Corporate Venture Capital, Value Creation, and Innovation

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We analyze how corporate venture capital (CVC) differs from independent venture capital (IVC) in nurturing innovation in entrepreneurial firms. We find that CVC-backed firms are more innovative, as measured by their patenting outcome, although they are younger, riskier, and less profitable than IVC-backed firms. Our baseline results continue to hold in a propensity score matching analysis of IPO firms and a difference-in-differences analysis of the universe of VC-backed entrepreneurial firms. We present evidence consistent with two possible underlying mechanisms: CVC's greater industry knowledge due to the technological fit between their parent firms and entrepreneurial firms and CVC's greater tolerance for failure. (*JEL* G24, G23, O31)

The role of innovation as a critical driver of a nation's long-term economic growth and competitive advantage has been well established in the literature since Schumpeter. However, the optimal organizational form for nurturing innovation by U.S. corporations is still an open question that has been the subject of an important policy debate in recent years. For example, as Lerner (2012) points out, whereas researchers in corporate research laboratories account for

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We are grateful for comments and suggestions from two anonymous referees, David Hirshleifer (the editor), Brian Broughman, Mara Faccio, Joan Farre-Mensa, Thomas Hellmann, William Kerr, Josh Lerner, Laura Lindsey, Ramana Nanda, Manju Puri, Krishnamurthy Subramanian, and Fei Xie. We also thank conference participants at the 2013 Western Finance Association meetings, the 2012 Law and Entrepreneurship Retreat, the 2012 China International Corporate Governance Conference at Tsinghua University, the 2011 NBER Entrepreneurship Workshop, the 2011 inaugural SFS Finance Cavalcade Conference, the 2011 FIRS Conference, the 2011 Sun Trust FSU Finance Spring Beach Conference, and the 2011 Annual Conference on Entrepreneurship and Innovation at Northwestern University, and seminar participants at Harvard Business School, Indiana University, Boston College, Purdue University, and University of South Florida. We thank Zhong Zhang for his excellent research assistance. We alone are responsible for any errors or omissions. Thomas Chemmanur acknowledges summer research support from Boston College. Xuan Tian acknowledges research support from the Mary Jane Geyer Cain Faculty Fellowship from Indiana University. Send correspondence to Thomas J. Chemmanur, Professor of Finance, Carroll School of Management, Boston College, Chestnut Hill, MA 02467, USA; telephone: (617) 552-3980. E-mail: chemmanu@bc.edu.

doi:10.1093/rfs/hhu033 Advance Access publication May 31, 2014

two thirds of all U.S. research, it is not obvious that the current corporate setting is the best organizational form to nurture innovation, perhaps because large firms provide researchers with too little contingent compensation. On the other hand, he suggests that, while independent venture capital (IVC) firms have done great things for innovation, they have done so only in a few targeted industries, are subject to booms and busts (where funds from limited partners are either in oversupply or very scarce), and are vulnerable to mercurial public markets.[1] Lerner (2012) therefore suggests that perhaps the best way to motivate innovation is a "hybrid" model, such as a corporate venture capital (CVC) program, that combines features of corporate research laboratories and venture-backed start-ups "within a powerful system that consistently and efficiently produces new ideas."

U.S. corporations started establishing CVC funds as early as the 1960s. Over the years, CVC investments accounted for on average 7% of the venture capital industry. More recently, the share of CVC investments has increased significantly, reaching 15% by the end of 2011, according to the National Venture Capital Association. Corporations view establishing CVC subsidiaries as an effective way to conduct research and development (R&D) activities externally and to expose their management to new technologies and an entrepreneurial way of thinking (Chesbrough 2002; MacMillan et al. 2008). Not surprisingly, corporations with CVC subsidiaries enjoy a significant increase in their own innovation productivity and higher firm values (Dushnitsky and Lenox 2005, 2006). To the best of our knowledge, however, the effect of CVC financing on the innovation productivity of entrepreneurial firms backed by them has not been explored. The objective of this paper is to fill this gap in the literature by analyzing the relative efficiency of CVCs and IVCs in nurturing innovation by the entrepreneurial firms backed by them.

The relative ability of CVCs and IVCs in nurturing innovation is ultimately an empirical question. CVCs may be superior to IVCs in nurturing innovation, because the unique organizational and compensation structure of CVC may allow them to be more supportive of risky innovative activity. First, CVC funds are structured as subsidiaries of corporations, unlike IVC funds, which are structured as limited partnerships and are restricted by a contractually enforced ten-year lifespan. This means that CVCs have longer investment horizons than do IVCs. Second, as corporate subsidiaries, CVCs pursue both the strategic objectives of their parent companies and financial objectives, whereas IVCs' sole investment goal is to achieve high financial returns. Third, the performance-based compensation structure (i.e., 2% of management fees and 20% of carried interest) enjoyed by IVC fund managers is normally not found in CVC funds: CVC fund managers are compensated by a fixed salary and corporate bonuses that are tied to their parent company's financial

[1] Also, the traditional venture capital industry has been shrinking since the financial crisis and has underperformed over the previous decade (Harris, Jenkinson, and Kaplan Forthcoming).

performance. The above three differences between CVCs and IVCs, namely, longer investment horizons, not being purely focused on financial returns, and the lack of purely performance-driven compensation schemes, may allow CVCs to be more open to experimentation and to occasional failures in their portfolio firms (necessary for motivating successful innovation) compared with IVCs. Further, the presence of a corporate parent may provide CVCs with a unique knowledge of the industry and the technology used by their portfolio firms, which is absent in IVCs. This superior industry and technology expertise of CVCs may enhance their ability to better use the soft information they receive about their portfolio firms' research and development (R&D) activities, thus allowing them to better assess and nurture these new ventures' technologies and products. Taken together, the above factors may allow CVCs to be more effective than IVCs in nurturing innovation in their portfolio firms.

However, the unique organizational structure of CVCs may also adversely affect their ability to foster innovation in their portfolio firms compared with IVCs. CVCs are structured as subsidiaries of corporations and have to procure the amount they invest in their portfolio firms from their corporate parents. This means that CVCs are subject to centralized resource allocation and associated corporate socialism (Rajan, Zingales, and Servaes 2000; Scharfstein and Stein 2000), which may foster mediocrity in R&D activities (Williamson 1985; Seru 2014). In addition, as corporate subsidiaries, CVCs pursue the strategic objectives of parent companies and their fund managers' compensation is tied to parent firm financial performance. Therefore, CVCs may be incentivized to use corporate parents' deep industry and technology expertise to exploit, rather than nurture, the entrepreneurial firms they invest in and hence impede innovation in these firms.[2] In contrast, IVCs may be more efficient in their resource allocation because they are structured as limited partnerships and have full control over the capital committed by their limited partners. In addition, IVCs pursue purely financial returns and their fund managers are compensated based on financial performance. Further, IVCs are known to significantly contribute to entrepreneurial firms' development: for example, they professionalize their management teams (Hellmann and Puri 2002) and foster collaborative relationships through strategic alliances among their portfolio firms (Lindsey 2008). Finally, IVCs also tend to specialize to a great extent (Gompers, Kovner, and Lerner 2009) and may thus possess the knowledge necessary to understand the industry-specific innovation process. Overall, their more efficient resource allocation, higher powered compensation schemes, and specialized industry expertise may make IVCs superior to CVCs in nurturing innovation.

[2] Hellmann (2002) explicitly models a situation in which entrepreneurs seek financing from IVCs instead of CVCs because of their fear of being exploited by CVCs when their start-ups are in potential competition with CVC parent companies in the product market.

To address our research question, we first examine the innovation output of initial public offering (IPO) firms backed by CVCs versus those backed by IVCs. As has now become standard in the innovation literature (e.g., Aghion et al. 2005; Kogan et al. 2012; and Seru 2014), we use the National Bureau of Economics Research (NBER) Patent Citation database to construct two measures of innovation output: the number of patents generated by a firm as our measure of the "quantity" of innovation, and the number of future citations received per patent as our measure of the impact or "quality" of innovation. We find that CVC-backed firms produce more patents and patents that are of higher quality. Specifically, as compared with IVC-backed firms, CVC-backed IPO firms produce 26.9% more patents in the three years before IPO and these patents receive 17.6% more citations. In the first four years after IPO, including the IPO year, CVC-backed firms produce 44.9% more patents that receive 13.2% more future citations. Our baseline results are robust to alternative innovation measures (such as patent generality and patent originality) and a subsample analysis of IPO firms with nonzero patents.

The above baseline results are consistent with two possible interpretations: the superior ability of CVCs to nurture innovation (a treatment effect), as well as the superior ability of CVCs to identify and select entrepreneurial firms with higher innovation potential (a selection effect). To disentangle these two effects, an ideal experiment would be to evaluate the innovation output of entrepreneurial firms under the random assignment of IVC and CVC investors. Because such an experiment is infeasible to implement, we use the propensity score matching procedure, which allows us to minimize the difference in observable characteristics between these two types of firms and thereby disentangle the treatment effect from a selection effect to some extent. We match the two types of firms at the IPO year using a wide set of dimensions known to affect innovation output. Our propensity score matching analysis results show that CVC-backed firms are characterized by an average of 25% higher innovation output pre-IPO and an average of 45% higher innovation output post-IPO. Although we cannot completely rule out the selection effect, these differences are more likely to be attributable to a treatment effect; that is, CVCs have a superior ability to nurture innovation in their entrepreneurial firms.

Although the IPO sample allows us to effectively control for a wide set of firm characteristics that affect innovation, it is potentially subject to survivorship bias and a sample selection problem because CVCs, compared with IVCs, may take only the most innovative firms public.[3] To address this concern, we examine a sample consisting of the universe of VC-backed entrepreneurial firms. We hand-match the universe of VC-backed firms from

[3] Importantly, the reason why we focus only on IPO firms in our baseline analysis is due to data limitations: we do not observe private firms' accounting and ownership information and therefore cannot control for important innovation determinants based on this information.

the VentureXpert database to the patent information available from the United States Patent and Trademark Office (USPTO) based on entrepreneurial firm name and location. Using this sample, we conduct the difference-in-differences (DiD) analysis to examine the effects of the first round of IVC and CVC investments on entrepreneurial firms' subsequent innovation output. We find that entrepreneurial firms enjoy a significantly larger long-term increase in innovation output if they obtain their first financing round from CVCs rather than from IVCs. Specifically, although these two groups of firms exhibit a similar level of innovation output at the first investment round date, CVC-backed firms exhibit momentum in their innovation output and outperform IVC-backed firms over five years after the first investment round. We further show that this result is not driven by IPO successes alone, because we find similar evidence when we split the sample based on their exit outcomes and the current status: firms that eventually go public (the firms in our baseline sample), firms that are acquired by another company, firms that are written off, and firms that are still under active VC investment.

Another potential concern is that our results are due to CVCs investing in more mature firms that are likely to be more innovative to begin with. To address this concern, we delve deeper into the characteristics of CVC- versus IVC-backed firms and show that CVC-backed entrepreneurial firms are in fact younger and riskier at the VC investment round date. They spend significantly more on R&D than do IVC-backed firms, which is consistent with the greater innovation output of CVC-backed firms. CVC-backed firms are less profitable in the years immediately after IPO as compared with IVC-backed firms, although they start catching up in profitability in later years. CVC-backed firms not only receive their first VC financing but also go public at a younger age than do IVC-backed firms.

Finally, we explore two possible underlying economic mechanisms through which CVCs may better nurture innovation than do IVCs. First, we find that entrepreneurial firms that operate close to the industrial expertise of the CVC's parent company (i.e., have a better "technological fit" with the parent firm) are more innovative. This finding is consistent with the superior technological expertise of CVCs allowing them to better evaluate the quality of the entrepreneurial firm's R&D projects and to better advise these entrepreneurial firms. Because an entrepreneurial firm is more likely to establish a strategic alliance with a CVC parent with which it has a technological fit, this is also consistent with Robinson (2008), who argues that strategic alliances help overcome incentive problems and are therefore more conducive to supporting risky innovation. Second, we evaluate the argument made by the existing theoretical literature that greater tolerance for failure by principals may motivate greater innovative activity by their agents. In their theoretical analysis, Hirshleifer and Thakor (1992) show that, because of managers' concern for personal reputation development, punishing managers for early failure results in firms avoiding socially desirable, but risky, projects. In a somewhat similar vein, Manso (2011) argues that, because innovation is a complex activity, the optimal way to motivate innovation is to show tolerance for failure in the short run and provide rewards for success in the long run. In this context, failure tolerance may be defined as the extent to which VCs allow entrepreneurial firms additional time to overcome temporary setbacks or failures in the innovation process. Therefore, following Tian and Wang (2014), we measure tolerance for failure as the amount of time that venture capitalists allow entrepreneurial firms to bring their project to fruition before stopping their investment in these firms. We find that CVCs are more failure tolerant than are IVCs, and the failure tolerance of VC investors positively affects the innovation output of portfolio firms. The evidence suggests that greater tolerance for failure is another important mechanism that allows CVCs to better nurture innovation compared with IVCs.

One limitation of our study is that we cannot conclusively distinguish between situations in which CVCs have a superior ability to select ventures that are ripe for an improvement in innovation output and in which they cause higher innovation output in their portfolio firms. However, the findings from our propensity score matching analysis and our DiD analysis suggest that the difference in innovation output between CVC- and IVC-backed firms is more likely due to a treatment effect, although we cannot entirely rule out the possibility that our results are driven, at least partially, by a selection effect as well.

