ESSAYS ON ENTREPRENEURIAL FINANCE: THE ROLE OF CORPORATE VENTURE CAPITAL AND ITS PERFORMANCE IMPLICATIONS

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ESSAYS ON ENTREPRENEURIAL FINANCE: THE ROLE OF CORPORATE VENTURE CAPITAL AND ITS PERFORMANCE IMPLICATIONS

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I dedicate this thesis to my family.

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SUMMARY

My dissertation is focused on developing a better understanding of the technology and innovation strategies of corporations and their impacts on firm performance. I am particularly interested in corporate venture capital (CVC), which serves as a strategy for accessing external technology for corporate investors and as an alternative source of financing and complementary assets for start-ups. I have investigated the conditions under which corporate investors and start-ups achieve the strategic goals by establishing CVC ties, and on estimating the technological and financial gains created by the CVC ties. Specifically, I have concentrated on *when* and *where* CVC ties are established in order to maximize economic value. The former relates to a *timing* issue, whereas the latter is a *space* issue of CVC investments.

In the first essay, I examine corporate investors' decisions to establish CVC ties and their subsequent strategic actions. Consistent with the real options perspective on CVC investments, I find that CVC investments can help corporate investors effectively search for and select future acquisition or licensing partners by reducing asymmetric information and uncertainty that may characterize markets for technology. Specifically, CVC investments facilitate the external acquisition of technology by substituting for a corporate investor's absorptive capacity, as reflected by its upstream research capabilities. CVC investments instead complement the portfolio of internally generated new products, since they allow highly productive corporate investors to shift their focus onto exploratory initiatives with the objective of selecting future technology and partners. Finally, CVC investments facilitate exploratory investments in distant technological areas

that are subsequently integrated through licensing or acquisitions. These findings contribute to emerging research on the organization and financing patterns of external R&D activities.

In the second essay, I investigate the nature of the relationship between technological spillovers and capital gains created by CVC investments for corporate investors. Using a simple equilibrium model and data from the global bio-pharmaceutical industry between 1986 and 2007, I find that these technological spillovers and capital gains are complements. This complementarity is enhanced when CVC investments are made in post-IPO and technologically diversified start-ups. Beyond providing a broad benchmark for heterogeneous returns on CVC investments, this study has important implications for corporate investors and start-ups. In particular, to the extent that capital gain is greatly determined by changes in the market values of start-ups, it implies that CVC investments can create value for start-ups as well as corporate investors. These mutual benefits can be greatly determined by *when* (*e.g.*, post-IPO start-ups) and *where* (*e.g.*, technologically diversified start-ups) CVC investments are made.

In the third essay, I analyze the contextual factors that impact the probability of start-ups' obtaining financing through independent venture capitalists and corporate investors. The systematic empirical evidence based on a three-stage game theoretic model suggests that start-ups that possess better evaluated technology tend to be financed through independent venture capitalists, rather than corporate investors. In contrast, start-ups tend to be financed through corporate investors, rather than independent venture capitalists, when their intellectual properties are effectively protected and their research pipelines contain multiple products. These findings provide a theoretical basis to explain

why several types of investors co-exist in the entrepreneurial financing market. Moreover, the existence of such determinants indicates that, although investors traditionally have been viewed as the powerful partner that dominates the investment decision, start-ups are also active decision makers in investment ties.

CHAPTER I

INTRODUCTION

Intensive research and development (R&D) competition and substantial complexity in product development create an incentive for corporations to enhance their innovations. It is, however, well recognized that no single corporation has all necessary internal resources to achieve innovation because the sources of innovation are often broadly distributed across different organizations, industries, and sectors (Powell *et al*., 1996). To cope with this limitation, corporations often choose a variety of organizational and financial arrangements for their external R&D activities. These arrangements contain several forms of external technology acquisition strategy, including corporate venture capital (CVC), acquisition, licensing, and strategic alliance. External R&D activities are particularly important for the bio-pharmaceutical industry, which has faced severe productivity challenges in the last decade and where significant levels of uncertainty and adverse selection problems are common (Arora and Gambardella, 1990 and 1994). As a result, effective decisions on external R&D activities are critical in generating profits for growth (*e.g.*, Nicholson *et al.*, 2005; Higgins and Rodriguez, 2006).

The emphasis on CVC as a strategy of collaboration between incumbents and start-ups continues to expand for several compelling reasons. These reasons include the escalating cost and cycle time of product development, increasing complexity of technology, and pursuit of efficient distribution of complementary assets. Corporate investors often use CVC investments as an ex-ante evaluation mechanism that helps them to effectively search for and select future technology partners (Gompers and Lerner, 1998). As a result, CVC investments may contribute to help corporate investors facilitate innovation, strategic renewal, and organizational learning. In contrast, start-ups can use CVC investments as an alternative source of complementary assets and financing. Start-

ups often face the "valley of death", which describes the period of transition when a developing technology is deemed to be promising, but too new to validate its commercial potential, making it difficult to attract sources of financing. During this transition CVC provides not only capital but also complementary assets that would not be available from traditional funding sources such as independent venture capitalists and banks, playing an increasingly more important role in the entrepreneurial finance market.

The rise of CVC activities across organizational boundaries in the 1990s and 2000s has attracted an emerging wave of research on the motivations of corporate investors. This literature suggests that corporate investors make CVC investments in order to redirect and guide their internal R&D activities through the utilization of knowledge spillovers originating from start-ups (*e.g.*, Gompers and Lerner, 1998; Hellmann, 2002; Dushnitsky and Lenox, 2005a and b, Benson and Ziedonis, 2010). As such, CVC investments can allow corporate investors to access novel technologies with lower risk by reducing asymmetric information and uncertainty. This reduction in asymmetric information and uncertainty also contributes to a larger supply of external technologies available to corporate investors for subsequent external R&D activities.

Although these studies have greatly improved our understanding of the conditions under which corporate investors can source external technology pursued by start-ups, they do not fully identify some of the key factors driving the optimal balance between CVC investments and other external technology acquisition strategies, with a particular focus on the time of these strategies. Moreover, many questions remain to be addressed for the motives of start-ups that raise funds from their projects from corporate investors rather than traditional funding sources and performance implications followed by establishing CVC ties. In this thesis, I ask the following question: What can we suggest to both corporate investors and start-ups about how to manage and benefit from CVC investments? This question is examined in greater detail in the following three essays.

1.1 Essay I

The first essay examines how CVC investments can aid corporate investors in achieving their strategic goals in the market for technology. It also examines what particular benefits that may not be realized by other types of external R&D activity are created by CVC investments. To address these issues, I provide a theoretical framework that suggests that CVC investments help corporate investors effectively search for and select future acquisition and licensing partners. I capture this timing issue associated with CVC investments, acquisition, and licensing in both my theoretical and empirical analyses. In a broad sense, these issues help us understand why several types of external R&D activities co-exist in the market for technology.

Using a novel dataset that includes a sample of 1,210 observations, corresponding to the internal and external R&D activities of 59 unique pharmaceutical firms during the years between 1985 and 2007, I first show that firms possessing high absorptive capacity, with particular reference to their ability to identify, assimilate, and utilize external knowledge (Cohen and Levinthal, 1989), are likely to simultaneously engage in internal and external R&D activities, as widely supported in the management literature. However, and consistent with a real options perspective, I also show that conditional on the external utilization of technology markets these firms are likely to directly engage in licensing and acquisition, relative to making CVC investments. This is because these firms face relatively lower uncertainty and information asymmetry, thereby enhancing their ability to effectively evaluate and select technology partners.

In contrast, and consistent with the literature on CVC as a window on future technology, I show that conditional on the external utilization of technology markets, firms experiencing relatively high internal productivity are more likely to make CVC investments prior to engaging in an acquisition or license because these firms can afford to nurture nascent technologies. In essence, since CVC investments are by their very nature exploratory initiatives (*e.g.,* Schildt *et al.*, 2005; Dushnitsky and Lenox, 2005b;

Basu *et al.*, 2011), a firm with strong internal productivity can shift its focus to future technology partners and future productivity, thereby allocating a greater portfolio of its external activity to CVC relative to licensing or acquisitions. These effects of absorptive capacity and internal R&D productivity on the incentives to undertake CVC investments help us understand how firms balance these investments with other R&D activities.

Finally, I use a real options perspective to address the issue of what corporate investors ultimately do with their CVC investments *ex post*. Indeed, I find that conditional upon making CVC investments, firms making such investments in technologically diversified fields are more likely to engage in subsequent acquisition or licensing. In other words, I show that CVC has an option value in that it provides an entry mechanism into more technologically unrelated markets that present greater investment uncertainties.

This essay makes two main contributions. First, it contributes to an emerging research on the organization and financing patterns of external R&D activities (*e.g.*, Aghion and Tirole, 1994; Mathews, 2006; Robinson, 2008; Fulghieri and Sevilir, 2009). This essay, unlike the extant literature which has focused on a singly type of external R&D activity, suggests that CVC investments should be considered in conjunction with other types of external R&D activity. This approach, I believe, is more appropriate because firms often pursue an R&D strategy which is composed of several types of external R&D activity simultaneously and sequentially. Second, this study also contributes to the literature on optimal organization and financing arrangements between corporate investors and start-ups (*e.g.*, Hellmann, 2002; Katila *et al.*, 2008; Dushnitsky and Shaver, 2009). Unlike that literature, however, which has investigated how resource constraints and appropriation problems affect the establishments of CVC ties, this study suggests that CVC investments can be greatly determined by timing, which ultimately affects the level of asymmetric information and uncertainty found in the market for technology.

1.2 Essay II

In the second essay, I analyze the nature of relationship between technological spillovers and capital gains created by CVC investments and identify the factors associated with the relationship. The technological spillovers come from exposure and access to external technologies and products, while the capital gains come through the selling of stocks in an IPO, acquisitions of start-ups by third-parties, or other types of liquidation events. An example is the investment by the CVC arm of Eli Lilly and Company in Millennium Pharmaceuticals Inc., in 1995. Eli Lilly received technological benefits from the collaborative research efforts into the genetic causes of atherosclerosis and congestive heart failure – it also received a substantial financial gain from the IPO of Millennium Pharmaceuticals in 1996.

An understanding of these issues is important because it sheds light on the motives of corporate investors and on whether CVC investments ultimately create a positive total return for corporate investors. Moreover, to the extent that capital gains are largely a reflection of the changes in the market values of start-ups in which CVC investments are made, the nature of the interaction indicates whether CVC investments create mutual benefits between corporate investors and start-ups. Such a mutuality of benefits may well play a key role in determining the success or failure of CVC investments. Beyond just the nature of the relationship, my understanding of contextual factors impacting the relationship is important because it can help corporate investors balance technological and financial benefits (*e.g.*, Gompers and Lerner, 2004) and thus increase the total return created by CVC investments. In addition, these contextual factors can be understood to facilitate the mutual benefits between corporate investors and start-ups.

To address these issues, I develop a simple and flexible model that analyzes the nature of the relationship between technological spillovers and capital gains, and gives

rise to testable empirical implications. By evaluating the technological and financial benefits created by 71 bio-pharmaceutical corporate investors between 1985 and 2005, I present novel and systematic evidence that supports the existence of a positive relationship between these two benefits. Moreover, consistent with the predictions made in the model, my findings suggest that this positive relationship is enhanced when CVC investments are made in post-IPO and technologically diversified start-ups, respectively.

This essay contributes to different strands of the literature. First, it contributes to the literature on CVC investments by providing systematic estimates of technological and financial benefits crated by CVC investments and their relationship. The essay thus extends the prior studies that have focused on either one of the two benefits and helps better evaluate the costs and benefits of CVC investments. Second, and more broadly, this study contributes to the literature on the way in which firms organize and finance their R&D investments. While one perspective suggests that active pursuit of capital gains can come at the cost of technological benefits (*e.g.*, Rind, 1981; Chesbrough, 2002; Gompers and Lerner, 2004), an alternative perspective is that corporate investors can pursue these two benefits simultaneously. My findings are consistent with the latter perspective. Thus, corporate investors can use CVC investments as a strategy to facilitate their external R&D activities at a lower cost.

1.3 Essay III

The third essay is focused on start-ups' financial arrangements for their growth and success by investigating the trade-offs involved with their choice between corporate investors (CVCs) and independent venture capitalists (IVCs) and its performance implications. It studies two interrelated questions: (1) When do start-ups finance their

projects from CVCs and IVCs? and (2) How do these two entrepreneurial financing sources create value for start-ups?

To analyze these issues, I develop a three-stage game theoretic model that distinguishes CVCs and IVCs in several ways, some of which are as follows. First, unlike IVCs that primarily pursue capital gains, CVCs seek strategic benefits from technological spillovers originated from start-ups as well as capital gains (MacMillan *et al*., 2008). Second, start-ups face a substantial risk of appropriation when they disclose their technology/products to CVCs. IVCs have a minimal chance to appropriate start-ups' technology compared with CVCs because they do not normally seek such strategic benefits sought by CVCs. Third, CVCs can provide their assets and capabilities, including technological and R&D support, product development assistance, manufacturing capacities, and access to marketing and distribution channels, to create value for start-ups. In contrast, IVCs can help start-ups access the capital markets by better signaling start-ups' value to the capital markets. My model considers these unique attributes of these two financing sources and relates start-ups' costs and benefits of associating with their choices.

By analyzing 3,885 fundraising records of 616 bio-pharmaceutical start-ups between 1985 and 2006, I first find that start-ups tend to finance their projects from CVCs rather than IVCs when they are in the later stages and need a relatively small amount of capital. Second, start-ups that possess better evaluated technology tend to raise funds for their projects from IVCs rather than CVCs. Third, start-ups tend to raise funds for their projects from CVCs rather than IVCs when their intellectual property is effectively protected and their research pipelines contain multiple products. Finally, while

financing from IVCs contributes to increasing start-ups' Tobin's q and valuation, financing from CVCs contributes to enhancing forward patent citations.

This study contributes to various strands of finance and management literature. First, it contributes to the literature on the formation of CVC investment ties (*e.g.*, Hellmann, 2002; Katila et al., 2008; Dushnitsky and Shaver, 2009). While the existing studies take the perspective of CVCs by assuming that investors dominate entrepreneurial finance decisions, this study takes the perspective of start-ups that can also be active decision-makers in their investment ties. Second, this study contributes to the literature on the trade-offs between the better evaluation of projects and the threat of appropriation (*e.g.*, Bhattacharya and Ritter, 1983; Gans *et al*., 2008). While much of this literature considers a single type of investor, this study advances our understanding about why several types of investors co-exist in the entrepreneurial finance market by highlighting the heterogeneous natures of different financing sources.

CHAPTER II

CORPORATE VENTURE CAPITAL AS AN EX-ANTE EVALUATION MECHANISM IN THE MARKET FOR TECHNOLOGY

2.1 Introduction

Why do firms make corporate venture capital (CVC) investments? A growing body of literature has suggested that firms often make CVC investments in research-intensive start-ups to help facilitate innovation, strategic renewal, and organizational learning.[1] This question, however, remains unresolved since firms can satisfy such strategic motives through engaging in other types of external R&D activity, such as acquisition and licensing. Indeed, we know little about why firms particularly choose to make CVC investments among the various types of external R&D activities available to them. The answer to this question is critical in helping us understand two interrelated questions: 1) how CVC investments can aid firms to achieve their strategic goals in the market for technology, and 2) what particular benefits, which may not be realized by other types of external R&D activity, are created by CVC investments. In a broad sense these issues help us understand why several types of external R&D activity co-exist in the market for technology.

[1] For example, these strategic motives of CVC investments have been discussed in several studies including Sykes (1986 and 1990), Siegel *et al.* (1988), Gompers and Lerner (1998), Anand and Galetovic (2000), Chesbrough (2002), Hellmann (2002), Maula and Murray (2002), Dushnitsky and Lenox (2005a, 2005b, and 2006), Nicholson *et al.* (2005), Wadhwa and Kotha (2006), Allen and Hevert (2007), Benson and Ziedonis (2008 and 2010), Katila *et al.* (2008), Keil *et al.* (2008), Dushnitsky and Shaver (2009), and Fulghieri and Sevilir (2009). Moreover, several surveys have reported that corporate investors make CVC investments primarily to pursue strategic motives (e.g., Siegel *et al.*, 1988; Corporate Strategy Board, 2000; Kann, 2000; Asset Alternatives, 2002; Birkinshaw *et al.*, 2002; PriceWaterhouseCoopers, 2006; MacMillan *et al.*, 2008).

To address these issues I build on two different research streams. The first is the literature on CVC as a window for future technology (*e.g.*, Gompers and Lerner, 1998; Dushnitsky and Lenox, 2005a, 2005b, and 2006; Wadhwa and Kotha, 2006; Keil *et al.*, 2008). This literature suggests that corporate investors make CVC investments in order to redirect and guide their internal R&D activities through the utilization of knowledge spillovers originating from start-ups. As such, CVC investments can help corporate investors effectively search for and select future acquisition or licensing partners by reducing asymmetric information and uncertainty that may characterize markets for technology, thereby allowing them to access novel technologies with lower risk. This reduction in asymmetric information and uncertainty eventually contributes to a larger supply of external technologies available to corporate investors for subsequent licensing or acquisition. On the other hand, if corporate investors do not choose to engage in a subsequent acquisition or license, they can liquidate the start-up's equity from their investment portfolio.

The second research stream I consider is the literature on real options (*e.g.*, Van De Vrande *et al.*, 2006; Benson and Ziedonis, 2008 and 2010; Li and Mahoney, 2011; Van De Vrande and Vanhaverbeke, 2009; Krychowski and Quélin, 2010; Ziedonis, 2007). Real options theory can be readily integrated with the literature on CVC as a window for future technology. This framework indeed suggests that corporate investors use CVC investments as an option to proceed or defer other types of external R&D activity. From this perspective, there are three distinguishable characteristics of CVC investments that affect their option value. These are low commitment, high reversibility, and high independency. First, low commitment suggests that CVC investments, unlike

acquisitions and licenses, often require smaller financial and organizational commitment (McGrath and Nerkar, 2004; Van De Vrande *et al.*, 2006). Second, high reversibility implies that corporate investors can liquidate their equity investment if they decide not to engage in a subsequent acquisition or license with the portfolio firm. Finally, high independency suggests that CVC investments generally do not directly affect the current organizational and technological resources of corporate investors. In summary, these characteristics collectively allow CVC investors to stay nimble and provide them with the opportunity to move in and out of nascent technological opportunities more quickly.

The synthesis of the above frameworks allows us to identify some of the key factors driving the optimal balance between external technology acquisition strategies, with a particular focus on the timing of these strategies. Indeed, I first show that firms possessing high absorptive capacity, with particular reference to their ability to identify, assimilate, and utilize external knowledge (Cohen and Levinthal, 1989), are likely to simultaneously engage in internal and external R&D activities, as widely supported in the management literature. However, and consistent with a real options perspective, I also show that conditional on the external utilization of technology markets these firms are likely to directly engage in licensing or acquisition, relative to making CVC investments. This is because these firms face relatively lower uncertainty and information asymmetry, thereby enhancing their ability to effectively evaluate and select technology partners. In other words, I propose and find that CVC investments and a firm's absorptive capacity are substitute drivers in their attempts to be innovative through the use of technology markets.

In contrast, and consistent with the literature on CVC as a window on future technology, I show that conditional on the external utilization of technology markets,

firms experiencing relatively high internal productivity are more likely to make CVC investments prior to engaging in an acquisition or license because these firms can afford to nurture nascent technologies. In essence, since CVC investments are by their very nature exploratory initiatives (*e.g.,* Schildt *et al.*, 2005; Dushnitsky and Lenox, 2005b; Basu *et al.*, 2011), a firm with strong internal productivity can shift its focus to *future* technology partners and *future* productivity, thereby allocating a greater portion of its external activity to CVC relative to licensing or acquisitions.

The effect of absorptive capacity and internal R&D productivity on the incentives to undertake CVC investments helps us understand how firms balance these investments with other R&D activities. I also use a real option perspective to address the issue of what corporate investors ultimately do with their CVC investments *ex post*. Indeed, I argue that conditional upon making CVC investments, firms making such investments in technologically diversified fields are more likely to engage in subsequent acquisition or licensing. In other words, I show that CVC has an option value in that it provides an entry mechanism into more technologically unrelated markets that present greater investment uncertainties.

This chapter is organized as follows. The next section presents my theoretical framework and hypotheses. The subsequent section describes my empirical strategy and data. I then report empirical results and conclude.

2.2 Theory and Hypothesis Development

2.2.1 Related Literature

Research intensive firms often need to reach out beyond their boundaries in order to enhance research productivity. They can access the external technology market in a number of ways, for example, through acquisitions, licenses, corporate venture capital

investments, alliances, and joint ventures. For the purposes of this study I focus on three specific modes of technology acquisition: licensing, acquisitions and CVC investments. While prior research has already demonstrated the individual importance of each of these in enhancing productivity, I focus on the possible role that CVC investments play as a potential *ex ante* evaluation mechanism in the market for technology.[2]

Because uncertainty regarding future payoffs associated with technologies generated outside a firm's boundaries is common, firms should have the capacity and capability to evaluate external knowledge (Cohen and Levinthal, 1989 and 1990). In order to improve this capability firms often use a stage-gate process which adds new technological information to their information base stepwise (Van De Vrande *et al.*, 2006). If a particular type of external R&D activity can be used to increase this familiarity, at a low enough cost, prior to engaging in other types of external R&D activity which may require substantial and irreversible investments, then this activity can function like a stage-gate process, thereby reducing uncertainty and adverse selection.

My theoretical framework assumes that firms use CVC investments in exactly this manner. In particular, I argue that CVC investments serve as an *ex ante* evaluation mechanism that corporate investors use to identify and select potential future licensing partners or acquisition targets. Through a CVC investment program, which includes identifying, evaluating, selecting, and monitoring external technologies, corporate investors are able to access and observe new and novel technologies (Siegel *et al.*, 1988; Gompers and Lerner, 1998). For example, CVC investment programs also allow

[2] See for example, acquisitions (*e.g.,* Bradley *et al.* 1988; Ravenscraft and Scherer, 1989; Houston *et al.*, 2001; Higgins and Rodriguez, 2006; Ceccagnoli and Higgins, 2011), licensing (*e.g.*, Grindley and Nickerson, 1996; Lin, 1996; Arora *et al*., 2001; Cassiman *et al.*, 2005), and CVC investments (*e.g.*, Gompers and Lerner, 1998; Dushnitsky and Lenox, 2005a, 2005b, and 2006; Dushnitsky and Shaver, 2009; Benson and Ziedonis, 2008 and 2010).

corporate investors to visit the business sites of start-ups or sit on the board of directors (Bottazzi *et al.,* 2004).[3] This process helps corporate investors obtain better information and provides learning opportunities about external technologies. It also provides a lower risk mechanism for corporate investors to invest in technologies that may be less related to their existing technologies (Kulatilaka and Toschi, 2010), an issue which I explore more fully below.

