# Pipes or Shackles? How Ties to Incumbents Shape Startup Innovation

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# Pipes or Shackles? How Ties to Incumbents Shape Startup Innovation

Startups are increasingly turning to the incumbent firms in their industries for venture capital. However, there remain significant gaps in our understanding of how these relationships influence the way they innovate. I highlight an important tension for startups in these relationships - on the one hand they provide valuable downstream expertise to help startups adapt their technologies to product environments, but on the other they expose startups to norms and mindsets that push them in less novel technological directions in their inventions. Crucially, I show that each of these effects can vary depending on which employees of the incumbent firm the startup has access to, and how those connections are made. Startups who interact with the incumbent firm's corporate executives are pushed in more conservative technological directions than those who interact with the incumbent firm's scientists/technologists. How effectively startups can navigate these relationships also depends on the backgrounds of the incumbent firm employees who are in charge of managing them. These individuals act as the interface between the two firms, and I find that their tenure in the incumbent organization prior to taking up these roles is a crucial determinant of their ability to effectively connect startups to valuable expertise within this firm. My findings illustrate how interfirm relationships can expose firms to their partners' limitations in addition to their strengths, something that research in this domain has largely overlooked. Furthermore, a partnership between the same pair of firms could lead to quite different exchanges and outcomes depending on the nature of the interactions underlying it. Accounting for these, conceptually and empirically, can help us better understand how collaborative relationships shape firms' innovation outcomes.

How entrepreneurial firms engage with incumbents is a significant question for scholars of innovation, since the nature of these relationships can shape the development of firms, technologies and industries (e.g. Marx & Hsu, 2015; Schumpeter, 1942; Teece, 1986). Corporate venture capital, the practice of incumbent firms making equity investments in startups, has become one of the most prominent manifestations of collaborative exchange between these two types of firms in recent times. The practice has seen unprecedented growth over the past decade, with nearly half of all the venture capital in the US now invested in rounds featuring corporate participation (NVCA, 2017).

The growth of this practice has led to fierce debate among practitioners about the value of these relationships for startups' innovation efforts (e.g. CB Insights, 2016). Though a nascent and growing body of academic research has started to examine this question, the findings remain equivocal. While some studies have found a positive relationship between CVC investment and the rate of startup innovation (e.g. Alvarez-Garrido & Dushnitsky, 2016), others find a negative or insignificant relationship (e.g. Pahnke, Katila, & Eisenhardt, 2015). While there is broad agreement among scholars that established firms control resources that could be of value to startups, the debate has centered on whether these relationships allow startups to access these resources effectively.

I make two significant additions to the research on this question. First, incumbent firms in an industry generally control a wide variety of resources that could potentially be of use to startups. This includes knowledge and expertise, physical assets, networks of external relationships etc. We have a relatively limited understanding of which of these resources can in practice be effectively leveraged by entrepreneurial firms through these relationships or indeed in what ways they help with the latter's innovation processes. I sharpen the notion of 'resource access' in these relationships to argue that the value addition for startups comes primarily from being able to access expertise with respect to the downstream innovation challenges of developing their technologies into products, i.e. adapting technologies to their application environments. This is a challenge that startups frequently struggle with, and I argue that established firms can effectively help them overcome their internal limitations with respect to this step in the innovation process.

At the same time, I argue that in focusing all our attention on the resources of the incumbent firms and whether or not startups can access them, we may be overlooking the fact that incumbent firms also embody some deeply ingrained limitations to the pursuit of technologies and business models that deviate from the status-quo (Tripsas and Gavetti 2000; Benner and Tushman 2003). Indeed, this is one of the reasons they attempt to 'externalize' their innovation activities in the first place. Research has thus far not considered whether and how these limitations may influence the innovation efforts of these firms' external partners. Startups with ties to these firms will be exposed to norms and mindsets that are predisposed to favor incremental gains over radical changes. Consequently, I argue that these startups are likely to be pushed in more conservative technological directions in their subsequent inventions. In combination, these two arguments suggest that startups face a basic tension in these relationships between accessing valuable expertise that helps them develop their technologies towards commercial application, and being exposed to norms and mindsets that push their inventive activities in more conservative directions.

Second, I argue that both of these influences can vary substantially depending on who in the incumbent firm the startups get access to and how those connections are made. The incumbent firms in these relationships are generally large, complex organizations with numerous employees spread out over a multitude of divisions, functions and locations (Pahnke et al., 2015). The different parts of this organization are likely to embody distinct forms of knowledge and resources, as well as distinct incentive structures and norms (Almeida & Phene, 2004). Hence, the expertise startups are able to access via these relationships, as well as the type of influence they come under can vary depending on backgrounds and motivations of the specific people within the established firm they interact with.

This is an issue that research on interfirm relationships in general has largely overlooked. The theoretical lenses most commonly employed to study interfirm relationships share in common the analytical device of characterizing ‘the firm’ in these relationships as monoliths, as represented in fig 1a (Ghosh & Rosenkopf, 2014; Lumineau & Oliveira, 2018). However, relationships between organizations are generally more akin to the schematic representation in figure 1b, in that different parts of the organization may be involved in different relationships. Consequently, the types of interactions underlying each of these relationships may be quite different due to the within-firm heterogeneity in how different relationships are managed.

FIGURE 1 HERE

Abstracting away from these distinctions has enabled us to apply certain theories and analytical tools that have helped us address questions such as, who should a firm partner with, or what type of governance structure should be used for the partnership. However, these simplifications also limit our ability to address issues relating to how the partnership is organized and managed within the firm. This includes questions like, which personnel from the two firms should be interacting, how should they be incentivized, what should their functional backgrounds be etc... This is fundamentally an organizational design problem, one that present approaches to studying interfirm relationships aren’t best suited to addressing. In this paper I will argue and demonstrate how taking account of these issues may allow us greater explanatory power into how interfirm relationships shape firm outcomes.

To develop my arguments and hypotheses I draw on existing theory in conjunction with a qualitative examination of these relationships in the context of the life sciences. I then test these on a sample of entrepreneurial firms that raised venture capital funding between 2001 and 2010. Using a combination of matching and instrumental variable approaches to account for selection, I find that these relationships are associated with a decline in the technological novelty of the entrepreneurial firm’s inventions, compared to similar startups that raise capital at the same time from non-corporate sources. Importantly, I find that this negative effect is accentuated when the entrepreneurial firm has greater access to the incumbent’s firm’s corporate executives, but that it is alleviated when the entrepreneurial firm has greater access to the incumbent firm’s scientists / technologists. This provides some support for the mechanism driving the baseline effect while demonstrating how the outcomes associated with these relationships for startups can depend fundamentally on the type of access they get to the established firm.

At the same time, I also find that these relationships with incumbent firms have a positive effect on entrepreneurial firms' capacity to advance their technologies into product prototypes. This is a step in the innovation process that has been identified in prior research as being particularly challenging for startups since it often necessitates bringing together expertise in a wide range of areas (Iansiti & West, 1997; Kapoor & Klueter, 2015). An established firm can be a particularly valuable ally at this stage by facilitating access to this expertise more efficiently than startups can typically access it through other avenues. This positive effect is significantly enhanced if the individuals managing these investments on behalf of the incumbent firm have greater prior experience at the firm in other roles. This experience enables these individuals to identify where specific expertise is located within the firm and facilitate startups' access to it more effectively.

This study contributes to research on interfirm relationships and innovation (Phelps, Heidl, & Wadhwa, 2012). While there is a substantial body of research on how firms' performance is shaped by their partners' resources, we have a more limited understanding of how firms are affected by their partners' weaknesses or limitations. Viewing these influences in concert can help us recognize important tradeoffs that explain how these relationships shape outcomes. Also, the results indicate that a relationship between the same pair of firms could be associated with different outcomes depending on the interactions underlying it – who is involved, what are their backgrounds, how are they incentivized etc. These are issues that existing research on interfirm relationships has largely abstracted away from. Accounting for these distinctions may help us better understand how collaborative relationships shape the way firms innovate.

This study also contributes to the literature on entrepreneurial innovation. Incumbent firms now play a sizable role as investors in entrepreneurial ventures. My investigations advance extant understanding of precisely where the benefits of these exchanges are likely to come from for entrepreneurs, and what some of the side effects may be from an innovation standpoint. I also highlight an interesting paradox in relation to corporate venture capital investment – i.e. while the objective of the established firm is to identify and invest in firms that are likely to drive radical technological change, the act of investing itself can cause a decline in the propensity of the entrepreneur to bring about such an outcome. This is of interest to entrepreneurs but also to incumbent firms since it influences what they stand to gain from these investments.

## BACKGROUND

The Schumpeterian view of economic growth driven by technological progress posits a clear link between entrepreneurship and innovation (Schumpeter, 1942). Building on these influential ideas, later work on technological innovation has demonstrated that entrepreneurial firms possess some inherent advantages in pioneering technological change, putting them in an instrumental position to be the harbinger of industry transformation (e.g. Henderson, 1993). These characteristics of entrepreneurial firms make them attractive partners for larger, more established organizations, who typically embody significant inertia towards the pursuit of path breaking technologies and business models internally (e.g. Christensen, 1997; Tripsas & Gavetti, 2000). Startups for their part could also benefit from these partnerships since they can facilitate access to valuable resources such as knowledge and complementary assets (Teece, 1986). Corporate venture capital investments represent the confluence of these imperatives, on the part of established firm they are a window into novel emerging technologies and on the part of the entrepreneurial firm a gateway to important resources to fuel their innovation processes (Dushnitsky, 2012). The practice has seen extraordinary growth over the past decade. From 2011 to 2016 the number of established firms making venture capital investments globally has more than tripled, with a significant proportion of these new investors being from non-tech sectors like consumer goods, retail, oil and gas, and automotive (Wu, 2016).

Much of the research on this phenomenon has examined the drivers and implications of these relationships from the perspective of the firms making the investments, i.e. the established firm (Paik & Woo, 2017). Research examining these relationships from the perspective of the entrepreneurial firm has primarily been focused on antecedents, examining the conditions under which entrepreneurial firms can overcome appropriability concerns and enter into these relationships (Dushnitsky & Shaver, 2009; Katila, Rosenberger, & Eisenhardt, 2008).

More recently, scholars have begun to investigate the effect of CVC investment on startups' innovation outcomes. The results have however been equivocal. Alvarez-Garrido and Dushnitsky (2016) compare the effect of CVC investors to conventional VCs on entrepreneurial firms' rate of innovation in the biotech industry. They find that the effect of having CVC investment on the rate of innovation of startups is positive, arguing that these relationships allow startups to tap into valuable complementary assets. Kim and Park (2017) similarly report a positive relationship between CVC investment and the rate of patenting, though only if the startup receives CVC investment in the first three years of its life. On the other hand, Pahnke et al. (2015) find that the effect of having a CVC investor on the rate at which entrepreneurial firms innovate is either insignificant or negative. In explaining their results, these authors suggest that organizational complexity and internal conflicts within the established firm may be limiting entrepreneurs' access to the valuable resources that exist within these firms.

From the perspective of the startup, these studies have primarily focused on resource access, i.e. they broadly acknowledge that valuable resources exist in established firms but differ on whether or not startups can effectively access these resources. I will add to this research by identifying specifically what type of resources startups can benefit from in these relationships and how. In addition, I will demonstrate that these relationships can also expose startups to norms and mindsets that compel them in more conservative technological directions with respect to their subsequent inventions. Finally, I will show that each of these influences can vary depending on who in the established firm the startup gets access to and how those connections are made.

My empirical context is the life sciences. To build my arguments, I will draw on existing theory as well as qualitative information gained from a range of interviews I conducted with startup and investment personnel in this context. I interviewed founders/managers of startups that had received venture capital from incumbent firms, as well the employees of the these firms responsible for making and managing these investments. I also interviewed other individuals with a relevant perspective on the relationships between the firms such as established firm personnel not associated with the corporate venture capital division who have had interactions with portfolio companies and other independent venture capital investors who have co-invested with the corporate investors. I also spent time with scientists at a University affiliated biotechnology institute to understand the nature of the technical challenges in this domain (Eisenhardt & Graebner, 2007).