Our paper contributes to the ongoing debate about the optimal organizational form for nurturing innovation in entrepreneurial firms. One question that arises from our finding that CVCs are better than IVCs in nurturing innovation is why the two organizational forms coexist and why the majority of entrepreneurial firms continue to be funded by IVCs alone. One possible answer to the above question is that CVCs may be able to better nurture innovation only in firms within certain innovative industries in which the advantages of CVCs relative to IVCs, namely, better technological fit between the CVC corporate parent and the entrepreneurial firm and the greater failure tolerance of CVCs, dominate. On the other hand, for entrepreneurial firms in other industries, the disadvantage of CVCs relative to IVCs, namely, the centralized resource allocation associated with CVCs obtaining funding from their corporate parents and the potential conflicts of interest between a CVC's corporate parent and the entrepreneurial firm, may dominate, making IVCs the preferred source of financing.[4]

Our empirical findings shed light on the theoretical literature on corporate innovation and the role of financial intermediaries in fostering innovation. The evidence that CVC-backed firms are more innovative than are IVC-backed firms provides some support for the theories of Aghion and Tirole (1994) and Fulghieri and Sevilir (2009). These studies identify asymmetric information

4 Our industry-level analysis discussed in Section 3.1 provides some support for this conjecture.

and moral hazard as key impediments to internal corporate innovation and categorize circumstances when entrepreneurial firms funded by CVCs are more innovative than are those funded by IVCs. To the extent that we document that CVCs are more failure tolerant than are IVCs, and that the failure tolerance of a CVC is positively related to the innovation undertaken by firms backed by it, our paper also provides further support for the failure tolerance hypothesis of Manso (2011). Finally, Hellmann (2002) argues that CVCs may invest in entrepreneurial firms mainly to benefit the CVC parent. In contrast, our findings indicate that CVC backing actually benefits the innovation productivity of entrepreneurial firms.

Our paper also extends the existing empirical literature on corporate venture capital. Existing studies find that CVC-backed firms tend to be either competitors of the CVC's parent firms or have technologies complementary to them (Masulis and Nahata 2009). Further, CVC portfolio firms are more likely to go public (Gompers and Lerner 2000; Gompers 2002), obtain higher valuation at the IPO date (Ivanov and Xie 2010), attract more reputable financial market players during the IPO process, and have better post-IPO long-run stock returns (Chemmanur, Loutskina, and Tian 2012).[5] While this literature is consistent with the notion that the financial markets view CVC-backed firms as superior to IVC-backed firms in some dimension affecting future cash flows, ours is the first paper that points to a source of this superiority by explicitly showing that CVC financing increases the innovation productivity of entrepreneurial firms.

Finally, our paper contributes to the emerging body of literature exploring the drivers of technological innovation within firms. Spiegel and Tookes (2008) and Ferreira, Manso, and Silva (2014) link the private versus public status of firms to the nature and extent of innovations generated by these firms. Seru (2014) shows that the conglomerate organizational form adversely affects innovation productivity and attributes this finding to incentive problems faced by inventors who become less productive when confronted with centralized resource allocation. Hirshleifer, Low, and Teoh (2012) find that overconfident CEOs invest more in R&D, obtain more patents and patent citations, and achieve higher innovative efficiency. Other studies evaluate how the institutional and market settings affect firms' innovation (e.g., Acharya and Subramanian 2009; Aghion, Van Reenen, and Zingales 2013; Chemmanur and Tian 2013; He and Tian 2013; Cornaggia et al. Forthcoming; Fang, Tian, and Tice Forthcoming). Finally, the empirical literature showing that VCs collectively contribute to technological innovation (e.g., Kortum and Lerner 2000; Tian and Wang 2014) is also related to our paper.

[5] There is also a strategy literature that empirically examines the effect of establishing a CVC program on the parent firm's innovativeness, value, and mergers and acquisitions transactions (see, e.g., Dushnitsky and Lenox 2005, 2006; Benson and Ziedonis 2010). Note, however, that none of the above papers study the relation between backing by CVCs and the extent of innovation by the entrepreneurial firm.

The rest of the paper is organized as follows. Section 1 compares the institutional features of CVCs and IVCs and their implications for nurturing innovation. Section 2 reports our sample selection procedures and summary statistics. Section 3 presents our empirical results. Section 4 examines two mechanisms that allow CVCs to nurture innovation to a greater extent. Section 5 concludes the paper.

1. Institutional Comparison of CVCs and IVCs

CVC and IVC funds share the same investment domain and a number of institutional features but are characterized by different organizational and corporate structures. First of all, CVCs are typically stand-alone subsidiaries of nonfinancial corporations and they invest in new ventures on behalf of their corporate parents. CVCs enjoy an almost unlimited (at least initially unrestricted) life span. In contrast, IVCs are usually structured as limited partnerships that are subject to a contractually enforced ten-year life (with the option of an extension of at most two years). In addition, CVCs are solely funded by their corporate parents and are not contractually limited in their ability to draw capital from a parent company as needed. However, IVCs' fund-draws are limited by the amount of capital initially committed by their limited partners. The longer investment horizons and relatively unconstrained capital supply of CVCs allow them to be more open to experimentation and exploration and to invest in long-term innovative ventures that may not generate immediate financial returns but have a high upside potential.

Second, CVC and IVC funds use different managerial compensation practices and incentive alignment schemes (Dushnitsky and Shapira 2010). According to a 2000 survey conducted by Frederic W. Cook & Co., a vast majority of CVC funds (68% of the respondents) do not enjoy high-powered performance-based compensation schemes (carried interest incentives) that are standard for IVC funds. Instead, CVC fund managers are typically compensated through a fixed salary and annual bonuses that are tied to the parent company's performance, which is traditional in the corporate world. The survey also indicates that almost none of the CVC funds follow the traditional VC model of requiring employees to coinvest; they also do not permit voluntary coinvestment by CVC fund management members. Overall, such practices alter CVC fund managers' incentives and are a double-edged sword in terms of nurturing innovation in the entrepreneurial firms in which they invest. On the one hand, the lack of high-powered compensation schemes allow CVC fund managers to be more failure tolerant (Manso 2011) and therefore to better nurture innovation. On the other hand, the fact that CVC fund managers' compensation is tied to their parent company's performance may increase their incentives to advance the interests of their corporate parents at the expense of the entrepreneurial firms they back, which, in turn, may impede innovation in these firms. In other words, this incentive to help their corporate parent may motivate CVCs to pursue exploitive, rather than nurturing, strategies toward entrepreneurial firms.

Third, unlike IVCs whose sole objective is to pursue financial returns, CVCs generally have a strategic mission to enhance the competitive advantage of their parents by bringing new ideas or technologies to these parent companies (MacMillan et al. 2008). Therefore, CVCs pursue both strategic and financial goals. Consequently, it is common for CVCs to seek commonalities between their corporate parents and the new ventures they back. A closely linked entrepreneurial firm could take advantage of the CVC parent company's manufacturing plants, distribution channels, technology, or brand and adopt the CVC parent company's business practices to build, sell, or service its own products. The corporate parent, in return, receives a window into new technologies and markets from the entrepreneurial firm and as a result could improve its existing business (MacMillan et al. 2008). Therefore, the presence of a corporate parent provides CVCs with a unique knowledge of the industry and the technology used by the entrepreneurial firms in which they invest. Such a technological fit between entrepreneurial firms and CVCs' corporate parent companies allow CVCs to have superior industry and technology expertise and to have a better understanding of the entrepreneurial firms' technologies, which may help nurture innovation in these portfolio firms.[6] The CVC organizational form may also allow the transfer of soft information related to innovative projects between the CVC corporate parent and the entrepreneurial firm, a fact that may be harder to accomplish in the setting of an IVC firm.[7]

In summary, on the one hand, the unique features of CVCs, namely, the longer investment horizons, less performance-driven compensation schemes, and industry and technology support from their parent firms, allow CVCs to provide better technological support and to be more failure tolerant toward the entrepreneurial firms they fund, enabling them to nurture innovation in these firms to a greater extent than do IVCs. On the other hand, CVCs' need to procure resources from their corporate parents and their focus on enhancing their parent firm's performance may hamper their incentives and reduce their efficiency in nurturing innovation in these entrepreneurial firms.

2. Data and Sample Selection

2.1 Identifying CVCs

To identify CVC investors, we start with the list of 1,846 VCs that enjoy investments from corporations as reported by the Thomson VentureXpert database. Using various sources of information (Factiva, Google, Lexus/Nexus, etc.), we manually identify VCs with a unique corporate parent. We find

6 Chesbrough (2002) argues that CVCs have a competitive advantage over IVCs because of their superior knowledge of markets and technologies, strong balance sheets, and ability to be a long-term investor.

7 A similar argument has been made by Seru (2014) in the context of decentralized versus centralized organizations.

that out of 1,846 potential CVC firms: (1) 456 firms cannot be considered as a CVC because they are funded by financial companies, partnerships, or multiple corporate parents and (2) 466 are CVC/IVC firms that have a foreign or unknown parent. This leaves us with 926 distinct CVC firms, out of which 562 are affiliated with publicly traded parent firms. We define an entrepreneurial firm as a CVC-backed firm if it receives financing from at least one CVC investor.

For each CVC firm in our sample, we find the characteristics of the corporate parent, such as industry and size. Specifically, we match the sample of CVCs to the Compustat database to identify publicly traded corporate parents and to the Dun & Bradstreet (D&B) database to identify privately held corporate parents. This matching allows us to identify the primary SIC code for the CVC corporate parent. We then use these SIC codes in our analysis of whether the technological fit between corporate parents and entrepreneurial firms contributes to CVCs' abilities to nurture innovation.

2.2 Baseline sample

We obtain the list of IPO firms that went public between 1980 and 2004. We focus our main analyses based on a sample of IPO firms because of the lack of private firms' financial data availability: we do not observe private firms' accounting and ownership information and therefore cannot control for important drivers of innovation for private firms. We obtain the list of IPOs from the Securities Data Company (SDC) Global New Issues Database.[8] In line with other IPOs studies, we eliminate equity offerings of financial institutions (SIC codes between 6000 and 6999) and regulated utilities and issues with an offer price below $5. The IPO should issue ordinary common shares and should not be a unit offering, closed-end fund, real estate investment trust, or an American depositary receipt. Moreover, the issuing firm must be present on the Compustat annual industrial database for the fiscal year prior to the offering.

We merge this IPO list with VentureXpert to consistently identify VC-backed IPO firms. We find that 287 IPO firms have venture investments as reported by VentureXpert but are classified as non-VC-backed in SDC. We consider these firms to be VC-backed. Similarly, 365 firms are classified as VC-backed in SDC but are not recorded in VentureXpert. We exclude these IPO firms from consideration if the information on the identity of the investing VCs is unavailable through SDC and VentureXpert. We also exclude IPO firms with investments from VCs that we are unable to classify or those in which the data on venture investment are inconsistent across two databases. We end with 2,129 VC-backed IPO firms, of which 462 are CVC-backed.

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[8] The sample period ends in 2004 to allow for the availability of three years post-IPO innovation output and of five years post-IPO operating performance in the NBER Patent Citation database and Compustat, respectively.

2.3 Measuring innovation

Following the existing literature (e.g., Kogan et al. 2012; Seru 2014), we use patent-based metrics to capture firm innovativeness. Whereas earlier studies use R&D expenditures as a proxy for the innovation activity, we use the patent-based measures, which are better proxies because they capture the actual innovation output and capture how effectively a firm has used its innovation inputs (both observable and unobservable). We obtain information on entrepreneurial firm's patenting from the NBER Patent Citation database (see Hall, Jaffe, and Trajtenberg 2001 for details). The database provides detailed information on more than three million patents granted by the USPTO from 1976 to 2006, including patent assignee names, the number of citations received by each patent, and a patent's application as well as grant year. The span of the innovation data limits our ability to expand our IPO sample beyond 2004. We use the NBER bridge file to Compustat to match patents to IPO firms. This link allows us to consistently evaluate the innovation activity for IPO firms starting well before they go public.

The NBER patent database is subject to two types of truncation problems. We follow the innovation literature to correct for the truncation problems. First, patents are recorded in the database only after they are granted and the lag between patent applications and patent grants is significant (about two years on average). As we approach the last few years for which there are patent data available (e.g., 2005 and 2006 in the database used in this paper), we observe a smaller number of patent applications that are eventually granted. This is because many patent applications filed during these years were still under review and had not been granted until 2006. Following Hall, Jaffe, and Trajtenberg (2001, 2005), we correct for the truncation bias in patent counts using the "weight factors" computed from the application-grant empirical distribution. The second type of truncation problem is stemming from citation counts. Patents tend to receive citations over a long period of time, so the citation counts of more recent patents are significantly downward biased. Following Hall, Jaffe, and Trajtenberg (2001, 2005), the citation truncation is corrected by estimating the shape of the citation-lag distribution.

The NBER patent database is unlikely to be subject to survivorship bias. An eventually granted patent application is counted and attributed to the applying firm at the time when the patent application is submitted, even if the firm is later acquired or goes bankrupt. In addition, patent citations attribute to a patent, but not a firm. Hence, a patent assigned to an acquired or bankrupt firm can continue to receive citations for many years even after it goes out of existence.