With more information and a reduction in risk, corporate investors can more effectively decide *if* and *when* to eventually integrate their portfolio holding. If the corporate investor chooses not to internalize a portfolio holding, it can still choose to hold that investment through a liquidity event, potentially providing a financial return back to the CVC investment program or fund. They may choose not to integrate for a number of reasons; for example, the portfolio company's technology may not have progressed sufficiently. Regardless of the reason, however, the use of a CVC investment program helps mitigate risk by helping the corporate investor to avoid committing substantial resources to an inappropriate technology partner or research program.

2.2.2 Model Specification

In this section I integrate some of the ideas outlined above within a stylized discrete choice model, which will allow us to better structure the development of my hypotheses. In particular, I start by arguing that, to introduce new products or processes, a firm makes a three-stage R&D decision that can be summarized as follows. At the first stage, a firm faces two options: Invest only in internal R&D activities and develop its own technologies (*Internal R&D only*) or invest in internal R&D activities and engage in

[3] As board members, corporate investors gain access to more information than would be available without such involvement (Katila *et al.*, 2008).

at least one type of external R&D activity (*Internal and External R&D*).[4] At the second stage, conditional on the choice of *Internal and External R&D*, firms can engage in acquisitions or licensing (*Acq./Lic.*) or make CVC investments (*CVC*). Finally, at the third stage, conditional on the choice of *CVC*, firms can engage in subsequent acquisitions or licensing with the firms in which they have made CVC investments (*Post CVC Acq./Lic.*), or continue to hold the firms in their portfolio or liquidate (*Other*).

Consistent with this decision tree, I define $y_i \in \{0,1,2,3\}$ as the alternative that each firm *i* chooses, which may incorporate a set of sequential activities as follows. $y_i = 0$ corresponds to *Internal R&D only*. $y_i = 1$ corresponds to a firm engaging in *Internal and External R&D* at the first stage and acquisition or licensing without prior CVC investments at the second stage. $y_i = 2$ corresponds to a firm engaging in *Internal and External R&D* at the first stage, a CVC investment at the second stage, and acquisition or licensing at the post-CVC third stage. $y_i = 3$ corresponds to a firm engaging in *Internal and External R&D* at the first stage, a CVC investment at the second stage, and some *Other* unspecified event post-CVC which is different than an acquisition or license, such as maintaining the CVC in the firm's portfolio or liquidation.

The payoffs associated with this decision tree are specified as follows. Let V_1 denote the payoff to the firm if it chooses *Internal R&D only* and V_2 if it chooses *Internal and External R&D* at the first stage. Let V_3 denote the payoff to the firm if it chooses *Acq./Lic.* and V_4 if it chooses *CVC* at the second stage. Finally, let V_5 denote the payoff to the firm if it chooses *Post CVC Acq./Lic.* and V_6 if it chooses *Other* at the third stage. The description of the decision tree and a summary of these choices are presented in Figure 2.1 and Table 2.1.

[4] Although a firm could in principle also engage exclusively in external R&D activities, I exclude this possibility from the menu of choices. Indeed, in my setting, the pharmaceutical industry, I do not observe firms that exclusively engage in external R&D activities without conducting internal R&D. As such, the data would not allow the identification of the drivers of this choice.

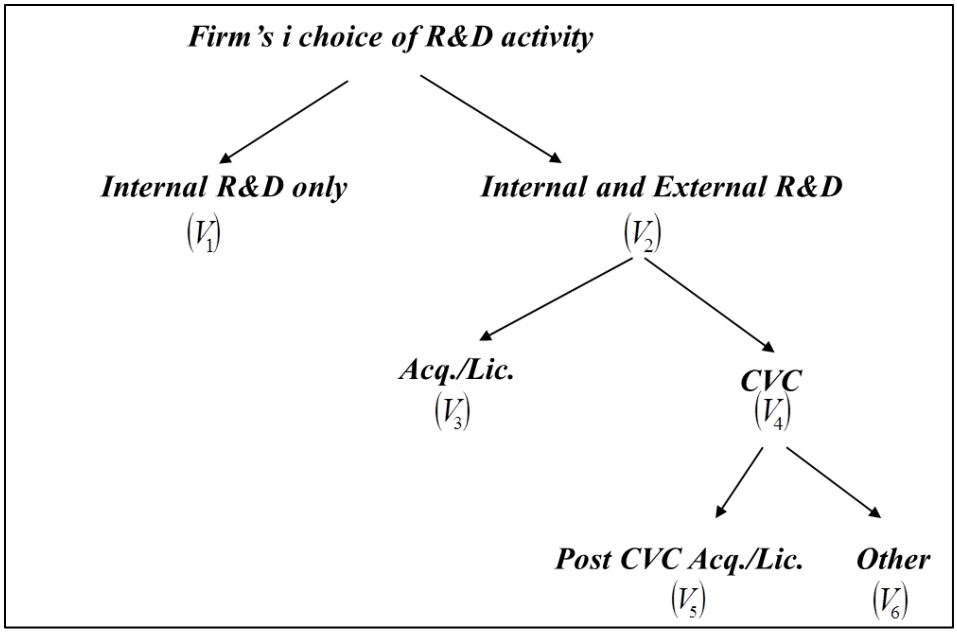


Figure 2.1. A three-stage sequential decision model

Table 2.1. Specification of choice variable

Choice	Specification
1. *Internal R&D only*	Firms that engage in internal R&D activities only ($y_i = 0$)
2. *Internal and External R&D*	Firms that engage in internal R&D activities and at least one of the above types of external R&D activities simultaneously ($y_i \neq 0$)
2.1. *Acq./Lic.*	Firms that engage in acquisition or licensing without prior CVC investments ($y_i = 1$)
2.2. *CVC*	Firms that make CVC investments ($y_i > 1$)
2.2.1. *Post CVC Acq./Lic.*	Firms that engage in subsequent acquisition or licensing with partner firms in which they made CVC investments previously ($y_i = 2$)
2.2.2 *Other*	Firms that do not engage in subsequent acquisition or licensing with partner firms in which they made CVC investments previously ($y_i = 3$).

If I further incorporate additive stochastic components to each payoff, assume that these are independent and identically distributed across payoffs with a Type 1 extreme value distribution which are observed by the firm but not the econometrician, and normalize the payoffs to achieve identification, I can define the probabilities for each firm choice as follows (Amemiya, 1981; Maddala, 1983), where I omit the subscript i for simplicity:

Stage 1:

$$\Pr(\textit{Internal R\&D only}) = [\exp(V_1)]/[(\exp(V_1) + \exp(V_2)] = 1/1 + \exp(V_1 - V_2) \quad (1.1)$$

$$\Pr(\textit{Internal and External R\&D}) = [\exp(V_2)]/[\exp(V_1) + \exp(V_2)] = 1/1 + \exp(V_2 - V_1) \quad (1.2)$$

Stage 2:

$$\Pr(\textit{Acq./Lic.}|\textit{Internal and External R\&D}) = [\exp(V_3)]/[\exp(V_3) + \exp(V_4) = 1/1 + \exp(V_4 - V_3) \quad (1.3)$$

$$\Pr(\textit{CVC}|\textit{Internal and External R\&D}) = [\exp(V_4)]/[\exp(V_3) + \exp(V_4)] = 1/1 + \exp(V_3 - V_4) \quad (1.4)$$

Stage 3:

$$\Pr(\textit{Post CVC Acq./Lic.} \mid \textit{CVC, Int. and Ext. R\&D}) = [\exp(V_5)]/[\exp(V_5) + \exp(V_6)] = 1/1 + \exp(V_6 - V_5). \quad (1.5)$$

$$\Pr(\textit{Other} \mid \textit{CVC, Int. and Ext. R\&D}) = [\exp(V_6)]/[\exp(V_5) + \exp(V_6)] = 1/1 + \exp(V_5 - V_6). \quad (1.6)$$

In what follows, I will use equations (1.1)-(1.6) to better articulate my hypotheses with reference to the relative payoffs affecting each probability of interest.

2.2.3 Hypothesis Development

The simplified discrete choice model depicted in Figure 2.1 implies that the three-stage sequential choices faced by firms can be influenced by specific contextual factors. For example, while a particular variable may impact the choice between *Internal R&D only* and *Internal and External R&D* (Stage 1), another variable may impact the choice between *Acq./Lic.* and *CVC* (Stage 2) and/or *Post CVC Acq./Lic.* and *Other* (Stage 3). Moreover, a variable that impacts the choice between *Internal R&D only* and *Internal and External R&D* (Stage 1) could also impact the choice between *Acq./Lic.* and *CVC* (Stage 2) and/or the *Post CVC Acq./Lic.* and *Other* (Stage 3). I develop my hypotheses by identifying relevant factors that affect these sequential choices. I group these factors by corresponding stage.

Stage 1: Absorptive capacity

The extant literature widely recognizes that a firm's capacity to be innovative through external R&D activities is greatly determined by its internal competency in identifying and integrating appropriate external technologies or know-how. This competency or "absorptive capacity" (Cohen and Levinthal, 1989 and 1990) stresses the importance of a firm's stock of prior knowledge to effectively identify, evaluate, integrate, and commercialize external technologies. In my model, I argue that absorptive capacity impacts a firm's choice between *Internal R&D only* and *Internal and External R&D* at the first stage and also between *Acq./Lic.* and *CVC* at the second stage.

Because sufficient absorptive capacity is often critical to increase marginal returns to external R&D activities, it can help a firm engage in several types of external R&D activity (*e.g.*, Arora and Gambardella, 1990 and 1994; Cockburn and Henderson, 1998; Dushnitsky and Lenox, 2005b; Cassiman and Veugelers, 2006). These increases in marginal returns are often achieved by reductions in the uncertainty and information asymmetries associated with the nature and value of external technologies. A firm that possesses insufficient absorptive capacity, in contrast, can face higher levels of uncertainty, finding it more difficult to have successful external R&D activities. As a result, higher absorptive capacity increases the payoffs from *Internal and External R&D* (V_2), which decreases the relative payoffs from the first stage choice ($V_1 - V_2$). In other words, a firm that possesses high absorptive capacity faces relatively lower uncertainty and information asymmetry, thereby enhancing its capacity to effectively evaluate and select technology partners, and *vice versa*. I thus posit the following:

> *Hypothesis 1. Firms possessing higher absorptive capacity are more likely to engage in internal and external R&D activities simultaneously, relative to engaging in only internal R&D activities.*

This hypothesis has been widely examined in the existing literature (*e.g.*, Cassiman and Veugelers, 2006). However, my revisit of this issue is important because, while the existing literature has considered absorptive capacity an important factor that determines

a firm's innovative performance through external R&D activities, my model suggests that absorptive capacity is a critical condition under which the firm engages in several different types of external R&D activity. A deeper understanding of this issue helps us to effectively address how absorptive capacity can work in the context of CVC relative to other choices available to a firm.

Stage 2: Absorptive capacity and internal productivity

At the second stage, absorptive capacity can also determine a firm's choice between *Acq./Lic.* and *CVC*. I argue that conditional on having sufficient absorptive capacity to engage in *Internal and External R&D*, firms possessing higher levels of absorptive capacity tend to engage in acquisitions or licenses without prior CVC investments. These firms can effectively evaluate external technologies without the additional information obtained through CVC investments. This high level of absorptive capacity may also decrease the value of CVC investments as real options because the associated uncertainty and information asymmetry are lower.[5] In this instance V_3 increases, V_4 decreases, and the difference $(V_3 - V_4)$ increases. Firms possessing insufficient absorptive capacity, in contrast, would be more inclined to make CVC investments prior to engaging in acquisitions or licenses. These firms may need either more information or more time to learn about external technologies. The use of these types of investments may help attenuate uncertainty or information asymmetries, thereby increasing V_4 and decreasing $(V_3 - V_4)$. As such, conditional on choosing *Internal and External R&D*, I hypothesize:

> *Hypothesis 2a. Firms possessing higher absorptive capacity are less likely to make CVC investments, relative to engaging in acquisition or licensing.*

At first blush, this hypothesis may appear to contradict Dushnitsky and Lenox (2005b), who find that firms possessing greater absorptive capacity tend to make more CVC

[5] A central prediction of real options theory is that the greater the *ex-ante* uncertainty or variation of expected future payoffs, the greater the value of the initial option investment, because the option value is realized through the resolution of uncertainty (Ziedonis, 2007).

investments. My prediction, however, extends rather than contradicts their work because it focuses on how absorptive capacity impacts a firm's choice of CVC investment *relative* to acquisitions or licensing.

Next, I consider how internal productivity influences a firm's choice between *Acq./Lic.* and *CVC*. A firm experiencing declining internal productivity may need to choose *Acq./Lic.* over *CVC* because it has an immediate technological need. Existing technologies which can be obtained via acquisition or license will be more effective than nascent technologies in improving current productivity (Higgins and Rodriguez, 2006). A firm with robust internal productivity, in contrast, may have the ability to focus on nurturing nascent technologies which could be used to enhance *future* productivity; thus, it is more likely to choose *CVC* rather than *Acq./Lic.*.

Firms have constrained R&D budgets that get split between internal and external research efforts. Funds flowing to external R&D efforts can ebb and flow between investments, depending on the current needs of the firm. For example, a firm with strong internal productivity can shift a greater portion of its external activity to CVC relative to licensing or acquisitions. This shift or focus on *future* technology partners and *future* productivity increases V_4 and thereby decreases $(V_3 - V_4)$. In contrast, a firm experiencing declining internal productivity is more likely to engage in acquisition or licensing to fulfill immediate technological needs, shifting funds away from CVC investments. This focus on current productivity needs increases V_3, which increases $(V_3 - V_4)$. As such, conditional on choosing *Internal and External R&D*, I hypothesize:

> *Hypothesis 2b. Firms experiencing high internal productivity are more likely to make CVC investments, relative to engaging in acquisition or licensing.*

Stage 3: Technological diversification

At the third stage firms again face two options. They can integrate the portfolio firm technology either through a license or acquisition (*Post CVC Acq./Lic.*) or they can

continue to maintain the firm in their portfolio (*Other*). The choice between the two for the corporate investor can be understood in terms of the exercise, or not, of a real option. For us, this exercise choice is dependent upon a firm's intention or desire to diversify its technologies. This theoretical expansion complements the existing literature (Dushnitsky and Shaver, 2009) that analyzes the impact of technological relatedness on the formation of a CVC tie.

From my perspective, corporate investors that invest in more technologically diversified fields can increase the probability of engaging in subsequent acquisition or licensing (*Post CVC Acq./Lic*.). This occurs because CVC investments give corporate investors access to a greater range of technological fields, which potentially increases outcomes on the upside, while limiting exposure on the downside. With the passage of time, corporate investors obtain additional information about portfolio companies, thereby reducing associated uncertainty. Moreover, they can truncate the left-hand tail of a performance distribution by more effectively choosing not to engage in a subsequent acquisition or license (*Post CVC Acq./Lic.*). This creates a performance distribution curve that is skewed to the right, yielding asymmetric pay-offs (McGrath and Nerkar, 2004). In other words, corporate investors that invest in technologically diversified fields increase the probability of choosing *Post CVC Acq./Lic.* because more can be learned at a fixed cost thereby increasing the relative payoffs from acquiring technology post-CVC either through an acquisition of the portfolio company or a licensing transaction, $(V_5 - V_6)$. Corporate investors that invest in technologically undiversified fields, in contrast, increase their probability of choosing *Other* post-CVC, because there is less to be learned (Schildt *et al.*, 2005; Sapienza *et al.*, 2004), thus decreasing $(V_5 - V_6)$.

Note that, contrary to my prediction, it can be argued that corporate investors that invest in technologically undiversified fields would be more likely to choose *Post CVC Acq./Lic.* because similar knowledge bases can increase the "marginal rate of learning". This approach seems reasonable in the context of other types of external R&D activity (*e.g.*, Lee and Lieberman, 2010; Villalonga and McGahan, 2005), but less so in the context of CVC investments. CVC investments are by their very nature exploratory rather than exploitative initiatives and typically provide an entry mechanism into technologically unrelated markets (*e.g.,* Schildt *et al.*, 2005; Dushnitsky and Lenox, 2005b; Basu *et al.*, 2011). With the passage of time the CVC portfolio firms will continue to mature, asymmetric information will diminish and the underlying technological distance between them may also decline. Hence, I formulate the following

> *Hypothesis 3. Firms making CVC investments in technologically diversified fields are more likely to engage in subsequent acquisition or licensing, relative to not engaging in subsequent acquisition or licensing.*

The expected impacts of my focal variables on the relative payoffs at various stages are summarized in Table 2.2.

Table 2.2. Impact of the variables of interest

	$(V_1 - V_2)$: Payoff from *Internal R&D only* relative to *Internal and External R&D*	$(V_3 - V_4)$: Payoff from *Acq./Lic.* relative to *CVC* (conditional on *Internal and External R&D*)	$(V_5 - V_6)$: Payoff from *Post CVC Acq./Lic.* relative to *Other* (conditional on *CVC*)
Absorptive capacity	–	+	
Internal productivity		–	
Technological diversity			+

2.3 Empirical Specification and Data

2.3.1 Empirical Specification

I provide a variety of empirical tests for my theory, including preliminary evidence based on two-sample means test, the use of my benchmark specification based on the sequential logit model, and other robustness tests that include the use of a multinomial logit model and a test of the independence of irrelevant alternatives assumption on which the multinomial logit is based.

As outlined in the previous section, as a benchmark model I use a three-stage sequential model with a hierarchical structure of sequential decisions. In particular, I assume that each choice at each stage is made according to a dichotomous logit model using the sample that is "at risk". The choice probabilities corresponding to equations (1.1) to (1. 6) can be estimated, setting relative payoffs as functions of observed firm, industry, and choice specific characteristics. In particular, the probability of *Internal and External R&D* (Stage 1), is defined as

$$\Pr(Internal\ and\ External\ R\&D) = \Pr(y_i > 0) = L(\theta_1 X_i + \theta_2 C_1), \quad (2.1)$$

where L represents the binomial logit function. X_i is a vector of observable characteristics of firm i, C_1 is a vector of attributes at Stage 1, θ_1 and θ_2 are parameter vectors to be estimated.

The probability of choosing *CVC* conditional on *Internal and External R&D* (Stage 2) is

$$\begin{aligned}\Pr(CVC|Internal\ and\ External\ R\&D) &= \Pr(y_i > 1\ |y_i \neq 0) \\ &= L(\theta_3 X_i + \theta_4 C_2)\end{aligned} \quad (2.2)$$

where C_2 is a vector of attributes at Stage 2, and θ_3 and θ_4 are parameter vectors.

The probability of choosing *Other* conditional on *Internal and External R&D* and *CVC* (Stage 3) is

$$\Pr(Other|Internal\ and\ External\ R\&D, CVC) = \Pr(y_i = 3|y_i > 1) = L(\theta_5 X_i + \theta_6 C_3) \quad (2.3)$$

where C_3 is a vector of attributes at Stage 3 and θ_5 and θ_6 are parameter vectors to be estimated. The most direct method of estimating the parameter vectors, θ_1, ..., θ_6, is to proceed to the successive estimation of logit models with a smaller number of responses using maximum likelihood. I therefore estimate equation (2.1) first, with a simple logit, with all observations in the sample; I then estimate (2.2) using a logit model with all observations for which $y_i \neq 0$; and finally I estimate (2.3), again with a simple logit model, with all observations for which $y_i > 1$.

2.3.2 Data

My dataset is based on 1,210 observations, corresponding to the internal and external R&D activities of 59 unique pharmaceutical firms during the years between 1985 and 2007, a period of great expansion in external R&D activities in this industry (Ceccagnoli and Higgins, 2011; MacMillan *et al.*, 2008).[6] My primary data source is the Deloitte Recap database (www.recap.com), which tracks the entire lifecycle of portfolio companies making CVC investments in the biopharmaceutical industry, from founding through all rounds of financing to final disposition. As a result I am able to identify the time of investment and any subsequent investments, licenses or acquisitions involving the CVC investing firms.

For each of my corporate investors (pharmaceutical firms) I also reconstruct their drug pipeline using data from *PharmaProjects*. This data contains the history and

[6] I limit my analysis to this period for two reasons. First, the beginning of the sample, 1985, represents the first year following the passage of Hatch-Waxman, which established the current regulatory regime for the pharmaceutical industry. Second, I lack pipeline information for the post-2007 period, as further discussed below.

progress of more than 36,500 drugs that have been developed since 1980. Next, I utilize patent data from the NBER to construct patent stocks for each investor and external partner, to build a measure of technological diversity. Finally, financial data is collected from *Compustat* and scientific publication data is gathered from *Web of Science*. Descriptive statistics and correlations for my variables are reported in Table 2.3. All financial variables are in constant 2007 dollars.

Table 2.3. Descriptive statistics and correlations

Mean and standard deviation

	All sample		$y_i = 0$		$y_i = 1$		$y_i = 2$		$y_i = 3$	
Variable	Mean	S. D.	Mean	S. D.	Mean	S. D.	Mean	S. D.	Mean	S. D.
1. Choice (y_i)	1.01	0.91	0.00	0.00	1.00	0.00	2.00	0.00	3.00	0.00
2. Absorptive capacity	1.28	1.96	0.37	0.83	1.74	2.31	1.47	1.80	1.43	1.65
3. Internal productivity	5.89	9.92	1.45	3.71	7.36	10.86	8.90	12.35	8.68	10.94
4. Technological diversity	0.96	0.11	0.97	0.11	0.96	0.11	0.96	0.06	0.94	0.10
5. Firm size	12.00	17.60	6.99	15.52	15.07	19.33	11.33	13.81	11.41	13.21
6. Financial slack	4.84	8.72	2.38	5.25	6.19	10.36	4.92	6.54	4.98	7.66
7. Prior alliance intensity	361.19	2732.18	698.97	3694.89	271.82	2561.06	55.58	168.49	95.51	372.33
8. Investor's technological capability	370.22	1107.26	282.42	1163.35	437.93	1188.59	213.31	324.80	390.99	861.29
9. Research-intensive firm's technological capability	30.97	85.66	3.35	13.34	40.77	92.24	43.62	110.46	49.43	120.88
No. of observations	1210		356		625		89		140	

Correlations

	1	2	3	4	5	6	7	8
1. Choice (y_i)								
2. Absorptive capacity	0.11**							
3. Internal productivity	0.18***	0.58***						
4. Technological diversity	-0.05	0.13***	0.05					
5. Firm size	0.09*	0.45***	0.50***	0.15***				
6. Financial slack	0.06	0.47***	0.26***	0.12***	0.68***			
7. Prior alliance intensity	-0.08*	-0.16***	-0.12**	-0.13***	-0.20***	-0.15***		
8. Investor's technological capability	0.11**	0.37***	0.10**	0.17***	0.59***	0.53***	-0.17***	
9. Research-intensive firm's technological capability	0.17***	0.32***	0.35***	0.04	0.10**	0.08*	-0.07*	0.12***

Notes. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Dependent variable: Choice of R&D activity.