I will now develop my hypotheses relating to the central tension in these relationships for startups, the fact they can facilitate access to resources that support technological development while also enforcing some constraints on the novelty of the startups' technologies. The focus of this paper is on the factors that influence the exchanges that occur between the firms *after* they form a relationship. Some of these factors are likely to also play a role in the process of selection, i.e. the decision by the established firm and the startup to form the relationship. For instance, the limitations that prevail within established firms may also influence which startups they choose to invest in. I will discuss the separation of treatment and selection effects extensively in the methods section, and will employ a few different empirical approaches to deal with this issue. However, since the primary focus of this study is on the influences that arise after the relationship is formed, my theoretical arguments will be restricted to this part of the process.

## HYPOTHESES

### Novelty of technological discoveries

Managers are boundedly rational and must therefore rely on simplified representations of their environments to derive their strategic beliefs (Simon, 1955). As firms establish themselves and their business models, the mental models that prevail among its managers can harden around the practices that produced success, leading to 'core rigidities' that can limit the firm's ability to pursue new directions (Leonard-Barton, 1992). Furthermore, as these firms focus on gains in efficiency, the processes and incentive structures put in place can "trigger internal biases for certainty and predictable results", that can stunt the pursuit of new technologies and business models that deviate from the status quo (Benner & Tushman, 2003: 239). These limitations are an important driver of attempts by established firms in a widening range of industries to ‘externalize’ their innovation processes, i.e. pursue innovation outside the boundaries of the firm (Chesbrough, 2003, 2006). Making venture capital investments is an important part of this approach. The logic from the perspective of the established firm is that the ingrained limitations it faces to pursuing path breaking technologies are less likely to play a role when the innovation activity is separated from the main body of the organization.

Though these limitations are well studied in terms of how they shape the firms’ own strategic decisions with respect to technological innovation, there is very little research examining whether and how they affect the firms’ partners. It is unlikely that these limitations cease to become relevant once the innovative activity is situated outside the boundaries of this firm, given it still exercises some control over resource flows and decision making that guides this activity (Christensen & Bower, 1996). This is an especially pertinent issue from the perspective of the entrepreneurial firms that are tied to established firms. Indeed, the entrepreneurs I interviewed described this as the most significant challenge they faced in their dealings with incumbent firms. Encountering a deeply rooted resistance to deviations from the status quo in terms of technology, process or even strategy was a theme that arose with remarkable regularity across the different founders’ experiences with incumbent firms. For instance, one successful entrepreneur whose firm had received investment from the corporate venturing arm of a major pharma firm recounted that, though access to the resources within the incumbent firm was “*freely offered*”, the difficulty with dealing with such firms has more to do with the mindset of corporate executives, describing these as follows:

“*... the most important thing (for incumbent firm executives) was just to keep your head down, and not make anybody notice you. Sticking your neck out for anything was hard to get anyone in (the incumbent firm) to do …. What is the upside to that person? …. They could be wrong, what if (there is) a major issue… then you’re an idiot, and you get fired. Even if it is just* *a 5% chance you'll be wrong… why would I take that risk? ... As a result, you have these organizations that, by their very nature were unwilling to take risks, unwilling to try things...”*

Another entrepreneur, who raised capital from a different incumbent firm, but whose venture subsequently failed, described the underlying difference as one of culture, and in the attitudes towards risk that are embodied in the two firms:

*“They're just, in my opinion, trying to reconcile the irreconcilable, which is, the extremely risk-averse process of (incumbent firm) R&D with the inherently risky world of early stage (startups)… In that setting I am managing risk, they are eliminating risk… It is a culture thing…”*

Another founder, who was facing some serious challenges in relation to his firm's existing developmental pipeline, described his attempt at pursuing a novel new strategic direction to supplement the firm's existing efforts as being opposed by the firm's corporate investor. He describes the reaction of the investor as:

*“There was no listening… it was, ‘This is crazy, this is insane, there are all these complexities involved’…. (They) had this view of 'stick to your knitting'... And things that get outside the range of 'normal'? (shakes head) …”*

I make the argument that the ingrained resistance to path breaking changes that pervades established organizations can influence the innovative efforts of entrepreneurial firms they invest in and make them more conformist to the prevailing technological trajectories. The diffusion of norms and perceptions across organizational boundaries can occur when firms engage with each other. Specifically, we know that larger, more successful organizations tend to exercise an outsize influence on the smaller firms they come in contact with (Guler et al., 2002; Haunschild, 1993). In the context of CVC investments, startups are likely to be significantly imprinted by the perceptions prevailing among the established firm's managers given the legitimacy arising from the latter firm's size and longevity. Furthermore, there is an important dynamic of resource dependence operating between the firms that is likely to enhance the influence of the established firm on the startup (Perrow, 1986). The most common routes by which entrepreneurs achieve a profitable outcome is through the listing of their firm on the public markets (IPO) or if their firm is acquired. The latter route is significantly more common than the former in most industries, and the acquirers in these cases generally belong to the same set of incumbent firms that engage in making CVC investments (NVCA, 2017). Hence, the corporate investor, in addition to being a gateway to valuable resources, also represents a potential buyer. Consequently, entrepreneurs are likely to take careful cognizance of the preferences expressed by managers in these firms, as these could also be at play when this company is evaluating an acquisition candidate. Even if the entrepreneur does not countenance the possibility of being acquired by the investing incumbent firm, they may perceive the views of managers within these firms as being representative of those in the industry more broadly, a possibility that the entrepreneurs I interviewed were conscious of, as the quote below from one of them illustrates:

*"They (incumbent firm personnel) can give you more clarity on what choices you can make as a small biotech that would make you either more or less attractive as an acquisition candidate... you have insight on what parameters you can pull and play with.*"

Even if the entrepreneurs themselves are not swayed by these considerations, the other investors in the firm also stand to profit from an acquisition. Consequently, if a manager from an established firm expresses certain preferences or views about a technology (say, during a board meeting), the other investors in the startups are likely to use their influence over the entrepreneurs to move them in a direction that conforms to these preferences. Startups that raise capital solely from independent (i.e. non-corporate) VCs face similar pressures with regards to exit. However, they are not exposed to the views and preferences of incumbent firm managers in the same way. This leads to my first hypothesis.

*Hypothesis 1: Entrepreneurial firms receiving investment from incumbent firms will produce fewer technologically path-breaking inventions than comparable others who do not receive this type of investment.*

**From Discovery to Development - Crossing the 'Valley of Death'**

Incumbent firms in an industry generally control a wide variety of resources that could potentially be of use to startups. We have a relatively imprecise understanding of which of these resources can in practice be effectively leveraged by entrepreneurial firms through these relationships or indeed in what ways they help with the latter's innovation processes. The experiences of the entrepreneurial firms I studied qualitatively suggested that the primary resource of value they accessed through their relationships with incumbent firms is experiential knowledge of how to turn a technological invention or scientific discovery into a commercially oriented product or application prototype. Scholars have stressed that the steps that follow invention are also central to innovation, and deserve more attention (Kapoor & Klueter 2015). I will briefly review some of the existing research on this topic to identify the challenges startups face at this stage, and examine why access to the expertise of established firms may be particularly valuable in dealing with those challenges.

The transformation of an invention, i.e. a technological or scientific discovery, into a product or application prototype for development is an important, yet often overlooked step in the innovation process. Morton (1965) describes it as the transformation of 'Physics to function'. This step consists of adapting a technology to a particular product or process environment, and it bridges the gap between research and development. Iansiti and West (1999) demonstrate the critical role this step plays in determining the firms' success in a number of high technology areas. They also show that the challenges associated with transforming high quality research into high quality products or processes can be subtle and difficult (Iansiti, 1995). This step often necessitates the confluence of different types of knowledge and expertise, including expertise of the technology itself but also of the market and the norms of the industry (Kapoor & Klueter, 2015).

In the life-sciences this step is referred to as the '*Valley of Death*' due to the proportion of inventions that fail to make it past this stage. Dessain & Fishman (2017: 5) describe this step as follows, "… the beginning of the VoD (is) the moment a provisional patent is filed for a discovery… and the end (is) when the intellectual property identified in that patent has become a realized invention, an animal-tested molecule that can be submitted to the US Food and Drug Administration (FDA) for approval of testing in humans. At that point, money is much easier to come by and the technology will live or die on the basis of its merits”.

Transforming a discovery/molecule into a potential treatment for a specific condition requires bringing together a wide array of expertise on different technologies as well on formulation, dosage, regulations etc. Large amounts of data need to be collected on in-vitro and animal models to demonstrate the safety of the drug as well as to examine its mechanisms of action. A plan and process need to be put in place to manufacture batch quantities of the drug. Typically, the compound is administered in conjunction with other treatments which necessitates expertise with a wider span of therapeutic agents and their interactions. Furthermore, knowledge of prior efforts at drug development in the same space is crucial since regulatory authorities often use these as precedent to guide their response to applications (Burns, 2012; Dessain & Fishman, 2017).

This step is likely to be a particularly important one for startups. Transforming their technology into a prototype product or application can serve as a signal of validation to potential customers, investors and acquirers (Hsu & Ziedonis, 2013). And as one founder noted, failure at this stage can be very costly:

*“During the early stages, you can only afford so many of those mistakes if you are a small company, the confidence in your program gets reduced each time you fail.”*

The demands associated with this step are distinct from those of the technological invention/discovery stage in that they are not primarily based on creativity or big breakthrough ideas. At this stage, experiential knowledge becomes particularly valuable, since many of the challenges faced are likely to have been encountered in similar forms by others in the past. Having access to this type of knowledge can be critical, since it allows these firms to solve problems efficiently in terms of capital and time.

Established firms in high technology industries typically have wide-ranging experience in managing this step (Iansiti & West, 1997). These firms have extensive research labs and large product pipelines meaning that the routines associated with driving discoveries into the development stage are likely to be well developed. I argue that having an established firm as an investor can prove to be particularly valuable at this stage in making up the shortfalls for the entrepreneurial firm. This point came through very distinctly in my interviews. For instance, the managing partner at a venture capital firm focused on the life sciences who had co-invested with corporate VCs in stressed this benefit, suggesting:

*"(The corporate investors) know a lot about development and what is going on, and can share a lot about the trends or lessons learned and what the FDA is now saying or whatever. That is really valuable…. It is not very innovative, it is really (about) experience …"*

Expertise at this step is also likely to be a major differentiator between corporate and independent venture capitalists. Though the partners in independent venture capital firms may have some operating experience, they are unlikely to have the spread of knowledge and expertise across different domains that is often called on in taking the step from research to development. As a corporate VC partner I interviewed pointed out:

*"If they run into technical problems, we can give them practical information like... when we ran into this problem, this clinical research organization or this entity, they were helping us out, why don't you call them… whereas the financial VC is more like, we ran into a problem, now can we find another person to join the company to fix this..."*

Entrepreneurial firms who do not have access to this type of resource typically hire external consultants to supply expertise in areas where they are internally lacking. However, there are some limitations to this approach. Typically, the problems firms encounter at this stage are highly specific technical issues, for instance in the life sciences it may be an adverse reaction to a particular bodily enzyme that raises the toxicity of the drug. Hence the expertise required is also highly specific and limited to the particular problem at hand. There is likely to be significant cost associated with identifying an external consultant with expertise pertaining to that particular topic, and then defining a contract with them specific to solving that problem. Furthermore, it is also unlikely that the same consultant will have the expertise to deal with multiple such problems which means that the startup then has to repeat this costly process for each issue it encounters. Established firms typically retain a lot of this expertise in-house, and being able to substitute the organizational mechanisms within these firms for the market based mechanisms of hiring external consultants can lower these search and contracting costs for entrepreneurs (Dyer & Singh, 1998; Williamson, 1985). Hence, I argue that entrepreneurial firms with corporate investors are likely to display a greater propensity to drive their discoveries into development than firms who are funded by other types of investors.