We construct two measures for a firm's annual innovation output.[9] The first measure, *Ln*(*Patents*), is the natural logarithm of annual truncation-adjusted

[9] We construct the innovation variables based on the patent application year. As suggested by the innovation literature (e.g., Griliches, Hall, and Pakes 1987), the application year is more important than the grant year because it is closer to the time of the actual innovation.

patent count for a firm. Specifically, this variable counts the number of patent applications filed in that year that is eventually granted. However, a simple count of patents may not distinguish breakthrough innovations from incremental technological discoveries.[10] Therefore, we construct the second measure, *Ln*(*Citations/Patent*), that intends to capture the importance of patents by counting the number of citations received by each patent in the subsequent years. To better capture the impact of patents, we exclude self-citations when we compute citations per patent, but our results are robust to including self-citations. To avoid losing firm-year observations with zero patents or zero citations per patent, we add one to the actual values when taking natural logarithm.

It is important to note that using patenting activity to measure corporate innovation is not without limitations. For example, different industries have various innovation propensity and duration. Young firms in some industries might abstain from patenting for competitive reasons. Therefore, fewer patents generated in an industry might not necessarily be reflective of a less innovative industry. However, we believe that an adequate control for heterogeneity across industries and firms should alleviate this concern and lead to reasonable inferences that can be applicable across industries and firms.

Table 1 Panel A reports the summary statistics for innovation output of IPO firms based on IPO firm-year observations. The sample covers three years prior to and four years after the portfolio firm IPO date. The distribution of patents is right skewed. On average, an entrepreneurial firm has 2.5 patents per year. If we break down the sample into CVC- and IVC-backed firms, we find that CVC-backed entrepreneurial firms have a larger number of patents; that is, an average CVC-backed firm has four patents per year, whereas an average IVC-backed firm has 1.6 patents. The impact of patents measured by the number of citations per patent exhibits similar trends. On average, a firm's patent receives 2.3 citations, and CVC-backed firms generate patents with a larger impact (3.2 citations per patent) than do those filed by IVC-backed firms (1.8 citations per patent).

2.4 Control variables

Following the innovation literature, we obtain IPO firm financial information from Compustat and construct a number of firm characteristics that affect firms' innovation output. These control variables include firm size (*Ln*(*Total Assets*)), profitability (*ROA*), R&D expenditures (*R&D in Total Assets*), asset tangibility (*PPE in Total Assets*), leverage level (*Leverage*), capital investment (*CE in Total Assets*), product market competition captured by the Herfindahl index based on sales (*Herfindahl*), growth opportunities (*Tobin's q*), financial constraints (*KZ Index*), and firm age at the IPO year (*Ln*(*Age at IPO*)). To mitigate nonlinear

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[10] Griliches, Hall, and Pakes (1987) show that the distribution of the value of patents is extremely skewed, that is, most of the value is concentrated in a small number of patents.

Table 1
Summary statistics

Panel A: IPO firm's innovation productivity (observation unit: IPO firm-year)

	Mean	SD	N
Patents: Full sample	2.48	14.45	9,425
Patents : CVC-backed firms	4.02	18.49	3,314
Patents : IVC-backed firms	1.64	11.61	6,111
Citations/patent: Full sample	2.28	9.30	9,425
Citations/patent: CVC-backed firms	3.20	10.97	3,314
Citations/patent: IVC-backed firms	1.78	8.21	6,111

Panel B: Control variables (observation unit: IPO firm)

	Mean	SD	P25	Median	P75	N
Assets (million)	110.06	240.75	16.25	54.03	101.93	1,859
ROA	−0.01	0.27	−0.16	0.07	0.16	1,859
R&D in total assets	0.10	0.13	0.00	0.07	0.14	1,859
PPE in total assets	0.23	0.25	0.08	0.15	0.29	1,859
Leverage	0.10	0.18	0.01	0.02	0.12	1,859
CE in total assets	0.08	0.09	0.02	0.05	0.09	1,859
HHI of industry sales	0.25	0.33	0.02	0.11	0.37	1,859
Tobin's q	4.28	6.51	1.85	2.77	4.30	1,859
KZ index	−20.95	49.70	−18.83	−6.37	−0.62	1,859

This table reports the descriptive statistics for the sample of individual investments by CVCs and IVCs from 1980 to 2004. Panel A presents the summary statistics for firms' innovation output. The observation unit in Panel A is IPO firm-year. Panel B presents the summary statistics for other control variables. The unit of observation in Panel B is IPO firm. The main data sources are the Thomson VentureXpert database, the NBER Patent Citation database, and Compustat.

effects of product market competition on innovation (Aghion et al. 2005), we also include the squared Herfindal index (*Herfindahl Squared)* in our baseline regressions.

Table 1 Panel B provides summary statistics of the control variables: the observational unit is an IPO firm. On average, an IPO firm in our sample has book value of assets of \$110 million, ROA of −1%, R&D-to-asset ratio of 10%, PPE-to-assets ratio of 23%, leverage ratio of 10%, capital expenditure of 8%, Herfindahl index of 0.25, and Tobin's q of 4.3. These VC-backed IPO characteristics are similar to those reported in other IPO studies.

In Table 2 we compare the maturity (Panel A) and the operating performance (Panel B) of CVC- and IVC-backed IPO firms. We capture firm maturity by firm age at both the first VC investment year and the IPO year. We measure firm age at the first VC investment year as the number of years between the firm founding year and the first VC investment year. Similarly, a firm's age at the IPO year is the number of years from a firm's founding year to its IPO year. To compare post-IPO operating performance, we match CVC- and IVC-backed firms based on IPO year, 49 Fama-French industry classifications (available at Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html), and firm total assets at IPO year to minimize potential biases. We ensure a unique match of IVC-backed IPO firm for each CVC-backed IPO firm.

Table 2
Firm age and operating performance of CVC- and IVC-backed firms

Panel A: Firm age

Year	CVC	IVC	Difference
In first VC funding year (mean)	2.05	5.11	–3.46***
In first VC funding year (median)	1.00	2.00	–1.00***
In IPO year (mean)	6.53	10.31	–3.77***
In IPO year (median)	5.00	7.00	–2.00***

Panel B: Operating performance

Year	CVC	IVC	Difference
1. ROA			
0	−0.190	−0.016	−0.144***
1	−0.299	−0.113	−0.186***
2	−0.380	−0.150	−0.230***
3	−0.303	−0.131	−0.172***
4	−0.225	−0.139	−0.085***
5	−0.217	−0.126	−0.092***
2. Profit margin			
0	−2.412	−0.940	−1.472***
1	−2.260	−0.947	−1.313***
2	−2.501	−0.873	−1.628***
3	−1.670	−0.779	−0.891***
4	−1.301	−0.731	−0.570***
5	−1.035	−0.836	−0.199
3. R&D in total assets			
0	0.137	0.094	0.043***
1	0.192	0.117	0.075***
2	0.215	0.128	0.087***
3	0.228	0.130	0.098***
4	0.198	0.136	0.062***
5	0.199	0.144	0.056**

This table reports the univariate analysis of the characteristics of CVC- and IVC-backed IPO firms. Panel A reports firm age, both at the first VC investment year and at the IPO year. Panel B presents the operating performance measures at the IPO year and up to five years after IPO. *ROA* is net income divided by total assets; *Profit Margin* is the ratio of net income to sales; and *R&D in Total Assets* is a ratio of R&D expenditures to total assets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A shows that CVC-backed firms are significantly younger than are IVC-backed firms, both in the first VC investment year and in the IPO year. The mean age differences between these two groups of firms are 3.5 years and 3.8 years at the first VC investment year and the IPO year, respectively. Panel B shows that CVC-backed firms exhibit significantly poorer operating performance post-IPO (years zero to year five) than do IVC-backed firms, even after controlling for firm IPO year, industry, and firm size. CVC-backed IPOs underperform IVC-backed IPOs by 14.4% in terms of ROA and 147.2% in terms of profit margin in the IPO year. However, CVC-backed IPOs' profitability improves significantly over four years post-IPO and their profit margin is statistically insignificant from that of IVC-backed firms in year five. The evidence suggests that CVC-backed firms quickly catch up with IVC-backed firms in terms of operating performance. Panel B also shows that CVC-backed firms persistently exhibit higher R&D in post-IPO years than do IVC-backed firms.

The poorer operating performance of CVC-backed firms immediately after IPO may reflect the fact that they are younger at the time of IPO compared with IVC-backed firms. An alternative explanation for this finding is that it generally takes a long time for firms to commercialize their innovation output and enjoy the return from undertaking innovation. Therefore, CVC-backed firms' higher innovativeness (as we show in the next section) may not be completely reflected in their current cash flows, and hence they underperform when we use cash-flow-based performance metrics to gauge their operating performance.

2.5 Round financing

To understand the characteristics of entrepreneurial firms financed by CVCs and IVCs, we obtain VC round-by-round investments from VentureXpert. We retrieve information about all entrepreneurial firms that obtain venture capital financing between 1980 and 2004. We exclude financial firms, firms with unclassified venture capital investments (e.g., those with foreign VC investors) and those with missing or inconsistent data, and we obtain 24,549 distinct entrepreneurial firms.

VentureXpert provides detailed information on individual financing rounds, including the entrepreneurial firm's development stage at the first VC investment round, the date the firm was established, the date and investment amount of each financing round, and the identity of the investing venture capital investors. We update and fill in the missing observations for the date when the firm was established. We use Jay Ritter's database (available at http://bear.cba.ufl.edu/ritter/ipodata.htm) for the subset of firms that go public and D&B and CorpTech Explore Databases for firms remaining private. We further update and cross-reference this information with other databases. For example, we fill in the missing values for SIC codes using Compustat for already public firms and D&B and CorpTech Explore Databases for private firms.

Finally, to be able to effectively control for the quality of IVCs coinvesting with CVCs, we obtain the list of IVCs from VentureXpert. We aggregate this data to the IVC firm level and construct three reputation measures for each IVC and the financing round date: (1) age of an IVC firm, (2) number of rounds an IVC firm participated in since 1965, and (3) total dollar amount invested since 1965.

3. Empirical Results

The objective of our study is to compare the innovation output of CVC- and IVC-backed firms. In our baseline analysis, we examine the innovation output of firms going public pre- and post-IPO and report the results in Section 3.1. In Section 3.2 we examine firms' innovation output using propensity score matched pairs of CVC- and IVC-backed IPO firms. In Section 3.3 we extend our baseline analysis and evaluate the innovation output of all VC-backed firms (as opposed to comparing only firms that eventually went public) in a difference-in-differences setting. In Section 3.4 we explore the investment patterns of CVCs and IVCs to address alternative interpretations of our main results.

3.1 Baseline findings

We start by examining the innovation output of CVC- and IVC-backed firms prior to IPO. Because young entrepreneurial firms' innovation is relatively sporadic, we consider a cumulative innovation over the three-year period prior to the IPO date (see, e.g., Lerner, Sorensen, and Stromberg 2011 for a similar setting). To evaluate the effect of CVC backing, we use three measures for the degree of CVC participation: *CVC Backing Dummy*, which equals one if the firm is classified as a CVC-backed IPO and zero if the firm is classified as an IVC-backed IPO, *Number of CVCs*, which counts the number of CVCs in an investing VC syndicate, and *CVC Share*, which measures the percentage investment made by the CVCs within a VC syndicate. We control for a number of firm characteristics shown in the literature that affect a firm's innovation output as described in Section 2.4. The control variables are measured as of the entrepreneurial firm's IPO year. We include industry and year fixed effects and cluster standard errors at the lead VC firm level. The observational unit in this analysis is the IPO firm.

Table 3 reports the ordinary least squares (OLS) regression results for pre-IPO innovation output of CVC- and IVC-backed IPO firms.[11] In Panel A, the dependent variable is the total number of patents filed by the IPO firm in the three years prior to its IPO year. The coefficient estimates of the three CVC backing variables are all positive and statistically significant, suggesting that CVC backing is associated with a higher level of innovation output of the firm three years prior to IPO. Economically, based on the coefficient estimate of *CVC Backing Dummy* in Column (1), a CVC-backed IPO firm generates 26.9% more patents than an IVC-backed IPO firm in the three years prior to IPO. Based on the coefficient estimate of *Number of CVCs* reported in Column (2), one additional CVC investor in the investing VC syndicate increases the firm's number of patents by 15.9% in the three years prior to IPO.

Panel B of Table 3 presents a similar analysis for the patent quality measure. The coefficient estimates of CVC backing variables are all positive and significant, suggesting that CVC-backed firms generate patents with higher quality (i.e., larger impact). Based on the coefficient estimate of *CVC Backing Dummy* in Column (4), patents generated by CVC-backed firms in the three years prior to IPO receive 17.6% more citations compared with those generated by IVC-backed firms.

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[11] In addition to OLS regressions reported in this section, we use a Tobit model that takes into consideration the nonnegative and censored nature of patent and citation data. We also run a Poisson model and a negative binomial model when the dependent variable is the number of patents to take care of the discrete nature of patent counts. The results are similar in these unreported analyses.