My discrete dependent variable, *Choice*, is null when a corporate investor (pharmaceutical firm) reports positive R&D investments in any given year (information collected from Compustat) but does not engage in any external R&D activity as reported by Deloitte Recap in that year $(y_i = 0)$. *Choice* is greater than zero when an investor reports positive R&D investments in a given year and engages in either: 1) an acquisition or a license (as a buyer) in that year *without* a prior CVC investment in the target (or partner) firm $(y_i = 1)$; 2) a CVC investment with subsequent acquisition or license with the target (or partner) firm $(y_i = 2)$; 3) a CVC investment without any subsequent acquisition or license $(y_i = 3)$. Table 2.4 presents the distribution of this choice variable over time.

Table 2.4. Distribution of R&D choice variable through time

year	*Internal R&D only* $(y_i = 0)$	*Acq./Lic.* $(y_i = 1)$	*Post CVC Acq./Lic.* $(y_i = 2)$	*Other* $(y_i = 3)$	*Internal and External R&D* $(y_i \neq 0)$	*CVC* $(y_i > 1)$
1985	16	4	2	1	7	3
1986	14	9	0	1	10	1
1987	13	11	2	0	13	2
1988	15	11	1	3	15	4
1989	19	7	1	2	10	3
1990	18	16	1	4	21	5
1991	20	19	3	3	25	6
1992	24	14	8	11	33	19
1993	20	18	2	9	29	11
1994	20	22	9	10	41	19
1995	15	30	7	11	48	18
1996	10	35	11	15	61	26
1997	12	37	6	13	56	19
1998	13	42	10	6	58	16
1999	12	40	11	9	60	20
2000	11	37	6	6	49	12

Table 2.4. continued

2001	10	44	4	12	60	16
2002	10	41	4	9	54	13
2003	13	40	0	8	48	8
2004	14	40	0	6	46	6
2005	19	38	0	1	39	1
2006	19	36	0	0	36	0
2007	19	34	1	0	35	1
1985-1989	77	42	6	7	55	13
1990-1999	164	273	68	91	432	159
2000-2007	115	310	15	42	367	57
Total	356	625	89	140	854	229

Notes. This table reports R&D decisions regarding internal R&D and external technology acquisition activities by year. The first four columns tabulate my discrete dependent variable $y_i \in \{0,1,2,3\}$ by year. While $y_i \neq 0$ denote *Internal and External R&D,* $y_i > 1$ denotes *CVC* (with or without a subsequent acquisition or licensing) at the second stage.

Independent variables

Absorptive capacity. Several different measures of absorptive capacity have been proposed in the literature. The most widely used, partly due to its availability for public companies, is R&D intensity. This is also the measure used by Cohen and Levinthal in their pioneering work on this topic (1989, 1990). Arora and Gambardella (1994) argue that a firm's basic research capabilities are particularly effective in capturing a firm's ability to evaluate and select external knowledge (Arora and Gambardella, 1994), which is a critical capability in the context of CVC investments. Measures of upstream research capabilities have been shown to be key drivers of the potential complementarity between a firm's internal and external R&D activities (Cassiman and Veugelers, 2006). In particular, Cassiman and Veugelers (2006) use responses on the importance, for the innovation process, of information from research institutes and universities as reflecting a firm's absorptive capacity. Along these lines, scholars have measured a firm's ability to select and evaluate external knowledge using a firm's human capital, including the

number of a firm's R&D employees with a doctorate degree (Veugelers, 1997) or the number of scientific publications of a firm's employees (Arora and Gambardella, 1994; Cockburn and Henderson, 1998). Following the literature, and considering data availability, I therefore use the number of scientific papers published by firm employees (scaled by one hundred) to estimate absorptive capacity.

Internal productivity. Since I analyze an industry whose revenue stream is dependent upon new products, I use drug pipeline data to measure internal productivity. First, I create counts of the number of drugs in each stage of development (preclinical, Phase 1, Phase 2, Phase 3). This raw count is biased towards earlier-stage products, given their larger relative number. As such, I multiply the number of drugs in each stage of development by a transition probability that broadly approximates the chance of receiving FDA approval (Higgins and Rodriguez, 2006). Unlike a raw count this measure places more weight on later-stage products. Prior research has demonstrated that shocks or gaps in the later-stage pipeline will cause companies to enter the external technology markets (*e.g.*, Higgins and Rodriguez, 2006; Chan *et al.* 2007; Danzon *et al.,* 2007).

Technological diversity. I estimate technological diversity, which is inversely related to technological proximity, between corporate (pharmaceutical) investors and portfolio (biotechnology) firms using the 3-digit patent classification listed on each firm's patents (*e.g.*, Jaffe, 1986; Ahuja, 2000). Using these patent classes, I compute the number of patents that share the 3-digit patent class between corporate investors and portfolio firms. This number is then divided by the stock of the corporate investor's successful patent applications and depreciated by 15% annually (Hall *et al*., 2005) and subtracted from one. Measures computed on samples with few patents or those limited to a single

patent class can generate both biased and imprecise measures of proximity (Benner and Waldfogel, 2008). In order to avoid this potential pitfall I use all patent applications by the biotechnology (portfolio) firms.

Control variables

Firm size. Firm size can impact a firm's decision on R&D activities. While larger firms can benefit from economies of scale and scope (Henderson and Cockburn, 1996), smaller firms are often more nimble and can make faster decisions on R&D activities (Acs and Audretsch, 1987). Thus, I measure firm size by their total assets.

Financial slack. Financial slack, which is defined as the availability of funds in order to take advantage of profitable investment opportunities, can also impact a firm's decision on R&D activities. The pecking order theory of finance suggests that firms tend to use internally generated funds in the form of retained earnings before turning to external sources because the external costs of monitoring and risk of asymmetric information are substantial (Myers, 1984). As such, I follow Geiger and Cashen (2002) and estimate financial slack using retained earnings.

Prior alliance intensity. Firms previously engaged in alliances are likely to continue to enter new alliances because of their path-dependent nature and learning effects on R&D activities (Rothaermel and Deeds, 2006). I estimate a firm's prior alliance intensity by calculating their stock of previous alliances normalized by their real total assets. CVC investments, acquisitions, and licenses are excluded from this measure.

Corporate investor's technological capability. Prior research has demonstrated a relationship between the technological capabilities of a firm and its R&D activities (Arora and Gambardella, 1994). I control for the technological capability of my corporate

investors by their stock of successful patent applications, depreciated by 15% annually (Hall *et al*., 2005).

Research intensive firm's technological capability. Research-intensive (biotechnology) firms' technological capabilities can also impact corporate investors' R&D activity decisions (Ziedonis, 2007). Similar to my previous measure, I estimate the research-intensive firms' technological capabilities by calculating their stock of successful patent applications, depreciated by 15% annually (Hall *et al.*, 2005).

Therapeutic category and year fixed effects. In some of the empirical specifications I include therapeutic fixed effects using the Anatomical Therapeutic Classification (ATC) defined by the World Health Organization (http://www.who.int). For my purposes, I used ten dummy variables corresponding to the first-level of the ATC. I also include time dummies corresponding to the year of the reported R&D activity during the 1985-2007 study period.

2.4 Empirical Findings

2.4.1 Nonparametric Statistics

Table 2.5 reports two-sample mean tests comparing my variables of interest across a pharmaceutical firm's R&D activity decision. Note that consistent with Hypothesis 1, Panel A demonstrates that the mean of *Absorptive capacity* is significantly greater for the firms that choose *Internal and External R&D* over the firms that choose *Internal R&D only*. Panel B demonstrates that the mean of *Absorptive capacity* is significantly greater for the firms that choose *Acq./Lic.* versus the firms that choose *CVC*, consistent with Hypothesis 2a. Panel B also demonstrates that the mean of *Internal productivity* is significantly greater for firms that choose *CVC* compared to those that

choose *Acq./Lic.*, consistent with Hypothesis 2b. Finally, Panel C demonstrates that the mean of *Technological diversity* is significantly greater for firms that choose *Post CVC Acq./Lic.* compared to those that choose *Other*, consistent with Hypothesis 3. Collectively, these results provide some non-parametric statistics suggesting that my data are broadly consistent with my theoretical predictions.

Table 2.5. Hypotheses test using the two-group means test

Panel A: First stage choices

	$(y_i = 0)$	$(y_i \neq 0)$	Difference
Absorptive capacity	0.37	1.66	-1.29 ***
	(0.04)	(0.07)	
N	356	854	

Panel B: Second stage choices

	$(y_i = 1)$	$(y_i > 1)$	Difference
Absorptive capacity	1.74	1.44	0.30 **
	(0.09)	(0.11)	
N	625	229	
Internal productivity	7.36	8.77	-1.41 **
	(0.43)	(0.76)	
N	625	229	

Panel C: Third stage choices

	$(y_i = 2)$	$(y_i = 3)$	Difference
Technological diversity	0.96	0.94	0.01 **
	(0.01)	(0.01)	
N	61	101	

Notes. This table reports two-group means tests that compare the means of the variables of interest by the firms' R&D decisions by stages, as represented in Figure 2.1. I estimate the following t-statistics: $t = [(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)]/[({s_1}^2/n_1) + ({s_2}^2/n_2)]^{0.5}$, where $\bar{x}_1$ and $\bar{x}_2$ are two group means with normal populations of size n_1 and n_2, unknown means μ_1 and μ_2, and unknown standard deviations s_1 and s_2. Standard errors are presented in parentheses and ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

2.4.2 Benchmark Model: Sequential Logit

My benchmark results are presented in Table 2.6. I present specifications without (Models 1, 2, 3) and with (Models 4, 5, 6) therapeutic categories and year fixed-effects. The Pseudo (McFadden) R-squares suggest that models with therapeutic categories and year fixed-effects (Models 4, 5, 6) fit the data substantially better. As such, I will focus

my comments on these models (Models 4, 5, 6), noting that results from Models (1, 2, 3) are qualitatively similar.

With reference to and consistent with Hypothesis 1, the findings suggest that *Absorptive capacity* has a positive and significant effect on the probability of choosing *Internal and External R&D* at the first transition (or stage). The effect is large, since the elasticity, not reported in the table, suggests that a 1% increase in the number of publications of the focal firm leads to a 6% *increase* in the probability of choosing *Internal and External R&D* at the first transition (or stage), with the effect statistically significant at the 1% significance level.

The effect of *Absorptive capacity* is reversed at the second stage. Indeed, I find that *Absorptive capacity* has a negative and significant effect on the probability of making a *CVC* investment conditional on *Internal and External R&D* (second transition). The elasticity, not reported, suggests that a 1% increase in the number of publications leads to a 6% *decrease* in the probability of *CVC* conditional on *Internal and External R&D*, with the elasticity statistically significant at the 1% significance level. This suggests that conditional on both *Internal and External R&D,* firms possessing high *Absorptive capacity* tend to choose *Acq./Lic.* rather than *CVC*, supporting Hypothesis 2a.

At the second stage of the decision tree depicted in Figure 2.1, and consistent with my prediction made in Hypothesis 2b, the findings show that *Internal productivity* has a positive and significant effect, conditional on *Internal and External R&D*, on the probability of choosing *CVC* rather than *Acq./Lic.* The estimated elasticity, not reported in the table, suggests that a 1% increase in the number of drugs in the pipeline leads to a

6% *increase* in the probability of making a *CVC* investment conditional on *Internal and External R&D*, with the elasticity statistically significant at the 5% significance level.

Finally, consistent with Hypothesis 3, I find that *Technological diversity* has a significant and negative effect on the probability of choosing *Other* at the third transition. This implies that a corporate investor (pharmaceutical firms), conditional on engaging in both *Internal and External R&D* and making *CVC* investments in technologically diversified fields, is more likely to choose *Post CVC Acq./Lic.*, e.g. to strengthen its relationship with the portfolio firm through a license or acquisition post-CVC investment. The size of this effect is rather large, since the estimates imply that a 1% increase in my measure of *Technological diversity* leads to a 76% increase in the probability of making a license or acquisition with a portfolio firm conditional on *Internal and External R&D* and a *CVC* investment.

Table 2.6. Benchmark results: Sequential logit

Model	1	2	3	4	5	6
Transition	1st	2nd	3rd	1st	2nd	3rd
Choice of R&D (y_i)	*Internal and External R&D* ($y_i \neq 0$)	*CVC* conditional on *Int. & Ext. R&D* ($y_i > 1 \mid y_i \neq 0$)	*Other* conditional on *Int. & Ext. R&D* and *CVC* ($y_i = 3 \mid y_i \neq 0, y_i > 1$)	*Internal and External R&D* ($y_i \neq 0$)	*CVC* conditional on *Int. & Ext. R&D* ($y_i > 1 \mid y_i \neq 0$)	*Other* conditional on *Int. & Ext. R&D* and *CVC* ($y_i = 3 \mid y_i \neq 0, y_i > 1$)
Absorptive capacity	0.5386*	-0.1813*	-0.0807	0.9350**	-0.3141***	-0.3589*
	(0.2858)	(0.0944)	(0.1230)	(0.4506)	(0.0992)	(0.2019)
Internal productivity	0.1477***	0.0348**	-0.0033	0.0671	0.0689***	0.0939***
	(0.0470)	(0.0171)	(0.0224)	(0.0505)	(0.0243)	(0.0278)
Technological diversity		-0.4766	-4.5503**		0.2840	-4.3288*
		(1.3412)	(1.8584)		(1.2518)	(2.5800)
Firm size	0.0088	-0.0368**	0.0387**	0.0095	-0.0364	0.0074
	(0.0376)	(0.0182)	(0.0170)	(0.0320)	(0.0261)	(0.0274)
Financial slack	-0.0034	0.0267	-0.0196	0.0220	0.0248	0.0277

Table 2.6. continued

	(0.0815)	(0.0232)	(0.0277)	(0.0754)	(0.0412)	(0.0493)
Prior alliance intensity	-0.0000	-0.0003	0.0008	-0.0000	0.0001	0.0019*
	(0.0000)	(0.0004)	(0.0007)	(0.0000)	(0.0004)	(0.0010)
Investor's technological capability	0.0000	0.0003	0.0012**	-0.0002	0.0002	0.0017***
	(0.0002)	(0.0003)	(0.0005)	(0.0002)	(0.0005)	(0.0006)
Research-intensive firm's technological capability		0.0002	0.0006		0.0019**	0.0026**
		(0.0011)	(0.0005)		(0.0009)	(0.0011)
Constant	-0.0504	-0.0511	4.1449***	-0.8138	-0.9730	4.5132*
	(0.1958)	(1.2627)	(1.6064)	(0.5367)	(1.3957)	(2.3396)
ATC specific effect	No	No	No	Yes	Yes	Yes
Year specific effect	No	No	No	Yes	Yes	Yes
N	1210	519	162	1210	506	158
Log likelihood	-6.1e+02	-3.1e+02	-1.0e+02	-5.6e+02	-2.7e+02	-86.5447
Prob>χ^2	0.0033	0.2013	0.0823	0.0000	0.0000	0.0000
pseudo R^2	0.170	0.032	0.060	0.237	0.136	0.162

Notes. Robust standard errors clustered by firms are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

2.4.3 Robustness Checks

I test the sensitivity of my results to the hypothesized structure of the decision tree outlined in Figure 2.1. In particular, note that in my final dataset, I can only exploit 158 CVC transactions to identify the effect of about 20 covariates (in the benchmark model with ATC and year effects) on the focal firms' decision to engage in *Post CVC Acq./Lic.* conditional on *Internal and External R&D* and *CVC*. As a robustness check, I consider a simpler two-stage model, shown in Figure 2.2, obtained by collapsing the second and third levels of my benchmark three-stage decision process. In this case, conditional on *Internal and External R&D* (in the second stage) focal firms face the mutually exclusive options of *Acq./Lic.*, *Post CVC Acq./Lic.*, or *Other*. I estimate this model in two stages. First stage estimation and results are identical to the first stage sequential logit results, in which I use the full sample to estimate the probability that a firm engages in *Internal and*

External R&D based on a simple logit model (these are presented in the columns related to the first transition in Table 2.6).

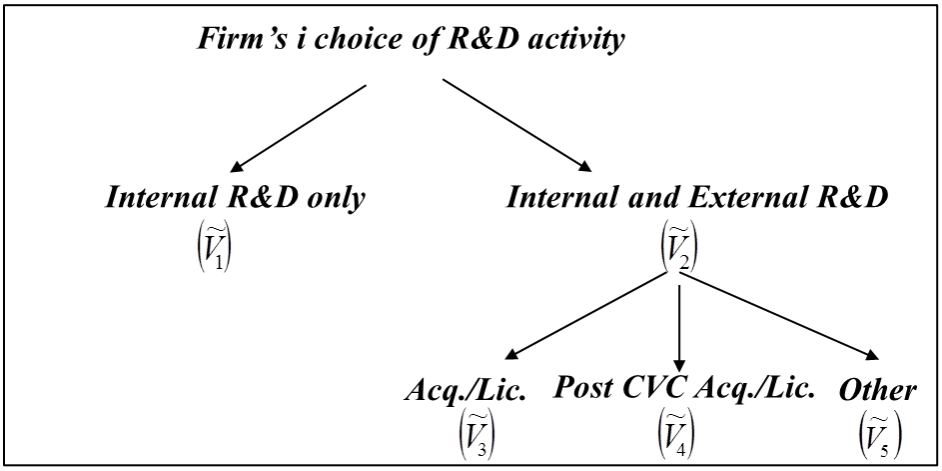


Figure 2.2. Sensitivity analysis: A two stage sequential decision model

In the second stage, I instead use a multinomial logit model using the external R&D activities of firms that engage in *Internal and External R&D*. These estimates are presented in Table 2.7. I only show estimates obtained controlling for both ATC and year fixed effects, since these are jointly significant and provide substantially better fit (as measured by the McFadden "pseudo" R-square). In Model 1 I normalize the payoffs of the second stage depicted in Figure 2.2 by the payoffs from *Acq./Lic.*$(\tilde{V}_3)$, e.g. the base group of the multinomial logit is $(y_i = 1)$. As such, Model 1 estimates provide information about the impact of covariates on the payoffs from choosing *Post CVC Acq./Lic.* $(y_i = 2)$ or *Other* $(y_i = 3)$ relative to choosing *Acq./Lic.*. In Model 2 payoffs from second-stage choices are normalized by the payoffs from *Post CVC Acq./Lic.* $(\tilde{V}_4)$, e.g. the base group of the multinomial logit is $(y_i = 2)$.

The negative coefficients on *Absorptive capacity* in Model (1) provide additional support for my prediction made in Hypothesis 2a. They suggest that *Absorptive capacity*

decreases both the payoffs from *Post CVC Acq./Lic.* and *Other* relative to *Acq./Lic.*. The joint effect of the two coefficients (not shown) is significant at the 1% significance level.

I also find further support for Hypothesis 2b, since *Internal productivity* increases both payoffs from *Post CVC Acq./Lic.* and *Other* relative to *Acq./Lic.*, and the joint effect (not shown) is positive and significant at the 1% level.

This model, in particular the third column of Table 2.7, also shows that the coefficient on *Technological diversity* is negative and significant at the 10% significance level, suggesting that the payoffs from *Post CVC Acq./Lic.* relative to keeping the minority equity investment or liquidating it (*Other*) are higher when investor and portfolio firms are technologically diverse. This result is consistent with Hypothesis 3.

Table 2.7. Two-stage model: Multinomial logit results for second stage choice

Model	(1)		(2)
Base group	*Acq./Lic.* conditional on *Int. & Ext. R&D* ($y_i = 1$)		*Post CVC Acq./Lic.* conditional on *Int. & Ext. R&D* ($y_i = 2$)
Choice of R&D (y_i)	*Post CVC Acq./Lic.* conditional on *Int. & Ext. R&D* ($y_i = 2 \mid y_i \neq 0$)	*Other* conditional on *Int. & Ext. R&D* ($y_i = 3 \mid y_i \neq 0$)	*Other* conditional on *Int. & Ext. R&D* ($y_i = 3 \mid y_i \neq 0$)
Absorptive capacity	-0.2457	-0.4040***	-0.1583
	(0.1613)	(0.1187)	(0.2055)
Internal productivity	0.0433	0.0910***	0.0476
	(0.0295)	(0.0298)	(0.0310)
Technological diversity	1.7889	-0.4798	-2.2687*
	(1.5098)	(1.2487)	(1.3039)
Firm size	-0.0605*	-0.0336	0.0268
	(0.0349)	(0.0272)	(0.0305)
Financial slack	0.0651	0.0112	-0.0539
	(0.0652)	(0.0427)	(0.0636)
Prior alliance intensity	-0.0008*	0.0001	0.0010*
	(0.0005)	(0.0004)	(0.0006)
Investor's technological capability	-0.0006	0.0006	0.0012*
	(0.0007)	(0.0005)	(0.0006)
Research-intensive firm's technological capability	0.0008	0.0023**	0.0015
	(0.0009)	(0.0011)	(0.0010)
Constant	-3.7854**	-2.6803*	1.1051

Table 2.7. continued

	(1.6388)	(1.5401)	(1.7496)
ATC specific effect	Yes	Yes	Yes
Year specific effect	Yes	Yes	Yes
N=519			
Log likelihood=-366.033			
pseudo R^2=0.148			

Notes. The first stage estimates of the two-stage model outlined in Figure 2.2 are identical to the first transition (stage) estimates of the three-stage model presented in Table 2.6 and summarized in Figure 2.1. Robust standard errors adjusted for 39 firm-clusters are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Last, I checked the sensitivity of the multinomial logit results to the potential violation of the independence of irrelevant alternatives (IIA) property. Lack of independence of the error terms across choices would lead to wrong inferences on the effect of the examined variables on the relative attractiveness of different alternatives, because such inferences would critically depend on the alternatives under consideration. A robust way to test the sensitivity of the results to violation of the IIA property is to estimate the model on the sample obtained excluding a subset of choices. Since I consider three alternatives in the second stage of Figure 2.2, this amounts to estimating a series of logit models. The results, presented in Table 2.8, suggest that the effect of the covariates on the relative payoff of each choice remains unchanged. The Wald tests of the difference between the coefficient estimated with the full multinomial logit model for all three alternatives and those obtained from the restricted multinomial models in which one alternative is in turn excluded cannot reject the null hypothesis that these coefficients are equal, as evidenced by the p-values of the Wald test indicated in Table 8.[7]

Table 2.8. Testing the independence of irrelevant alternatives assumption

[7] Full and restricted models are jointly estimated using the seemingly unrelated regression model.