*Hypothesis 2: Entrepreneurial firms receiving investment from incumbent firms will drive more discoveries into development than comparable others who do not receive this type of investment.*

The previous two hypotheses lay out what I believe to be a central tension in these relationships for startups – on the one hand they facilitate access to valuable resources and on the other they expose startups to norms that can constrain the novelty of the technological directions they pursue. While these are the patterns that I expect to see on average, the way these influences play out in a particular relationship can also depend on the nature of the interactions underlying that relationship. Given the size and complexity of the typical established firm that engages in CVC investing, there can be substantial variation in the type of access that startups get to these firms, i.e. who they interact with and how effective those interactions are. These are issues that research on interfirm relationships has largely abstracted away from. I will explore how variations in the interactions underlying these relationships can importantly influence the patterns described in the previous two hypotheses.

**Scientists vs Suits**

The first hypothesis was based on the argument that on average, CVC relationships will tend to suppress entrepreneurial firms' propensities to pursue technologically path breaking inventions. However, this influence could vary depending on who in the established firm the entrepreneurs interact with. Specifically, I distinguish between interactions with two types of incumbent firm personnel – those whose responsibilities are principally *technology* focused, like scientists or technologists, and those whose responsibilities are principally *market* focused, like corporate executives. Scholars have frequently highlighted the distinctions between these two classes of personnel within high technology firms, particularly that the resistance within these firms to path breaking technological shifts can vary significantly across different parts of the firm (e.g. Burgelman, 1991; Gavetti, Henderson, & Giorgi, 2003; Tripsas & Gavetti, 2000).

The mental models of managers in these different roles are developed under distinct incentive structures and institutional environments. Scientists and technologists are to a greater degree members of knowledge communities that go beyond their firm's boundaries. They often publish research in academic journals and attend conferences to present research and engage with their peers (Henderson & Cockburn, 1994). Consequently, their status within their institutional field is likely to be derived more from being associated with significant technological or scientific advancements than their firm's share price or sales figures. An entrepreneurial firm which interacts directly with these individuals is therefore more likely to receive feedback that pushes them in directions that are most interesting from a technological standpoint.

On the contrary, corporate executives are likely to operate in environments where market related imperatives are likely to be much more pronounced. Specifically, they are more likely to fall prey to Christensen's (1997) patterns of resource dependence, being most concerned with the existence of a market for technologies. An overwhelming focus on meeting the needs of present customers can be a significant impediment to the pursuit of radical technological innovation. Research also shows that these executives are particularly likely to be affected by 'competency traps', making them most resistant to deviating from formulas that were successful in the past (Finkelstein, 1992; Greve, 1998; Miller & Chen, 1994). Furthermore, the emphasis on quarterly reporting and demonstrating growth are likely to reinforce a more short-term view, which in relation to technology makes them less inclined to be favorably disposed towards projects where the market isn't immediately visible (Benner & Tushman, 2003). Hence, I argue that entrepreneurial firms that have heightened access to these individuals are likely to be pushed in technological directions that conform more closely to the status quo.

*Hypothesis 3a: Conditional on CVC investment, entrepreneurial firms with greater access to the established firm's corporate executives will produce fewer technologically path-breaking inventions than those without this type of access.*

*Hypothesis 3b: Conditional on CVC investment, entrepreneurial firms with greater access to the established firm's scientists/technologists will produce more technologically path-breaking inventions than those without this type of access*

From the perspective of transforming technologies into product prototypes, the distinction between these two types of personnel is less clear. The challenges associated with this step may be related to a range of different types of expertise including science, regulations, sourcing, manufacturing etc. This expertise may be located anywhere within the organization, hence access to corporate executives may be valuable in this respect, as may access to scientists. Note that the baseline I am comparing these against is a situation in which the startup does not have access to either of these parts of the organization, which prior research has suggested may often be the case (Pahnke et al., 2015). Hence on average, we would expect that improved access to either of these parts of the larger organization should be helpful to the startup in obtaining access to expertise that helps them adapt their technologies to a product or process environment. Hence,

*Hypothesis 4a: Conditional on CVC investment, entrepreneurial firms with greater access to the established firm's corporate executives will drive more discoveries into development than those without this type of access.*

*Hypothesis 4b: Conditional on CVC investment, entrepreneurial firms with greater access to the established firm's scientists/technologists will drive more discoveries into development than those without this type of access*

**The Role of Boundary Spanners**

Established firms typically have a specific group of employees tasked with making and managing their venture capital investments. These individuals often form a separate division within the company, though in some cases they may be senior managerial personnel within the companies' business development or other divisions. They are the primary points of contact between the two firms, and can play a central role in making connections for the entrepreneurs within the incumbent firm (Dushnitsky & Shapira, 2010; Lerner, 2013). They typically also become members or observers of the startup's board making them the main channel by which the established firm can influence the strategic decision of the startup. While there is some research suggesting that boundary spanners can play an important role in shaping knowledge flows in interfirm relationships, this remains a topic that has not received a great deal of attention from organizational scholars (Gatignon, 2017; Lumineau & Oliveira, 2018; Perrone, Zaheer, & McEvily, 2003).

My arguments in relation to H1 were based on the relatively well-established idea that a focus on incremental and short-term gains within established firms can engender cognitive frameworks among the managers in these firms that make them less favorably disposed to technologies or business models that are radical or path breaking (Benner & Tushman, 2003; Eggers & Kaplan, 2013). Research examining the processes by which managers are institutionalized into these ways of thinking suggests that one of the most important determinants of the extent of this imprinting is the tenure or duration of time managers have spent within these organizations. A manager who has spent many years in an organization is likelier to embody the cognitive frameworks that pervade within it than a relatively new recruit (Higgins, 2005; Marquis & Tilcsik, 2013).

I argue that the extent to which startups are pushed in conservative technological directions by these relationships will depend on the extent to which the individuals acting on behalf of the established firm embody the norms of technological conservatism that pervade these organizations. In the context of CVC investments, the investment managers that play the role of boundary spanners may be individuals who have moved laterally into these positions from within the organization or individuals who have been externally recruited for the purpose of making and managing these investments (Dushnitsky & Shapira, 2010). This is likely to be a significant distinction in terms of the type of influence these individuals have on the technological choices of the startup. I will examine how the tenure of these individuals within the established firm, i.e. the number of years they have spent in the firm prior to taking up their CVC roles moderates the influence of these relationships on the novelty of the startups' inventions. I argue that individuals who have spent longer periods within the established firm prior to taking up CVC roles are more likely to push startups in technological directions that conform more closely to the status quo. Their tenures within the established firm in other roles mean that they are more likely to embody the limiting cognitive frameworks that pervade these organizations. These limitations are likely to be reflected in the way these individuals evaluate technological choices, especially at the early stages given the high levels of uncertainty. Consequently, they are more likely to provide input that moves the startups under their influence in more conservative technological directions. Hence,

*Hypothesis 5: Conditional on CVC investment, entrepreneurial firms will produce fewer technologically path-breaking inventions, the longer the tenure of their investment managers in the incumbent organization in non-CVC roles.*

As discussed in relation to H2, overcoming the challenges associated with driving a technological discovery into development often relies on deep technical and contextual knowledge. Focused consultations with experts in the appropriate area or personnel with prior experience specific to the problem are most likely to add value to startups in these situations. There are however two challenges associated with accessing this type of expertise for startups, (i) identifying the appropriate persons within the incumbent firm with the expertise to be able to help them solve the specific challenge they are facing and (ii) persuading these persons to commit some of their time and energy towards helping the startup.

The first of these steps can be tricky given the size and complexity of the established organizations that make these investments. As previously mentioned, the number of different divisions, functions and levels mean there is likely to be a great deal of heterogeneity in the types of knowledge and expertise that exists within these firms. Consequently, it can be a nontrivial task to pinpoint the appropriate source of expertise in relation to a particular issue (Singh, Hansen, & Podolny, 2010). The second step can be difficult, given that helping portfolio startups is typically not a part of the job description of these experts within incumbent firms. They normally have full time responsibilities within the company which have nothing to do with the corporate venturing arm. Consequently, there is no strong incentive compelling them to spend any time thinking about the problems faced by these entrepreneurial firms.

My interviews suggest that investment managers can play a pivotal role in determining how effectively entrepreneurial firms are able to overcome these challenges. In this context, having investment managers with strong and extensive networks within the incumbent organization can help with both of the aforementioned challenges. These networks can be helpful in locating the appropriate source of expertise for a particular problem the entrepreneurial firm is facing (Borgatti & Cross, 2003). Also, we know from prior research that cohesive networks can be an important source of social capital (Coleman, 1988; Uzzi, 1997). Investment managers who possess greater social capital are more likely to be able to persuade experts within these firms to dedicate their time and energy towards helping the entrepreneurial firm overcome a particular problem. This can become particularly valuable in the absence of a strong monetary incentive (Granovetter, 1985). This point was noted by an entrepreneur with experience as CEO of multiple companies that received CVC investment,

*"Usually you work with your investor representative to help you navigate the larger organization and based on cultural impact that they (the investor representatives) have had, those (incumbent firm) resources are willing to dedicate some time to you…but there is nothing from an incentives perspective compelling them to do so."*

I argue that the investment manager's prior tenure within the incumbent firm is likely to be closely related to both their knowledge of the organization and their social capital within it. Hence, their tenure should be an important determinant of their ability to facilitate access to the appropriate expertise for their portfolio startups. This is based on the reasoning that an investor who has had a prior career working in an operating role within the firm is likely to have a better understanding of the types of expertise available within the firm and where it is located, than an investor who joined the company to work in its investment arm. Similarly, the former is also likely to have a more extensive network of connections within the organization, and is consequently more likely to possess the social capital to forge connections that lead to more meaningful exchange for the startup. As the prior quote illustrates, the standing of these individuals within these organizations can be an important determinant of their ability to persuade their colleagues to take the time to assist the startup. Consequently,

*Hypothesis 6: Conditional on CVC investment, entrepreneurial firms will drive more discoveries into development, the longer the tenure of their investment managers in the incumbent organization in non-CVC roles.*

## METHODS

I tested these hypotheses using data on US based entrepreneurial firms in the life sciences that raised venture capital funding over the ten year period between 2001 and 2010. I employed a number of commercially available data sources as well as hand collecting data for some of my variables. I obtained venture capital data from the *Venture Xpert* database, which is among the most commonly used sources of data on investments. Kaplan and Lerner (2016) report that it has the widest coverage of funding events of any commercially available venture capital database. To characterize firms' innovation, I employed data from the Informa *Pharmaprojects* database which provides detailed tracking of drug candidates from the commencement of pre-clinical trials to the completion of phase 3, failure or withdrawal. A range of studies in management have employed this data source to construct variables relating to clinical trials (Kapoor & Klueter, 2015; Sosa, 2013). I also employed patent data from the USPTO's *patentsview* database. This is a new database that has the advantage of being directly populated and updated by the USPTO. I obtained information on the locations of established firms' facilities from annual reports, websites and inventor locations from their patents. I hand collected information on the investment managers of each established firm from a range of sources - I identified the names of the individuals in charge of investments for each company using the *Greyhouse venture capital directories,* the *Galante venture capital and private equity directories*, archived versions of company webpages on the internet archive, company SEC filings and historic company press releases. Subsequently, I collected information on the career histories of each of these individuals through manual searches on *Linkedin*, supplemented by information from *Bloomberg* and archived webpages. I obtained information on the acquisitions and IPOs of startups from *SDC Platinum* and *Informa Medtrack* databases.