Table 3
Pre-IPO innovation productivity of CVC- and IVC-backed IPO firms

	Panel A: Ln(patents)			Panel B: Ln(citations/patent)		
	(1)	(2)	(3)	(4)	(5)	(6)
CVC backing dummy	0.269***			0.176**		
	(3.02)			(2.21)		
Number of CVCs		0.159***			0.066*	
		(2.91)			(1.75)	
CVC share			0.618**			0.471**
			(2.17)			(2.09)
Ln(total assets)	0.201***	0.192***	0.212***	0.060*	0.060*	0.067**
	(4.72)	(4.59)	(5.04)	(1.82)	(1.83)	(2.03)
ROA	0.061	0.085	0.015	−0.055	−0.068	−0.080
	(0.34)	(0.47)	(0.08)	(0.38)	(0.47)	(0.55)
R&D in total assets	1.564***	1.569***	1.577***	0.348	0.346	0.359
	(2.78)	(2.78)	(2.76)	(1.12)	(1.11)	(1.14)
PPE in total assets	−0.136	−0.153	−0.129	−0.148	−0.151	−0.143
	(1.03)	(1.15)	(0.97)	(1.24)	(1.26)	(1.20)
Leverage	−0.286	−0.249	−0.325	−0.394**	−0.397**	−0.415**
	(1.18)	(1.03)	(1.33)	(2.33)	(2.34)	(2.46)
CE in total assets	0.044	0.058	0.033	0.361	0.369	0.352
	(0.14)	(0.18)	(0.10)	(1.18)	(1.21)	(1.15)
HHI	−0.261	−0.254	−0.315	−0.168	−0.176	−0.205
	(0.80)	(0.78)	(0.96)	(0.54)	(0.57)	(0.66)
HHI^2	0.165	0.158	0.204	0.007	0.009	0.036
	(0.53)	(0.51)	(0.65)	(0.03)	(0.03)	(0.13)
Tobin's q	0.016**	0.016**	0.016**	0.014*	0.014*	0.014*
	(2.08)	(2.08)	(2.04)	(1.88)	(1.93)	(1.87)
KZ index	−0.004	−0.004	−0.003	0.004	0.004	0.004
	(0.39)	(0.44)	(0.34)	(0.52)	(0.51)	(0.57)
Ln(age at IPO)	−0.021	−0.020	−0.022	0.011	0.010	0.011
	(0.56)	(0.53)	(0.58)	(0.31)	(0.29)	(0.24)
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Observations	1,834	1,834	1,834	1,834	1,834	1,834
R^2	0.26	0.26	0.25	0.16	0.16	0.16

This table reports the results of pre-IPO innovation analysis. The dependent variable is the natural logarithm of the total number of patents generated three years prior to the IPO in Panel A and the natural logarithm of the number of citations per patent for the patents generated three years prior to the IPO in Panel B. The main variables of interest are a CVC backing dummy, the number of CVCs, and CVC share in the total VC investment. The set of control variables includes the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the HHI of industry sales index, the HHI squared, Tobin's q, the KZ index, and the natural logarithm of firm age at the IPO year. The unit of observation is IPO firm. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

We are aware of the possible look-ahead bias introduced by taking the values of control variables at the firm's IPO year in the above specifications. Unfortunately, the financial information for IPO firms prior to going public is not available. We include these variables to control for firm characteristics that can potentially affect innovation productivity. However, given the above reservations, we do not draw any inferences based on these control variables' coefficient estimates. The analysis without controls for IPO firm characteristics results in both statistically and economically stronger results. For example, after excluding controls for IPO firm characteristics, the coefficient estimate of *CVC Backing Dummy* is 0.343 (t-statistics = 4.18) in Column (1), where the dependent variable is patent quantity, and the coefficient estimate of

CVC Backing Dummy is 0.227 (t-statistics = 3.18) in Column (4), where the dependent variable is patent quality.

Table 4 presents the analysis of the post-IPO innovation output of CVC- and IVC-backed firms. The dependent variables are based on the innovation output over the four-year period post IPO (including the IPO year). Panel A suggests that CVC-backed firms have higher innovation quantity in the years post IPO. The results are both economically and statistically significant. The coefficient estimate of *CVC Backing Dummy* in Column (1) suggests that a CVC-backed firm is able to generate 44.9% more patents than an IVC-backed firm within the first four years after IPO. One additional CVC investor in the VC syndicate increases the firm's number of patents by 21.9% within the first four years after IPO.

In Panel B, we evaluate the impact of CVC backing on the quality of patents generated by the firms post IPO. The coefficient estimates of CVC-backing variables are all positive and significant, suggesting that CVC-backed IPO firms generate patents with higher quality. Specifically, as reported in Column (4), patents generated by CVC-backed firms within the first four years post IPO receive 13.2% more citations than those generated by IVC-backed firms.[12]

In Table 4 we control for a comprehensive set of industry and firm characteristics that may affect firm innovation output. Consistent with previous literature, we find that firms that are larger (more total assets), have fewer tangible assets (lower PPE in total assets), have higher growth options (higher Tobin's q), and have lower leverage are more innovative. A larger R&D spending, which can be viewed as a larger innovation input, is associated with more innovation output. Product market competition, profitability, and financial constraints do not significantly affect an IPO firm's innovation output.

To further capture the underlying quality and fundamental nature of innovation output, we follow Hall, Jaffe, and Trajtenberg (2001) and define two alternative innovation proxies: patent generality and patent originality. Patents that are cited by a wider array of technology classes of patents are viewed as having greater generality. We define a patent's generality score as one minus the Herfindahl index of the three-digit technology class distribution of all the patents that cite it. The higher a patent's generality score, the more the patent is being drawn upon by a diverse array of subsequent patents. Similarly, patents that cite a wider array of technology classes of patents are viewed as having greater originality. We define a patent's originality score as one minus the Herfindahl index of the three-digit technology class distribution of all the patents it cites. The higher a patent's originality score, the more the patent draws

12 Lerner, Sorensen, and Stromberg (2011) study how private equity investment affects firm innovation by examining patent citations of a sample of LBO firms. They find that patents filed four years after the LBO transaction garner 57.4% more citations than those filed in the year of the LBO transaction. We find that patents filed by CVC-backed firms receive 13.2% more citations than those filed by IVC-backed firms in the first four years after IPO. Although the setting in our paper is different from that in Lerner, Sorensen, and Stromberg (2011), the effect of CVC financing on patent citations is generally smaller than that of private equity funds.

Table 4
Post-IPO innovation productivity of CVC- and IVC-backed firms

	Panel A: Ln(patents)			Panel B: Ln(citations/patent)		
	(1)	(2)	(3)	(4)	(5)	(6)
CVC backing dummy	0.449***			0.132*		
	(4.01)			(1.91)		
Number of CVCs		0.219***			0.057*	
		(3.66)			(1.64)	
CVC share			0.812**			0.434**
			(2.19)			(2.10)
Ln(total assets)	0.365***	0.358***	0.387***	0.079**	0.078**	0.083**
	(6.60)	(6.47)	(7.00)	(2.21)	(2.18)	(2.35)
ROA	0.214	0.220	0.120	−0.035	−0.039	−0.047
	(1.01)	(1.02)	(0.56)	(−0.25)	(−0.28)	(−0.34)
R&D in total assets	1.732**	1.734**	1.743**	0.420	0.420	0.432
	(2.51)	(2.50)	(2.47)	(1.48)	(1.48)	(1.53)
PPE in total assets	−0.459**	−0.476**	−0.443**	−0.242	−0.246	−0.240
	(2.47)	(2.55)	(2.36)	(−1.47)	(−1.49)	(−1.46)
Leverage	−0.632**	−0.603*	−0.711**	−0.660***	−0.657***	−0.671***
	(2.03)	(1.93)	(2.26)	(−3.11)	(−3.09)	(−3.18)
CE in total assets	0.524	0.547	0.513	0.288	0.294	0.278
	(1.13)	(1.19)	(1.11)	(0.71)	(0.73)	(0.69)
HHI	−0.440	−0.443	−0.526	−0.007	−0.010	−0.036
	(0.99)	(1.00)	(1.18)	(−0.02)	(−0.03)	(−0.11)
HHI^2	0.086	0.082	0.144	−0.245	−0.245	−0.220
	(0.20)	(0.19)	(0.34)	(−0.73)	(−0.73)	(−0.66)
Tobin's q	0.037***	0.038***	0.038***	0.011**	0.011**	0.011**
	(5.59)	(5.61)	(5.46)	(2.04)	(2.09)	(2.03)
KZ index	−0.004	−0.004	−0.003	0.002	0.002	0.002
	(0.38)	(0.43)	(0.30)	(0.18)	(0.17)	(0.20)
Ln(Age at IPO)	−0.118**	−0.118**	−0.121**	−0.010	−0.010	−0.010
	(2.24)	(2.24)	(2.29)	(−0.24)	(−0.25)	(−0.24)
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Observations	1,834	1,834	1,834	1,834	1,834	1,834
R^2	0.330	0.329	0.325	0.208	0.207	0.207

This table reports the results of post-IPO innovation analysis. The dependent variable is the natural logarithm of the total number of patents generated four years after IPO in Panel A and the natural logarithm of the number of citations per patent for patents generated four years after IPO in Panel B. The main variables of interest are a CVC backing dummy, the number of CVCs, and CVC share in the total VC investment. The set of control variables includes the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the HHI of industry sales index, the HHI squared, Tobin's q, the KZ index, and the natural logarithm of firm age at the IPO year. The unit of observation is IPO firm. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

upon a diverse array of existing knowledge. We then average the individual patents' generality and originality scores at the IPO firm level and compute *Generality* and *Originality*, respectively.

Table 5 reports the results of our baseline regressions with the dependent variable replaced by *Generality* in Panel A and by *Originality* in Panel B. Because generality and originality scores are bounded between 0 and 1, we use a Tobit model to estimate the effect of CVC financing. For IPO firms that generate no patents in either the three years before or the four years after IPO, their patent generality and originality scores are undefined and are therefore treated as missing. To save space, we suppress the coefficient estimates of all controls. In both panels, Columns (1)–(3) report the results for patents produced

Table 5
Patent generality and originality regressions

Panel A: Patent generality

	Prior-IPO			Post-IPO		
	(1)	(2)	(3)	(4)	(5)	(6)
CVC backing dummy	0.080***			0.069**		
	(7.80)			(1.98)		
Number of CVCs		0.029***			0.031*	
		(6.33)			(1.88)	
CVC share			0.194***			0.097
			(7.10)			(0.89)
Controls	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Observations	677	677	677	788	788	788
Pseudo R^2	0.137	0.136	0.136	0.209	0.208	0.206

Panel B: Patent originality

	(1)	(2)	(3)	(4)	(5)	(6)
CVC backing dummy	0.050***			0.068***		
	(4.79)			(9.48)		
Number of CVCs		0.021***			0.039***	
		(4.51)			(12.12)	
CVC share			0.161***			0.159***
			(5.90)			(8.39)
Controls	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Industry fixed effects	yes	yes	yes	yes	yes	yes
Observations	677	677	677	788	788	788
Pseudo R^2	0.140	0.139	0.140	0.236	0.238	0.234

This table reports the Tobit regression results for the generality and originality of patents generated by CVC- and IVC-backed IPO firms both prior to and after IPO. The dependent variable is the generality score of patents in Panel A and the originality score of patents in Panel B. The main variables of interest are a CVC backing dummy, the number of CVCs, and CVC share. Other independent variables include the natural logarithm of firm assets, return on assets, R&D scaled by firm assets, PPE scaled by firm assets, firm leverage, capital expenditure scaled by firm assets, the Herfindahl index, the Herfindahl index squared, Tobin's q, the KZ index, and the natural logarithm of firm age at IPO year. The unit of observation is IPO firm. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

prior to IPO and Columns (4)–(6) report the results for patents produced after IPO. In Panel A, the coefficient estimates of the CVC backing variables are all positive and significant, except for that in Column (6), suggesting that patents generated by CVC-backed IPO firms are cited by subsequent patents that are from a wider array of technology classes than those produced by IVC-backed IPO firms. In Panel B, the coefficient estimates of the CVC backing variables are all positive and significant at the 1% level. The evidence indicates that patents generated by CVC-backed IPO firms have a greater originality score.

In an untabulated analysis, we also undertake an industry-by-industry analysis to examine the industries in which the positive effect of CVC financing on innovation is more pronounced. Following the existing innovation literature (e.g., Atanassov, Nanda, and Seru 2007; Tian and Wang 2014), we group our sample firms into four categories based on the technological nature of patents: (1) Pharmaceutical, medical instrumentation, and chemicals (hereafter Pharmaceutical), (2) Computers, communications, and electrical (hereafter Computers and electrical), (3) Software programming and internet applications (hereafter Software), and (4) Other miscellaneous patents (hereafter Low-tech). If a firm has no patents, we classify it into one of the above four categories on the basis of the type of patents that are most frequently produced by the firm's industry. We find that the Pharmaceutical and the Computers and electrical industries generate a larger number of patents and their patents receive more citations than do the other two groups of industries. We also find that the positive effect of CVC financing on the innovation output of the entrepreneurial firms is mainly focused in these two groups of industries. CVC-backed firms, however, do not appear to be more innovative than IVC-backed firms if they are in the other two groups of industries that are overall less innovative.

Finally, we examine a subsample of IPO firms that generate at least one patent prior to or after IPO, given the concern that a large number of firms never file a patent in our sample. In an untabulated analysis, we find that our baseline results continue to hold in this subsample. For example, the coefficient estimate of *CVC Backing Dummy* is 0.357 (t-statistics = 2.38) in the regression in which the dependent variable is the total number of patents generated by the IPO firm in the first four years after it goes public.