	Payoffs from *Other* relative to *Acq./Lic.*		Payoffs from *Post CVC Acq./Lic.* relative to *Acq./Lic.*		Payoffs from *Other* relative to *Post CVC Acq./Lic.*	
Main variables	(*Post CVC Acq./Lic.* is excluded)		(*Other* is excluded)		(*Acq./Lic.* is excluded)	
	Coefficient estimate	Wald test, p-value[+]	Coefficient estimate	Wald Test, p-value[+]	Coefficient estimate	Wald Test, p-value[+]
Absorptive capacity	-0.260 ** (0.108)	0.289	-0.102 (0.141)	0.589	-0.285 (0.178)	0.213
Internal productivity	0.069 *** (0.026)	0.728	0.013 (0.027)	0.624	0.081 ** (0.036)	0.314
Technological diversity	-1.074 (0.893)	0.303	0.510 (1.050)	0.192	-5.544 * (3.114)	0.116
All 23 covariates, including ATC and year fixed effects		0.851		0.917		0.719
Number of observations	519	519	519	519	519	519

Notes. All estimates are obtained conditional on firms engaging in *Internal and External R&D*, e.g. are based on the second stage of the decision tree outlined in Figure 2.2. I then test the sensitivity of the results to violation of the IIA property by estimating a series of logit models obtained by excluding a subset of choices. The reported Wald test is a test of the null hypothesis that the coefficient from the corresponding logit is equal to the corresponding coefficient using multinomial logit, whereby both models are jointly estimated using the seemingly unrelated regression model. Failure to reject suggests that results are not sensitive to the IIA assumption. Standard errors are robust to heterosckedasticity and clustered by firm in italics. ***, **,*: Significantly different than zero at the 1%, 5%, and 10% confidence levels.

2.5 Discussion and Conclusion

In this study I present a perspective in which CVC investments can be used as an ex-ante evaluation mechanism which helps corporate investors effectively search for and select future technology partners. In summary, and consistent with this framework, I find that CVC investments are complementary to licensing and acquisitions, since they facilitate future transactions. In particular, my results suggest that CVC investments facilitate the external acquisition of technology by substituting for a firm's absorptive capacity, as reflected by its upstream research capabilities. CVC investments instead complement the portfolio of internally generated new products, since they allow highly

productive firms to shift their focus onto exploratory initiatives whose objective is to select future technology and partners. Finally, CVC investments facilitate exploratory investments in distant technological areas that are subsequently integrated through licensing or acquisitions.

This paper contributes to several strands of the literature. First, it contributes to an emerging research on the organization and financing patterns of external R&D activities (*e.g.*, Aghion and Tirole, 1994; Mathews, 2006; Robinson, 2008; Fulghieri and Sevilir, 2009). This study, unlike the extant literature which has focused on a single type of external R&D activity, suggests that CVC investments should be considered in conjunction with other types of external R&D activity. This approach, I believe, is more appropriate because firms often pursue an R&D strategy which is comprised of several types of external R&D activity simultaneously.

Second, this study also contributes to the literature on optimal organization and financing arrangements between corporate investors and start-ups (*e.g.*, Hellmann, 2002; Katila *et al.*, 2008; Dushnitsky and Shaver, 2009). Unlike that literature, however, which has investigated how resource constraints and appropriation problems affect CVC investments, my study suggests that CVC investments can be greatly determined by timing, which ultimately affects the level of asymmetric information and uncertainty found in the market for technology.

Finally, this study is particularly important for the pharmaceutical industry, which has faced severe productivity challenges in the last decade and where significant levels of uncertainty and adverse selection problems are common (Arora and Gambardella, 1990 and 1994). As a result, effective decisions on external R&D activity are critical in generating profits for growth (*e.g.*, Nicholson *et al.*, 2005; Higgins and Rodriguez, 2006; Ceccagnoli and Higgins, 2011). My findings imply that several types of external R&D activity co-exist, each fulfilling their own strategic role in this industry. This is also

consistent with prior work which suggests that the external strategies of large pharmaceutical firms, which include alliances, as well as majority and minority equity investments in smaller biotechnology companies, are complementary since they are positively correlated (Arora and Gambardella, 1990). From this point of view, I extend this literature by providing evidence on the sources of such complementarities.

This study has also important implications for managers. In particular, it implies that managers should consider the timing issue of each type of external R&D activity to maximize firm productivity. This implication is particularly important in the pharmaceutical industry, which has a long product development cycle. This study also implies that I need to better understand how various types of external R&D activities affect one another. My findings suggest that one type of external R&D activity cannot be used independently from other types of activities; a consolidated perspective on the various types of external R&D activities is needed.

Finally, my focus on the pharmaceutical industry suggests that my findings need to be interpreted carefully in the context of other industries. This notion is important because each industry has its own technological and managerial environment (e.g., development cycles are very different across industries) and uses CVC investments according to its own context.

CHAPTER III

COMPLEMENTS OR SUBSTITUTES? TECHNOLOGICAL SPILLOVERS AND CAPITAL GAINS CREATED BY CORPORATE VENTURE CAPITAL INVESTMENTS

3.1 Introduction

Unlike independent venture capitalists that primarily pursue financial returns, corporate investors benefit from technological as well as financial returns from their investments.[8] The technological benefits come from exposure and access to external technologies and products, while the financial return can come through the selling of stocks in an IPO, acquisitions of portfolios by third-parties, or other types of liquidation events. An example is the investment by the corporate venture capital (CVC) arm of Eli Lilly and Company in Millennium Pharmaceuticals Inc., in 1995. Eli Lilly received technological benefits from the collaborative research efforts into the genetic causes of atherosclerosis and congestive heart failure – it also received a substantial financial gain from the IPO of Millennium Pharmaceuticals in 1996.

It is well recognized that technological returns are important in CVC investments though reliable measures are hard to obtain because of the difficulty in isolating and estimating these returns. As a result, we know little about the nature of interaction, if it exists, between the technological and financial returns from CVC investments. I believe

[8] These two types of return have been respectively discussed in the existing literature. Technological return created by CVC investments has been analyzed in Gompers and Lerner (1998), Anand and Galetovic (2000), Chesbrough (2002), Hellmann (2002), Maula and Murray (2002), Dushnitsky and Lenox (2005a, 2005b, and 2006), Wadhwa and Kotha (2006), Katila et al. (2008), Keil et al. (2008), Benson and Ziedonis (2008), Dushnitsky and Shaver (2009), and Fulghieri and Sevilir (2009). Financial return created by CVC investments has been investigated in Sykes (1986), Gompers and Lerner (1998), Maula and Murray (2002), Henderson and Leleux (2003), Allen and Hevert (2007), and Benson and Ziedonis (2010). Moreover, several surveys have reported that corporate investors make CVC investments to pursue these two types of return (e.g., Siegel et al., 1988; Corporate Strategic Board, 2000; Kann, 2000; Asset Alternatives, 2002; Birkinshaw et al., 2002; PriceWaterhouseCoopers, 2006; MacMillan et al., 2008).

that an understanding of this interaction is important because it sheds light on the motives of corporate investors and on whether CVC investments ultimately create a positive total return for corporate investors. Moreover, to the extent that financial return is largely a reflection of the changes in the market values of portfolios, the nature of the interaction indicates whether or not CVC investments create mutual benefits between corporate investors and portfolios. Such a mutuality of benefits may well play a key role in determining the success or failure of CVC investments.

Beyond just the nature of the interaction, my understanding of contextual factors impacting the interaction is important because it can help corporate investors balance technological and financial returns (e.g., Gompers and Lerner, 2004) and thus increase the total return created by CVC investments. For example, consider if technological and financial returns are indeed complements and the complementarity is affected by investment- or firm-specific factors. In this case, corporate investors should be taking advantage of these contextual factors to maximize their total return. Since corporate investors can be reasonably assumed to want to maximize their total return, understanding the conditions under which technological and financial returns are complements is more practical and important than merely identifying the existence of complementarity. In addition, these contextual factors can be understood to facilitate the mutual benefits between corporate investors and portfolios. Hence, in my paper I will pursue two interrelated questions: (1) Are technological and financial returns created by CVC investments complements, substitutes, or independent? (2) What contextual factors impact the interaction between technological and financial returns?

To address these questions, I develop a simple and flexible model that analyzes the nature of the relationship between technological and financial returns and gives rise to testable implications. By evaluating the technological and financial returns created by 71 bio-pharmaceutical corporate investors between 1985 and 2005, I present novel and systematic evidence that supports the existence of complementarity between these two types of return. Moreover, consistent with the predictions, my findings suggest that this complementarity is enhanced when CVC investments are made in post-IPO and technologically diversified portfolios, respectively.

My study contributes to different strands of the literature. First, it contributes to the literature on CVC investments by providing systematic estimates of technological and financial returns and the nature of their relationship. To the best of my knowledge, this study is the first to systematically estimate both technological and financial returns. Thus, my study extends the prior studies in the literature that have focused on either one of the two types of return and thus helps better evaluate the costs and benefits of CVC investments.

Second, and more broadly, this paper contributes to the literature on the way in which firms organize and finance their R&D investments. While one perspective suggests that active pursuit of financial return can come at the cost of technological return (e.g., Rind, 1981; Chesbrough, 2002; Gompers and Lerner, 2004), an alternative perspective is that corporate investors can pursue technological and financial returns simultaneously. My findings are consistent with the latter perspective. Thus, corporate investors can use CVC investments as a strategy to facilitate their external R&D activities at a lower cost.

Finally, my paper develops and tests hypotheses about the conditions under which portfolios would be expected to capture a larger share of the value created in CVC investments and the possible impact on financial and technological returns and their complementarity. I argue that the complementarity can reflect, in part, the existence of mutual benefits between corporate investors and, hence, conditions under which portfolios are being provided stronger incentives.

This paper is organized as follows. The next section presents my analytical framework and hypotheses. The subsequent section describes my empirical strategy and data. I then report empirical results and conclude.

3.2 Model and Hypothesis Development

3.2.1 Related Literature

The existing literature on technological return created by CVC investments is often related to technology spillovers or transfers that originate from portfolios (Anand and Galetovic, 2000; Hellmann, 2002). For example, pharmaceutical firms that get locked into specific research programs often make CVC investments primarily to learn about, license, and acquire innovative technologies pursued by biotech firms (Ceccagnoli and Higgins, 2011). These CVC investments can take the form of pure equity investments or equity plus additional rights such as licensing and collaboration agreements in the development, marketing, and sales of products (Hamermesh et al., 2007). As a result, corporate investors can obtain several types of technological return: innovative ideas (Dushnitsky and Lenox, 2005a and 2005b; Wadhwa and Kotha, 2006; Keil et al., 2008), a window into future technology (Siegel et al., 1988; Yost and Devlin, 1993; Gompers and Lerner, 1998; Alter and Buchsbaum, 2002; Benson and Ziedonis,

2008), a capacity to select future technology partners (Folta, 1998; Van De Vrande et al., 2006; Van De Vrande and Vanhaverbeke, 2009; Li and Mahoney, 2011), and market penetration (Maula and Murray, 2002; Lipuma, 2007). Considering this wide range of technological returns created by CVC investments, I define technological return in a fairly comprehensive way as the change in corporate investors' research productivity that results from the new knowledge, processes, and products from CVC investments.

The existing literature on technological return investigates the conditions under which corporate investors can source external technology pursued by portfolios. For example, Dushnitsky and Lenox (2005a and 2005b) argue that firms make more CVC investments in industries with weak intellectual property protection because technology spillovers can easily occur in such industries. Wadhwa and Kotha (2006) and Keil et al. (2008) find evidence that corporate investors' technological performance hinges on their technological diversity and relatedness to portfolios. Katila et al. (2008) and Dushnitsky and Shaver (2009) find that, under a regime of weak intellectual property protection, fewer CVC investments are made when portfolios target the same industry as corporate investors. A limitation of many of these studies is that indirect evidence is used to infer the technological progress from CVC investments. I believe that my paper contributes to the literature by attempting to isolate and estimate the technological return created by CVC investments in a specific context.

Another strand of the literature offers a real options view that CVC investments represent an option to proceed or defer subsequent external R&D activities (e.g., Folta, 1998; Van De Vrande et al., 2006; Van De Vrande and Vanhaverbeke, 2009; Li and Mahoney, 2011). The notion is that corporate investors can use the new information

obtained from CVC investments to decide on future R&D activities. For example, Folta (1998) finds that CVC investments economize on the cost of committing resources to the technology with an uncertain value in domains in which learning about growth opportunities dominates investment activities. Van De Vrande et al. (2006) suggest that firms can be better off using CVC investments that are reversible and involve a low level of commitment in the early stage of technology development.

Although technological return has been the focus of much of the literature on CVC investments, surveys find that financial return is also regarded as an important motive in making CVC investments. For example, MacMillan et al. (2008) report that fifty percent of their sample CVC programs invest primarily for technological return, but that financial return is a requirement, while twenty percent of the sample programs invest primarily for financial return but technological return is requirement. The remaining thirty percent are split equally between pursuing only financial or only technological returns. It is argued that the financial return makes it possible to maintain CVC programs (Hardymon et al., 1983; Siegel et al., 1988; Gompers and Lerner, 2004). The paucity of available data on the financial return from individual CVC investments makes it hard to definitively ascertain whether or not CVC investments ultimately create positive financial return (Allen and Hevert, 2007).

Evidence on financial return is often limited to case studies (e.g., Sykes, 1986; Gompers and Lerner, 1998; Chesbrough, 2002) or comparisons of the IPO performances of portfolios financed by corporate investors and independent venture capitalists (e.g., Gompers and Lerner, 1998; Maula and Murray, 2002; Henderson and Leleux, 2003). For example, Gompers and Lerner (1998) find that corporate investors fare as well as

independent venture capitalists by using the IPO rate of portfolios. Maula and Murray (2002) find that portfolios that are financed jointly by corporate investors and independent venture capitalists have a higher valuation at IPO than those financed by only independent venture capitalists. Henderson and Leleux (2003) find that portfolios engaged in prior collaboration with corporate investors are more likely to have an IPO than those not financed by corporate investors. Benson and Ziedonis (2010) find that portfolios financed by corporate investors tend to show the negative cumulative abnormal return (CAR) in their acquisitions. Allen and Hevert (2007) find that the distribution of financial return is wide and bimodal, with thirty percent of CVC programs achieving IRRs greater than forty percent and an equal proportion with returns of negative twenty percent or worse.

There is, however, little theory and empirical evidence to guide us on the nature of the interaction between financial and technological returns. To the extent that several surveys have repeatedly emphasized the technological and financial returns as important motives for CVC investments, this gap in the literature is somewhat surprising.

3.2.2 Interaction between Technological Spillovers and Capital Gains

Complementarity is understood to exist if increasing one variable raises the return to increasing the other variable.[9] By the same token, decreasing one variable can raise the return to increasing the other variable. This is the case of substitutability.

[9] This definition is used in a set of studies that examine the complementarity of two variables (e.g., Milgrom and Roberts, 1990; Athey and Stern, 1998; Persico, 2000; Siggelkow, 2002; Cassiman and Veugelers, 2006; Loskhin et al., 2007). More formally, my definition of complementarity is originated from the supermodular function that exhibits complementarities among its arguments. A function $f: R^k \rightarrow R$ is supermodular if $f(x \vee y) + f(x \wedge y) \geq f(x) + f(y)$ for all $x, y \in R^k$, where $x \vee y$ denotes the componentwise maximum and $x \wedge y$ the componentwise minimum of x and y. This function is equivalent to $f(x \vee y) - f(x \wedge y) \geq f(x) - f(x \wedge y) + f(y) - f(x \wedge y)$ and $f(x \vee y) - f(y) \geq f(x) - f(x \wedge y)$. These reformulations make clear the sense in which complementarity exists if the change resulting from increasing two arguments together is greater than that resulting from increasing two arguments separately.

I set up a simple model to study the nature of interaction between technological and financial returns and associated factors that impact the interaction. To begin, suppose that a corporate investor decides on the level of its CVC investment, denoted by C. For this investment, the corporate investor receives an ownership of a fraction β (of the shares) of the portfolio. The fraction β depends on the bargaining power of the corporate investor relative to the portfolio and on the need to provide appropriate incentives to the portfolio.

I assume that the corporate investor can obtain two types of technology flows from the CVC investment: first, it has the right to purchase/license technology developed by the portfolio firm; second, the corporate investor benefits through a positive spillover (for which the portfolio is not compensated) effect on its ongoing internal R&D. In the former case, the amount paid to the portfolio is given by π. Since I have normalized the rest of the value of the portfolio to zero, this is also the value (say at IPO or when acquired by a third party) of the portfolio. Given the corporate investor's β fractional ownership of the portfolio, its financial return, denoted by F, can be expressed as:

$$F = (\beta\pi - C)/C. \quad (1)$$

I assume that the amount π that the corporate investor pays may be well below the economic value of the technology purchased/licensed from the portfolio. I take this economic value to have a form $\theta C^{1/2}$, where θ represents the research productivity associated with the CVC investment. The ability of the corporate investor to pay significantly less than the economic value can be affected by the relative bargaining power of the corporate investor and portfolio as well as the extent to which the

technology can be appropriated by the corporate investor. I denote the appropriability of the technology and value expropriation by α, such that:

$$\pi = (1 - \alpha)\theta C^{1/2}. \quad (2)$$

Hence, when the corporate investor finds it more difficult to appropriate the technology developed by the portfolio or is in a weaker bargaining position, I can expect π to be higher.

It is supposed that the positive spillover effect from CVC investments is such that the corporate investor can increase its internal R&D productivity by utilizing the information or knowledge obtained through the CVC investment. Specifically, I assume that the additional number of new technology (e.g., knowledge/innovation) is given by $kC^{1/2}$, where k can be understood as the corporate investor's ability to generate new technology from the information or knowledge developed. If the value of each innovative product/technology is expected to be ω, then the value created by the spillover effect can be expressed as $\omega kC^{1/2}$. Thus, from the perspective of the corporate investor, the economic value V created by the CVC investment is given by:

$$V = [\alpha + \beta(1 - \alpha)]\theta C^{1/2} + \omega kC^{1/2} - C, \quad (3)$$

A corporate investor can maximize the expected economic value of CVC investments by choosing to invest at the level of C^* such that:

$$C^* = arg\,max(V) = ([\alpha + \beta(1 - \alpha)]\theta + \omega k)^2. \quad (4)$$

Note that an increase in the productivity parameter θ leads to a higher level of CVC investment C and thus increases the financial return as well as the technological return (e.g., generation of new technology/innovation/product). It is also noteworthy that a decrease in the appropriability parameter α (by typing the financial return F more closely

to the overall value produced) tends to increase the correlation between the financial and technological returns. Note, however, that the types of CVC investment that produce the more value for the corporate investor are those with a greater amount of appropriability – and, hence, somewhat lower financial returns. My simple model offers a possible perspective on complementarity – that attractive CVC investment opportunities will induce more investments and generate financial gains as well as technological gains, those for which the portfolio is compensated, as well as those for which it is not. In what follows, I discuss the notion of complementarity between financial and technological returns more broadly in the context of the existing literature. I will also draw upon the model and my discussion of the literature to obtain empirical hypotheses that I subsequently test.

The complementarity predicted by the model is generally consistent with the anecdotal evidence of "influence" and "sorting" effects, which suggest that corporate investors can add value to portfolios in several ways (Sørensen, 2007). Though not formally developed in the model, the former suggests that corporate investors can increase the market value of portfolios through providing their complementary assets and commercialization capabilities (Park and Steensma, 2011). The latter indicates that corporate investors have a capacity to select promising portfolios (such as those with higher θ in the model) and provide positive signals to other stakeholders about the qualities of portfolios, resulting in increases in the market value of portfolios (Stuart et al., 1999; Shane and Scott, 2002). As a result, corporate investors can obtain the technological return by using the technology spillovers originated from portfolios and also obtain the financial return by increasing the market values of portfolios through

CVC investments. These mutual benefits created by CVC investments can result in the existence of complementarity between technological and financial returns.

The prediction of complementarity is also consistent with the "window for future technology" perspective. This perspective suggests that corporate investors make CVC investments to track future technological trajectories and identify future technology partners. Because corporate investors can obtain better information about technologies pursued by portfolios through CVC investments, they can effectively decide to formally integrate the technologies through subsequent acquisition and licensing, thereby reducing some risk and adverse selection prior to committing substantial resources in integrating the technologies. Corporate investors that obtain the technological return by effectively identifying portfolios can also obtain the financial return because the subsequent acquisition and licensing will tend to increase the market value of portfolios, resulting in the existence of complementarity between technological and financial returns.[10]

Conversely, financial return created by CVC investments can increase the technological return in several ways. First, corporate investors should maintain a certain level of financial return expected internally to support their CVC programs (Siegel et al., 1988; Jensen, 1993; Gomper and Lerner, 2004). Unless CVC programs can demonstrate tangible results within a few years, they are likely to be hard-pressed to justify ongoing funding and senior management support (Hardymon et al., 1983). Second, if the financial return is sufficient so that CVC programs exist for a substantial period of time, these

[10] For example, if a corporate investor integrates the technology pursued by a portfolio through the subsequent licensing, the portfolio can obtain additional revenues (Caves et al., 1983; Katz and Shapiro, 1985), enhancing demand (Shepard, 1987), facilitating collusion (Arora and Gambardella, 1990 and 1994; Lin, 1996; Cassiman and Veugelers, 2006), and complementary assets (Katila et al., 2008; Basu et al., 2009; Maula et al., 2009). Moreover, if the corporate investor acquires the portfolio to integrate the technology, the acquisition per se is a harvesting event that realizes the financial return as well as the technological return.

corporate investors can increase the marginal rate of technological return due to learning effects. These learning effects occur because the accumulated experiences of CVC investments provide the corporate investors with common skills, shared languages, and similar cognitive structures that enable the two firms to effectively and efficiently communicate and learn from each other, enhancing learning and thereby increasing the technological return (Lane and Lubatkin, 1998; Mowery et al., 1996). Finally, sufficient financial return often allows corporate investors to access more and better potential portfolios, resulting in increasing the technological return. Taken all together, I can expect to see the existence of complementarity between technological and financial returns created by CVC investments. A testable hypothesis is:

> *Hypothesis 1. Technological and financial returns created by CVC investments are likely to be complements.*

3.2.3 Contextual Factors Impacting the Complementarity

In this section, I bring together some ideas about contextual factors that impact complementarity between technological and financial returns by relying on a stylized discrete choice model, which will allow us to better structure the development of my hypotheses. In particular, I will consider four sub-groups of CVC investments using technological and financial returns as two demarcation lines as depicted in Figure 3.1. For obtaining these sub-groups, I split the sample between CVC investments generating technological and financial returns above and below the means, respectively. Group I represents CVC investments that result in low technological and low financial returns; group II are those with low technological and high financial returns; group III has high technological and low financial returns; and, finally, group IV has high technological and

high financial returns. Complementarity between technological and financial returns would result in sub-groups I and IV being more populated. To examine the contextual factors that tend to promote complementarity, I will search for factors that impact the likelihood of CVC investments with returns in these two sub-groups.