**Empirical Design - Instrumental Variable Estimation in Matched Sample**

The formation of relationships between established firms and startups is the result of a complex two-sided matching process, i.e. they are not randomly assigned. The startups that receive investment from a particular established firm may therefore be distinct from others in systematic ways that also affect their innovation outcomes. This restricts my ability to make strong causal claims in this study. I will however attempt to limit the biases caused by selection issues through my empirical design, and will subsequently carry out a number of tests to probe alternative explanations for the results that I find. I first compile a sample of startups that are closely matched on observables and then employ an instrumental variable to predict 'treatment' within this matched sample.

**Matching**

To compile my sample, I started by identifying every investment made by an established firm in a biotech startup based in the United States between 2001 and 2011. Following prior literature, I did not include investments made by firms that have no strategic connection to the life sciences such as financial institutions (Dushnitsky & Lenox, 2006). The majority of the CVC investors in my sample are large pharmaceutical companies. This initial sample consists 71 established firms who made investments in 272 startups. Note that I only included the initial investment by an investor in a startup in this sample, i.e. I did not include follow-on rounds by the same investor in the same startup (Dushnitsky & Shaver, 2009). Then, for each of these investments, I identified a plausible set of 'counterfactuals', i.e. a set of alternative investments that may have been made by that investor. In doing so I accounted for characteristics that are considered by the investor in making their choice (Pahnke et al., 2015) and used Coarsened Exact Matching (CEM) to identify the relevant counterfactuals for each treatment (Iacus, King, Porro, & Katz, 2012).

For each investment by an established firm in a startup (i.e. a 'treatment'), I identified other startups that raised venture capital from conventional (non-corporate) VCs (i.e. 'controls') that matched these 'treated' startups on five important bases. First, I require that the control startups raised capital *within a year* of the treated one, i.e. in the same year, the previous year or the following year. Second, the control startups must be in the same location (Metropolitan Statistical Area) as the treated startup. The matching of firms by location is particularly significant since this limits the potential for locational advantages such as co-location with a university to bias the results. Third, the control startups must be in the same biotechnology sub-category as the treated startup as classified by the venture xpert database (e.g. therapeutics, diagnostics etc.). I then match startups on the level of development of their technologies based on two variables. First, the total number of 'novel' patents filed by the startup as of the focal year, where a novel patent is one which embodies a combination of subclasses that have never previously appeared together in a patent (Fleming, 2001; Funk, 2014). Secondly, the total number of drugs the startup has put into clinical trials as of the focal year. I choose these two variables intentionally to correspond to the pre-treatment values of my two outcomes of interest. Since I am examining how the 'treatment' affects the startups' ability to subsequently make novel inventions and to drive drugs into trial, it is important that the treated and control startups match each other as closely as possible ex-ante on these variables. I categorize the startups into seven coarsened 'bins' on each of these variables in line with the CEM procedure and require that startups match on these. The seven bins are 0, 1-3, 4-6, 7-10, 11-20, 21-50, and greater than

50. The matching procedure leaves me with a sample of 217 treated startups that raised capital from 63 incumbent firms matched to 568 control startups. In addition, I also control for other important variables such as the total number of patents filed and the age of the company as of the year of investment. I don't include these in the matching procedure to limit further loss of observations. I also check the robustness of my results to a range of deviations in the matching criteria.

**Instrumental Variable**

To instrument for 'treatment' within this matched sample, I need a source of variation in the formation of these relationships that is not also related to the subsequent innovation performance of the startup. For this, I will draw on variations in the amount of capital available to the established firm for new investments at different points in time. The logic here is that, all else being equal, a corporate investor is more likely to invest in a startup at a time when it is flush with capital than when it has more limited means. If the source of this variation in capital availability is not related to the subsequent innovativeness of the startup through any other channel (other than whether or not it receives investment from this firm), the instrument would satisfy the exclusion restriction.

The funds that are invested by corporate venturing divisions/arms are allocated by their parent companies (Dushnitsky, 2012). These funds are therefore subject to the budgetary processes that typify a large corporation in that they are generally based on requests and allocation on an annual basis. This is an important distinction between these firms and conventional venture capital firms, in that the latter operate via a 'fund' that is made up of capital from limited partners which typically have a lifespan of ten years (Gompers & Lerner, 2004). This distinction is critical in light of the fact that venture capital investments are typically of two types – first time investments and follow-on investments. Startups typically raise venture capital in stages (e.g. Seed, Series A, Series B etc.). A follow-on investment is when a startup raises capital from one of its existing investors, i.e. a firm which has already invested capital in the startup in a previous round. From the investor's perspective, follow-on investments are important for two reasons. First, it allows the investor to maintain their proportion of equity ownership in the startup. Failing to make these investments would result in this proportion being diluted which would mean that the financial rewards they would realize in the event of a successful exit would be similarly reduced (Kaplan and Stromberg 2003). Secondly, there is a strong social norm among venture capital investors that they continue to back the startups they invest in. This social contract is not just between the investor and the startup but between the different investors who are jointly backing the startup. Violation of these norms can be costly for the investor in terms of subsequent investment opportunities (see Zhelyazkov & Gulati, 2016 for a detailed discussion on these norms).

Conventional VC firms typically plan in advance for follow-on rounds by maintaining what is commonly referred to in the industry as 'dry-powder', i.e. capital in reserve for follow-on investments in the startups they have already invested in. Managing this process is trickier for corporate investors due to the more annualized norms of the budgetary process in the companies which provide their capital. Consequently, their ability to reserve capital for investment in future years is more limited, and the amount of capital available to a corporate VC to make a 'new' (i.e. first-time) investment in a startup is likely to be inversely proportional to the number of startups in its existing portfolio who are raising capital in that year. All else being equal, a startup is more likely to be able to raise capital from a particular corporate investor in a particular year if *fewer* of the latter's pre-existing portfolio companies are raising follow-on rounds in the same year. This, i.e. the number of existing portfolio companies raising capital in the focal year will be my instrumental variable. While it should have predictive power over whether or not a startup receives investment from that firm in that year, it should not through any other channel affect the subsequent innovativeness of the startup.

**Estimation**

Each row in my data represents an established firm – startup dyad. The 'treated' rows represent actual investments made by established firms in startups, whereas the 'control' rows represent the counterfactual investments constructed based on the matching procedure described above. I use dummy variables to restrict comparisons to within these matched sets of observations. In the use of the instrumental variable, the 'treatment' I am predicting in the first stage is binary, making it likely that the underlying CEF is non-linear and indicating the use of a probit or logit model (Wooldridge, 2010). However, using the predicted values from a non-linear first stage in a linear second stage leads to biased estimates (this is known as the forbidden regression) (Hausman, 1975). I employ two different approaches that avoid this problem. First, I follow the approach recommended by Angrist and Pischke (2008: 191), who suggest, "Instead of plugging in nonlinear fitted values (in the second stage), we can use the nonlinear fitted values as instruments. In other words use (the nonlinear fitted values) as an instrument for (the binary treatment indicator) in a conventional 2sls procedure… if the nonlinear model gives a better approximation to the first stage CEF than the linear model, the resulting 2sls estimates will be more efficient than those using a linear first stage." In accordance with this, I run a probit model to predict 'treatment', i.e. CVC investment which includes the instrument as well as all the other covariates and the matching dummies. I then obtain the fitted values from this model which I use to instrument for treatment in a conventional 2SLS model.

As an alternative to this, I also used the estimation approach commonly referred to as a 'treatment effects' model or an 'endogenous binary variable' model, which is essentially an analog of the Heckman model for sample selection applied to the issue of endogenous selection into treatment (Heckman, 1978; Shaver, 1998). This approach is commonly employed when the outcome associated with a self-selected (dichotomous) treatment decision needs to be modeled (Clougherty, Duso, & Muck, 2016; Mulotte, Dussauge, & Mitchell, 2013). A probit model is used to estimate treatment which includes the exogenous instrument as a predictor, and a correction based on this model is applied to the second stage which estimates the effect of treatment on the outcomes of interest (see Cameron & Trivedi, 2005 sec 25.3.4; Wooldridge, 2010 sec 21.4.1). I used the 'etregress' (formerly treatreg) function in Stata 15 to carry out this estimation.

**Dependent Variables**

To capture the technological novelty of an entrepreneurial firm's inventions, I employed a measure based on combinations of patent subclasses that has been used in prior research (Fleming, 2007; Funk, 2014; Strumsky & Lobo, 2015). The USPTO classification system relies on a combination of main classes and subclasses to characterize patent technologies. At the subclass level, there are over 100,000 choices available and most patents are classified into multiple subclasses. The measure I employed characterizes a patent as being 'novel' if it embodies a combination of subclasses that has never been used before. This characterization of novelty is consistent with ideas of innovation being a process of discovering distinct ways to recombine knowledge (Fleming, 2001). Furthermore, it conforms well to the questions at hand in this study since it is an ex-ante characterization of technological novelty. This contrasts with citation based characterizations which capture how a particular invention was received and used by its audience which is indicative more of knowledge flows than technology. My dependent variable is the log of 1 + the count of the number of patent applications filed by a firm that embody a unique combination of subclasses, i.e. a count of *novel patents*, in the 5 years following the year of investment.

To characterize the entrepreneurial firm's propensity to drive discoveries into development, I used a count of the number of *new drugs* in development, i.e. the number of new drugs belonging to the entrepreneurial firm that enter phase 1 of clinical trials. Converting technological discoveries into products for development is among the most challenging steps of the innovation process in the life sciences, with a low success rate. Particularly for entrepreneurial firms, this step represents a major milestone as it alleviates much of the uncertainty surrounding their technology (Rothaermel & Deeds, 2004). This is a measure that has been used in some prior studies pertaining to this industry (e.g. Hess & Rothaermel, 2011; Kapoor & Klueter, 2015). Since this measure is highly skewed, I take the log of 1 + the number of new drugs that enter the development stage in the 5 years following the year of investment as my dependent variable.

## Independent Variables

*CVC Investment*

The principal independent variable of interest is *CVC Investment* which is a binary variable representing whether the startup received venture capital investment from the incumbent firm in the focal year. To instrument for this variable, I used a count of the *follow-on rounds* of capital raised in the focal year by biotech startups that are already part of the established firm's portfolio. The higher this value, the smaller the amount of capital available to the established firm for new investments and consequently the lower the likelihood that the startup will receive investment from this firm.

*Interactions with Scientists vs Corporate Executives*

To examine hypotheses 3 and 4, I need to determine which parts of the established firm the entrepreneurial firm is interacting with. Since observing these interactions directly is difficult, I need to obtain a proxy based on some characteristics that can be measured. I draw on the fact that locational overlap with a particular division of the incumbent firm is likely to be correlated with elevated levels of interaction with the personnel in that division for the startup. I characterize interactions with scientists/technologists to be more likely to occur if the entrepreneurial firm is co-located with an R&D site of the established firm, and interactions with corporate executives to be more likely to occur if it is co-located with the established firm's headquarters. Based on the way large pharmaceutical firms are typically organized, the more market oriented functions and senior corporate executives are likely to be located at headquarters whereas technology focused personnel are primarily located at R&D sites (Alcacer & Delgado, 2016). Note that I am not claiming that these interactions will always occur corresponding to co-location, just that co-location of each type makes the corresponding type of interaction more likely to occur. So on average, an entrepreneurial firm that is located in the same city as its CVC investor's headquarters is more likely to have interactions with the latter's corporate executives than a firm that is located elsewhere. Furthermore, the fact that my matching approach requires that matched treated and control firms be in the same location limits some of the confounding factors that could cause a bias. For instance, my results are unlikely to be biased by agglomeration or spillover effects associated with any particular location since both treated and control firms will be equally subject to these influences.