Overall, the evidence presented above suggests that CVC financing is positively related to the innovation output of their portfolio firms, both prior to and after IPO. CVC-backed IPO firms generate both a larger number of patents and patents with higher quality compared with IVC-backed firms.

3.2 Propensity score matching analysis

Whereas the documented difference in the innovation output between CVC- and IVC-backed firms appears to be due to the CVCs' ability to better nurture innovation, our baseline results could also be attributed to other potential interpretations. One possible interpretation is that CVCs and IVCs might invest in and/or take to the IPO market radically different types of firms. In other words, CVCs may have superior selection abilities to identify entrepreneurial firms with high innovation potential to begin with.

To gauge how CVC- and IVC-backed firms differ in their observable characteristics, we report the univariate comparisons between these two groups of firms in Columns (1)–(3) of Table 6 Panel A. The results suggest that CVC-backed firms are slightly larger, less profitable, spend significantly more on R&D, and have less fixed assets. They come from more concentrated industries and have higher growth options (Tobin's q). Given that the characteristics of these two groups of firms are quite different, a regression-based analysis is likely to provide us with an inaccurate estimate of CVCs' impact on the innovation productivity of entrepreneurial firms. In this section, we compare the innovation output of CVC- and IVC-backed firms within the propensity score matched pairs of entrepreneurial firms.

The propensity score matching approach allows us to disentangle the treatment and the selection effect of CVC financing on the innovation output of entrepreneurial firms based on observable firm characteristics. The results

Table 6
Propensity score matching: Diagnostic tests

	Panel A Comparing sample characteristics					Panel B Probit regressions	
		Prematch		Postmatch		Prematch	Postmatch
	CVC-backed (1)	IVC-backed (2)	Difference (3)	IVC-backed (4)	Difference (5)	(1)	(2)
Ln(total assets)	4.161	3.938	0.222***	4.132	0.029	0.280***	−0.043
			(3.80)		(0.41)	(5.41)	(0.85)
ROA	−0.154	0.018	−0.172***	−0.084	−0.070***	−1.235***	−0.394**
			(11.62)		(3.61)	(6.64)	(2.14)
R&D in total assets	0.135	0.092	0.042***	0.111	0.023	−0.267	0.0758
			(5.87)		(1.51)	(0.73)	(0.22)
PPE in total assets	0.166	0.228	−0.062***	0.168	−0.002	0.237	0.032
			(5.34)		(0.16)	(0.68)	(0.08)
Leverage	0.052	0.103	−0.051***	0.056	−0.003	−1.556***	0.299
			(5.74)		(0.38)	(4.16)	(0.71)
CE in total assets	0.064	0.073	−0.009*	0.062	0.002	0.284	−0.904
			(1.91)		(0.43)	(0.40)	(1.18)
HHI	0.145	0.251	−0.106***	0.145	0.000	−0.681	0.744
			(6.24)		(0.02)	(1.41)	(1.51)
HHI^2	0.070	0.166	−0.095***	0.068	0.002	0.144	−0.549
			(5.71)		(0.15)	(0.28)	(0.98)
Tobin's q	6.328	3.892	2.436***	5.517	0.811	0.011**	0.011
			(6.43)		(1.40)	(2.09)	(1.24)
KZ index	−31.934	−31.584	−0.350	−32.699	0.765	0.001	0.001*
			(0.03)		(0.09)	(1.17)	(1.73)
Age at IPO	6.555	9.448	−2.893***	7.015	−0.460	−0.011**	0.004
			(5.20)		(0.81)	(2.13)	(0.67)
Industry fixed effects						yes	yes
Year fixed effects						yes	yes
observations						1,700	1,644
Pseudo R^2						0.161	0.013
p-value forfChi^2						0.001	0.99

This table presents the diagnostic tests of the propensity score matching. Panel A reports the pairwise comparisons of the variables on which the matching is performed (except for industry and year indicator variables) both prematch and postmatch. Panel B reports the parameter estimates from the probit model used in estimating the propensity scores for the treatment and control groups. The dependent variable in Panel B equals one if the IPO firm is CVC backed (treatment firm) and zero if it is IVC backed (control firm). The probit is run at the IPO firm level, and all covariates included in the regression are as reported in Compustat for the IPO year. The Prematch column contains the parameter estimates of the probit estimated on the entire sample, prior to matching. This model is used to generate the propensity scores for matching. The Postmatch column contains the parameter estimates of the probit estimated on the subsample of matched treatment and control observations, after matching. The t-statistics for comparison of means tests are reported in parenthesis. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

of our baseline analysis are consistent with both selection and treatment: the superior ability of CVCs to nurture innovation and the superior skill of CVCs to select firms with higher innovation potential. To disentangle these two effects, an ideal experiment would be to evaluate the innovation of entrepreneurial firms under the random assignment of IVC and CVC investors. Although such an experiment is not feasible to implement, the propensity score matching analysis allows us to minimize the effect of selection based on observables and is therefore the second-best approach.

We use a nearest-neighbor matching implementation of the propensity score matching approach originally developed by Rosenbaum and Rubin (1983).[13] The propensity scores are estimated based on a probit regression at the IPO firm level with the dependent variable being a binary variable equal to one for CVC-backed firms and zero for IVC-backed firms. We use a set of control variables measured at the IPO year as matching dimensions. We incorporate industry and year fixed effects to absorb any time- and industry-specific heterogeneity not captured by firm characteristics. The probit model is estimated across 1,700 firms containing non-missing data for all of the matching dimension variables. We present the estimation results in Column (1) of Table 6, Panel B, labeled "Prematch." We observe the same significant differences between CVC- and IVC-backed firm characteristics as with those reported in Column (3) in Panel A. The results also show that the specification captures a significant amount of variation in the choice variable, as indicated by a pseudo-R^2 of 16.1% and a p-value from the χ^2 test of the overall model fitness well below 0.01.

We then use the propensity score (i.e., the predicted probability) from the "Prematch" probit regression and perform a nearest-neighbor propensity score matching with replacement. Because the number of IVC-backed firms significantly exceeds the number of CVC-backed firms, we use the three nearest neighboring IVC-backed firms that come from the same industry-year IPO group as our main control group firms.

We conduct diagnostic tests to assess the accuracy of the matching procedure. First, we report the univariate comparison between CVC- and IVC-backed firms for the matched pairs and report the results in Columns (4) and (5) of Panel A. We observe statistically insignificant differences between IVC- and CVC-backed firms across all but one characteristic. Next, we rerun the probit model restricted to the matched sample and reported the results in Column (2) of Panel B, labeled "Postmatch." The magnitude of the probit regression coefficients decline dramatically. None of the industry and year dummies is statistically significant in the "Postmatch" column, whereas a majority of them are statistically significant in the "Prematch" column. In addition, the pseudo-R^2 drops dramatically from 16.1% prior to the matching to 1.3% post matching, and a χ^2 test for the overall model fitness shows that we cannot reject the null

[13] Smith and Todd (2005) offer a discussion of matching procedures and recommendations.

hypothesis that all of the coefficient estimates of independent variables are zero (with a p-value of 0.99). In both diagnostic tests, the only dimension of the CVC-backed firms that we cannot match well with IVC-backed firms is the ROA. We observe that even after the match CVC-backed firms are less profitable than are IVC-backed firms. However, the fact that CVC-backed firms are at earlier stages of their development and therefore are less profitable only biases our innovation analysis against our finding a treatment effect of CVC financing. Thus, the matching process removes meaningful differences along observable dimensions between these two groups of firms.

Table 7 reports the innovation output analysis using the propensity score matched pairs of IPO firms. We report a wide set of results for different numbers of nearest neighbors used and different limitations on the pool of control firms (year, industry, or industry-year). Panel A reports the quality of innovation output. We find that, even after we non-parametrically control for firm characteristics (using propensity score matching), CVC-backed IPO firms still have a higher innovation output, both pre- and post-IPO. The CVC-backed firms obtain 25% $\sim$ 40% more patents pre-IPO and 38% $\sim$ 60% more patents post-IPO. We report the innovation quality results in Panel B. CVC-backed firms also tend to generate better quality patents pre-IPO and about the same quality of patents post-IPO than do IVC-backed firms.

In summary, the findings from our propensity score matching analysis suggest that CVC-backed firms are more innovative. One caution is that, because the lack of pre-IPO financial variables does not allow us to match CVC- and IVC-backed firms based on pretreatment (before the firms receive the first round VC financing) firm characteristics, we cannot fully eliminate superior CVC selection ability as an alternative explanation for our results. However, given the natural bias of entrepreneurs against CVC investors due to potential conflicts of interest (Hellmann 2002), and the fact that CVCs tend to co-invest with IVCs who typically lead the investment syndicate, we find that our results are unlikely to be entirely driven by CVCs' superior selection ability. Overall, our propensity score analysis suggests that there is a significant treatment effect of CVC backing on innovation by entrepreneurial firms backed by them.

3.3 The difference-in-differences approach

A reasonable concern regarding the analysis so far is that our study only focuses on the sample of entrepreneurial firms that eventually go public. It is possible that our results are driven by the fact that, compared to IVCs, CVCs are more likely to bring their most innovative firms public. It is also possible that our analysis based on the sample of IPO firms introduces survivorship bias issues. Therefore, drawing conclusions solely based on an analysis of IPO firms could be misleading.

To address these concerns, we now implement our analysis of innovation intensity based on the entire universe of VC-backed entrepreneurial firms from

Table 7
Propensity score matching results

Nearest neighbors	Exact match	Pre-IPO			Post-IPO		
		CVC-	IVC-	Difference	CVC-	IVC-	Difference
Panel A: Ln(patents)							
Unmatched		1.215	0.605	0.610***	1.929	1.094	0.834***
One	No restriction	1.215	0.814	0.401***	1.929	1.328	0.601***
	Industry	1.215	0.974	0.242*	1.929	1.496	0.432**
	Year	1.215	0.897	0.318**	1.929	1.392	0.537***
	Industry and year	1.215	0.854	0.361**	1.929	1.421	0.508***
Three	No restriction	1.215	0.994	0.222*	1.929	1.572	0.356**
	Industry	1.215	0.958	0.257**	1.929	1.505	0.424***
	Year	1.215	0.922	0.294**	1.929	1.459	0.470***
	Industry and year	1.215	0.978	0.237**	1.929	1.519	0.410***
Five	No restriction	1.215	0.965	0.250***	1.929	1.527	0.401***
	Industry	1.215	0.978	0.237**	1.929	1.543	0.386***
	Year	1.215	0.916	0.299***	1.929	1.474	0.455***
	Industry and year	1.215	0.963	0.252**	1.929	1.490	0.438***
Panel B: Ln(citations per patent)							
Unmatched		1.007	0.638	0.369***	1.087	0.837	0.250***
One	No restriction	1.007	0.850	0.157	1.087	0.899	0.188**
	Industry	1.007	0.933	0.074	1.087	1.019	0.067
	Year	1.007	0.772	0.235**	1.087	0.921	0.166
	Industry and year	1.007	0.755	0.252**	1.087	0.992	0.095
Three	No restriction	1.007	0.856	0.151	1.087	1.010	0.077
	Industry	1.007	0.928	0.079	1.087	1.026	0.060
	Year	1.007	0.827	0.180*	1.087	0.950	0.136
	Industry and year	1.007	0.859	0.148	1.087	1.022	0.065
Five	No restriction	1.007	0.829	0.178*	1.087	0.961	0.126
	Industry	1.007	0.849	0.158*	1.087	0.988	0.099
	Year	1.007	0.840	0.167*	1.087	0.959	0.128
	Industry and year	1.007	0.848	0.159*	1.087	1.010	0.077

This table reports the differences in innovation output based on a sample in which CVC-backed IPO firms are matched to IVC-backed IPO firms using the propensity score matching algorithm with various restrictions. We vary two dimensions of matching: the number of nearest neighbors used in the matching varies from one to five as specified in the first column; we also consider various exact matches from matching the firms based on the propensity score value solely to forcing the matching firms to be from the same industry or IPO year or both. The treatment group is defined as all CVC-backed IPO firms. The control group is defined as a set of IVC-backed IPO firms. Panel A reports the differences in mean natural logarithm of patent counts, and Panel B reports the natural logarithm of number of non-self citations per patent. We report both unmatched and matched pairs of innovation output characteristics. The analysis is conducted for both three years pre-IPO period and four years post-IPO period. *Difference* is the average difference in the innovation output characteristics between treated and matched control firms. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

VentureXpert during our sample period. We classify these firms based on their exit outcomes and current investment status into one of four categories: firms that eventually go public, firms that are acquired by another company, firms that are written off by the VC investors, and firms that are still under active VC investment.[14] We hand-collect patent information from the USPTO (available

[14] VentureXpert does not mark all written-down firms as write-offs. Therefore, in addition to the write-offs marked by VentureXpert, we classify a firm as a write-off if it did not receive any financing within a ten-year span after its very last venture financing round, based on the fact that venture partnerships require investment liquidation within ten years from the inception of the fund in the majority of the cases. For robustness, we consider an alternative cutoff for classifying write-off firms if the entrepreneurial firm did not receive any follow-on financing within a five-year span after its very last financing round. Our results are robust to either classification.