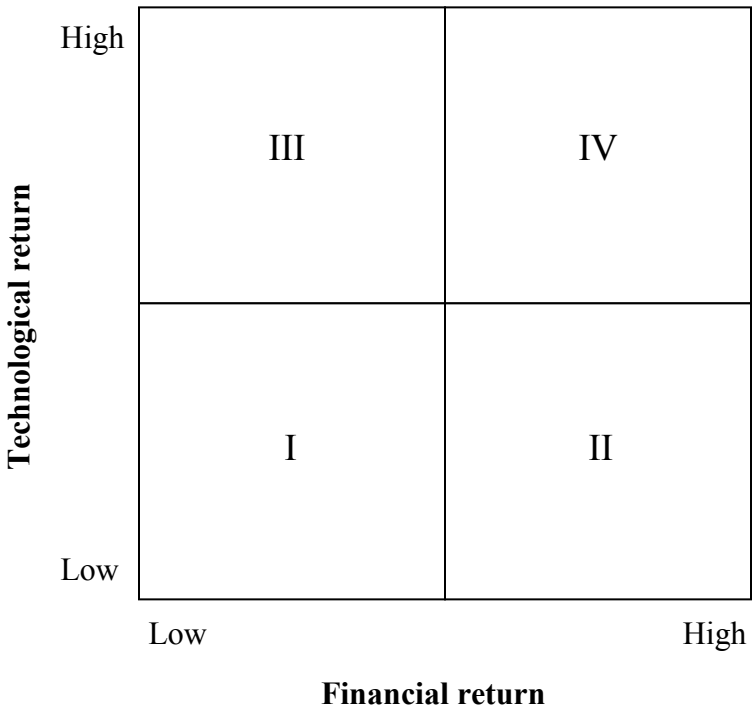


Figure 3.1. Types of return along the technological and financial returns

Post-IPO portfolio

It has been argued that start-ups have several mechanisms, including patent, trade secrets, and timing their CVC financing to coincide with later funding rounds, to avoid unexpected technological spillovers or transfers (Lerner and Merges, 1998; Katila et al., 2008). These mechanisms exist because start-ups often view corporate investors suspiciously due to the perception that corporate investors' intents may be to expropriate their technologies (Katila et al., 2008; Dushnitsky and Shaver, 2009). Start-ups often choose to time their CVC financing because acquiring and maintaining patents and trade secrets can be costly, yet ineffective at protecting their technologies.

This timing mechanism is more critical for early stage start-ups because it may be easier for corporate investors to appropriate these start-ups' technologies (Katila and Mang, 2003). Specifically, these early stage start-ups may find it more difficult to protect their technologies from potential appropriation because their premature technologies are not fully embodied in their products (Katila et al., 2008). Corporate investors also find it easier to influence the product portfolios and strategic agendas of the early stage start-ups (Sahlman, 1990; Rivkin, 2000). In this early stage regime, corporate investors can obtain substantial technological return by either appropriating or influencing their portfolios' technologies, products, and strategic agendas. As suggested by my model, the greater the technological return corporate investors obtain in this regime, the less financial return they gain because their technological return can come at the cost of destroying the market values of portfolios and thus decreases their financial return that is largely determined by the market values of portfolios. This occurs because technologies are often the most important assets for these portfolios. As a result, I would not expect strong complementarity between technological and financial returns in the early stage regime.

In the later stage regime, start-ups can more readily transfer their technologies to increase their revenues or market values through licensing or acquisition because they can relatively easily protect their technologies that are fully embodied in their products. Beyond obtaining substantial technological return in this regime, corporate investors can also gain a greater financial return than in the early stage regime -- because start-ups can more effectively protect their technologies and, hence, their market values. As a result, I can expect a stronger complementarity between technological and financial returns in this

later stage regime. As such, using portfolios' IPOs as a demarcation line between these early and later stage regimes, I hypothesize:

> *Hypothesis 2. CVC investments made in post-IPO portfolios are likely to enhance the complementarity between technological and financial returns.*

Technological diversity

From the real option view on CVC investments, corporate investors that invest in more technologically diversified fields can obtain greater technological return (Ceccagnoli et al., 2011). This occurs because these corporate investors can access to a greater range of technological fields, which potentially increases outcomes on the upside, while limiting exposure on the downside. With the passage of time, they can truncate the left-hand tails of a performance distribution by avoiding technological fields that are unpromising. This creates a performance distribution curve that is skewed to the right, yielding asymmetric pay-offs (McGrath and Nerkar, 2004).

In the high technological diversity regime, corporate investors can expect greater financial return than one that would be gained in the low technological diversity regime. This expectation is because start-ups that obtain financing from technologically diversified corporate investors are likely to find it easier to protect their technologies from the risk of corporate investors' appropriation and, thereby, to protect their market values. Moreover, these corporate investors are less likely to immediately become future competent rivals in their technological space because they would need substantial time and resources to do so. Thus, I can expect strong complementarity between technological and financial returns in this high technological diversity regime.

Note that, contrary to the real option view, it can be argued that corporate investors that invest in technologically undiversified fields would obtain a substantial technological return because similar knowledge bases can increase the "marginal rate of learning." In this low technological diversity regime, these corporate investors can easily appropriate start-ups' technologies because of their similar knowledge bases and thus can destroy the market values of portfolios, resulting in a weak complementarity between technological and financial returns. In addition, these corporate investors are more likely to quickly become rivals, and thus destroy the market value of portfolios, than corporate investors in technologically diversified fields. Hence, I formulate the following

> *Hypothesis 3. CVC investments made in technologically diversified portfolios are likely to enhance the complementarity between the technological and financial returns.*

3.3. Empirical Strategy and Data

3.3.1 Empirical Strategy

Three econometric approaches are widely used to test for complementarity: the "correlation," "production function," and "direct regression" approaches (Athey and Stern, 1998). The correlation approach, which has been popular due to its simplicity, tests conditional correlations based on the residuals of reduced form regressions of the variables of interest on all observable exogenous variables (Arora, 1996; Lokshin et al., 2007). The production function approach tests a simple one-tailed t-test on the interaction term of the two variables of interest in the regression of a performance variable and thus examines the cross-derivative of the two variables. This approach is feasible only if a reasonable performance variable exists. However, in this study, it is difficult to find an appropriate performance variable (e.g., total return created by CVC investments). Finally,

the direct regression approach tests a one-tailed t-test on one variable of interest and all observable exogenous variables in the regression of the other variable of interest. Although these approaches can provide supportive evidence of complementarity, they cannot serve as definitive tests (Cassiman and Veugelers, 2006) because the estimated correlation and coefficients may be the result of common omitted exogenous variables (e.g., unobserved heterogeneity).[11] These approaches provide consistent test statistics for finding complementarity only if unobserved heterogeneity does not exist in the model. Note that such a condition, however, is almost impossible to satisfy in applications such as strategy and other fields in management, in which the performance measure is usually associated with firm-level performance (Athey and Stern, 1998).

Using the correlation and direct regression approaches, I seek evidence that supports the existence of complementarity between technological and financial returns. For a more definitive test, I then use the "indirect" approach that examines complementarity through an exclusion restriction on the regressions of the variables of interest, technological and financial returns.[12] For example, I assume that the number of firms making CVC investments in a year (i.e., CVC fraction) is exogenous and affects only technological return. If technological and financial returns are complements, I should find a positive effect of CVC fraction on financial return as well as technological

[11] More specifically, Athey and Stern (1998) present how particular forms of unobserved heterogeneity can bias test statistics from these approaches in specific directions under two assumptions: two elements are independent or complements. Under the former assumption, the presence of positive correlation between the unobserved heterogeneity of the two elements yields (1) positive correlation between the two elements and (2) a positive estimate of the interaction effect in an OLS or 2SLS productivity regression. Thus, positive correlation in the unobservables results in a force for a positive bias in the estimate of interaction effects in a productivity regression. Under the latter assumption, if unobserved heterogeneity of two elements is independent, the bias on the interaction effect will always be negative.

[12] Following Cassiman and Veugelers (2006), I regress the nonexclusive elements on the assumed exogenous control variables, Z_i, as in the following model: $T_i = Z_i\gamma_1 + \varepsilon_1$, $F_i = Z_i\gamma_2 + \varepsilon_2$, $E[\varepsilon_1] = E[\varepsilon_2] = 0$, $Cov[\varepsilon_1, \varepsilon_2] = \rho$. A variable that should directly affect only one of T or F, in the presence of complementarity, shows up significant in both regressions because the complementarity induces an indirect effect from this variable on the other F or T, respectively.

return because the complementarity induces an indirect effect from technological upon financial return. This indirect approach is important for two reasons. First, this approach provides a less noisy empirical assessment of complementarity than the other approaches (Cassiman and Veugelers, 2006). Second, this approach does not require an appropriate dependent variable that is necessary for the production function approach to be regressed upon the interaction term of the variables of interest.

To find contextual factors that may impact the return complementarity, I focus on searching for factors that significantly and positively impact the likelihood of CVC investments in sub-groups I and IV, as depicted in Figure 3.1. These factors can explain the joint occurrence of technological and financial returns and thus complementarity between these two types of return. I also estimate the correlation coefficients between technological and financial returns in different regimes (e.g., pre- and post-IPO regimes and high and low technological diversity regimes). If these regimes greatly impact the return complementarity, I will observe significantly different correlation coefficients across regimes.

3.3.2 Data

My data on CVC investments are drawn from the *Deloitte Recap* database. Because this study focuses on technological and financial returns created by CVC investments, I restrict my attention to firms that have at least a minimal probability of making CVC investments by selecting only those that have made at least one CVC investment. My data contain 1,491 firm-year observations that include 71 bio-pharmaceutical firms (i.e., corporate investors) between 1985 and 2005. From this source I obtain information on CVC investment arrangements such as the identities of corporate

investors and portfolios and the dates, valuations, prices, funding amounts, and rounds of individual CVC investments.

By focusing on the bio-pharmaceutical industry between 1985 and 2005, I gain several advantages in analyzing technological and financial returns. First, this concentration in a single industry allows us to use unique data sets that contain sufficient information to estimate technological and financial returns. Second, it is very hard to compare technological and financial returns across industries because each industry has its own technological and financial environments. Notwithstanding this concentration, my theoretical and empirical implications should be, albeit to a somewhat lesser extent, applicable to other research-intensive industries. Furthermore, the time period between 1985 and 2006 is reasonable for investigating these two types of return because it can be characterized as one of great expansion for the industry and intensive CVC investments (MacMillan *et al.*, 2008).

These observations created from the *Deloitte Recap* database are matched to drug pipeline data from the *PharmaProjects* database. This product pipeline data contains the history and progress of more than 36,500 drugs that have been developed since 1980. The number of drugs in each stage of development, which are classified as preclinical, Phase I, Phase II, and Phase III, is obtained and used to estimate technological return.

This dataset is then combined with NBER patent data to estimate patent stock and technological diversity. To appropriately match with the NBER patent data, I used PDPC O and *Compustat* GVKEY. The use of these two identification systems alleviates a potent ial mismatching problem, in which assignee names do not necessarily correspond to the r ecords within *Deliotte Recap* or *Compustat*, and appropriately tracks the changes of paten

t ownership. Financial and accounting data is collected from *Compustat*.

3.3.3 Measuring Technological and Financial Returns

I measure two types of returns created by CVC investments. The first measure is technological return and reflects the extent to which CVC investments contribute to the research productivity of corporate investors. This measure primarily uses the information of products (e.g., drugs) within the research pipelines of corporate investors. The second measure is financial return and estimates the geometric average return (e.g., constant rate of return) on CVC investments.

Technological return should estimate the portion of research productivity created by CVC investments rather than other factors that possibly impact the research productivity. I begin with a regression model:

$$y_i = u_0 + \Pi_i u_1 + e_i, \quad (5)$$

where y_i is the number of products and is weighted by transition probabilities for advancing to the next stage within research pipeline,[13] u_0 and u_1 are parameter vectors, and Π_i is a set of variables that possibly impact research productivity other than CVC investments. Π_i includes firm size (e.g., total assets), internal R&D (e.g., R&D expenditures), external R&D (e.g., prior alliance stock including acquisition, licensing, and collaborative research), and technological stock (e.g., patent stock). I predict base ŷ from the base regression that *does not* include the CVC amount as an independent variable as presented in Table 3.1 (please see Models 1, 3, and 5).

[13] The transition probabilities for advancing to the next stage are 0.71, 0.44, and 0.69 in Phase I, II, and III, respectively (Grabowski and Kyle, 2008). For example, if 100 compounds are in Phase I, 21 compounds can emerge in the market. Phase I is the earliest trials in the life of a new compound or treatment and is usually small trials, recruiting anything up to about 30 patients or a lot less. Phase II expands trials to patients who have same type of disease and aims to find out the extant, side-effects, appropriate usage of compounds. Phase III compares new compounds with the best currently available treatment (the standard treatment) and releases them if they pass.

Table 3.1. Regressions for estimating technological return

Panel A: OLS regressions predicting the number of products

	OLS					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Number of products (weighted)	Number of products (weighted)	Number of products (total)	Number of products (total)	Number of products (pre-clinical)	Number of products (pre-clinical)
CVC amount		0.0394***		0.0996***		0.1073***
		(0.0106)		(0.0294)		(0.0276)
Size	0.3026***	0.2565**	0.7071**	0.5906*	1.3588***	1.2334***
	(0.1150)	(0.1118)	(0.3154)	(0.3073)	(0.3238)	(0.3205)
Internal R&D (t-1)	0.0006	0.0006	0.0018	0.0018	0.0004	0.0004
	(0.0010)	(0.0010)	(0.0029)	(0.0028)	(0.0021)	(0.0020)
Internal R&D (t)	0.0024***	0.0024**	0.0067**	0.0066**	0.0045**	0.0044**
	(0.0009)	(0.0009)	(0.0026)	(0.0026)	(0.0019)	(0.0019)
Patents	-0.0074***	-0.0072***	-0.0206***	-0.0202***	-0.0134***	-0.0130***
	(0.0010)	(0.0010)	(0.0030)	(0.0029)	(0.0023)	(0.0023)
External R&D	0.0396***	0.0352***	0.1102***	0.0991***	0.1060***	0.0941***
	(0.0080)	(0.0080)	(0.0207)	(0.0208)	(0.0223)	(0.0215)
Constant	-1.1131*	-0.9028	-2.4905	-1.9593	-5.3414***	-4.7693***
	(0.6125)	(0.5968)	(1.6886)	(1.6481)	(1.7453)	(1.7228)
N	901	901	901	901	901	901
F	73.6656	64.3872	85.5742	72.8932	44.1121	39.4661
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.4568	0.4713	0.4994	0.5128	0.2601	0.2739

Panel B: Descriptive statistics for three types of technological return

	N	Mean	Median	S.D.	Min.	Max.
Technological return (weighted)	901	3.63e-09	-0.1411	0.7680	-0.9194	9.4525
Technological return (total)	901	-3.52e-08	-0.3564	1.9392	-2.3216	23.8680
Technological return (pre-clinical)	901	-2.65e-09	-0.3838	2.0886	-2.5004	25.7058

Notes. For the definitions of variables, please see Appendix A. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

I also predict treated ŷ from the treated regression that *does* include CVC amount as an independent variable (please see Models 2, 4, and 6). I then calculate the differences between the treated ŷ and base ŷ (i.e., treated ŷ-base ŷ) to use these differences to proxy for the effect of CVC investments on a firm's research productivity. Because treated ŷ can be viewed as a projection onto the linear space spanned by CVC amount, which is not projected in base ŷ, along with Π_i, this measure can be understood as technological return, which is isolated from those of other factors (e.g., Π_i) on the number of products, created by CVC investments. For robustness measure, I use three measures of the number

of products, including the number of products weighted by the probabilities of advancing to the next stage within stage I, II, and III (e.g., Models 1 and 2), the total number of products within stage I, II, and III (e.g., Models 3 and 4), and the number of products within pre-clinical stage (e.g., Models 5 and 6). I use the estimates calculated from Models 1 and 2 as a proxy of technological return in the following analyses. Panel B reports descriptive statistics for the estimates calculated from Models 1 and 2, 3 and 4, and 5 and 6, respectively. For example, technological return (weighted) is the estimates calculated from Models 1 and 2.

As noted, I estimate the geometric average return on CVC investments as a proxy of financial return by using the information from *Deloitte Recap* that provides the prices and dates of stocks at several points, including purchase, IPO, and last valuation. I construct this variable as follows:

$$g_n = (1 + r_c)^{\frac{1}{n}} - 1, \tag{6}$$

where g_n is the geometric average return applicable on each subset period *n*, r_c is the cumulative return over the entire period, and *n* is the number of equal subset periods to average the return. For the sample in which CVC investments are made in pre-IPO portfolios that *do* go public afterward, r_c is estimated by using IPO price per share. For the sample in which CVC investments are made in post-IPO portfolios or pre-IPO portfolios that *do not* go public afterward, r_c is estimated by using the last funding activity price. The last funding activity includes acquisition and other forms of fund-raising activities by portfolios. I finally calculated the weighted mean of g_n with the amounts of individual CVC investments for firm *i* in year t.

This geometric average return can directly gauge the financial performance of CVC investments. Prior studies on CVC investments have been hampered in estimating financial return because of the lack of data availability in which researchers cannot directly observe *when* and *how* corporate investors liquidate their investments. As a result, IPO rate and IPO post-valuation are widely used to measure financial return on CVC investments (e.g., Gompers and Lerner, 1998; Maula and Murray, 2002; Henderson and Leleux, 2003). These IPO-based measures, however, have serious problems in measuring financial return. First, inconsistent with a widely held assumption that most CVC investments are made in pre-IPO portfolios, a substantial number of CVC investments are made in post-IPO portfolios.[14] Second, such measures are not normalized by the holding period of stock; therefore, it is impossible to obtain a sense of return rate in equal subset periods.

3.3.4 Independent Variables and Control Variables

Post-IPO. One of my independent variables is whether corporate investors make their investments in pre- or post-IPO portfolios. I therefore simply construct an indicator variable that equals one if firm *i* makes CVC investments in post-IPO portfolios and zero otherwise.

Technological diversity. The U.S. Patent Office has developed a highly elaborate classification system for the technology to which the patented inventions belong, consisting of about 400 main patent classes and over 120,000 patent sub-classes. Using these patent classes, I calculate the number of patents (e.g., *p*) that share first three digits of patent class between firm *i* and its portfolios and then calculate technological diversity

[14] For example, my sample indicates that 43 percent of CVC investments (e.g., 338 out of 796 CVC investments) were made in post-IPO portfolios.

by using [1/(1+*p*)]. Thus, a greater number of this estimate would indicate more technological diversity between firm *i* and its portfolios.

R&D intensity. Coupled with the absorptive capacity discussion, a firm's ability to evaluate, assimilate, and apply new technology can impact technological and financial returns. To control this absorptive capacity, I control the amount of R&D expenses divided by total assets. This variable is estimated at t and t-1, where t denotes the year in which CVC investments are made.

Size. Since Schumpeter (1943)'s work, firm size has traditionally been an important control variable to estimate a firm's technological performance. While larger firms may enjoy economies of scale and scope, smaller firms are associated with less bureaucracy and thus may make decisions more efficiently on technological activities (Acs and Audretsch, 1987). I use total assets to control firm size.

Growth rate. I include a number of measures (e.g., growth rate, cash flow, and leverage) commonly used in the analysis of financial performance as control variables because this financial performance can determine the level of resources that allow making CVC investments. I control growth rate calculated as the annual percent change in revenues.

Cash flow. This variable is estimated as net income after interest and taxes plus depreciation and amortization.

Leverage. This variable calculates the degree to which the firm is leveraged using the ratio of its total debt to total assets.

Multinationality. Corporate investors can use CVC investments to expand their international markets rather than to pursue technological and financial returns. To control

this strategic motive of CVC investments, I use an indicator variable that equals one if firm *i* involves in international markets and zero otherwise.

Headquarter (U.S.). Because each country has its own institutional environment, a firm's location can impact technological and financial returns. To control this institutional impact, I use an indicator variable that equals one if firm *i* is headquartered in U.S. and zero otherwise.

SIC(28). Because each industry has its own technological and managerial context, industrial specific effects on technological and financial returns should be controlled. Although this study focuses on the bio-pharmaceutical industry, I use an indicator variable that equals one if the first two digits of SIC code are 28 and zero otherwise to more elaborately control these industrial specific effects.

3.4 Empirical Findings

3.4.1 Descriptive Statistics

Table 3.2 reports descriptive statistics for a sample of 1,491 firm-year observations that include 71 corporate investors between 1985 and 2005. This table reports the mean (Mean) and standard deviation (S.D.) of variables used in the following analyses. The column of all samples includes all the observations in the dataset. The column of high (low) technological return includes the observations above (below) the mean of technological return. The mean and standard deviation of financial return in the column of all samples indicate that, on average, corporate investors gain 14.57 percent geometric average return and the distribution is widely dispersed. This great standard deviation is consistent with Allen and Hevert (2007)'s finding that corporate investors' financial gains are widely dispersed and bimodally distributed. Note that consistent with

Hypothesis 1, the mean of financial return is greater for the corporate investors that obtain high technological return (e.g., high technological return) over the corporate investors that obtain low technological return (e.g., low technological return). This consistency is supportive for a notion that technological and financial returns are complements. However, this finding needs to be interpreted with caution because it may be biased by unobserved heterogeneity.

By the econometrics method I used to estimate technological return, it is natural that the mean of technological is close to zero. Note that Table 3.1 demonstrates that CVC amount indicates positive and significant coefficients in the regressions predicting the number of products (please see Models 2, 4, and 6). Based on this result, positive (negative) technological return can be understood as having relatively greater (smaller) impact of CVC amount on the number of products.