I collected information on the headquarters locations of each of the established firms in my sample. I then coded *HQ overlap* as 1 if the entrepreneurial firm is located in the same MSA as the established firm's headquarters in the five years following investment, and 0 otherwise. To obtain information on the location of R&D sites, I used the inventor locations from the firm's patents. For each year, I identified the location (MSA) of the inventors listed on the firm's patents. Arranging them in descending order of frequency I manually verified if these locations correspond to the firm's largest R&D centers for a number of the established firms in my sample and find this to be the case. Furthermore, I dropped all locations that do not have at least 5 percent of the firm's inventors in it, as these are unlikely to be sites operated by the company directly. In this way, I identified all the locations in which a company has an R&D site for each of the years of interest. I then compared the location of the entrepreneurial firm with the locations of the established firm's R&D sites in the five years following the investment and coded *R&D overlap* as 1 if the entrepreneurial firm was located in the same MSA as one of the established firm's R&D sites, and 0 otherwise.

*Pre-CVC Tenure*

To test hypotheses 5 and 6, I need information on the *pre-CVC tenure* of the firm's investment personnel. This variable necessitates information on the names of the individuals managing CVC investments for each firm in each year, and subsequently for each of these individuals I need information on their career histories including their different roles within the company. To carry out the first step I used various venture capital directories from previous years (*Galante* and *Greyhouse*), press releases and SEC filings by the firm, archived webpages of the firm' websites as well as targeted linkedin searches. Using these sources, I obtained information on investors for the firms responsible for over 90% of the investments in my sample. Next, I obtained information on the year in which these individuals started their roles as CVC investors within these companies, the year in which they ceased to be in these roles and the year in which they joined the company in any capacity. For this, my primary source of information was linkedin, supplemented by information from Bloomberg, press releases and company websites (both present and archived versions). Using this data, I calculated the number of years the individual was with the company before they started their role as a CVC investor. For each firm in each year, I take the average of this measure across all its investors who were active at that point in time which I label *pre-CVC tenure*.

I also include a number of control variables that could be related both to CVC investment as well as the entrepreneurial firm's innovation outcomes. I include a count of total patents accrued by the firm in the 5 years following the investment (*patent count*), as this is also a factor that could be correlated with CVC investment, in addition to being related to the number of novel patents the firm develops or the number of drugs it places into clinical trials. I include a count of the total number of patents the startup has filed as of the year of investment (*pre-investment patents*). This is an indicator of the firm's technological capabilities which could be related to the likelihood that the firm will receive investment from an established firm as well as its ability to innovate. I also include *pre-investment novel patents* and *pre-investment drugs in trial* as controls. I control for the age of the startup (*firm age)*, since this may be correlated to the level of the startup's development which could affect both investment and innovation outcomes. I control for whether the startup is acquired in the five years following investment. To the extent that CVC investment helps with this outcome, there may be a correlation between this variable and the treatment indicator. Furthermore, it could also influence the innovation outcomes of interest. Startups typically make extensive use of external alliances to support research as well as commercialization in this industry. If a startup is particularly attractive as a partner it may also be more likely to receive CVC investment. Also, more partnerships may enhance the ability of the startup to innovate. To account for this, I control for the number of such alliances the startup enters in the five years prior to investment (*Pre-investment Alliances*) as well as in the five years following investment (*Post-investment Alliances*). Another factor that could be related to whether the startup receives investment from the focal established firm is the technological distance between the two firms. This distance could also be related to the type of interactions between the two firms following investment, including how the established firm influences the startup's innovation activities. To account for this I control for the technological distance between the two firms in the five years leading upto investment (*pre-investment tech distance*) as well as in the five years following investment (*post-investment tech distance*). I measure technological distance as the Euclidean distance between the vectors indicating the proportion of each of the two firms' patents in each technological class, for the patents filed in the relevant period (Vasudeva, Zaheer, & Hernandez, 2013). Finally, the extent to which the established firm can influence the startup may be affected by the number of other VCs who also invest in the same period. Hence, I control for the *number of investors* who invest in the startup in the focal year.

## RESULTS

Table 1 shows the summary statistics and correlations. Each observation in the sample represents an investment, with the 'treated' rows being realized CVC investments and the matched 'control' rows being counterfactuals. I implement the matching design in my estimation models by including dummy variables for each of the matched 'strata' of observations obtained from the CEM procedure previously described. The mean number of 'path-breaking' patents filed by startups in the five years following investment is around 0.8, whereas the mean number of drugs that startups push into phase 1 of clinical trials over the same period is 0.5. These low numbers are in line with our understanding that both of these are difficult outcomes to achieve.

INSERT TABLES 1 and 2 HERE

Table 2 shows the models examining the effect of CVC investment on the technological novelty of the startup's inventions. The dependent variable in these models is a logged count of the number of novel patents filed by the startup in the five years following investment. Model 1 examines the relationship between CVC investment and this variable with all the controls included and with comparisons restricted to within the matched sets of startups. We see a negative and significant relationship between *CVC Investment* and the number of novel patents which provides support for hypothesis 1. The magnitude of this effect (from model 2) suggests that treatment corresponds to an approximately 30% decline in the dependent variable, holding all the other variables at their means. Models 3, 4 and 5 estimate this relationship using the instrumental variable *Follow on Rounds Raised* to predict treatment. Model 2 is a probit model in which we predict *CVC investment* using all the covariates as well as this instrument. As anticipated, we find a significant negative relationship between the instrument, i.e. the number of follow-on rounds raise by the other startups in the established firm's portfolio and *CVC investment*. We then use the fitted values from this probit model as the instrument in a conventional two stage least squares estimation which is shown in models 3 and 4 (Angrist and Pischke, 2008; see previous section for a full description of the rationale driving this estimation approach). The F value of the excluded instrument is 66, well below the commonly used threshold of 10, suggesting that the instrument is a good predictor of treatment (Stock & Yogo, 2002). Model 4 shows the second stage, and we find again that there is a negative and significant relationship between CVC investment and the number of novel patents the startup produces. Model 5 is the endogenous binary variable estimator (the 'treatment effects' model) which employs the correction for selection into treatment based on the first stage probit analogous to a Heckman model. Once more we see that the relationships between CVC Investment and Novel Patents is negative and significant. In combination, these results lend support to hypothesis 1.

INSERT TABLE 3 HERE

Table 3 shows the results pertaining to new drugs that enter the development stage. The dependent variable in these models is a logged count of the number of drugs that enter phase 1 of clinical trials in the five years following investment. All the models include dummy variables restricting comparisons to within matched sets of startups. Model 6 examines the relationship between *CVC Investment* and this variable. We find a positive and significant relationship, as anticipated in hypothesis 2. The effect size (from model 6) corresponds to an average increase in the dependent variable of about 58% corresponding to treatment. Given the very low number of drugs that startups on average are able to put into phase 1 of trials (mean of 0.5), and the value associated with making this leap, this effect is economically quite significant. Similar to the previous table, we also estimate this effect using the number of follow-on rounds raised by other portfolio startups as an instrument. Model 7 is the probit model predicting treatment (which is identical to model 2), and models 8 and 9 show the 2SLS estimates. Model 9 shows that the instrumental variable estimates also reveal a positive and significant relationship between CVC investment and the number of drugs the startup gets into development. The estimates from the treatment effects model is shown in model 10 and in this case again we see a positive and significant coefficient on the *CVC Investment* variable, thus we have strong support for hypothesis 2.

INSERT TABLE 4 AND FIGURE 2 HERE

Next, I consider hypotheses 3 and 4, which argued that the influence a CVC relationship has on the startup is significantly altered by which part of the established firm this relationship is with. To test this hypothesis, I interact the 'treatment' variable, i.e. CVC investment with dummy variables indicating whether the entrepreneurial firm is co-located with the established firm's headquarters (*HQ overlap*) or one of its R&D centers (*R&D Overlap*). The results are shown in models 11 and 12 of table 4. Note that the direct effects of the overlap variables are collinear with the matched strata dummies since entrepreneurial firms within matched strata have the same location. The baseline against which each of these interactions effects must be interpreted is the startup having no locational overlap with either the established firm's headquarters or an R&D site. Model 11 shows the interaction effects in relation to the number of novel patents the startups files. We observe that there is a negative and significant estimate for the interaction of the treatment indicator and *HQ overlap*, whereas the coefficient associated with the interaction between the treatment indicator and *R&D overlap* is positive and significant. This would suggest that being co-located with the established firm's headquarters is associated with an amplification of the negative effect of CVC investment on the number of novel patents filed by the firm, whereas being co-located with an R&D site is associated with a significant alleviation of this negative effect, in line with hypotheses 3a and 3b. Furthermore, the magnitude of these effects would suggest that being collocated with HQ causes the negative effect to nearly triple in size, while being collocated with an R&D site roughly nullifies the effect. Figure 2 shows a visualization of these interaction effects.

Model 12 uses the number of new drugs the startup drives into development as the DV. Hypotheses 4a and 4b were that we should see positive effects on both these interaction terms. However, the estimates shown in model 12 suggest that both these estimates are statistically indistinguishable from zero. Hence hypotheses 4a and 4b are not supported. I will discuss the implications of these results in the next section.

INSERT TABLE 5 AND FIGURE 3 HERE

Models 13 and 14 of table 5 introduce the *Pre CVC Tenure* variable and pertain to hypotheses 5 and 6, which suggest that CVC relationships with established firms whose investors have greater prior experience in the firm in other roles limits the number of path-breaking inventions startups produce but that helps them drive more discoveries into development. Note that the size of the sample declines slightly in these modes. This is because I was unable to obtain data on the individual investors for all the established firms in the sample, meaning that some of the investments of in the original sample had to be dropped. I test the hypotheses by estimating the interaction effect of the CVC investment variable with a measure of *Pre CVC Tenure*, which is the average number of years the established firm's investors have worked in non-CVC roles within the parent company prior to commencing their investment responsibilities.

Model 12 uses the number of novel patents as the DV. We observe no significant interaction effect between CVC Investment and Pre-CVC Tenure. Hence, we find no support for the hypothesis that boundary spanners with longer tenures in the incumbent firm are associated with an amplification of the negative relationship between these relationships and the novelty of startups' inventions (i.e. hypothesis 5). Model 13 examines this interaction effect with respect to the number of drugs the startup drives into development. The positive and significant coefficient on the interaction term in model 13 offers support to hypothesis 6. The magnitude of this coefficient suggests that on average each additional year of pre CVC experience at the same firm can boost the main effect of treatment by about 20%. Figure 3 shows this graphically.

**Additional Considerations and Robustness Checks**

While I try in a number of different ways to delineate the treatment effect from those relating to selection, some important concerns remain. I was unable to employ an instrumental variables approach in relation to the interaction effects due to the presence of multiple endogenous covariates. In the case of the locational overlap with headquarters vs R&D, one concern may be that in each of these cases the relevant part of the firm that is collocated with these startups could also be playing a significant role with selection, i.e. the choice to invest in that startup in the first place. So for instance a startup that is collocated with an R&D site may end up receiving investment from that established firm's CVC arm because its technology was noticed by employees within this R&D site who then recommended that the firm invest in this startup. The source of bias here lies in the potential for systematic differences in the processes employed in deciding to invest in the startups collocated with R&D and those collocated with headquarters. The employees at HQ may value different things from those at an R&D site and hence may choose accordingly. Consequently, the outcomes we observe, i.e. startups collocated with headquarters becoming more technologically conservative, may just be a product of this selection process. To empirically examine whether this may be driving the results I draw on the important role played by co-investment networks in sourcing investment opportunities for VCs. Research shows that VC firms tend to invest together repeatedly, and that the VCs who have invested in a startup typically play an important role in determining who else is invited to invest in that startup (Hochberg, Ljungqvist, & Lu, 2007; Sorenson & Stuart, 2001). VC's therefore often learn of opportunities to make investments through their network of partners with whom they have previously co-invested. To examine whether the role played by headquarters or R&D employees in the selection process could be driving the observed results, I will re-examine these results focusing only on those investments that are likely to have been sourced through these co-investment networks. In these cases, the different selection mechanisms between startups collocated with headquarters and R&D take on less importance since these investments are likely to have been sourced via a different channel altogether. I do this by identifying investments by established firms in startups, where the startup already had as an investor a VC firm with co-investment ties to the established firm. In other words, one of the VCs previously invested in this startup also has a pre-existing tie with the established firm. In these cases, it becomes much more likely that the mechanism by which this investment happens is based on information sharing via the co-investment network and not because they were identified by employees from headquarters or an R&D site. Models 15 and 16 in table 6 shows the results from models in which only investments with these characteristics, i.e. a pre-existing tie are included. We see that the results are not materially altered either in terms of magnitude or significance from those in table 4. Once more we see the negative and significant relationship with respect to the interaction with *HQ Overlap* and a positive relationship with respect to the interaction with *R&D Overlap*. The latter coefficient has a p value of 0.053. This result gives us some confidence that the findings are indeed driven primarily by the interactions that happen between the startup and the established firm post investment.