Table 8
Innovation by all VC-backed entrepreneurial firms

Panel A: Univariate comparisons

	All VC-backed firms (1)	Going public firms (2)	Acquired firms (3)	Written-off firms (4)	Active inv. firms (5)
CVC-backed firms	1.76	5.74	1.69	0.86	1.11
IVC-backed firms	1.13	3.65	1.12	0.50	0.77
Difference	0.63***	2.08***	0.57**	0.36*	0.34**
(t-statistics)	(4.04)	(2.75)	(1.98)	(1.71)	(2.32)

Panel B: Difference-in-differences approach

	(1)	(2)	(3)	(4)	(5)
One year after * CVC	0.003	0.009	0.030	−0.028	−0.005
	(0.21)	(0.22)	(1.54)	(−1.12)	(−0.26)
Two years after * CVC	0.021*	0.040*	0.042**	−0.015	0.012
	(1.82)	(1.95)	(2.15)	(−0.59)	(1.61)
Three years after * CVC	0.036***	0.066*	0.075***	−0.007	0.017*
	(2.81)	(1.70)	(3.81)	(−0.28)	(1.89)
Four years after * CVC	0.048***	0.016	0.113***	0.020	0.033
	(3.21)	(1.36)	(5.06)	(0.66)	(1.41)
Five years after * CVC	0.075***	0.053*	0.102***	−0.034	0.079***
	(4.55)	(1.85)	(4.15)	(0.93)	(3.04)
One year after	0.022***	0.034***	0.019***	−0.003	0.022***
	(7.11)	(3.22)	(3.76)	(−0.45)	(4.66)
Two years after	0.025***	0.049***	0.014***	−0.029***	0.024***
	(7.51)	(4.18)	(2.61)	(−3.20)	(4.55)
Three years after	0.017***	0.055***	0.011*	−0.056***	0.008
	(4.40)	(4.23)	(1.81)	(−4.85)	(1.21)
Four years after	0.000	0.076	−0.009	−0.087***	−0.021**
	(0.04)	(4.86)	(−1.16)	(−5.85)	(−2.55)
Five years after	−0.013**	0.076***	0.018**	−0.105***	−0.048***
	(−2.36)	(4.17)	(2.08)	(−1.12)	(−4.87)
Year fixed effects	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes
Observations	106,713	11,834	24,296	9,693	60,230
R^2	0.548	0.687	0.592	0.578	0.492

This table reports the innovation output by all VC-backed entrepreneurial firms. Panel A reports the mean number of patents for all the VC-backed entrepreneurial firms (Column 1), the entrepreneurial firms that eventually go public (Column 2), the entrepreneurial firms that are acquired by another company (Column 3), the entrepreneurial firms that are written off by the VC (Column 4), and the entrepreneurial firms that are still under active investment (Column 5). Panel B reports the changes in entrepreneurial firms' innovation dynamic upon the first VC entrance using the DiD approach. The sample contains the annual innovation data for five years after the first VC investment year. The unit of observations is entrepreneurial firm-year. The dependent variable is the natural logarithm of the number of patents. All regressions include firm fixed effects. The main data source is the VentureXpert database and the USPTO. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

at www.uspto.gov) and manually match it to these entrepreneurial firms based on firm name and geographic location. For brevity, we only report results based on patent counts. Our analysis of patent citations produces qualitatively similar results.

Table 8 Panel A reports the univariate comparisons of patent counts of CVC- and IVC-backed firms. In Column (1), the sample includes all VC-backed entrepreneurial firms. We find that CVC-backed firms on average generate 0.6 more patents. The differences are statistically significant at the 1% level. In Columns (2)–(5), we break down the sample based on the exit outcomes of entrepreneurial firms. Specifically, in Column (2), we report the results of firms that eventually go public; in Column (3), we report firms that are acquired by another company; in Column (4), we report firms that are written off; and in Column (5), we report firms still under active VC investment. We observe that, regardless of the firms' exit outcomes and current status, CVC-backed firms generate a larger number of patents than do IVC-backed firms.

Similar to our main analysis that is based on a sample of IPO firms, our study based on the sample of all VC-backed entrepreneurial firms is also subject to the concern that the results are due to CVCs' superior selection ability. We explore the difference-in-differences (DiD) analysis around the first VC investment year that mitigates this concern to a significant extent. Specifically, we construct a panel data set that captures entrepreneurial firms' annual innovation output around the first VC investment year and estimate the following regression:

$$Innovation_{i,t}=\beta_s\sum_{s=1}^{5}After_{i,t}^{s}+\gamma_s\sum_{s=1}^{5}After_{i,t}^{s}\times CVC_i+Year_t+Firm_i+\varepsilon_{i,t},$$

where $After_{i,t}^{s}$ is a dummy variable that equals one if year t is s years after the first investment round in firm $i$and zero otherwise. CVC_i is a dummy variable that equals one if the first investment round is CVC-backed and zero otherwise. The coefficient estimates of β_s reflect the changes in portfolio firms' innovation output since the first VC investment round. The coefficients of interest are γ_s, which capture the incremental innovation output associated with CVC backing in the years after the first investment round. The sample covers a five-year period for each entrepreneurial firm starting from the date of the first financing round. The specification controls for time-invariant heterogeneity across CVC- and IVC-backed firms via the firm fixed effects. The calendar year fixed effects capture the aggregate changes in patenting rates in the U.S. economy. We cluster standard errors by the first investment round year.

Table 8 Panel B reports the results of our DiD analysis based on the firm's exit type. Column (1) includes all portfolio firms; Column (2) reports the results for firms that eventually go public; Column (3) reports the results for acquired firms; Column (4) reports the results for written-off firms; and Column (5) reports the results for firms still under active VC investment. We find that γ_s are all positive and significant two years after the first investment round (see Column (1)). CVC-backed entrepreneurial firms exhibit a substantially larger jump in innovation output compared with IVC-backed firms after the first CVC (IVC) investment year. More interestingly, the innovation output of CVC- and IVC-backed firms are similar during the first financing round year as γ_1 is insignificant in all columns. However, CVC-backed firms seem to quickly gain momentum and increasingly outperform IVC-backed firms in subsequent years. The magnitudes of γ_s coefficients are monotonically increasing from γ_2 and are statistically significant. We find a similar finding for entrepreneurial firms that go public, that are acquired, and that are still under active VC investment. The only exception is the written-off firms that appear in Column (4), for

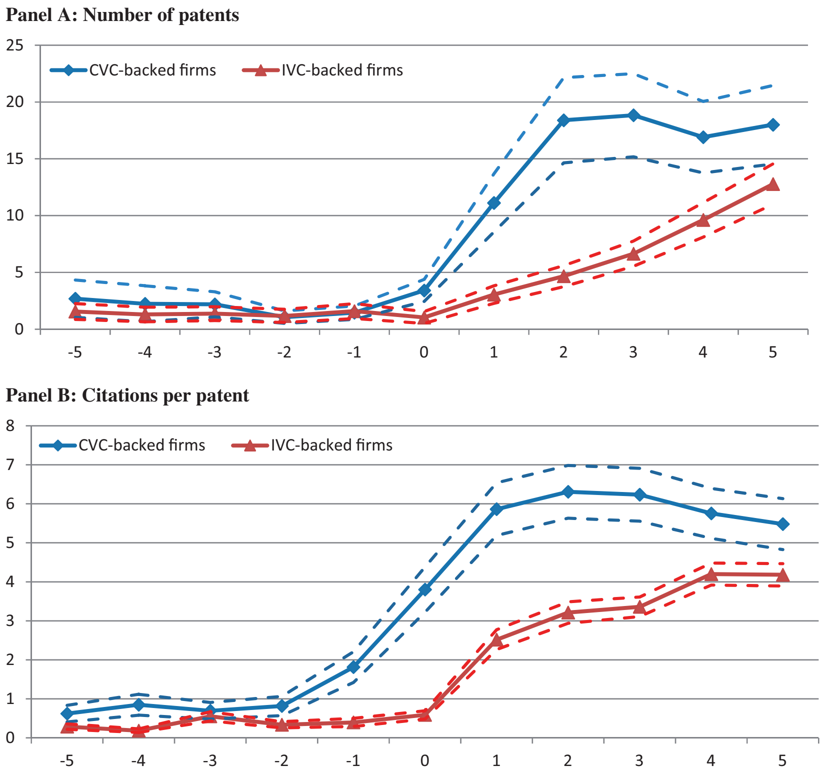

Figure 1
Innovation around the first CVC (IVC) investment year
This figure shows patterns for patent counts (Panel A) and citations per patent (Panel B). Solid lines represent the average number of patents (citations per patent) for CVC-backed firms and IVC-backed firms five years before and after the first CVC (IVC) investment year. Dashed lines represent standard deviations of the mean values. The main data sources are the VentureXpert database and the NBER Patent Citation database.

which CVC- and IVC-backed firms do not exhibit any significant differences in innovation output after the first investment round.

Finally, we present the innovation dynamics that summarize the above findings graphically in Figure 1. Panel A shows the number of patents for CVC- and IVC-backed firms over an eleven-year period centered on the first CVC (IVC) investment round year, and Panel B depicts the citations per patent over the same period. We observe that the two lines representing the innovation output are trending closely in parallel in the five years leading to the first CVC (IVC) round year. However, after the first VC investment round, these two lines start to diverge with the line representing CVC-backed firms well above the one representing IVC-backed firms.

Overall, the evidence presented in this section suggests that CVC-backed entrepreneurial firms exhibit a substantially larger jump in innovation output compared with IVC-backed firms after the first CVC (IVC) investment year.

3.4 Investment patterns

In the above analysis for the entire sample of VC-backed entrepreneurial firms, we attempt to eliminate portfolio firm heterogeneity using the full set of entrepreneurial firm fixed effects. To further ensure that our results are not driven by CVCs strategically investing in more mature firms that are capable of producing more (and better quality) patents, in this section we analyze whether CVCs indeed invest in more mature firms at the financing round date.

Table 9 reports the results of a probit analysis that uses VC round-by-round investments data. The observation unit is a financing round. The dependent variable is a dummy that equals one for financing rounds backed by CVCs and zero for financing rounds backed by IVCs. The independent variables can be classified into three categories. First, we analyze individual firm-round characteristics, such as entrepreneurial firm age at the round date, round number, total amount received by the firm this round, and total amount of prior investment. These variables reflect the maturity of the firm.

Second, we control for entrepreneurial firms' industry characteristics. Because we do not observe balance sheet data for portfolio firms, we measure their industry characteristics using aggregate variables for firms that are already publicly traded. Specifically, based on an entrepreneurial firm's SIC code, we construct industry-wide variables by averaging the characteristics of public firms in the same industry in the year prior to the financing round. These industry-wide variables include capital expenditures and R&D that are likely to capture the growth option features of the industry, sales growth over the three years prior to the financing round that reflects past industry growth, equal-weighted industry portfolio return over the six months prior to the financing round date that captures the effect of hot versus cold industries, the beta of the industry portfolio over the 36 months prior to the financing-round date that capture the systematic risk of the entrepreneurial firm, and the industry Herfindahl index and the market share of the largest firm in the industry based on prior-year sales that evaluate the degree of competition faced by the entrepreneurial firm. These variables allow us to compare the industry characteristics of CVC- versus IVC-backed firms.

Finally, we control for the reputation of IVCs who invest in the entrepreneurial firm prior to the round considered using three proxies: VC age, total number of rounds the VC has invested, and total amount the VC has invested by the financing round date.

Table 9 reports our results with the industry characteristics being constructed based on the 2-digit SIC industry definition.[15] First, we find that CVCs tend to invest in younger firms at earlier rounds: the coefficient estimates of firm age and round number are negative and significant at the 1% level. CVCs also invest in firms that require significantly larger investments (those with smaller

[15] We find similar results when we construct the industry characteristics based on 3-digit SIC, 4-digit SIC, or Fama-French industry definition.