Table 3.2. Summary statistics

	All samples		High technological return		Low technological return	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Technological return	0.0000	0.7680	0.7047	1.2944	-0.2277	0.1688
Financial return	0.1457	0.9255	0.2239	1.1650	0.0527	0.4962
Number of products (weighted)	2.6055	5.4781	1.8575	4.9635	3.4952	5.9149
Number of products (total)	6.9396	14.4105	4.8346	12.9005	9.4435	15.6677
Number of products (pre-clinical)	6.5667	14.8480	4.3049	12.8025	9.2570	16.5751
CVC amount	3.8299	15.9630	6.6361	21.1966	0.4922	1.8120
Size	7.5212	2.3173	6.5403	2.7733	7.9317	1.9585
Internal R&D (t-1)	745.2666	1181.0385	625.4763	988.4279	784.8449	1236.2181
Internal R&D (t)	785.1533	1248.0985	561.4600	948.8926	878.1125	1342.8215
Patents	57.7907	198.3860	24.7654	125.8403	97.0720	254.0742
External R&D	12.2280	21.0673	6.2012	14.0244	19.3965	25.3731
Return type	0.5064	0.5001	0.1222	0.3277	0.9633	0.1882
Post-IPO	0.8947	0.3070	0.8506	0.3567	0.9471	0.2239
Technological diversity	0.9070	0.2674	0.9145	0.2666	0.8979	0.2684
R&D intensity (t-1)	0.1379	0.1540	0.1816	0.2058	0.1235	0.1295
R&D intensity (t)	0.1370	0.1509	0.1818	0.2213	0.1184	0.1037
Growth rate	0.4098	2.2061	0.5063	2.9642	0.3787	1.8994
Cash flow	1.2382	2.1123	0.8898	1.5781	1.3826	2.2832
Leverage	0.3872	0.2027	0.3445	0.2106	0.4047	0.1969
Multinationality	0.2435	0.4293	0.1321	0.3388	0.3759	0.4847
Headquarter (U.S.)	0.4594	0.4985	0.2543	0.4357	0.7034	0.4571
SIC (28)	0.5815	0.4935	0.3383	0.4734	0.8708	0.3357

Notes. For the definitions of variables, please see Appendix A.

3.4.2 Existence of Complementarity

Table 3.3 documents correlation coefficients that examine the nature of the relationship between technological and financial returns. Panel A reports simple pairwise correlation coefficients among financial return at t, technological return at t, t+1, and t+2, where t denotes the year in which CVC investments are made. The correlation coefficients of interest are ones between financial return (t) and technological return (t), (t+1), and (t+2), respectively, presented in the first column. Consistent with my prediction made in Hypothesis 1, financial return (t) indicates significant and positive correlation coefficients with technological return (t), (t+1), and (t+2). These lagged correlation coefficients are not surprising because corporate investors may obtain technological return in a substantial time period even after CVC investments are made.

Table 3.3. Interaction test (Residual analysis)

Panel A: Correlations between financial and technological returns

	1	2	3
1. Financial return (t)	1		
2. Technological return (t)	0.274***	1	
3. Technological return (t+1)	0.193***	0.162***	1
4. Technological return (t+2)	0.070*	0.248***	0.183***

Panel B: Correlations between residuals generated from the regressions of financial and technological returns on all observable variables

	1	2	3
1. Residual-financial return (t)	1		
2. Residual-technological return (t)	0.295***	1	
3. Residual-technological return (t+1)	0.205***	0.160***	1
4. Residual-technological return (t+2)	0.062	0.268***	0.170***

Notes. For the definitions of variables, please see Appendix A. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

As noted, I use the correlation approach and report the results in Panel B. This table reports correlation coefficients among residuals generated from the ordinary least

square (OLS) regressions of financial return (t), technological return (t), (t+1), and (t+2) on all observable variables in the dataset, respectively. The correlation coefficients of interest are the ones between residual-financial return (t) and residual-technological return (t), (t+1), and (t+2), respectively, presented in the first column. Consistent with Hypothesis 1, residual-financial return (t) indicates positive and significant correlation coefficients with residual-technological return (t) and (t+1). Hence, using the correlation approach, I find supportive evidence that technological and financial returns are complements and that this complementarity is maintained for a year even after CVC investments are made.

For obtaining more robust evidence, I use the direct regression approach and report the results in Table 3.4. This table reports fixed and random effects regressions predicting technological return at t, t+1, and t+2. I estimate the following models: $T_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \mu_{it}$, where T denotes a set of technological return, X are independent variables of interest, and Z are control variables. The independent variable of interest is financial return. Models 1 through 3 report fixed effects and Models 4 through 6 report random effects regressions. Note that consistent with Hypothesis 1, financial return indicates significant and positive coefficients on technological return (t) and (t+1) as shown in Models 1, 2, 4, and 5. This result is consistent with my finding in the correlation approach and also suggests that technological and financial returns are complements and that this complementarity maintains for a year even after CVC investments are made.

Table 3.4. Interaction test (Regression analysis)

	Fixed effects			Random effects		
	(1)	(2)	(3)	(4)	(5)	(6)

Table 3.4. continued

Dependent variable	Technological return (t)	Technological return (t+1)	Technological return (t+2)	Technological return (t)	Technological return (t+1)	Technological return (t+2)
Financial return	0.2127***	0.1112*	0.0152	0.2313***	0.1357**	0.0443
	(0.0585)	(0.0620)	(0.0228)	(0.0633)	(0.0539)	(0.0273)
R&D intensity (t-1)	0.0645	-0.2254	-0.0953	0.0429	-0.1992	-0.0277
	(0.0759)	(0.2073)	(0.1398)	(0.0877)	(0.1565)	(0.0975)
R&D intensity (t)	-0.0778	0.1131	-0.2537	0.0057	0.2599	0.0003
	(0.1107)	(0.3039)	(0.2371)	(0.1279)	(0.2094)	(0.1595)
Size	-0.0557	-0.0345	-0.0450	0.0003	0.0067	0.0088
	(0.0492)	(0.0489)	(0.0569)	(0.0135)	(0.0195)	(0.0177)
Growth rate	0.0015	-0.0032	-0.0014	-0.0012	-0.0018	-0.0005
	(0.0024)	(0.0029)	(0.0051)	(0.0025)	(0.0032)	(0.0037)
Cash flow	-0.0061	-0.0055	-0.0074	0.0002	-0.0053	-0.0086
	(0.0216)	(0.0295)	(0.0252)	(0.0173)	(0.0224)	(0.0202)
Leverage	-0.1479*	-0.0623	0.0144	-0.1575**	-0.0914	-0.0504
	(0.0799)	(0.1286)	(0.1297)	(0.0769)	(0.1220)	(0.1148)
Multinationality				0.0106	0.0068	0.0072
				(0.0489)	(0.0519)	(0.0535)
Headquarter (U.S.)				-0.0415	-0.0313	-0.0259
				(0.0580)	(0.0655)	(0.0679)
SIC (28)				0.0847**	0.1100***	0.1230***
				(0.0355)	(0.0390)	(0.0424)
Constant	0.2563	0.1241	0.1914	-0.1221	-0.2014	-0.2586*
	(0.4639)	(0.4550)	(0.3497)	(0.1142)	(0.1402)	(0.1490)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Corporate investor fixed effects	Yes	Yes	Yes	No	No	No
N	893	830	787	893	830	787
$F(\chi^2)$	12.9518	4.4331	4.2161	137.9774	106.5523	102.7294
$Prob>F(\chi^2)$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Overall R^2	0.1332	0.0648	0.0252	0.1693	0.0807	0.0426

Notes. Robust standard errors are presented in parentheses. For the definitions of variables, please see Appendix A. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

The existence of complementarity can be tested by using the indirect approach. This approach, however, requires finding a reasonable variable that *does* impact either one of technological and financial returns and *does not* impact the other return. I hypothesize that two variables, including CVC fraction and CVC average amount, are likely to facilitate technological spillovers or transfers originated from start-ups in the industry and thus enhance technological return. CVC fraction is the number of firms that make CVC investments in the industry in the year. CVC average amount is the average

amount of CVC investments in the year. I also hypothesize that these two variables are *not* likely to directly impact financial return. These variables, however, may indirectly impact financial return because technological and financial returns are complements.

Table 3.5 reports the results of complementarity test using the indirect approach. This table reports fixed and random effects regressions predicting technological and financial returns at t. I estimate the following models: $R_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \mu_{it}$, where R denotes technological and financial returns, X are independent variables of interest, and Z are control variables. The independent variables of interest are CVC fraction and CVC average amount. Models 1 through 4 report corporate investor fixed effects, and Models 5 through 8 report corporate investor random effects regressions. Consistent with my prediction, CVC fraction indicates a significant and positive coefficient on technological return (t) as shown in Model 1 and also indicates a significant and positive coefficient, albeit to a lesser extent in the significance level, on financial return (t) as shown in Model 2. Similarly, the CVC average amount is significantly and positively related to technological return (t) as shown in Model 3. Similarly, the CVC amount is estimated with a significant and positive coefficient, albeit to a lesser extent in the significance level, when the dependent variable is financial return (t), as shown in Model 4. The weaker significances of CVC fraction and CVC average amount in Models 2 and 4 can be understood as reflecting the indirect effects of these variables on financial return. Taken together, I conclude that Hypothesis 1 is supported.

Table 3.5. Interaction test (Indirect approach)

	Fixed effects				Random effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Tech. return (t)	Fin. Return (t)	Tech. return (t)	Fin. Return (t)	Tech. return (t)	Fin. Return (t)	Tech. return (t)	Fin. Return (t)

Table 3.5. continued

CVC fraction	0.0271***	0.0186**			0.0228***	0.0139		
	(0.0065)	(0.0092)			(0.0040)	(0.0089)		
CVC average amount			0.0502***	0.0276*			0.0339***	0.0135
			(0.0146)	(0.0158)			(0.0080)	(0.0138)
R&D intensity (t-1)	0.1689	0.2844	0.1384	0.2733	0.1293	0.2947	0.0962	0.2819
	(0.1232)	(0.5379)	(0.1274)	(0.5466)	(0.0951)	(0.4748)	(0.0985)	(0.4768)
R&D intensity (t)	-0.2476*	-0.4459	-0.1657	-0.3553	-0.1737	-0.3014	-0.0804	-0.2255
	(0.1370)	(0.2865)	(0.1263)	(0.2729)	(0.1226)	(0.3500)	(0.1157)	(0.3379)
Size	-0.0456**	-0.0035	-0.0720***	-0.0134	0.0044	0.0517**	0.0023	0.0520**
	(0.0206)	(0.0487)	(0.0215)	(0.0534)	(0.0150)	(0.0240)	(0.0143)	(0.0240)
Growth rate	0.0045**	0.0020	0.0023	0.0006	0.0018	-0.0019	0.0001	-0.0026
	(0.0023)	(0.0043)	(0.0024)	(0.0044)	(0.0023)	(0.0039)	(0.0026)	(0.0039)
Cash flow	-0.0096	-0.0275	-0.0138	-0.0296	-0.0066	-0.0245	-0.0075	-0.0249
	(0.0247)	(0.0293)	(0.0244)	(0.0284)	(0.0184)	(0.0158)	(0.0185)	(0.0158)
Leverage	-0.1388	0.0923	-0.1565*	0.0783	-0.1473*	0.1377	-0.1530*	0.1369
	(0.0893)	(0.2464)	(0.0873)	(0.2442)	(0.0875)	(0.3005)	(0.0880)	(0.3001)
Multinationality					0.0116	-0.0154	0.0118	-0.0163
					(0.0522)	(0.0704)	(0.0522)	(0.0704)
Headquarter (U.S.)					-0.0182	0.0593	-0.0217	0.0547
					(0.0638)	(0.0802)	(0.0632)	(0.0809)
SIC (28)					0.1115***	0.1123	0.1114***	0.1108
					(0.0365)	(0.0770)	(0.0371)	(0.0776)
Constant	-0.5021*	-0.3665	0.3899**	0.2074	-0.8373***	-0.8058**	-0.2080*	-0.4044**
	(0.2876)	(0.5245)	(0.1593)	(0.4201)	(0.2016)	(0.3433)	(0.1212)	(0.1906)
Corporate investor fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
N	893	893	893	893	893	893	893	893
$F(\chi^2)$	7.4111	1.8034	6.4424	1.5721	72.0626	20.4156	49.8943	15.7409
$Prob>F(\chi^2)$	0.0000	0.1131	0.0000	0.1704	0.0000	0.0256	0.0000	0.1073
Overall R^2	0.0122	0.0021	0.0078	0.0002	0.0253	0.0117	0.0216	0.0097

Notes. Robust standard errors are presented in parentheses. For the definitions of variables, please see Appendix A. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

In Table 3.6, I use the ranking variables of technological and financial returns as normalized variables to compare the regression coefficients, rather than the significance levels, of CVC fraction and CVC average amount. I use fixed and random effects poisson regressions to predict the ranks of technological and financial returns (t). The greater rank denotes the greater technological or financial returns (t). Consistent with my finding in Table 3.5, CVC fraction has a significant and positive effect on technological return (t)

rank as shown in Model 1 and also a significant and positive effect, albeit to a lesser extent, on financial return (t) rank as shown in Model 2. Similarly, CVC average amount has a significant and positive relation to technological return (t) rank as shown in Model 3 and also a significant and positive relation, albeit to a lesser extent, to financial return (t) rank as shown in Model 4. The smaller regression coefficients of CVC fraction and CVC average amount in Models 2 and 4 can be understood as the indirect effect of these two variables on financial return. Hence, I conclude that my finding about the complementarity is robust.

Table 3.6. Interaction test (Ranking variables)

	Fixed effects				Random effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Tech. return (t) rank	Fin. Return (t) rank	Tech. return (t) rank	Fin. Return (t) rank	Tech. return (t) rank	Fin. Return (t) rank	Tech. return (t) rank	Fin. Return (t) rank
CVC fraction	0.0291***	0.0135***			0.0290***	0.0134***		
	(0.0004)	(0.0003)			(0.0004)	(0.0003)		
CVC average amount			0.0474***	0.0158***			0.0473***	0.0156***
			(0.0007)	(0.0005)			(0.0007)	(0.0005)
R&D intensity (t-1)	0.1811***	0.0573***	0.1493***	0.0587***	0.1808***	0.0572***	0.1491***	0.0584***
	(0.0127)	(0.0119)	(0.0127)	(0.0119)	(0.0127)	(0.0119)	(0.0127)	(0.0118)
R&D intensity (t)	-0.4956***	-0.1744***	-0.3610***	-0.0845***	-0.4945***	-0.1725***	-0.3598***	-0.0828***
	(0.0187)	(0.0160)	(0.0182)	(0.0157)	(0.0187)	(0.0159)	(0.0182)	(0.0156)
Size	-0.2192***	-0.0017	-0.2398***	-0.0031*	-0.2186***	-0.0009	-0.2391***	-0.0022
	(0.0021)	(0.0016)	(0.0022)	(0.0017)	(0.0021)	(0.0016)	(0.0022)	(0.0017)
Growth rate	0.0087***	-0.0004	0.0064***	-0.0014**	0.0087***	-0.0005	0.0064***	-0.0014**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Cash flow	-0.0879***	-0.0311***	-0.0907***	-0.0321***	-0.0876***	-0.0309***	-0.0905***	-0.0319***
	(0.0017)	(0.0009)	(0.0017)	(0.0009)	(0.0017)	(0.0009)	(0.0017)	(0.0009)
Leverage	-0.1509***	0.0190**	-0.1766***	0.0095	-0.1514***	0.0181**	-0.1770***	0.0088
	(0.0107)	(0.0085)	(0.0107)	(0.0085)	(0.0107)	(0.0085)	(0.0107)	(0.0085)
Multinationality					0.1380	0.0587	0.1608	0.0624
					(0.1862)	(0.0560)	(0.2045)	(0.0577)
Headquarter (U.S.)					-0.1030	0.0428	-0.1216	0.0339
					(0.1945)	(0.0585)	(0.2136)	(0.0602)
SIC (28)					-0.0232	0.0588	-0.0304	0.0556
					(0.1826)	(0.0584)	(0.1988)	(0.0602)
Constant	-0.5021*	-0.3665	0.3899**	0.2074	6.9851***	6.1252***	7.9204***	6.5143***
	(0.2876)	(0.5245)	(0.1593)	(0.4201)	(0.2558)	(0.0828)	(0.2791)	(0.0850)

Table 3.6. continued

Corporate investor fixed effects	Yes	Yes	Yes	Yes	No	No	No	No
N	891	891	891	891	893	893	893	893
χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob>χ^2	0.0000	0.1131	0.0000	0.1704	0.0000	0.0256	0.0000	0.1073

Notes. Standard errors are presented in parentheses. For the definitions of variables, please see Appendix A. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

3.4.3 Contextual Factors that Impact the Complementarity

Beyond just identifying the existence of complementarity between technological and financial returns, I explore contextual factors that impact the complementarity using the four sub-groups depicted in Figure 3.1. Table 3.7 reports fixed and random effect logit regressions predicting the likelihood of CVC investments in sub-group I or IV. I estimate the following models: $Pr(y = 1|X) = \frac{\exp(\alpha_0 + X_{it}\beta)}{1+\exp(\alpha_0 + X_{it}\beta)}$, where Pr denotes the probability of CVC investments in sub-group I or IV, and X are explanatory variables. The independent variables of interest are post-IPO and technological diversity. Models 1 through 3 report fixed effects and Models 4 through 6 report random effects logit regressions. Note that consistent with my prediction made in Hypothesis 2, post-IPO indicates positive and significant coefficients on the probability of CVC investments in sub-group I or IV as shown in Models 1 and 3. Thus, Hypothesis 2 is supported. Similarly, consistent with my prediction made in Hypothesis 3, technological diversity has a positive and significant effect on the probability of CVC investments in sub-group I or IV as shown in Models 2 and 3. Hence, Hypothesis 3 is supported.

Table 3.7. Regressions for identifying factors impacting the complementarity

	Fixed effects			Random effects		
	(1)	(2)	(3)	(4)	(5)	(6)
Return type	I or IV	I or IV	I or IV	I or IV	I or IV	I or IV
Post-IPO	1.6577***		1.6285***	1.7239***		1.5799***

Table 3.7. continued

	(0.3089)		(0.3299)	(0.2856)		(0.3010)
Technological diversity		2.4037***	2.3090***		2.3952***	2.2248***
		(0.4277)	(0.4404)		(0.3592)	(0.3657)
R&D intensity (t-1)	-0.3614	-0.4851	-0.4372	-0.7263	-0.7330	-0.7011
	(0.8415)	(0.8851)	(0.8948)	(0.7570)	(0.8005)	(0.8042)
R&D intensity (t)	-0.1616	0.2045	-0.0255	-1.3857	-0.7292	-1.0556
	(1.2818)	(1.2415)	(1.2949)	(1.0093)	(1.0333)	(1.0501)
Size	1.1583***	0.7779***	1.0096***	0.4255***	0.3992***	0.4863***
	(0.2468)	(0.2446)	(0.2535)	(0.0918)	(0.0948)	(0.0981)
Growth rate	0.0022	-0.0008	-0.0048	0.0248	0.0114	0.0121
	(0.0349)	(0.0341)	(0.0355)	(0.0378)	(0.0367)	(0.0380)
Cash flow	0.1012	0.0969	0.0803	-0.1384*	-0.0735	-0.1106
	(0.1140)	(0.1168)	(0.1206)	(0.0817)	(0.0876)	(0.0891)
Leverage	1.9185**	1.7659**	2.0342**	1.6110**	1.8575***	1.9262***
	(0.7793)	(0.7778)	(0.8033)	(0.6267)	(0.6624)	(0.6755)
Multinationality				0.5177	0.3312	0.4407
				(0.3761)	(0.4096)	(0.4078)
Headquarter (U.S.)				1.1030***	0.8023*	1.1095**
				(0.4101)	(0.4402)	(0.4450)
SIC (28)				-0.0930	-0.1272	-0.0846
				(0.4243)	(0.4538)	(0.4594)
Constant				-3.8028***	-2.4946*	-6.1027***
				(1.1220)	(1.3847)	(1.2521)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Corporate investor fixed effects	Yes	Yes	Yes	No	No	No
N	769	769	769	893	893	893
χ^2	122.0990	128.1025	153.4869	108.9163	106.6314	118.8932
Prob>χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.223	0.234	0.280			

Notes. Standard errors are presented in parentheses. For the definitions of variables, please see Appendix A. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

For obtaining more robust evidence, I examine correlation coefficients between technological and financial returns across different regimes (e.g., pre- versus post-IPO regimes and low versus high technological diversity regimes). In Table 3.8, pre-IPO (post-IPO) regime denotes corporate investors that make their investments in pre-IPO (post-IPO) portfolios. Low (high) technological diversity regime denotes corporate investors that have lower (higher) technological diversity than the mean (i.e., 0.9069). Panel A demonstrates that correlation coefficients between technological and financial

returns are greater in the post-IPO regime than the pre-IPO regime. Similarly, Panel B demonstrates that correlation coefficients between technological and financial returns are greater in the high technological diversity regime than the low technological diversity regime. Consistent with my findings in the fixed and random effects logit regressions, these results suggest that the complementarity between technological and financial returns is enhanced when CVC investments are made in post-IPO and technologically diversified portfolios, respectively. Hence, my findings are robust.

Table 3.8. Correlations for identifying factors impacting the complementarity

Panel A: Cohorted by post-IPO

	Post-IPO=1	Post-IPO=0
Correlation	0.413***	0.243**

Panel B: Cohorted by technological diversity

	Technological diversity≥0.9069	Technological diversity<0.9069
Correlation	0.422***	0.186*

Notes. For the definitions of variables, please see Appendix A. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

3.5 Discussion and Conclusion

In this study I investigate the nature of interaction between technological and financial returns created from CVC investments by systematically estimating these two types of return. Consistent with a simple model I develop in the paper, I find that technological and financial returns are complements. This complementarity is enhanced when CVC investments are made in post-IPO and technologically diversified portfolios, respectively.

Beyond providing a broad benchmark for heterogeneous returns on CVC investments, this study has important implications for corporate investors, start-ups, and researchers in strategy and finance. In particular, combined with anecdotal evidence in

the existing literature, it implies that CVC investments, as a strategy to accessing external technologies for corporate investors and alternative sources of financing for portfolios, can create value for portfolios as well as corporate investors. These mutual benefits can be greatly determined by when (e.g., post-IPO portfolios) and where (e.g., technologically diversified portfolios) CVC investments are made. Hence, my findings support the idea that an effective incentive mechanism (e.g., tax benefits) on CVC investments can serve to accelerate technological and managerial collaboration between corporate investors and start-ups. This implication is particularly important in the bio-pharmaceutical industry in which technological and managerial collaboration between bio-tech and pharmaceutical firms is critical to generating profitable growth through enhancing research productivity.

This study has a few limitations. First, it is limited within the context of the bio-pharmaceutical industry. Because the motives and decisions of CVC investments vary across industries, my findings should be interpreted with caution in the context of other industries. Finally, the proxy of financial return I used in the study is a hypothetical measure reached by using a belief that corporate investors primarily gain their financial return through IPOs and acquisitions. For more robust findings, it is needed to directly observe *when* and *how* corporate investors liquidate their CVC investments.