INSERT TABLE 6 HERE

Though not the main focus of this study, I also find in line with prior research that CVC relationships have a positive effect on the startups' rate of patenting (Alvarez-Garrido & Dushnitsky, 2016). This result is shown in model 17 of table 6. The dependent variable in this case is the log of 1 + the total number of patents filed by the startup in the five years following investment. Hence, my results suggest that startups who have these relationships with established firms tend to produce a greater volume of patents, but that they produce fewer technologically path-breaking patents. In conjunction, these results along with those on the transformation of inventions into product prototypes suggest that these relationships broadly push startups to stress exploitation over exploration in terms of their innovation activities (Benner & Tushman, 2003). This is an interesting result, and I will discuss it further in the next section. However, it also raises the possibility of another kind of selection issue, which is that startups intending to pursue paths that are more focused on exploitation and less on exploration could be preferentially self-selecting into these relationships. If this were the case then the patterns we observe may be a product of the difference in the strategic orientations of the startups that select into these two categories rather than due to the relationship itself. My qualitative investigations in this context suggest that this type of exploitative intent is rarely an overt driver of startups choosing to raise capital from a corporate investor. Furthermore, I require that the treated and control startups match closely on both the number of technologically novel patents and the number of drugs in clinical trials (i.e. my DVs), which reduces the likelihood that startups within a matched set vary significantly on their exploratory/exploitative intent. However, ruling this out empirically is difficult since distinctions in strategic orientations can be hard to discern. I try to get at this based on a measure of the extent to which the other investors in these startups are likely to be feeling pressured to achieve an exit. As previously mentioned, most VC firms operate via funds where they raise money from limited partners (often institutional investors) to invest over a fixed period, typically ten years, following which they are expected to deliver returns. As funds get closer towards their end dates, VCs typically feel increasing pressure to translate their investments into returns (Gompers & Lerner, 2004). This can lead them to push startups to focus on more exploitative activity that is likely to enable them to be acquired or IPO more quickly, rather than more exploratory innovation that would typically take longer to come to fruition. Hence, if it were the case that startups with more of an exploitation mindset are more likely to select into these relationships, we would expect to see that the investors in these startups are at later stages of their funds than the investors in startups which are similar in other ways but don't have these relationships. In other words, VCs with less time left on their funds would push their startups to seek out relationships with established firms as a way to enable a faster exit. To check whether this is the case, I calculate the age of the fund for each of the pre-existing investors in the startups in my sample, as of the focal year. I then compare these values between startups that receive CVC investment, i.e. the treated firms and their matched controls. Note that I only include conventional VCs in the calculation of this figure since the dynamics of capital raising and return I described does not apply in the same way to other types of investors. I find that the mean fund age for startups with CVC investment is 2.9 years whereas this value for startups with no CVC investment is 2.7 years, however a t-test reveals that this difference is not statistically significant, i.e. these two values are statistically indistinguishable from each other. While not definitive, this result offers further support to the notion that the results we observe are not driven purely by intentional selection into these relationships by startups that are more focused on exploitation.

An important milestone for entrepreneurial firms, especially those that are funded by venture capital is exit. As previously mentioned, acquisition by an established firm is the most common channel by which this is achieved in many industries. It is plausible that having investment from an established firm could make a startup a more appealing acquisition candidate, either to that established firm itself or to others. Hence, the fact that we observe that these firms file fewer novel patents may just be because they get acquired before they are able to do so. To rule this out, I re-estimate all my results without including any of the startups that were acquired in the five-year period following investment, and find them to be materially unaltered. In addition, I also include a dummy variable to control for whether the startup is eventually acquired in all my models. I will detail the implications of these results in the next section.

## DISCUSSION

Entrepreneurial firms rely on partnerships to access many of the resources they need to fuel their innovation efforts. Their relationships with established firms deriving from the latter making equity investments in them are among the fastest growing forms of interfirm partnership around the world. This study is an endeavor to understand some of the trade-offs inherent to these relationships for startups in the context of their innovation activities. I find that these relationships help startups progress from invention to innovation, i.e. from a technological discovery into the development of a commercial application. However, I also find that these relationships are associated with a decline in the technological novelty of startups' subsequent inventions.

In conjunction, these results reveal some important implications of these relationships but also raise some questions. While scholars have described resource access as being an important benefit of these relationships for startups, we still have a limited understanding of what types of resources can realistically be accessed by startups and how these resources can support startups' innovation efforts. My findings suggest that the resource related benefits of these relationships for startups arise primarily from being able to obtain effective and timely access to experiential and contextual knowledge, which is particularly valuable in overcoming the challenges associated with adapting technologies to commercial applications. This step can be challenging as it requires expertise on a wide range of technical, commercial and regulatory issues and startups rarely have all of it available in-house.

This distinction between technology and application has relevance beyond the life sciences. Startups in most technology enabled industries face these challenges, albeit in varying forms. For instance, a startup working with artificial intelligence typically has at its core a proprietary algorithm that serves as its technological engine. Transforming this into a commercially focused application (say, detecting fraudulent activity in banking) will generally involve challenges that are analogous to the ones I describe in the life sciences. My findings suggest that established firms, with the industry experience and contextual knowledge they embody, can substantially assist startups efforts in overcoming these challenges.

Central to my findings however is the fact that these benefits are accompanied by a push towards more conservative, less novel technologies in terms of startups' subsequent inventions. This is the fundamental trade-off inherent to these relationships – one between resources and constraints. Research has clearly demonstrated the limitations that often plague incumbent firms' managers in relation to pursuing path breaking technological directions, yet there is little work considering what impact these limitations may have on the innovative activities of these firms' partners. My empirical findings suggest that these imperatives can influence startups' strategic decision making via these relationships. More generally, research on interfirm relationships has largely focused on how firms are affected by their partners resources and capabilities. However, firms' strategies and outcomes may also be influenced by their partners' limitations or weaknesses. Taking these into account may help us build a more complete understanding of how firm performance is shaped by external relationships.

In combination, the findings suggest that these relationships with incumbent firms tend to push startups to focus on 'exploitation' over 'exploration' (Benner & Tushman, 2003). Note that this is not to argue that the limiting influence of the large firm on the startup is necessarily detrimental to the latter's performance. It may be the case that focusing on more exploitation at the cost of exploration is the optimal strategy for the startup at a given point in time. However, accounting for this type of influence is important from a theoretical perspective in thinking about how these relationships affect the types of technologies startups produce. From a practical standpoint, research has thus far largely stressed the potential for access to resources in these relationships, but it is also important for entrepreneurs to be aware of the potential for these relationships to impose constraints on their technological choices. From the incumbent firm's standpoint, the findings reveal something of a catch-22, in that these firms are seeking to obtain a window into path-breaking technologies by forming these partnerships, but by doing so they may be limiting the likelihood that the startup will produce these in the first place.

I also find that the nature and extent of both influences – i.e. resources and constraints, are importantly shaped by the nature of the interactions underlying these relationships. I find that the boundary spanners in these relationships play an important role in shaping what startups can obtain, specifically the strength of these individuals' networks within the incumbent firm is crucial in facilitating effective access to valuable expertise for the startup. I also find that the limiting influence of the established firm on the startup in these relationships depends on which part of the established firm the startup interacts with. Interacting with the more market oriented corporate executives is likely to amplify the effect, i.e. push startups in more conservative technological directions whereas interacting with the more technology focused personnel such as scientists/engineers significantly alleviates this influence.

These findings illustrate the broader point that a relationship between the same two firms could lead to different outcomes depending on the nature of the interactions underlying it. Research in this domain has largely abstracted away from these considerations. This issue is likely to be most salient in relationships where the potential for variance in the underlying interactions is highest. This would be the case for instance when the organizations under consideration are large/complex, or when the relationships are open ended, i.e. where the actions expected of each party in the relationship are not sharply defined ex-ante. While this is true of CVC relationships, it could also apply to various other types of interfirm relationships such as research collaborations.

Specific to CVC investments, scholars have previously suggested that lack of access to the established firm can limit the benefits of these relationships for entrepreneurial firms (Pahnke et al., 2015). My results indicate that, beyond just the extent of access, the nature of access matters in determining outcomes. In other words, the outcomes entrepreneurs experience as a consequence of their relationships with established firms depends on who in the established firms they interact with, and how effectively they are able to navigate this organization.

Interestingly, I find that the tenure of these boundary spanners has no effect on the degree to which startups are pushed in more conservative technological directions. This may be because these individuals, once they take on the role of investors, conform more closely to the norms of the venture capital industry more than those of the established firm. The incentive structures of these individuals may also be more akin to those of VCs than corporate employees (Lerner, 2013). I also find that being collocated with headquarters or an R&D site has no effect on startups' propensities to turn their technologies into product prototypes. This may be because the types of exchanges that add value in relation to this step tend to be specific, detailed and often quite onerous. These exchanges carry greater levels of information security concerns since they can involve the sharing of data and proprietary information (Katila et al., 2008). Consequently, these rarely happen without the active involvement of the investment manager, regardless of the entrepreneur's own levels of access to different parts of the firm.

There are some important limitations to this study. The empirical investigations are all focused on one particular context, i.e. the life sciences. This imposes some limitations on the generalizability of the findings. The CVC investors in this industry are primarily large, established pharmaceutical companies. These companies embody certain characteristics that can make them particularly prone to being inertial in terms of technological innovation. Consequently, it is questionable to what degree these firms are representative of corporate investors in other sectors, for instance those in information technology. However, the last few years have also seen significant growth of CVC investment by firms from more traditional industries such as automotive, consumer goods and oil and gas. Established firms in these industries are likely to display many of the same characteristics as large pharmaceutical companies. In terms of the empirics, while I have made a number of efforts to rule out concerns of selection and other firms of bias, some issues remain. I was unable to use an instrumental variables approach in relation to the models with interaction terms since these would require a number of additional exogenous instruments. Consequently, in these models there is greater concern that firms select into different states based on unobservable distinctions that are correlated with their innovation outcomes. At the very least, these models demonstrate certain strong associations which are interesting indicators of the way these relationships play out. Future research efforts will focus on obtaining clearer causal inference on these questions.

In combination, the results of this study would suggest that CVC investment can be helpful to entrepreneurial innovation in certain important ways. However, from the entrepreneurs' perspective it also suggests an important limiting influence in terms of the novelty of the ideas they pursue. Furthermore, these influences can vary based on which part of the established firm the entrepreneurs are able to access. These are issues that should be carefully considered by both startups and established firms prior to and over the course of a partnership.