Table 9
Patterns of CVC investments: Effect of firm and industry characteristics

	CVC-backed financing round			
Firm characteristics				
Firm age at round date	−0.016***	−0.017***	−0.017***	−0.016***
	(4.97)	(5.22)	(5.17)	(4.93)
Round number	−0.034***	−0.036***	−0.037***	−0.034***
	(3.52)	(3.83)	(3.92)	(3.51)
Log dollar amount invested this round	0.301***	0.293***	0.298***	0.302***
	(23.86)	(24.07)	(24.04)	(23.90)
Log total prior investment	−0.011***	−0.011***	−0.010**	−0.011***
	(2.59)	(2.59)	(2.47)	(2.60)
Average industry characteristics				
Capital expenditures	1.950***	2.067***	2.126***	1.982***
	(3.43)	(3.75)	(3.86)	(3.47)
R&D	0.034***	0.034***	0.034***	0.035***
	(3.83)	(3.88)	(3.82)	(3.99)
Sales growth over past 3 yr.	0.276***	0.254***	0.230***	0.264***
	(3.28)	(3.04)	(2.72)	(3.12)
Return on ind. portfolio over prior 6 mo.	0.045	0.027	0.020	0.044
	(1.20)	(0.72)	(0.52)	(1.18)
Beta	0.053***	0.057***	0.058***	0.054***
	(2.99)	(3.24)	(3.29)	(3.06)
HHI of industry sales	−0.694**	−0.680**	−0.627**	
	(2.20)	(2.18)	(1.99)	
Largest market share (sales)				−0.390**
				(2.46)
Average reputation of existing IVCs				
IVCs age	−0.016***			−0.017***
	(7.18)			(7.22)
Total number of rounds invested		−0.001***		
		(6.70)		
Total amount invested ($mil.)			−0.001***	
			(6.67)	
Internet company dummy	0.139***	0.145***	0.147***	0.133***
	(4.51)	(4.84)	(4.75)	(4.39)
Startup/seed stage at first rd. of VC financing	0.250***	0.259***	0.247***	0.247***
	(3.90)	(4.04)	(3.87)	(3.86)
Early stage at first round of VC financing	0.341***	0.354***	0.336***	0.339***
	(4.85)	(5.04)	(4.79)	(4.83)
Expansion stage at first round of VC financing	0.214***	0.231***	0.220***	0.212***
	(3.39)	(3.66)	(3.49)	(3.36)
Later stage at first round of VC financing	0.225***	0.238***	0.229***	0.223***
	(3.88)	(4.10)	(3.97)	(3.84)
Observations	26,359	26,358	26,358	26,359
Pseudo R^2	0.12	0.12	0.12	0.12

This table reports the results of the probit analysis that explores CVC investment patterns. The data set contains round investments by CVCs and IVCs. The dependent variable is equal to one for first CVC-firm round of financing and zero otherwise. Only first investment rounds by individual VCs are considered. The independent variables include (1) entrepreneurial firm characteristics, (2) entrepreneurial firm industry characteristics, and (3) reputation of the existing IVCs at the financing round. Robust t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

prior investment). Second, CVCs provide funding to more capital and R&D-intensive firms than do IVCs. The positive and significant coefficient estimate of industry beta suggests that CVC-backed firms come from riskier industries. These industries also tend to be more competitive as the coefficient estimates of the Herfindahl index and market share of the largest firm in the industry are negative.

In summary, we find that CVC-backed firms are more innovative than are IVC-backed firms. Although we cannot entirely rule out a selection effect, our evidence obtained from a propensity score matching analysis of CVC- versus IVC-backed IPO firms and the DiD analysis of all VC-backed entrepreneurial firms suggests that these findings are more likely due to a treatment effect; that is, CVCs appear to have a better ability to nurture innovation in their portfolio firms.

4. Possible Mechanisms

Our analysis so far shows that CVC-backed firms are more innovative than are IVC-backed firms, although they are younger, riskier, and less profitable. The next natural question is what the economic mechanisms are that allow CVCs to better nurture innovation as compared with IVCs. In this section, we examine two potential mechanisms: (1) the technological fit between CVCs' parent companies and the entrepreneurial firms backed by them, motivated by the theories of Robinson (2008) and Fulghieri and Sevilir (2009), and (2) tolerance for failure, motivated by Manso (2011) theory.

4.1 Technological fit

Fulghieri and Sevilir (2009) argue that under certain circumstances firms move from internal to external organization of projects to increase the speed of product innovation and to obtain a competitive advantage with respect to rival firms in their industry. Similarly, Robinson (2008) shows that firms would prefer to implement "long-shot" projects through strategic alliances rather than internally organized projects. He shows that strategic alliances help overcome the incentive problems associated with implementing these projects. By extension, entrepreneurial firms that are in close proximity to the technological expertise of the CVC corporate parent may obtain significant advantages in pursuing risky, long-shot innovation. Furthermore, as we argued previously, CVCs that operate in the same technological space with their entrepreneurial firms possess superior industry and technology expertise, so that such CVCs are better able to develop and nurture new ventures' technologies and product market prospects compared with CVCs that do not have such a "technological fit" (and also compared with IVCs).

In this section, we empirically study whether the technological fit between the CVC's parent company and the entrepreneurial firm is an underlying economic mechanism. Specifically, we examine whether a technological fit contributes to the superior innovation output of CVC-backed entrepreneurial firms. We define a technological fit dummy that equals one if the CVC parent company and the entrepreneurial firm share the same Fama-French industry and zero otherwise.[16] We expect CVC-backed entrepreneurial firms with a technological fit to be more innovative than both CVC-backed firms without a technological fit and IVC-backed firms.

Table 10 presents the result of our analysis. In Panel A we repeat our baseline regressions but split the CVC-backing dummy into two dummy variables: *CVC w/o technological fit* is a dummy that equals one if an entrepreneurial firm is backed by a CVC and the firm has a technological fit with at least one CVC parent company and zero otherwise. Similarly, *CVC w/o technological fit* is a dummy equal to one if an entrepreneurial firm is backed by a CVC and the firm does not have a technological fit with any of the CVC parents and zero otherwise. The omitted group is IVC-backed entrepreneurial firms. Thus, the coefficients of these two dummies represent respective CVCs' effects on innovation output of CVC-backed firms relative to IVC-backed firms. We report pre- and post-IPO innovation output in Columns (1) and (2), respectively. For brevity, we suppress the coefficient estimates of all control variables.

The coefficient estimates of *CVC w/ technologic fit*, β_1, are significantly higher than those of *CVC w/o technologic fit*, β_2, in both the pre- and post-IPO innovation output regressions. The results suggest that entrepreneurial firms with technological fit with a CVC's corporate parent generate 44.4% (62.2%) more patents than do IVC-backed firm pre-IPO (post-IPO). Although the CVC-backed portfolio firms that do not have a technological fit with CVC corporate parent do not generate higher innovation output than do IVC-backed firms pre-IPO, they do exhibit a 31% higher innovation output than IVC-backed firms do post-IPO. The differences in magnitudes between β_1 and β_2 are statistically significant, suggesting that entrepreneurial firms backed by CVCs with technological fit are more innovative than are firms backed by CVCs without technological fit.

We extend our analysis and examine the effect of technological fit on the innovation output using a DiD analysis within the pairs of propensity score matched IPO firms and report the results in Panel B of Table 10. The panel reports both the pre- and post-IPO innovation output results. In Columns (1)–(3) of Panel B we compare the pre- and post-IPO innovation output of IVC-backed firms to that of CVC-backed firms with a technological fit to a CVC's corporate parent. Columns (4)–(6) conduct a similar analysis between IVC-backed firms and CVC-backed firms without a technological fit. Column (7) reports the DiD estimates. For robustness, we present results based on different matching firm selection criteria. The DiD estimates are generally positive and statistically significant. This result is consistent with our findings reported in Panel A that

[16] Our results are robust to alternative definitions of technological fit; that is, technological fit is defined as the match when both the CVC's parent firm and the entrepreneurial firm are in the same 2-digit SIC or 3-digit SIC code. One concern is that Robinson (2008) argues that strategic alliances are used to pursue related diversification rather than to extend activity in the same line of business. To address this concern, we exclude the set of CVC-backed firms with "technological fit" if these entrepreneurial firms share the same 4-digic SIC code with CVC parent, and we find similar results.

Table 10
Mechanisms through which CVCs nurture innovation: Technological fit

Panel A: Regression analysis

	Pre-IPO Ln(patents) (1)	Post-IPO Ln(patents) (2)
CVC w/ technological fit β_1	0.444***	0.622***
	(3.34)	(3.83)
CVC w/o technological fit β_2	0.147	0.310**
	(1.50)	(2.48)
Other control variables	yes	yes
Year fixed effects	yes	yes
Industry fixed effects	yes	yes
F-statistics ($\beta_1 = \beta_2$)	4.00**	2.97*
Observations	1,834	1,834
R^2	0.269	0.337

Panel B: DiD analysis within propensity score matched pairs

Exact Match	Technological fit			No Technological fit			
	Treated (1)	Controls (2)	Difference (3)	Treated (4)	Controls (5)	Difference (6)	DiD (7)
Pre-IPO Ln(Patents)							
Unmatched	1.336	0.605	0.730***	1.124	0.605	0.518***	0.212**
			(6.93)			(5.24)	(2.03)
No restriction	1.336	1.098	0.238***	1.124	1.014	0.109	0.128
			(2.66)			(1.49)	(1.57)
Industry	1.336	1.069	0.266***	1.124	0.973	0.151*	0.116
			(3.04)			(1.83)	(1.36)
Year	1.336	0.974	0.362***	1.124	0.982	0.142	0.220**
			(4.26)			(1.61)	(2.26)
Industry and year	1.336	1.082	0.253***	1.124	0.999	0.125*	0.129*
			(2.92)			(1.82)	(1.71)
Post-IPO Ln(patents)							
Unmatched	2.139	1.094	1.044***	1.768	1.094	0.674***	0.370***
			(6.93)			(5.07)	(2.61)
No restriction	2.139	1.726	0.413**	1.768	1.555	0.213**	0.200
			(2.10)			(1.99)	(1.26)
Industry	2.139	1.597	0.542***	1.768	1.535	0.234**	0.309**
			(2.85)			(2.13)	(1.99)
Year	2.139	1.565	0.573***	1.768	1.478	0.291**	0.283*
			(3.00)			(2.53)	(1.79)
Industry and year	2.139	1.615	0.523***	1.768	1.545	0.224**	0.300*
			(2.73)			(2.08)	(1.93)

This table reports the analysis of the effect of technological fit between entrepreneurial firm and CVC's corporate parent on the pre-IPO and post-IPO innovation output of the entrepreneurial firms. Panel A reports the results of the regression analysis in which the dependent variables are the natural logarithm of the total number of patents generated three years prior to IPO in Column (1) and the natural logarithm of the total number of patents generated four years after IPO in Column (2). The set of control variables is the same as those in Table 3. Robust t-statistics are reported in parentheses. Panel B presents the results of the DiD analysis that uses the propensity score matching methodology to match each CVC-backed IPO firm with three nearest neighbor IVC-backed IPO firms. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

technological fit enhances the innovation output of entrepreneurial firms and is a possible economic mechanism through which CVCs better nurture innovation.

4.2 Tolerance for failure

The second possible mechanism responsible for CVCs' superiority in nurturing innovation over IVCs may be their ability to better understand the nature of the innovation process and hence their greater tolerance for the failure associated with innovation activities. Motivating and nurturing innovation is a complex and challenging task in most organizations, because the innovation process tends to be long, risky, and unpredictable (Holmstrom 1989). Using a principal-agent setting, Manso (2011) argues that the innovation process requires considerable experimentation on the part of the innovator and thus incurs a greater chance of failure.[17] As a result, a significant amount of failure tolerance on the part of VC investors is required to induce the optimal amount of innovation effort on the part of entrepreneurs.

As discussed in Section 1, a number of institutional features of CVCs may allow them to be more failure tolerant than IVCs. First, CVC funds have a much longer investment horizon, which may be necessary for nurturing innovation processes that are very long. Second, whereas IVCs pursue purely financial returns, CVCs pursue both financial returns and strategic (non-financial) benefits for their corporate parent companies. Finally, CVC fund managers are compensated through a fixed salary and corporate bonuses, and hence their compensation is not as sensitive to performance as IVC fund managers'. Taken together, these institutional features may allow CVCs to be more failure tolerant than IVCs.

We first examine whether CVCs are indeed more failure tolerant than are IVCs. Following Tian and Wang (2014), we construct the failure tolerance measure by using the CVC (IVC)'s average investment duration (in years) in their eventually failed ventures over the past ten years. This measure captures a VC investor's attitude toward failure by gauging her willingness to continue investing in an underperforming entrepreneurial firm before she "pulls the plug" (i.e., stops investing).[18]

Because this is a general test for VCs' attitude towards failure, we examine all VC firms covered by VentureXpert with non-missing values of failure tolerance in our sample period. In Panel A of Table 11, we report the univariate comparisons of failure tolerance between CVCs and IVCs. The mean difference in the failure tolerance measure between these two types of VCs is statistically significant at the 1% level, suggesting that CVCs on average tend to wait two more months than do IVCs before liquidating their underperforming ventures. We observe a similar pattern when we compare the median values of failure tolerance.

In Panel B of Table 11, we examine whether CVCs are more failure tolerant in a multivariate regression framework. The dependent variable is VC failure tolerance, and the main variable of interest is *CVC dummy*, which equals one

[17] In a controlled laboratory experiment, Ederer and Manso (2013) show that the combination of tolerance for early failure and reward for long-term success (which parallels to a larger degree to the compensation structure enjoyed by CVCs compared to that received by IVCs) is the optimal compensation scheme for motivating innovation.

[18] See Tian and Wang (2014) for a detailed discussion on the rationale and construction of these VC failure tolerance measures.