CHAPTER IV

START-UPS' CHOICE BETWEEN FINANCING FROM CORPORATE INVESTORS AND INDEPENDENT VENTURE CAPITALISTS AND ITS PERFORMANCE IMPLICATIONS

4.1 Introduction

Start-ups are often resource-constrained and encounter several unique options for funding to successfully exploit their entrepreneurial opportunities. A central idea in the entrepreneurial finance literature is that external investors differ substantially from one another in their investment objectives and behaviors and the range of services provided to start-ups. This heterogeneity among different types of investors can have important economic consequences. A prominent example is offered by the corporate venture capital literature, which is relatively small in the finance literature and claims that corporate investors (CVCs) can provide not only financial capital but also quick access to markets, technological assistance, and product recognition through the marketing, distribution, and research support for start-ups. This unique attribute of CVCs can benefit start-ups in several ways that independent venture capitalists (IVCs) may not be able to emulate. In contrast, CVCs can be less well-aligned with start-ups' economic interests than are IVCs because they may be more interested in the start-ups' resources for their own uses than the start-ups' successes (Hellmann, 2002; Katila et al., 2008). As a result, CVCs are often viewed suspiciously by start-ups and IVCs. This tension formed between start-ups' resource needs and appropriation concerns is ubiquitous in the formation of entrepreneurial investment ties and can impact start-ups' choice of financing from CVCs and IVCs and its subsequent performance.

Despite the importance of start-ups' financial arrangements for their growth and success, little attention has been devoted to investigating the trade-offs involved with their choice between CVCs and IVCs and its performance implications. This gap in the literature enables me to study two interrelated questions: (1) when do start-ups finance their projects from CVCs and IVCs? and (2) how do these two entrepreneurial financing sources create value for start-ups?[15] In most instances, the primary answer can be that start-ups finance their projects from CVCs when they need non-financial complementary assets that substantially influence their growth and success (Hellmann, 2002; Hsu, 2006). These questions, however, remain unsolved because IVCs also can provide such complementary assets by helping start-ups develop contracts with suppliers and customers (Gompers and Lerner, 2000; Hellmann and Puri, 2002; Casamatta, 2003; Hsu, 2004). These questions become even more complicated because start-ups often face a substantial risk of appropriation when they finance their projects from CVCs (Katila et al., 2008; Dushnitsky and Shaver, 2009; Fulghieri and Sevilir, 2009).

To address these issues, I develop a three-stage game theoretic model that distinguishes CVCs and IVCs in several ways, some of which are as follows. First, unlike IVCs that primarily pursue capital gains realized through the selling of stocks, CVCs seek strategic benefits from technological spillovers originated from start-ups as well as capital gains. CVCs are often motivated by these strategic benefits rather than capital gains (MacMillan et al., 2008). Second, start-ups face a substantial risk of appropriation when they disclose their technology/products to CVCs. IVCs have a minimal chance to

[15] Like many incumbents, start-ups can raise funds for their projects from several sources, including internal financing, IVCs, CVCs, private investors, banks, and other types of investors. This study focuses primarily on internal financing, IVCs, and CVCs because these sources are the most important sources of entrepreneurial financing.

appropriate start-ups' technology compared with CVCs because they do not normally seek such strategic benefits sought by CVCs. Third, CVCs can provide their assets and capabilities, including technological and R&D support, product development assistance, manufacturing capacities, and access to marketing and distribution channels, to create value for start-ups. In contrast, IVCs can help start-ups access the capital markets and the terms under which they access these markets and better communicate start-ups' value to the capital market. This model considers these unique attributes of CVCs and IVCs and relates start-ups' costs and benefits of associating with CVCs and IVCs. The emphasis in the model is that the tension between start-ups' resource needs and appropriation concerns is likely to be a primary factor in addressing the questions raised in this study.

By analyzing 3,885 fundraising records of 616 bio-pharmaceutical start-ups between 1985 and 2006, this study provides a number of new results on start-ups' financing choices and their performance implications. First, start-ups tend to finance their projects from CVCs rather than IVCs when they are in the later stages and need relatively small amount of capital. Second, CVCs tend to lead less syndicated investments compared with IVCs. Third, start-ups that possess better evaluated technology tend to raise funds for their projects from IVCs rather than CVCs. Fourth, start-ups tend to raise funds for their projects from CVCs rather than IVCs when their intellectual property is effectively protected and their research pipelines contain multiple products. Finally, while financing from IVCs contribute to increasing start-ups' Tobin's q and valuation, financing from CVCs contribute to enhancing forward patent citations.

This study contributes to various strands of finance and management literature. First, it contributes to the literature on the formation of CVC investment ties (e.g.,

Hellmann, 2002; Katila et al., 2008; Dushnitsky and Shaver, 2009; Fulghieri and Sevilir, 2009). While the existing studies take the perspective of CVCs by assuming that investors dominate entrepreneurial finance decisions, this study takes the perspective of start-ups that can also be active decision-makers in their investment ties. Some observations have indirectly indicated that start-ups are also active decision-makers in forming investment ties. First, investors do not always get their first-choice investment opportunities (Gompers, 2002; Hsu 2004; Santos and Eisenhardt, 2009). Second, CVCs tend to pay much by investing in overvalued transactions relative to IVCs (Gompers and Lerner, 1998). Third, start-ups have the greatest flexibility to choose among potential investors or simply avoid investment ties with some investors (Katila et al., 2008). Consistent with these observations, the existence of such determinants studied in this study indicates that start-ups are active decision-makers in forming their investment ties (Stuart et al., 1999; Maula et al., 2003).

Second, this study contributes to the literature on the trade-offs between the better evaluation of projects and the threat of appropriation (e.g., Bhattacharya and Ritter, 1983; Anton and Yao, 1994; Yosha, 1995; Ueda, 2004; Gans et al., 2008). While much of this literature considers a single type of investor, with the exception of Ueda (2004), this study advances our understanding about why several types of investors co-exist in the entrepreneurial financing market by highlighting the heterogeneous natures of CVCs and IVCs. By doing so, it helps start-ups to optimize their financial arrangements to enhance their growth and survival.

Finally, this study contributes to the literature on the contract design of control rights in bio-pharmaceutical alliances (Lerner et al., 2003; Higgins, 2007; Lerner and

Malmendier, 2010). While this line of studies focuses primarily on identifying the determinants of control rights, this study expands our knowledge regarding how different types of investors can impact the contract design of control rights in different ways.

This paper is organized as follows. The next section sets up the model, solves for the equilibrium, and makes hypotheses. Section 3 presents data, measures, and the empirical strategy. Section 4 reports the empirical results. Section 5 concludes.

4.2 Model and Hypotheses

4.2.1 The Set-up

Consider a risk-neutral world with information symmetry among agents and no discounting. A start-up possesses its technology (T), which greatly determines its fund-raising capacity, and it needs an amount of capital (F) to finance its project. CVCs and IVCs often evaluate T in different ways because they pursue their own motivations. Specifically, unlike IVCs that primarily pursue capital gains, CVCs often seek strategic benefits such as accessing the start-up's technology and technological spillovers originated from the start-up. T is indivisible and cannot be sold separately yet because it is a mixture of the start-up's research capacity and efforts and strategic agenda. The start-up can finance its project from a competitive pool of CVCs and IVCs. There are two possible future states of nature that we call success and failure. Success occurs with a probability (p). If the project fails, there is no return with $1 - p$. The project yields the following:

$$V = (pR - 1)F, \tag{1}$$

where V is the expected return from the project and R is the rate of return. These variables are common knowledge.

This set-up relates closely to Ueda's (2004) model, which analyzes the characteristics of start-ups that receive financing from a competitive pool of bank and IVCs. Her model suggests that start-ups characterized by relatively little collateral, high growth, high risk, and high profitability are likely to finance their projects from IVCs rather than banks. However, neither of the results/insights discussed in my model can be obtained by a simple extension of her study. My theoretical work is substantially different from her model because it examines a start-up's two direct financing sources, which are irrelevant with respect to collateral. Furthermore, this set-up differs considerably from the models that take the perspective of investors (e.g., Anand and Galetovic, 2000; Hellmann, 2002; Fulghieri and Sevilir, 2009) by taking the perspective of start-ups. For parsimony, this set-up assumes that information symmetry exists among agents. This assumption is consistent with the notion that CVCs and IVCs can have the specialized knowledge and expertise to finance start-ups even when information asymmetries deter public market investors from providing equity (Lerner et al., 2003). This simplification does not cause a problem for further discussion because the purpose of this model is primarily to make predictions, which can be empirically testable, regarding the determinants of start-ups' financing choice between CVCs and IVCs and its performance implications.

4.2.2 The Sequence of Events

A start-up first discloses its project and negotiates with IVCs rather than CVCs. This priority of IVCs is consistent with the stylized facts presented in Table 4.1, which indicates a notable pattern that IVCs tend to make their investments earlier than CVCs do. This pattern exists presumably because start-ups do not want to expose their

technology to the risk of appropriation by CVCs in their early stages (Lerner and Merges, 1998; Katila and Mang, 2003; Katila et al., 2008). Specifically, these early stage start-ups may find it more difficult to protect their technology from potential appropriation because their premature technology is not fully embodied in their products and readily protected by the legal mechanism. Some prior studies have suggested that both CVCs and IVCs may be able to appropriate start-ups' technology, and this threat of appropriation forces the start-ups to share some rent from the projects with these investors (Gorman and Sahlman, 1989; Hellmann and Puri, 2002; Ueda, 2004). This study, however, focuses on the risk of appropriation by CVCs because IVCs have a minimal chance to appropriate start-ups' technology compared with CVCs.

Table 4.1. Major corporate investors and independent venture capitalists

Panel A. Major corporate investors

Corporate investor	Number of investments	Amount of investments	Late-stage investment	Syndicated investment
Eli Lilly	36	387.24	0.89	0.08
Genetech	26	173.27	0.77	0.08
Elan	26	157.12	0.81	0.04
Pfizer	25	184.66	0.76	0.04
SmithKline	24	155.41	0.92	0.00
Warner-Lambert	19	66.09	0.89	0.11
Abbott	17	491.55	1.00	0.12
Ciba-Geigy	17	102.75	0.76	0.12
Genzyme	16	129.10	0.88	0.06
Novartis	15	306.42	0.93	0.13
Total	221	2153.61	8.61	0.78
(Mean)	(22.1)	(215.36)	(0.86)	(0.08)

Panel B. Major Independent venture capitalists

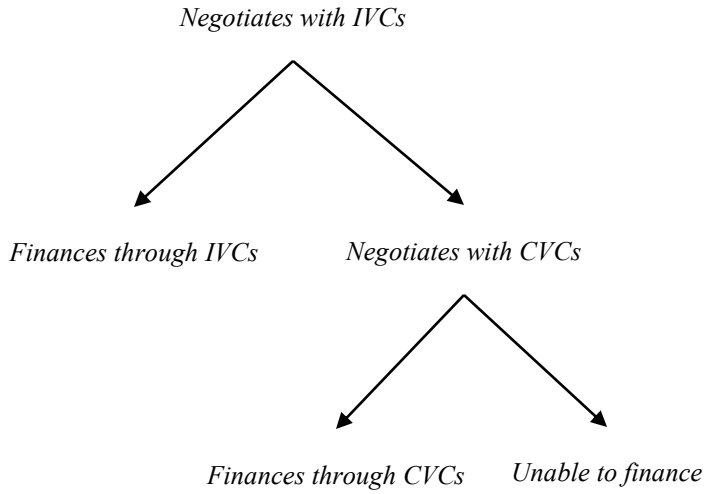
Independent venture capitalists	Number of investments	Amount of investments	Late-stage investment	Syndicated investment
Domain	44	477.82	0.20	0.89
NEA	33	512.63	0.27	1.00
H&Q	32	174.89	0.34	0.81
KPCB	32	170.73	0.09	0.88
Venture Investors	29	337.10	0.38	0.00
UKN	26	87.92	0.19	0.00
Alta	25	255.11	0.44	1.00

Table 4.1. continued

IVP	25	186.22	0.24	1.00
Mayfield	25	150.09	0.20	0.68
HCV	22	93.20	0.19	0.91
Total	293	2445.71	2.54	7.17
(Mean)	(29.30)	(244.57)	(0.25)	(0.72)

Notes. This table reports the number, amount, stage, and syndication of entrepreneurial finance by major corporate investors (CVCs) and independent venture capitalists (IVCs) included in the sample. These major investors are top-ten investors that record a high number of investments in each group. The amount of investments is calculated in millions of U.S. dollars. Late-stage investment denotes the ratio of investments made in the stages later than Series C (i.e., the median of investments stages in the sample) to total investments made by the investor. For example, Eli Lilly made 89% of its investments in the stages later than Series C. Syndicated investment denotes the ratio of investments syndicated with other CVCs or IVCs to total investments made by the investor. For example, Domain made 89% of its investments with other CVCs or IVCs.

If a negotiation with IVCs fails to finance a project, the start-up discloses the project and negotiates with CVCs. There is a crucial difference between negotiations with CVCs and IVCs. CVCs maintain a stronger negotiation position than IVCs because, even if the negotiation fails to finance the project, they are still able to benefit by appropriating the project. Figure 4.1 illustrates the three-stage model of a start-up's financing choice between CVCs and IVCs. Given the information symmetry among agents, the first stage of negotiation is irrelevant if the project is expected to be unprofitable, because IVCs will not finance it. As a result, IVCs are concerned only with whether or not they will finance the project and, if they do, the amount they will transfer to the start-up. In this situation, the contract can be described by just two parameters $\{\pi_{IVC}, F\}$, where π_{IVC} is the amount of conditional transfer from the IVCs to the start-up under the contract if the project yields V.



Notes. This figure illustrates a model of sequential choice of start-ups for external financing. A start-up discloses its project and negotiates with independent venture capitalists (IVCs) in the first stage. If this negotiation breaks up, the start-up discloses its project and negotiates with corporate investors (CVCs) in the second stage. The CVCs determine whether or not to finance in the third stage.

Figure 4.1. A model of sequential choice for external financing

The start-up can face two options in the second stage: raise funds from IVCs or negotiate with CVCs. If the start-up finances its project from the IVCs and the project is successful, the IVCs' expected payoff is $RF - F - \pi_{IVC} + T$, and the start-up's payoff is π_{IVC}. If the start-up finances its project from the IVCs and the project is not successful, the IVCs' expected payoff is $T - F$ and the start-up's payoff is $-T$. If the start-up fails to finance its project from IVCs and negotiates with CVCs, the IVCs and the start-up have zero net payoffs and T still belongs to the start-up.

If the start-up fails to raise funds from IVCs, it discloses its project and negotiates with CVCs. As mentioned, CVCs have a substantial chance of appropriating the start-up's technology for their own sake because they often pursue strategic benefits rather than capital gains (Hellmann, 2002; Dushnitsky and Lenox, 2006; MacMillan et al., 2008; Katila et al., 2008). More specifically, CVCs use their entrepreneurial investments

as exploratory initiatives to create boundary-spanning ties with start-ups that often pursue new technology (Dushnitsky and Lenox, 2005a and b; Wadhwa and Kotha, 2006; Basu et al., 2009). This notion is particularly validated because CVCs are often viewed suspiciously by start-ups and IVCs due to the perception that their intent may be to expropriate start-ups' technology (Katila et al., 2008; Dushnitsky and Shaver, 2009). Although IVCs can appropriate start-ups' technology by passing the project content to firms in which they have already invested and having these firms undertake the project, this motivation is much smaller or, more likely, marginal compared with that of CVCs.

If CVCs appropriate a start-up's technology, they should pay a certain amount of compensation to the start-up. The amount of compensation is often determined by the nature of appropriation. If the appropriation is not technology- and product-specific and does not hurt the start-up's intellectual property, the amount of compensation may not be great. In the other cases, the amount of compensation may be much greater. Let $C(V, q, \delta)$ be the expected amount of compensation by appropriation, where q is the parameter that indicates how tightly the start-up's technology (intellectual property) is protected and δ is the parameter that indicates how many following products can be developed by the start-up's technology. For example, the index q is large if the start-up finances the project in its later stage because its technology is more mature and more fully embodied in its product (Lerner and Merges, 1998; Katila et al., 2008). Because T is evaluated earlier than the future appropriation, I assume that q does not impact T. The index δ is great if the start-up is developing multiple following products in its research pipeline using its technology appropriated by the CVCs. It is assumed that $0 \leq C \leq V$

and that C is nondecreasing in V, q, and δ. Because $C \leq V$, CVCs are encouraged to appropriate the start-up's technology.

The CVCs determine whether or not to finance the project in the third stage. The contract states whether or not the CVCs finance F to undertake the project and the amount they will transfer to the start-up, π_{CVC}, under the contract if the project yields V. If the CVCs decline to finance the project, they can undertake the project on their own. If the CVCs do so, their expected payoff is $V - C$. If the CVCs decline to finance the project and do not undertake the project on their own, their payoff is zero. If the CVCs finance the project, their expected payoff is $V - F - \pi_{CVC} + T$, and the start-up's payoff is π_{CVC}. For simplicity, this model does not consider a repeated game, in which some stages repeat.

4.2.3 Equilibrium

I use the concept of a perfect Bayesian equilibrium to solve and characterize the equilibrium strategies of agents. Because this equilibrium must satisfy backward induction, I begin by solving an equilibrium strategy for the start-up and CVCs in the third stage. If the CVCs decline to finance the project, their optimal strategy is to appropriate the project because $0 \leq C \leq V$, resulting in the fact that their expected return is equal to $V - C$. As a result, the start-up should guarantee the CVCs a payoff at least as much as $V - C$ to encourage the CVCs to finance the project. If the CVCs finance the project, their expected payoff is $V - \pi_{CVC}$. Hence, if $V - C \leq V - \pi_{CVC}$ and $\pi_{CVC} \leq C$, the CVCs will finance the project. Because the start-up wants to maximize its payoff, which is equal to π_{CVC}, the following lemma immediately follows.

Lemma 1. Let U^{CVC} be the start-up's equilibrium payoff in the third stage; then $U^{CVC} = C$.

In equilibrium in the second stage, the start-up should raise funds from IVCs only if the contract gives it at least as much as U^{CVC}. Given this start-up's optimal strategy, IVCs' optimal strategy can be solved in two steps. First, the start-up's equilibrium payoff in the first stage is derived. Let U^{IVC} denote the start-up's equilibrium payoff if the start-up finances its project from IVCs. Second, I compare U^{CVC} and U^{IVC} to examine from which source the start-up will finance the project. The contract of IVCs often contains a term that π_{IVC} is proportional to V. Because of this term, U^{IVC} is maximized only if the IVCs' payoff, $K = RF - F - \pi_{IVC} + T$, is maximized. Thus, U^{IVC} is defined as a function of K.

Lemma 2. Let U^{IVC} be the start-up's equilibrium payoff in the first stage; then $U^{IVC} = K$.

Although it is possible to mathematically solve U^{IVC} with some additional restrictions in the model, this study uses the functional form of U^{IVC} that is non-decreasing in the variable of interest, T, in the following discussion. This simplification does not cause a problem because the main purpose of this equilibrium solution is to compare U^{IVC} and U^{CVC} with respect to the variables of interest. Furthermore, this simplification is helpful for parsimony. Note that if the IVCs' offer does not guarantee at least as much as U^{CVC} for the start-up, the start-up will not finance the project from the IVCs. In other words, if $U^{IVC} < U^{CVC}$, the IVCs are never able to attract the start-up because the start-up will raise funds from the CVCs. It is also noteworthy that U^{IVC} and U^{CVC} are independent because CVCs and IVCs have different motivations in their investments. The following proposition follows Lemma 1 and 2.

Proposition. The start-up finances its project from the independent venture capitalists if and only if

$$U^{IVC} \equiv K \geq U^{CVC} \equiv C, \quad (2)$$

and it finances its project from the corporate investors otherwise.

To be specific, let I be an index function such that, if equation (2) is satisfied, $I = 1$ and, if it is not, $I = 0$. In other words, if the start-up's characteristics give $I = 1$, then it finances its project from the IVCs. If the start-up's characteristics give $I = 0$, then it finances its project from the CVCs.

4.2.4 Empirical Implications

Note that I is nondecreasing in T; that is, if T is high, the start-up raises funds from IVCs and, if T is low, it does so from the CVCs.[16] This prediction is consistent with the notion that the amount of entrepreneurial financing by IVCs is significantly greater than that by CVCs (Gompers and Lerner, 1998). This notion is supported by the simple statistics presented in Table 4.1. Specifically, IVCs are expected to "swing for the fences" that they identify and finance start-ups that are working on technology with great market potential (National Research Council, 2009). This expectation exists because K is proportional to T and IVCs are often compensated through management fees based on fund size as well as a fraction of profit from their return on invested funds (Sahlman, 1990). In other words, start-ups with the great market potential of T can better attract IVCs that may provide sufficient capital for their projects rather than CVCs. Furthermore, these start-ups can alleviate the risk of appropriation by financing their projects from IVCs.

[16] This notion follows from the fact that the left-hand side of equation (2) is nondecreasing in T.