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**Figure 1: Accounting for the Locus of Interactions in Interfirm Relationships**

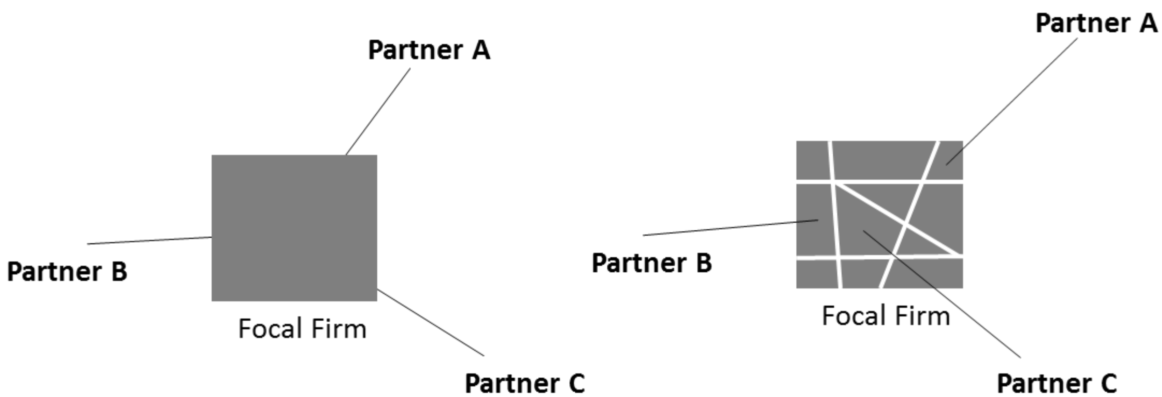



**Fig 1a** **Fig 1b**

**Figure 2: HQ vs R&D Overlap**

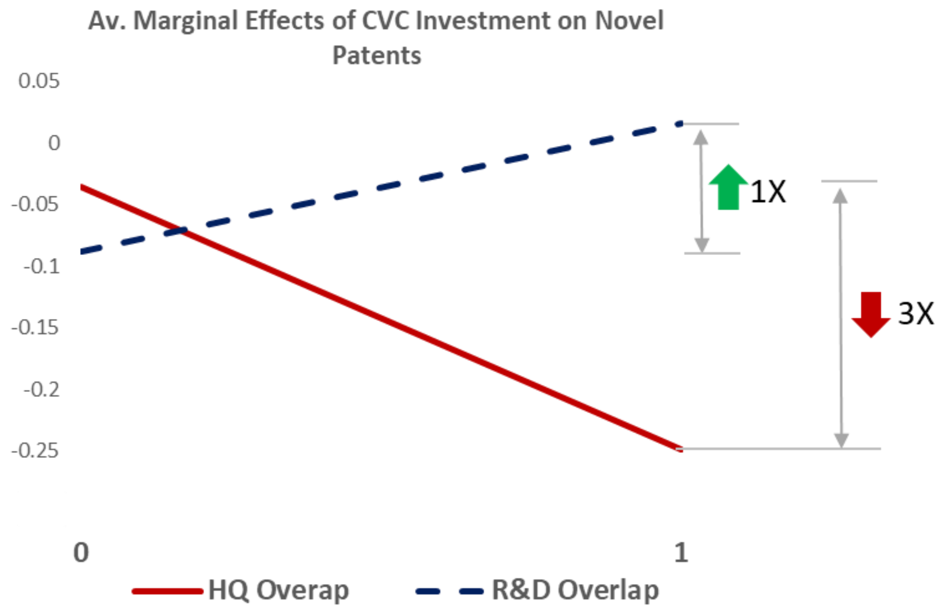
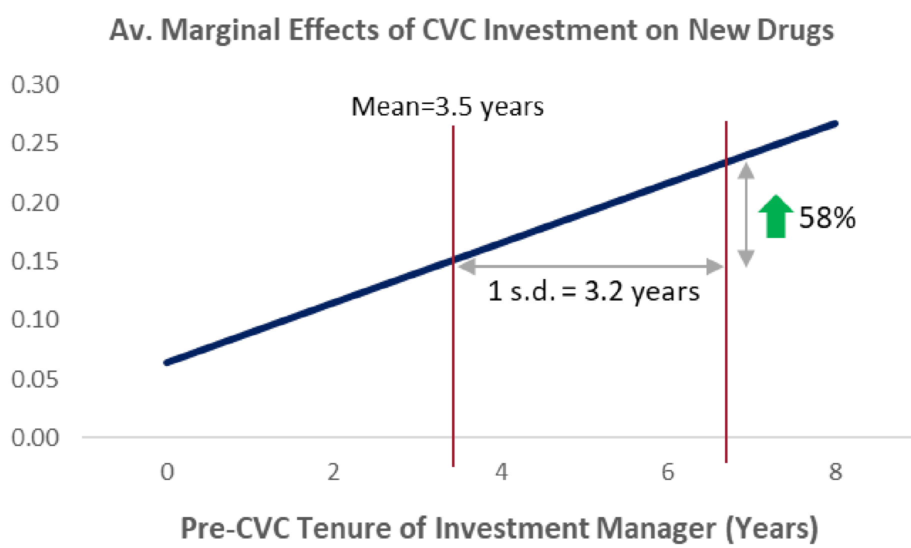



**Figure 3: Investment Manager's Pre-CVC Tenure**



## Table 1: Summary Statistics and Correlations

| Sl | Variable | Mean | SD | Min | Max | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Novel Patents | 0.82 | 2.21 | 0 | 36 | 1.00 | | | | | | | | | | | | | |
| 2 | New Drugs | 0.49 | 1.10 | 0 | 10 | 0.28 | 1.00 | | | | | | | | | | | | |
| 3 | CVC Investment | 0.22 | 0.42 | 0 | 1 | 0.18 | 0.15 | 1.00 | | | | | | | | | | | |
| 4 | Total New Patents Filed | 4.89 | 11.84 | 0 | 162 | 0.80 | 0.25 | 0.23 | 1.00 | | | | | | | | | | |
| 5 | Pre-Inv Patents | 2.03 | 8.11 | 0 | 236 | 0.43 | 0.10 | 0.20 | 0.56 | 1.00 | | | | | | | | | |
| 6 | Pre-Inv Drugs in Trial | 0.18 | 0.63 | 0 | 7 | 0.06 | 0.28 | 0.13 | 0.11 | 0.12 | 1.00 | | | | | | | | |
| 7 | Pre-Inv Novel Patents | 0.56 | 3.00 | 0 | 94 | 0.40 | 0.05 | 0.17 | 0.45 | 0.92 | 0.06 | 1.00 | | | | | | | |
| 8 | Has Acquisition | 0.13 | 0.34 | 0 | 1 | -0.09 | -0.10 | 0.02 | -0.08 | 0.00 | -0.05 | -0.01 | 1.00 | | | | | | |
| 9 | Company Age | 3.78 | 3.16 | 0 | 22 | 0.08 | 0.06 | 0.11 | 0.11 | 0.31 | 0.20 | 0.26 | 0.08 | 1.00 | | | | | |
| 10 | Pre-Inv Alliances | 1.16 | 3.44 | 0 | 35 | 0.14 | 0.19 | 0.07 | 0.13 | 0.13 | 0.05 | 0.05 | 0.11 | 0.25 | 1.00 | | | | |
| 11 | Post-Inv Alliances | 2.15 | 4.52 | 0 | 63 | 0.25 | 0.25 | 0.11 | 0.23 | 0.10 | -0.02 | 0.03 | -0.01 | 0.06 | 0.47 | 1.00 | | | |
| 12 | Pre-Inv Tech Dist | 0.44 | 0.22 | 0 | 1.26 | 0.05 | -0.02 | 0.04 | 0.06 | 0.07 | 0.02 | 0.04 | 0.04 | 0.16 | 0.08 | 0.06 | 1.00 | | |
| 13 | Post-Inv Tech Dist | 0.49 | 0.24 | 0 | 1 | -0.01 | -0.01 | 0.00 | 0.03 | 0.00 | -0.02 | -0.01 | -0.07 | 0.01 | -0.01 | 0.03 | 0.29 | 1.00 | |
| 14 | Num Other Investors | 1.91 | 1.83 | 0 | 12 | 0.09 | 0.10 | 0.44 | 0.09 | 0.05 | 0.03 | 0.06 | -0.01 | -0.15 | -0.03 | 0.07 | -0.03 | 0.05 | 1.00 |

Statistics shown pertain to 785 firms, i.e. 217 ‘treated’ startups who raised venture capital from 63 established firms 568 matched ‘control’ startups.

## Table 2: Effect of CVC Investment on Number of Novel Inventions

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| | Matching | Probit | IV 2SLS | | IV Trt Effect |
| | | | First Stage | Second Stage | |
| Dependent Variable -> | Novel Patents | CVC Investment | CVC Investment | Novel Patents | Novel Patents |
| CVC Investment | -0.062* | | | -0.646*** | -0.150*** |
| | (0.025) | | | (0.157) | (0.034) |
| Total New Patents Filed | 0.043*** | 0.020*** | -0.000 | 0.049*** | 0.043*** |
| | (0.003) | (0.004) | (0.001) | (0.002) | (0.003) |
| Pre-Inv Patents | -0.035*** | 0.000 | 0.001 | -0.038*** | -0.035*** |
| | (0.006) | (0.018) | (0.003) | (0.006) | (0.006) |
| Pre-Inv Drugs in Trial | 0.020 | 0.125 | -0.003 | 0.037 | 0.020 |
| | (0.019) | (0.216) | (0.040) | (0.029) | (0.019) |
| Pre-Inv Novel Patents | 0.169*** | 0.378** | 0.006 | 0.217*** | 0.175*** |
| | (0.044) | (0.124) | (0.020) | (0.048) | (0.044) |
| Has Acquisition | -0.087*** | 0.171+ | -0.001 | -0.078*** | -0.086*** |
| | (0.012) | (0.100) | (0.008) | (0.011) | (0.012) |
| Company Age | -0.005** | 0.049* | 0.000 | -0.000 | -0.004** |
| | (0.001) | (0.020) | (0.002) | (0.002) | (0.001) |
| Pre-Inv Alliances | 0.000 | 0.012 | 0.000 | -0.000 | 0.000 |
| | (0.002) | (0.008) | (0.001) | (0.002) | (0.002) |
| Post-Inv Alliances | 0.012*** | 0.023* | -0.000 | 0.012*** | 0.012*** |
| | (0.002) | (0.011) | (0.002) | (0.002) | (0.002) |
| Pre-Inv Tech Dist | 0.106* | 0.430 | -0.001 | 0.160** | 0.108* |
| | (0.043) | (0.280) | (0.024) | (0.053) | (0.044) |
| Post-Inv Tech Dist | -0.027 | -0.024 | -0.002 | -0.050 | -0.029 |
| | (0.043) | (0.185) | (0.014) | (0.051) | (0.044) |
| Num Other Investors | 0.023*** | 0.374*** | 0.001 | 0.047*** | 0.027*** |
| | (0.002) | (0.030) | (0.004) | (0.006) | (0.003) |
| Follow on Rds Raised | | -0.009* | | | |
| | | (0.004) | | | |
| Fitted Values IV | | | 0.955*** | | |
| | | | (0.128) | | |
| Matched Strata Dummies | Y | Y | Y | Y | Y |
| Number of Treated Firms | 217 | 217 | 217 | 217 | 217 |
| Number of Control Firms | 568 | 568 | 568 | 568 | 568 |

*** p<0.001 ** p<0.01 * p<0.05 + p<0.1; b – Logged variable; Standard errors reported in parentheses are heteroscedasticity robust and clustered by investing firm. The dependent variable 'Novel Patents' is a logged count of 1 + the number of novel patents filed by the firm in the 5 years following investment. Model 1 is an OLS regression which includes dummy variables to indicate the matched sets of firms obtained via coarsened exact matching (CEM). Model 2 is a probit regression estimating treatment, i.e. *CVC investment*. The exogenous instrument used is a count of the number of follow-on rounds of capital raised by the established firm's existing portfolio of startups in the year. Models 3 and 4 are the two stage least squares estimates. The instrument in model 4 (Fitted Values IV) are the fitted valued from model 3 (see pages 31-32 for a full description). Model 5 is the 'treatment effects' estimation which employs a correction for selection into treatment based on the probit model predicting *CVC Investment* using the instrumental variable.

