we believe our inclusion of the stock of past patents goes along way to control for these non-CVC activities aimed at acquiring external knowledge. Moreover, the results for the *Venture Proximity* analysis are consistent with the view of CVC as an important venue for learning and driving firm's innovative output. Other measures of absorptive capacity (such as R&D expenditure) may actually signify the fact that firms decide to adopt a more innovation-focused strategy relative and pursues alternative innovation efforts. *Venture Proximity*, however, is specific to firm's CVC activity and is not confounded with other contemporaneous innovation effort. Moreover, the results are consistent with a learning story: increases in firm patenting quality are highest when the venture's technological portfolio is close enough – but not too close – to the investing firm's technological portfolio.

The variable *Venture Proximity* is not without limitations. Notably, it is sensitive to the assumption that ventures' technological profiles mimic that of the industry they operate in. Due to the fact that many young ventures have not yet applied, or were granted, patents at the time of investment we cannot observe venture's knowledge base directly. Building a proximity measure for patent-holding ventures would have limited our sample significantly. We opt to infer their knowledge base from their line of business using Silverman's (1996) concordance.

As a final caveat, we recognize, once again, that firms self-selected to pursue CVC investments. We cast doubt on the possibility that self-selection is driving our results by presenting evidence of a significant, positive CVC-patenting relationship even within the subsample of firms who invest CVC. That is, a firm's output of quality patenting is associated not only with the existence of CVC investment effort, but also with the magnitude of the investment. However, we recognize that while these firms may (as our results suggest) see increases in their citation levels as they increase CVC investment, this does not necessarily mean that other firms would experience similar increases if they also choose to invest in new ventures.

For example, the performance of corporate venture capital programs may be driven by the structure of the programs themselves (Block and MacMillan, 1993; Siegel et al., 1988; Thornhill and Amit, 2000). Firms may espouse different goals when they establish corporate venture capital programs (Chesbrough, 2002). While we do not have data on program goals, to the extent that the governance of corporate venture capital programs is relatively constant within individual firms across time, our firm-effect specification should control for this unobserved heterogeneity.

6. Conclusion

Does participation in venture capital markets allows firms to access knowledge from entrepreneurial ventures that lead to innovation? To address this question, we explore the relationship between corporate venture capital investment and incumbent firm innovation by analyzing a sample of approximately 2300 public firms over a 20-year period. Our findings suggest that the level of citation-weighted patenting-output is positively related to the level of prior CVC investment. This finding is robust to different specifications to control for unobserved heterogeneity and the inclusion of firm R&D expenditures and size.

We further find that the association between CVC and firm innovation rates is greater when firms operate in an external context that permits capitalization on venture knowledge and possess the internal capabilities to leverage that knowledge. In particular, we present evidence that the relationship between CVC investment and quality patenting is strongest when intellectual property protection is weak. In addition, we find that a well developed internal research capability may be necessary to effectively learn via CVC investment. For a firm to learn from the ventures it invests, it must first possess sufficient absorptive capacity.

The findings of this study have important implications for the role of corporate venture capital programs in firms' overall innovation strategies. The dynamic capability view suggests that the ability to source external knowledge is critical to competitive success. While alternative inter-organizational forms such as technology alliances have been found to be important sources of external knowledge (Powell et al., 1996; Stuart, 2000), corporate venture capital programs have been the subject of little formal, empirical analysis. We conjecture that venturing activity might serve to satisfy incumbent firms' inclination towards introducing innovations by accessing an increasingly important source of knowledge—competent entrepreneurial startups. We present evidence that corporate venture capital programs may be instrumental in harvesting innovations from these entrepreneurial ventures in certain environments. As a result, we assert that corporate venture capital may be a vital part of a firm's innovation toolkit.

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