Table 11
Mechanisms through which CVCs nurture innovation: Failure tolerance

Panel A: Univariate analysis of VC failure tolerance

	CVCs	IVCs	Difference	Statistics
Mean	2.623	2.458	0.165***	3.24
Median	2.291	2.214	0.077***	4.23

Panel B: Multivariate analysis of VC failure tolerance

	(1)	(2)	(3)
CVC dummy	0.292**	0.337***	0.369***
	(2.43)	(2.84)	(3.07)
Past IPO exit	−0.099	−0.329**	0.047
	(0.67)	(2.23)	(0.34)
Industry expertise	−1.273***	−0.261*	−1.073***
	(9.90)	(1.67)	(7.83)
Stage expertise	0.476***	0.485***	0.288***
	(4.25)	(4.51)	(2.76)
Ln(VC age)	0.267***		
	(8.68)		
Ln(past no. of firms)		0.365***	
		(11.76)	
Ln(past fundraising)			0.114***
			(8.47)
Other control variables	yes	yes	yes
Year fixed effects	yes	yes	yes
Industry fixed effects	yes	yes	yes
Observations	14,772	14,904	15,257
R^2	0.19	0.21	0.19

Panel C: Multivariate analysis within propensity score matched pairs

	No restriction	Industry	Year	Industry and year
Diff. in pre-IPO Ln(patents)	0.238***	0.188***	0.159***	0.0754*
	(4.51)	(3.74)	(2.86)	(1.82)
Diff. in post-IPO Ln(patents)	0.514***	0.285***	0.450***	0.122*
	(7.24)	(4.22)	(6.70)	(1.91)

This table reports the analysis of the effect of VC failure tolerance on the pre-IPO and post-IPO innovation output of the entrepreneurial firms. Panel A reports the univariate analysis of the differences in failure tolerance between CVCs and IVCs. Panel B reports the results of the regression analysis. Panel C reports the analysis in which only the propensity score matched CVC- and IVC-backed firms are included. We adopt the following regression framework:

$$Ln(Innovation_{CVC}) - Ln(Innovation_{Matched\ IVC}) = \beta(Failure\ Tolerance_{CVC} - Failure\ Tolerance_{IVC})$$

$$+\delta' Controls + \varepsilon.$$

We use the propensity score matching methodology to match each CVC-backed IPO firm with three nearest neighbor IVC-backed IPO firms and report four different sets of results based on types of exact matched enforced. The standard errors in Panel C are clustered at the firm level. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

for CVCs and zero for IVCs. Following Tian and Wang (2014), we control for VC's past successful investment experience (*Past IPO Exit*), VC's expertise in certain industries measured by its industry concentration (*Industry Expertise*), VC's expertise in certain development stages of venture (*Stage Expertise*), and proxies for VC's reputation (*Ln*(*VC Age*), *Ln*(*Past No. of Firms*), and *Ln*(*Past Fundraising*)) in the regressions. The observational unit is VC firm-year in this analysis. The coefficient estimates of *CVC dummy* are all positive and significant. This finding suggests that CVCs are indeed more failure tolerant than are IVCs.

We then link this finding to our innovation output analysis. Similar to our analysis testing the technological fit mechanism, we examine whether the innovation output differences between propensity score matched pairs of CVC- and IVC-backed firms can be explained by the difference in failure tolerance of their respective VC investors. Given that the failure tolerance measure is continuous rather than dichotomous as in the case of our technological fit analysis, we implement the analysis by running the following regressions:

$$Ln(Innovation_{CVC}) - Ln(Innovation_{Matched\ IVC}) =$$

$$= \beta(Failure\ Tolerance_{CVC} - Failure\ Tolerance_{IVC}) + \delta' Controls + \varepsilon,$$

where $Innovation_{CVC} - Innovation_{Matched\ IVC}$ is the difference in the innovation output between a CVC-backed IPO firm and the average innovation output of the set of IVC-backed IPO firms that are propensity score matched to each CVC-backed firm. $Failure\ Tolerance_{CVC} - Failure\ Tolerance_{IVC}$ is the difference in failure tolerance between the respective sets of VCs investing in a CVC-backed firm and its matching IVC-backed firms.[19] If the difference in failure tolerance between the investors in the CVC- and IVC-backed firms explains the difference in the innovation output of these respective types of firms, then we expect the coefficient estimate of β to be positive and significant. If, however, the tolerance for failure is not a mechanism that contributes to CVCs' greater ability to nurture innovation, then β should be equal to zero.

Similar to our baseline regressions, we control for two sets of IPO firm characteristics measured at the IPO year: one set is associated with the CVC-backed firm, and the other set reflects the average characteristics of propensity score matched IVC-backed firms. For example, for the three nearest neighbors propensity score matched firms, we average the financial characteristics across these three IVC-backed firms and use the resulting averages as control variables.

Panel C of Table 11 reports our regression results. For brevity, we only report the β coefficient estimates and suppress the control variable coefficients. Regardless of the nearest neighbor restrictions imposed in our propensity score matching procedure, we find that the coefficient estimates of β are positive and significant both pre- and post-IPO. The evidence suggests that the difference in failure tolerance between CVCs and IVCs is able to explain the difference in the innovation output of their entrepreneurial firms.[20]

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19 If an entrepreneurial firm is financed by a VC syndicate that consists of multiple VC investors, we calculate the weighted average of the investing VCs' failure tolerance, with the weight of each VC being the investment made by that VC firm as a fraction of the total VC investment received by the portfolio firm.

20 In untabulated tests, we augment our baseline regression analysis reported in Tables 3 and 4 with the failure tolerance measure and find that failure tolerance has a positive effect on the innovation output of the entrepreneurial firms, whereas CVC backing variables continue to be positive and significant.

Finally, in an untabulated analysis, we include the VC failure tolerance variable in the OLS baseline regressions within CVC- backed firms and the propensity scored matched IVC-backed firms for the innovation output of firms pre- and post-IPO. This test allows us to check whether CVC financing still has a direct (residual) effect on innovation after controlling for failure tolerance. We find that, whereas the coefficient estimates on VC failure tolerance variable in these regressions are all positive and significant, the coefficient estimates on CVC financing variable are also still positive and significant at the 1% level. However, the magnitudes of the coefficient estimates on CVC financing variable are reduced quite substantially (for example, the coefficient estimate on *CVC Backing Dummy* is reduced to 0.171 when pre-IPO patent count is the dependent variable) once we include the VC failure tolerance variable, suggesting that the effect of CVC financing on innovation by entrepreneurial firms is at least partly mediated through failure tolerance.

Taken together, our results presented in Section 4 suggest that there are two possible underlying economic mechanisms through which CVCs nurture innovation to a greater extent than do IVCs: the technological fit between CVCs' parent firms and the entrepreneurial firms backed by them and greater failure tolerance by CVCs.

5. Conclusion

In this paper, we analyze how CVCs differ from IVCs in nurturing innovation in the entrepreneurial firms backed by them. We find that CVC-backed firms achieve a higher degree of innovation output, as measured by their patenting, although these firms are younger, riskier, and less profitable. Although our baseline results are based on entrepreneurial firms that eventually go public, we come to similar conclusions based on our analysis of the entire universe of VC-backed entrepreneurial firms, suggesting that our results are not driven by CVCs bringing their most innovative firms public. Although we cannot rule out the existence of a selection effect, we present a number of empirical tests suggesting that our results are unlikely to be entirely driven by the better selection ability on the part of CVCs. Instead, the results of our propensity score matching and difference-in-differences analyses suggest that there is a significant treatment effect of CVC financing on innovation. Our analysis reveals two possible mechanisms through which CVCs are able to better nurture innovation: the technological fit between CVCs' parent firms and the entrepreneurial firms backed by them and the greater failure tolerance by CVCs relative to IVCs.

References

Acharya, V., and K. Subramanian. 2009. Bankruptcy codes and innovation. *Review of Financial Studies* 22:4949–88.

Aghion, P., J. Van Reenen, and L. Zingales. 2013. Innovation and institutional ownership. *American Economic Review* 103:277–304.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. 2005. Competition and innovation: An inverted U relationship. *Quarterly Journal of Economics* 120:701–28.

Aghion, P., and J. Tirole. 1994. On the management of innovation. *Quarterly Journal of Economics* 109:1185–209.

Atanassov, J., V. Nanda, and A. Seru. 2007. Finance and innovation: The case of publicly traded firms. Working Paper, University of Oregon.

Benson, D., and R. Ziedonis. 2010. Corporate venture capital and the return to acquiring portfolio companies. *Journal of Financial Economics* 98:478–99.

Chemmanur, T., E. Loutskina, and X. Tian. 2012. Differences in financial market responses to backing by corporate versus independent venture capitalists. Working Paper, Boston College.

Chemmanur, T., and X. Tian. 2013. Anti-takeover provisions, innovation, and firm value: A regression discontinuity analysis. Working Paper, Boston College.

Chesbrough, H. W. 2002. Making sense of corporate venture capital. *Harvard Business Review* March: 4–11.

Cornaggia, J., Y. Mao, X. Tian, and B. Wolfe. Forthcoming. Does banking competition affect innovation? *Journal of Financial Economics*.

Dushnitsky, G., and M. Lenox. 2005. When do incumbents learn from entrepreneurial ventures? *Research Policy* 34:615–39.

———. 2006. When does corporate venture capital investment create firm value? *Journal of Business Venturing* 21:753–72.

Dushnitsky, G. and Z. B. Shapira. 2010. Entrepreneurial finance meets corporate reality: Comparing investment practices and performing of corporate and independent venture capitalists. *Strategic Management Journal* 31:990–1017.

Ederer, F., and G. Manso. 2013. Is pay-for-performance detrimental to innovation? *Management Science* 59:1496–513.

Fang, V., X. Tian, and S. Tice. Forthcoming. Does stock liquidity enhance or impede firm innovation. *Journal of Finance*.

Ferreira, D., G. Manso, and A. Silva. 2014. Incentives to innovate and the decision to go public or private. *Review of Financial Studies* 27:256–300.

Fulghieri, P., and M. Sevilir. 2009. Organization and financing of innovation, and the choice between corporate and independent venture capital. *Journal of Financial and Quantitative Analysis* 44: 1291–321.

Gompers, P. A. 2002. Corporations and the financing of innovation: The corporate venturing experience. *Federal Reserve Bank of Atlanta Economic Review*, Q4:1–17.

Gompers, P. A., and J. Lerner. 2000. The determinants of corporate venture capital success: Organizational structure, incentives, and complementarities. In *Concentrated ownership*. Ed. R. Morck. Chicago: University of Chicago Press.

Gompers, P. A., A. Kovner, and J. Lerner. 2009. Specialization and success: Evidence from venture capital. *Journal of Economics & Management Strategy* 18:817–45.

Griliches, Z., B. H. Hall, and A. Pakes. 1987. The value of patents as indicators of inventive activity. In *Economic policy and technological performance*, 97–124. Eds. P. Dasgupta, and P. Stoneman. Cambridge: Cambridge University Press.

Hall, B., A. Jaffe, and M. Trajtenberg. 2001. The NBER patent citations data file: Lessons, insights, and methodological tools. Working Paper 8498, NBER.

———. 2005. Market value and patent citations. *RAND Journal of Economics* 36:16–38.

Harris, R. S., T. Jenkinson, and S. N. Kaplan. Forthcoming. Private equity performance: What do we know? *Journal of Finance*.

He, J., and X. Tian. 2013. The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics* 109:856–78.

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

Hellmann, T., and M. Puri. 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. *Journal of Finance* 57:169–97.

Hirshleifer, D., A. Low, and S. H. Teoh. 2012. Are overconfident CEOs better innovators? *Journal of Finance* 67:1457–98.

Hirshleifer, D., and A. Thakor. 1992. Managerial conservatism, project choice, and debt. *Review of Financial Studies* 5:437–70.

Holmstrom, B. 1989. Agency costs and innovation. *Journal of Economic Behavior and Organization* 12:305–27.

Ivanov, V., and F. Xie. 2010. Do corporate venture capitalists add value to start-up firms? Evidence from IPOs and acquisitions of VC-backed companies. *Financial Management* 39:129–52.

Kogan, L., D. Papanikalaou, A. Seru, and N. Stoffman. 2012. Technological innovation and growth. Working Paper, MIT.

Kortum, S., and J. Lerner. 2000. Assessing contribution of venture capital to innovation. *RAND Journal of Economics* 31:674–92.

Lerner, J. 2012. *The architecture of innovation*: *The economics of creative organizations*. Cambridge: Harvard Business Review Press.

Lerner, J., M. Sorensen, and P. Stromberg. 2011. Private equity and long-run investment: The case of innovation. *Journal of Finance* 66:445–77.

Lindsey, L. 2008. Blurring firm boundaries: The role of venture capital in strategic alliances. *Journal of Finance* 63:1137–68.

MacMillan, I., E. Roberts, V. Livada, and A. Wang. 2008. Corporate venture capital (CVC) seeking innovation and strategic growth: Recent patterns in CVC mission, structure, and investment. National Institute of Standards and Technology, U.S. Department of Commerce.

Manso, G. 2011. Motivating innovation. *Journal of Finance* 66:1823–60.

Masulis, R., and R. Nahata. 2009. Financial contracting with strategic investors: Evidence from corporate venture capital backed IPOs. *Journal of Financial Intermediation* 18:599–631.

Rajan, R., H. Servaes, and L. Zingales. 2000. The cost of diversity: The diversification discount and inefficient investment. *Journal of Finance* 55:35–80.

Robinson, D. 2008. Strategic alliances and the boundaries of the firm. *Review of Financial Studies* 21: 649–81.

Rosenbaum, P., and D. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70:41–55.

Scharfstein, D., and J. Stein. 2000. The dark side of internal capital markets: Divisional rent-seeking and inefficient investment. *Journal of Finance* 55:2537–64.

Seru, A. 2014. Firm boundaries matters: Evidence from conglomerates and R&D activity. *Journal of Financial Economics* 111:381–405.

Solow, R. 1957. Technological change and the aggregate production function. *Review of Economics and Statistics* 39:312–20.

Spiegel, M., and H. Tookes. 2008. Dynamic competition, innovation and strategic financing. Working Paper, Yale University.

Smith, J., and P. Todd. 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics* 125:305–53.

Tian, X., and T. Wang. 2014. Tolerance for failure and corporate innovation. *Review of Financial Studies* 27:211–55.

Williams, O. 1985. *The economic institutions of capitalism*. London: The Free Press.