**Table 3: Effect of CVC Investment on the Number of New Drugs in Development**

| | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 |
|---|---|---|---|---|---|
| | Matching | Probit | IV 2SLS | | IV Trt Effect |
| | | | First Stage | Second Stage | |
| **Dependent Variable ->** | **New Drugs** | **CVC Investment** | **CVC Investment** | **New Drugs** | **New Drugs** |
| CVC Investment | 0.114*** | | | 0.282* | 0.152** |
| | (0.031) | | | (0.117) | (0.054) |
| Total New Patents Filed | 0.009*** | 0.020*** | -0.000 | 0.010*** | 0.009*** |
| | (0.001) | (0.004) | (0.001) | (0.001) | (0.001) |
| Pre-Inv Patents | -0.018*** | 0.000 | 0.001 | -0.022*** | -0.018*** |
| | (0.003) | (0.018) | (0.003) | (0.003) | (0.003) |
| Pre-Inv Drugs in Trial | 0.002 | 0.125 | -0.003 | 0.008 | 0.002 |
| | (0.048) | (0.216) | (0.040) | (0.050) | (0.048) |
| Pre-Inv Novel Patents | 0.183*** | 0.378** | 0.006 | 0.176*** | 0.180*** |
| | (0.033) | (0.124) | (0.020) | (0.035) | (0.033) |
| Has Acquisition | -0.102*** | 0.171+ | -0.001 | -0.109*** | -0.102*** |
| | (0.010) | (0.100) | (0.008) | (0.009) | (0.010) |
| Company Age | -0.013*** | 0.049* | 0.000 | -0.013*** | -0.013*** |
| | (0.002) | (0.020) | (0.002) | (0.002) | (0.002) |
| Pre-Inv Alliances | 0.009*** | 0.012 | 0.000 | 0.009*** | 0.009*** |
| | (0.002) | (0.008) | (0.001) | (0.002) | (0.002) |
| Post-Inv Alliances | 0.011** | 0.023* | -0.000 | 0.010** | 0.011** |
| | (0.003) | (0.011) | (0.002) | (0.003) | (0.003) |
| Pre-Inv Tech Dist | -0.147*** | 0.430 | -0.001 | -0.153*** | -0.148*** |
| | (0.021) | (0.280) | (0.024) | (0.023) | (0.020) |
| Post-Inv Tech Dist | 0.005 | -0.024 | -0.002 | 0.015 | 0.006 |
| | (0.033) | (0.185) | (0.014) | (0.031) | (0.033) |
| Num Other Investors | 0.008* | 0.374*** | 0.001 | 0.000 | 0.006 |
| | (0.004) | (0.030) | (0.004) | (0.006) | (0.004) |
| Follow on Rds Raised | | -0.009* | | | |
| | | (0.004) | | | |
| Fitted Values IV | | | 0.955*** | | |
| | | | (0.128) | | |
| Matched Strata Dummies | Y | Y | Y | Y | Y |
| Number of Treated Firms | 217 | 217 | 217 | 217 | 217 |
| Number of Control Firms | 568 | 568 | 568 | 568 | 568 |

*** p<0.001 ** p<0.01 * p<0.05 + p<0.1; b – Logged variable; Standard errors reported in parentheses are heteroscedasticity robust and clustered by investing firm. The dependent variable 'New Drugs is a logged count of 1 + the number of drugs the firm puts into clinical trials in the 5 years following investment. Model 6 is an OLS regression which includes dummy variables to indicate the matched sets of firms obtained via coarsened exact matching (CEM). Model 7 is a probit regression estimating treatment, i.e. *CVC investment*. The exogenous instrument used is a count of the number of follow-on rounds of capital raised by the established firm's existing portfolio of startups in the year. Models 8 and 9 are the two stage least squares estimates. The instrument in model 8 (Fitted Values IV) are the fitted valued from model 7 (see pages 31-32 for a full description). Model 10 is the 'treatment effects' estimation which employs a correction for selection into treatment based on the probit model predicting *CVC Investment* using the instrumental variable.

## Table 4: Effect of Collocation with HQ vs R&D

| Dependent Variable -> | Model 11<br>Novel Patents$_b$ | Model 12<br>New Drugs$_b$ |
|---|---|---|
| CVC Investment | -0.072* | 0.148*** |
| | (0.028) | (0.041) |
| **CVC Investment x HQ Overlap** | **-0.213*** | **-0.136** |
| | **(0.083)** | **(0.127)** |
| **CVC Investment x R&D Overlap** | **0.103*** | **-0.096** |
| | **(0.047)** | **(0.085)** |
| Total New Patents Filed | 0.043*** | 0.009*** |
| | (0.003) | (0.001) |
| Pre-Inv Patents | -0.035*** | -0.018*** |
| | (0.006) | (0.003) |
| Pre-Inv Drugs in Trial | 0.017 | -0.003 |
| | (0.020) | (0.049) |
| Pre-Inv Novel Patents | 0.167*** | 0.182*** |
| | (0.043) | (0.032) |
| Has Acquisition | -0.087*** | -0.101*** |
| | (0.012) | (0.011) |
| Company Age | -0.005** | -0.013*** |
| | (0.001) | (0.002) |
| Pre-Inv Alliances | 0.000 | 0.009*** |
| | (0.002) | (0.002) |
| Post-Inv Alliances | 0.012*** | 0.011** |
| | (0.002) | (0.003) |
| Pre-Inv Tech Dist | 0.104* | -0.149*** |
| | (0.043) | (0.020) |
| Post-Inv Tech Dist | -0.028 | 0.004 |
| | (0.043) | (0.033) |
| Num Other Investors | 0.024*** | 0.008* |
| | (0.002) | (0.004) |
| Matched Strata Dummies | Y | Y |
| Number of Treated Firms | 217 | 217 |
| Number of Control Firms | 568 | 568 |

*** p<0.001 ** p<0.01 * p<0.05 + p<0.1; b – Logged variable. Standard errors reported in parentheses are heteroscedasticity robust and clustered by investing firm. The dependent variable ‘Novel Patents’ is a logged count of the number of novel patents filed by the firm in the 5 years following investment. The dependent variable ‘New Drugs is a logged count of 1 + the number of drugs the startup puts into clinical trials in the 5 years following investment. The direct effects of HQ Overlap and R&D Overlap are not estimated since these variables do not change within matched groups of startups (startups are matched on location).

## Table 5: Effect of Investment Manager's Organizational Tenure

| Dependent Variable -> | Model 13 Novel Patents$_b$ | Model 14 New Drugs$_b$ |
|---|---|---|
| CVC Investment | -0.082* | 0.064+ |
| | (0.040) | (0.037) |
| Pre-CVC Tenure | -0.000 | 0.013 |
| | (0.008) | (0.013) |
| **CVC Investment x Pre-CVC Tenure** | **0.008** | **0.025**** |
| | **(0.007)** | **(0.009)** |
| Total New Patents Filed | 0.044*** | 0.009*** |
| | (0.003) | (0.001) |
| Pre-Inv Patents | -0.032*** | -0.020*** |
| | (0.007) | (0.003) |
| Pre-Inv Drugs in Trial | 0.024 | -0.006 |
| | (0.021) | (0.051) |
| Pre-Inv Novel Patents | 0.154* | 0.187*** |
| | (0.059) | (0.038) |
| Has Acquisition | -0.091*** | -0.095*** |
| | (0.011) | (0.011) |
| Company Age | -0.005** | -0.012*** |
| | (0.001) | (0.002) |
| Pre-Inv Alliances | 0.002 | 0.007*** |
| | (0.002) | (0.002) |
| Post-Inv Alliances | 0.011*** | 0.011** |
| | (0.002) | (0.004) |
| Pre-Inv Tech Dist | 0.104* | -0.150*** |
| | (0.047) | (0.020) |
| Post-Inv Tech Dist | -0.074 | -0.018 |
| | (0.047) | (0.037) |
| Num Other Investors | 0.023*** | 0.006 |
| | (0.002) | (0.004) |
| Matched Strata Dummies | Y | Y |
| Number of Treated Firms | 180 | 180 |
| Number of Control Firms | 537 | 537 |

*** p<0.001 ** p<0.01 * p<0.05 + p<0.1; b – Logged variable. Standard errors reported in parentheses are heteroscedasticity robust and clustered by investing firm. The dependent variable 'Novel Patents' is a logged count of the number of novel patents filed by the firm in the 5 years following investment. The dependent variable 'New Drugs is a logged count of 1 + the number of drugs the startup puts into clinical trials in the 5 years following investment. Pre CVC Tenure is the average number of years that the investment managers have spent within the organization in other roles prior to taking up their investment roles. Note that the number of firms in the sample drops because we don't have data on investment managers (and hence can't determine Pre CVC tenure) for some firms.

## Table 6: Robustness

| Dependent Variable -> | Model 15<br>Novel Patents$_b$ | Model 16<br>New Drugs$_b$ | Model 17<br>Total Patents$_b$ |
|---|---|---|---|
| **CVC Investment** | **-0.078*** | **0.154**** | **0.215*** |
| | **(0.037)** | **(0.048)** | **(0.083)** |
| **CVC Investment x HQ Overlap** | **-0.316*** | **-0.168** | |
| | **(0.134)** | **(0.196)** | |
| **CVC Investment x R&D Overlap** | **0.127+** | **-0.025** | |
| | **(0.064)** | **(0.113)** | |
| Total New Patents Filed | 0.043*** | 0.009*** | |
| | (0.003) | (0.001) | |
| Pre-Inv Patents | -0.035*** | -0.017*** | 0.076*** |
| | (0.006) | (0.004) | (0.009) |
| Pre-Inv Drugs in Trial | -0.012 | 0.039 | -0.367*** |
| | (0.030) | (0.068) | (0.101) |
| Pre-Inv Novel Patents | 0.192*** | 0.193*** | 0.095 |
| | (0.048) | (0.035) | (0.069) |
| Has Acquisition | -0.089*** | -0.101*** | -0.345*** |
| | (0.017) | (0.011) | (0.033) |
| Company Age | -0.003+ | -0.015*** | -0.042*** |
| | (0.002) | (0.003) | (0.004) |
| Pre-Inv Alliances | 0.001 | 0.010*** | -0.013+ |
| | (0.002) | (0.002) | (0.007) |
| Post-Inv Alliances | 0.014*** | 0.011** | 0.055*** |
| | (0.002) | (0.003) | (0.005) |
| Pre-Inv Tech Dist | 0.101* | -0.157*** | 0.154+ |
| | (0.046) | (0.023) | (0.083) |
| Post-Inv Tech Dist | 0.004 | -0.011 | 1.510*** |
| | (0.042) | (0.033) | (0.074) |
| Num Other Investors | 0.019*** | 0.008 | 0.059*** |
| | (0.003) | (0.006) | (0.009) |
| Matched Strata Dummies | Y | Y | Y |
| Number of Treated Firms | 144 | 144 | 217 |
| Number of Control Firms | 498 | 498 | 568 |

*** p<0.001 ** p<0.01 * p<0.05 + p<0.1; b – Logged variable. Standard errors reported in parentheses are heteroscedasticity robust and clustered by investing firm. The dependent variable 'Novel Patents' is a logged count of the number of novel patents filed by the firm in the 5 years following investment. The dependent variable 'New Drugs is a logged count of 1 + the number of drugs the startup puts into clinical trials in the 5 years following investment. Models 15 and 16 only include investments made by CVCs in startups to whose prior investors they already had ties. These are investments which are likely to have been brought about by these ties rather than through other channels.