In contrast, CVCs seek investment opportunities that are not greatly impacted by the market potential of T evaluated by IVCs but by technology-specific factors, including technological proximity, fitness, and breadth. This is because their strategic motivations are not necessarily fulfilled with the great market potential of T. CVCs can even be reluctant to make investments in start-ups with the great market potential of T because they would experience a high level of competition with IVCs to obtain the investment opportunities. These start-ups can be reluctant to finance their projects from CVCs because they may not want to take the risk of appropriation if they can successfully finance their projects from IVCs. I posit a hypothesis as follows:

> *Hypothesis 1. Start-ups that possess better evaluated technology (T) are more likely to finance their projects through independent venture capitalists rather than corporate investors.*

Equation (2) also indicates that start-ups' financing choice between CVCs and IVCs can be determined by how tightly their technology is protected. This is because I is nonincreasing in q; that is, the start-up raises funds from CVCs if its technology is securely protected and from IVCs if it is not.[17] This prediction is consistent with the perspective that emphasizes the tension between resource needs and appropriation concerns in CVC investment ties (Katila et al., 2008; Dushnitsky and Shaver, 2009; Maula et al., 2009). The central idea of this perspective is that, when start-ups consider whether or not to enter CVC investment ties, the resource needs push them toward the ties, while the appropriation concerns push them away. If start-ups can securely protect their technology and thus alleviate the appropriation concerns, they can readily utilize complementary assets provided by CVCs and enhance the resource needs in CVC

[17] This notion follows from the fact that the right-hand side of equation (2) is nondecreasing in q.

investment ties. As a consequence, CVCs become more attractive sources of financing for start-ups if the start-ups' technology is securely protected and vice versa. I posit the second hypothesis as follows:

> *Hypothesis 2. Start-ups that tightly protect their technology are more likely to finance their projects through corporate investors rather than independent venture capitalists.*

Note that the start-up's financing choice between CVCs and IVCs also depends on δ. This is because I is nonincreasing in δ -- that is, the start-up finances its project from CVCs if the amount of compensation by appropriation is large and from IVCs if the amount is not as high. If a start-up holds many following products in its research pipeline, the threat of CVCs to appropriate the current project weakens because high potential penalty can discourage CVCs from appropriating the start-up's technology. In the extreme case that $C = V$, the threat from CVCs is not effective at all. Furthermore, such a start-up may need more complementary assets provided only by CVCs, including manufacturing capacities and access to marketing and distribution channels, to successfully release their products in the markets. Hence, I posit the following hypothesis:

> *Hypothesis 3. Start-ups that possess multiple products in the research pipeline are more likely to finance their projects through corporate investors rather than independent venture capitalists.*

As noted, IVCs seek primarily to maximize their capital gains from invested funds by increasing the market values of start-ups in which they have invested because they are generally compensated with fixed management fees and profits from their return on investments. These investors can contribute to creating the market values of start-ups

by "professionalizing" start-ups' management, including providing managerial and industrial expertise on the strategic agendas of start-ups and signaling the value of start-ups to the capital market. In contrast, CVCs do not benefit commensurately from the changes in the market values of start-ups because they often pursue potential synergies between their existing assets and start-ups' technology rather than capital gains on their investments. Specifically, these investors seek opportunities for future research collaborations with start-ups and thus may expand the use of start-ups' technology by involving the subsequent research projects that utilize the technology.[18] Taken together, a testable hypothesis is:

> *Hypothesis 4. While financing from independent venture capitalists is likely to increase start-ups' valuations, financing from corporate investors is likely to expand the use of start-ups' technology.*

4.3 Data Sources and Empirical Strategy

4.3.1 Data

My primary data are drawn from the Deloitte ReCap database, which contains comprehensive bio-pharmaceutical alliance information. This database contains 30,000 deal announcements with the underlying press releases and 24,000 SEC-filed contracts, 14,000 bio-contacts, and round-by-round financing for over 700 bio-pharmaceutical start-ups. I use the 3,885 fundraising records of 629 start-ups between 1985 and 2006.

By focusing on the bio-pharmaceutical industry, I gain two advantages in analyzing start-ups' financing choices and their performance implications. First, this concentration on a single industry provides unique datasets that allow me to obtain

[18] For example, the corporate venture capital arm of Eli Lilly and Company made a Series C investment in a genomics group, Millennium Pharmaceuticals Inc., in 1995, resulting in collaborative research efforts investigating the genetic causes of atherosclerosis and congestive heart failure in 1997.

sufficient information to investigate the issues of this study. Second, it is very hard to compare start-ups' financing choices and their performance implications across industries because each industry has its own managerial and technological environments. Furthermore, the period between 1985 and 2006 is characterized as a time of great expansion of IVC and CVC financing activities in the industry, so it is appropriate as a research setting for this study (MacMillan et al., 2008).

These observations are matched to drug pipeline data provided by the PharmaProjects database. This database contains the history and progress of more than 36,500 drugs that have been developed since 1980. The stages of drug development are classified into the pre-clinical, Phase I, Phase II, Phase III, and launched stages. Phase I is human pharmacology and requires small trials, recruiting up to about 30 patients or a lot less. Phase II is therapeutic exploratory and expands trials to patients who have same type of disease to find out the extant, side-effects, and appropriate usage of drugs. Phase III is therapeutic confirmatory; it compares new drugs with the best currently available drugs or treatments and releases them if they pass.

These observations are then combined with NBER patent datasets to obtain patent information. To appropriately match these datasets, I use two identification variables: PDPCO and GVKEY. PDPCO was introduced in the NBER PDP project, which aims to facilitate the matching of patent data to the Compustat data maintained by Wharton Research Data Services. The use of PDPCO alleviates potential mismatching problems, in which assignee names do not necessarily correspond to the records within other databases, and tracks changes in patent ownership. The Compustat database provides accounting variables.

4.3.2 Measuring the Variables of Interest

There are many challenges in estimating the market potential of technology (T) because it is, in any case, multifaceted and heterogeneous and not directly observable. For these reasons, I use two measures that depend on the managerial and industrial expertise of CVCs and IVCs. The first measure is the number of investors (i.e., investor number) and estimates the degree to which the investor community widely recognizes a start-up's technology. The second measure is the amount of funding (i.e., funding amount) and estimates the degree to which the investor community highly recognizes a start-up's technology. Throughout the literature, patent information has been used intensively to estimate a start-up's technological capacity. However, the inherent weakness of patent-based measures has been also widely discussed in the literature (Patel and Pavitt, 1995; Jaffe and Trajtenberg, 2002; Graham and Higgins, 2007). Furthermore, given that bio-pharmaceutical firms patent prolifically, their patents can be a rather noisy measure to estimate T. Hence, these two measures of T can help me reach beyond the limitations of prior studies that depend on patent information in estimating T. A start-up's patent stock is still controlled in the empirical models.

Start-ups often protect their technology by several mechanisms, including patents, trade secrets, and timing their external financing to coincide with later funding rounds (Lerner and Merges, 1998; Katila et al., 2008). Unfortunately, the effectiveness of such legal defense mechanisms is invariant because this study focuses on a single industry. As a result, I use a start-up's external financing timing to estimate the parameter (q) that indicates how tightly a start-up's technology is protected. I create an indicator variable (i.e., IP protection) that equals one if a start-up finances its project after Series C, which

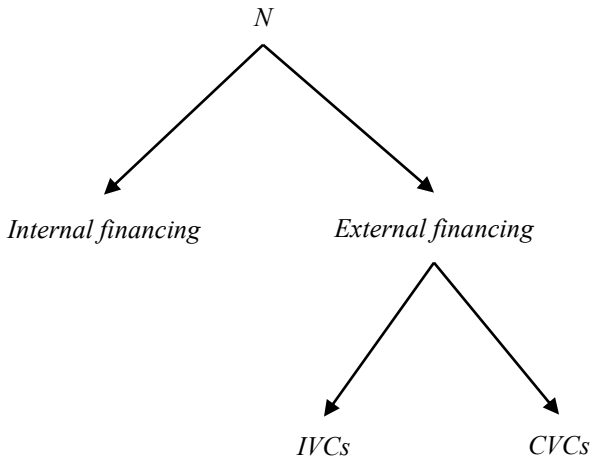
is the median round in the sample, and zero otherwise. The rounds are classified by 14 stages: founding, Series A, B, C, D, E, F, G, H, I, J, K, secondary, and private placement in order. Acquisitions and IPOs are excluded because these stages can be viewed as harvesting events rather than financing stages. It is assumed that there is likely to be great q when a start-up raises funds in the later stages because later timing tends to make it more difficult for external investors to appropriate the start-up's technology (Lerner and Merges, 1998). Specifically, it is easier for start-ups to protect from potential appropriation more mature technologies that are more fully embodied in products (Katila et al., 2008), while it is more difficult for investors to influence the start-up's product portfolios and strategic agendas with the later timing (Sahlman, 1990; Rivkin, 2000).

I use the number of drugs (i.e., future product) in a pre-clinical stage within a start-up's research pipeline from the PharmaProject database to estimate the parameter (δ) that indicates how many future products can be developed by the start-up's technology. The great number of drugs in the pre-clinical stage indicates many future products. For the definitions of variables, please see Appendix B.

4.3.3 Empirical Strategy

The two-sample means test and binary logistic regression are two common approaches that are widely used for analyzing dichotomous outcomes such as a start-up's financing choice between CVCs and IVCs. These approaches, however, do not fit a realistic situation under which a start-up can finance its project from more diverse sources that may impact its choice between CVCs and IVCs. To attenuate this concern, I consider an alternative financing source for start-ups, internal financing, as illustrated in Figure 4.2. A start-up chooses between internal and external financing in the first stage. If

the start-up chooses external financing, it has two subsequent options in the second stage: IVC financing and CVC financing. For these multiple options, I consider the multinomial logistic regression.



Notes. This figure illustrates a model of sequential choice of start-ups for internal and external financing. A start-up should decide to finance its project through internal financing or external financing in the first stage. If the start-up decides to finance its project through external financing in the first stage, it faces two options, including financing through independent venture capitalists (IVCs) and corporate investors (CVCs), in the second stage.

Figure 4.2. A model of sequential choice for internal and external financing

However, the multinomial logistic regression can provide only supportive evidence for the variables that impact a start-up's financing choice; it does not serve as a definitive approach. This limitation exists because the multinomial logistic regression may violate the independence of irrelevant alternatives (IIA) assumption in the model presented in Figure 4.2 that has a hierarchical structure of two-stage sequential decisions (Maddala, 1983). For example, given the decision-making process, the components of the error terms of IVC financing and CVC financing that pertain to the external financing are hypothesized to be jointly distributed.

To alleviate this concern, I use the sequential logistic regression for a more definitive test that alleviates the violation of the IIA assumption. While the nested multinomial logistic model is used when the set of alternatives faced by the decision-maker can be partitioned into subsets until the bottom level, the sequential logistic model is appropriate to use when a choice framework is the "elimination by aspects" process (Tversky, 1972). Because the elimination by aspects process is closely related to the decision-making depicted in Figure 4.2, I use the sequential logistic regression rather than the nested multinomial logistic regression.

For the sequential logistic regression, if I assume that each choice is made according to a dichotomous logit model, I can proceed as follows: Let $y_s = 0, 1, \ and \ 2$ if a start-up chooses internal financing in the first stage, and IVC financing and CVC financing given external financing in the second stage, respectively. Let L represent the binomial logit function. Then the probability of external financing is defined as

$$Pr(External\ financing) = Pr(y_s > 0) = L(\theta_1 X_i + \theta_2 C_1), \quad (3.1)$$

where X_i is a vector of the observable characteristics of start-up i, C_1 is a vector of the attributes of Transition 1, and θ_1 and θ_2 are parameter vectors. The conditional probability of choosing CVC financing given external financing is:

$$Pr(CVC\ financing|External\ financing) = Pr(y_s = 2|y_s > 0) \\ = L(\theta_3 X_i + \theta_4 C_2), \quad (3.2)$$

where C_2 is a vector of the attributes of Transition 2 and θ_3 and θ_4 are parameter vectors. The most direct method of estimating the parameter vectors, θ_1, ..., θ_4, is to proceed to the successive estimation of logit models with a smaller number of responses using the maximum likelihood. Therefore, I first estimate equation (3.1) with a logit model using

all observations in the sample; and I then estimate equation (3.2) with a logit model using observations for which $y_s > 0$.

To address concerns about the potential endogeneity problem, I use two-stage probit regressions that predict the probabilities of start-ups' financing through CVCs and IVCs. The variables of interest are instrumented by industry IPO, industry acquisition, and industry funding amount. For the definitions of these instrumental variables, please see Appendix B.

For a sensitivity analysis, I use the survival analysis that predicts the hazard of a start-up's financing through CVCs and IVCs. Specifically, I estimate the following models:

$$h_i(t) = (\beta_0 + Z_i\beta)t, \tag{4}$$

where h_i is the hazard for i $(i = 1, \dots, N)$, Z_i are case-specific predictors, and β is the slope parameter. As a corollary analysis, I use the cross-equation constraints of seemingly unrelated regressions to determine whether the coefficients of the independent variables of interest estimated in the survival analysis are significantly different across the two groups in which the events (failures) are defined as $y_s = 1$ and $y_s = 2$.

Finally, I estimate the performance metrics created by start-ups' financing choice between CVCs and IVCs. This estimation poses many challenges for several reasons. First, many start-ups do not provide observable financial records that might indicate their performances because they are often private companies. As a result, the existing studies in the entrepreneurial finance literature often use IPO information, including start-ups' IPO rate and IPO post-valuation, to estimate start-ups' performance. These IPO-based measures, however, have a serious problem in effectively measuring start-ups'

performance because, inconsistent with the widely held assumption that most CVCs and IVCs invest in pre-IPO start-ups, my sample indicates that 43% of CVC investments were made in post-IPO start-ups (Kang and Nanda, 2011). Second, it is hard to define what portion of the performance of start-ups is created by CVCs and IVCs because their performance is, by nature, the aggregate sum of the effects of many factors that may impact their operations. Third, even though I estimate the portion of start-ups' performance created by CVCs and IVCs, it is hard to estimate what elements of performance are respectively created by CVCs and IVCs because start-ups often use both IVCs and CVCs as their financing sources. Finally, in any case, the definition of performance is multifaceted and heterogeneous. To address these concerns, I use a simple econometric technique that will be discussed in the results section.

4.4 Empirical Results

4.4.1 Descriptive statistics

Table 4.1 reports the number, amount, stage, and syndication of entrepreneurial finance provided by major CVCs and IVCs included in the sample. The first two columns (i.e., number and amount of investments) indicates that major IVCs made significantly greater investments reaching, on average, $244 million in 293 rounds compared with $215 million in 221 rounds by CVCs. This finding is consistent with the notion that the amount of capital provided by IVCs is significantly greater than that provided by CVCs (Gompers and Lerner, 1998; MacMillan et al., 2008; National Venture Capital Association, 2010). The column of late-stage investment indicates that, while major CVCs made, on average, 86% of investments in the stages later than Series C, major IVCs made, on average, 25% of investments in the stages later than Series C. The column

of syndicated investment indicates that major IVCs made more syndicated investments reaching, on average, 72% of investments compared with, on average, 8% of investments syndicated by CVCs. This finding supports a widely held assumption that CVCs typically seek co-invest with IVCs and use them for identifying quality investment opportunities (Dushnitsky, 2006) because many CVCs tend to participate in the syndicated investments led by IVCs. Furthermore, an interesting interpretation for this finding is that CVCs tend to be reluctant to co-invest with IVCs when they are leading investors in the syndicated investments. This is because IVCs aligned with start-ups' interests can prevent the leakage of start-ups' technology and discourage potential appropriation by CVCs. A part of these findings are inconsistent with the findings presented in Chemmanur and Loutskina (2008). This inconsistency exists presumably because my study considers a set of bio-pharmaceutical start-ups compared with start-ups in a wider range of industries considered by their study. Moreover, my study categorizes syndicated investments made by both IVCs and CVCs into two groups by the nature of leading investor; their study considers CVC investments if a single CVC exists in the syndicated investments.

Table 4.2 reports the descriptive statistics of 3,885 fundraising observations of 616 bio-pharmaceutical start-ups between 1985 and 2006. Panel A reports the mean and standard deviation of variables used in the following analysis. The first column (i.e., all observations) includes all observations in the sample. The second and third columns (i.e., internal financing and external financing) include the observations in which start-ups finance their projects internally and through CVCs or IVCs. The last two columns (i.e., IVC and CVC) include the observations in which start-ups finance their projects through IVCs and CVCs, respectively. These two columns are the columns of interest and

indicate that start-ups financed from IVCs tend to have greater investor numbers reaching, on average, 1.816 investors compared with, on average, 1.167 investors of start-ups financed from CVCs. This finding is consistent with my prediction made in Hypothesis 1. However, these two groups of start-ups do not indicate significant difference in terms of funding amount. Start-ups financed from CVCs tend to have greater IP protection reaching, on average, 0.758, which indicates 75% of investments are made in the stages later than Series C, compared with, on average, 0.410 of start-ups financed from IVCs. Start-ups financed from CVCs tend to have greater future product reaching, on average, 2.971 compared with, on average, 1.012 of start-ups financed from IVCs. These two findings are consistent with my predictions made in Hypotheses 2 and 3. Furthermore, the variables of firm characteristics indicate that start-ups financed from CVCs are larger, invest more R&D resources, and possess more patents than do start-ups financed from IVCs. The variables of finance characteristics indicate that start-ups financed from CVCs tend to have greater prior financing from IVCs, CVCs, and major investors than do start-ups financed from IVCs. These distinguishable characteristics should be interpreted with caution because these start-ups are in different stages when they are financed from IVCs and CVCs.

Table 4.2. Descriptive statistics

Panel A. Descriptive statistics

	All observations		Internal financing		External financing (IVC or CVC)		IVC		CVC	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Choice variable										
1. Chosen	0.854	0.704	0.000	0.000	1.277	0.447	1.000	0.000	2.000	0.000
Variables of interest										
2. Investor number	1.429	0.750	1.009	0.104	1.637	0.840	1.816	0.876	1.167	0.489
3. Funding amount	1.968	1.005	2.179	1.074	1.896	0.969	1.896	0.986	1.895	0.926
4. IP protection	0.527	0.499	0.570	0.495	0.506	0.500	0.410	0.492	0.758	0.429
5. Future product	1.702	3.226	1.772	3.144	1.663	3.272	1.012	2.086	2.971	4.578
Firm characteristics										
6. Firm size	3.468	1.209	3.422	1.152	3.501	1.248	3.211	1.179	3.804	1.248
7. Internal R&D	2.352	1.221	2.273	1.315	2.410	1.145	2.169	1.043	2.657	1.194
8. Patent stock	0.996	1.280	1.088	1.389	0.951	1.221	0.787	1.089	1.378	1.427
9. International business	0.072	0.258	0.098	0.297	0.055	0.228	0.051	0.220	0.061	0.239
10. Location (U.S.)	0.969	0.175	0.975	0.156	0.964	0.186	0.952	0.214	0.980	0.141
Finance characteristics										
11. Prior IVC	0.697	0.460	0.566	0.496	0.762	0.426	0.734	0.442	0.834	0.372
12. Prior CVC	0.311	0.463	0.358	0.480	0.288	0.453	0.194	0.395	0.535	0.499
13. Major investor	0.131	0.337	0.000	0.000	0.195	0.397	0.153	0.360	0.307	0.462
N	3885		1286		2599		1880		719	

Panel B. Sample distribution through time

	All observations		Internal financing		IVC		CVC		Acquisition		IPO	
Year	Number	Amount	Number	Amount	Number	Amount	Number	Amount	Number	Amount	Number	Amount
1985	71	217	22	18	35	105	14	93	1	86	11	82
1986	96	261	33	17	53	177	10	67	1	300	33	425
1987	127	320	37	12	74	243	16	64	0	0	24	315
1988	155	494	37	13	88	354	30	127	0	0	9	118
1989	172	524	45	17	102	349	25	157	5	431	14	135

Table 4.2. continued

1990	178	623	37	57	116	442	25	123	4	183	14	193
1991	214	906	67	204	119	575	28	126	3	722	46	1585
1992	227	1009	66	175	119	578	42	255	1	23	57	2829
1993	248	1545	83	429	130	892	35	223	2	377	40	788
1994	222	1226	69	260	105	704	48	262	9	428	34	787
1995	299	1950	96	478	136	928	67	542	17	1363	35	882
1996	249	1699	67	289	122	869	60	540	12	2657	67	1977
1997	257	2285	62	557	129	1211	66	516	23	4080	41	1263
1998	224	2054	56	401	123	1234	45	418	25	3917	20	698
1999	223	2816	69	1067	98	1307	56	441	31	11804	17	2490
2000	277	6415	116	3162	118	2396	43	855	20	6570	59	4235
2001	183	4603	81	1390	68	2474	34	738	15	17609	7	405
2002	129	2779	55	991	45	1193	29	594	20	7374	8	3030
2003	168	3384	89	1204	55	1408	24	771	23	17150	10	503
2004	112	2616	62	1135	32	1086	18	393	9	4710	36	2176
2005	39	900	25	504	11	312	3	83	22	6649	21	1640
2006	15	368	12	271	2	89	1	8	7	10726	25	2231
Total	3885	39002	1286	12660	1880	18936	719	7404	250	97159	628	28787
(Mean)	(176.59)	(1772.82)	(58.45)	(575.49)	(85.45)	(860.74)	(32.68)	(336.58)	(11.36)	(4416.31)	(28.54)	(1308.50)

Panel C. Correlation coefficients among the variables of interest

	1	2	3	4
1. Chosen				
2. Investor number	0.118***			
3. Funding amount	-0.119***	0.209***		
4. IP protection	-0.105***	-0.315***	0.225***	
5. Future product	0.049*	-0.142***	0.244***	0.315***

Panel D. Means of the variables of interest between two groups of start-ups

	IVC	CVC	Difference
Investor number	1.816	1.167	0.649***
	(0.020)	(0.018)	(0.034)
N	1880	719	2599

Table 4.2. continued

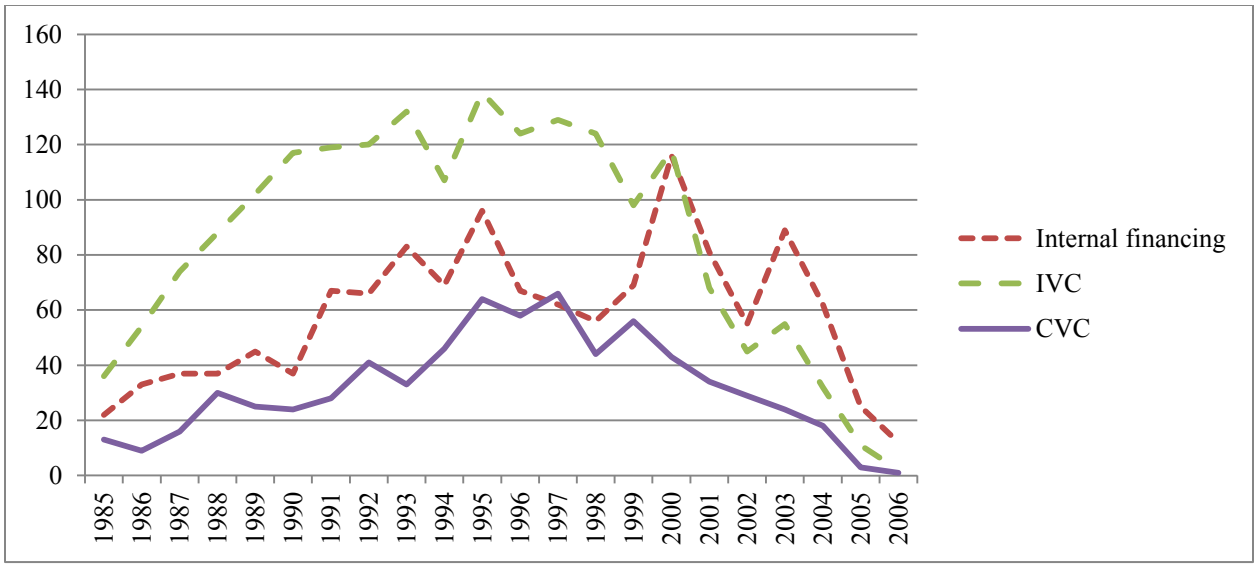
Funding amount	1.896	1.895	0.001
	(0.023)	(0.035)	(0.043)
N	1794	697	2491
IP protection	0.410	0.758	-0.348***
	(0.011)	(0.015)	(0.020)
N	1880	719	2599
Future product	1.012	2.971	-1.958***
	(0.075)	(0.235)	(0.197)
N	757	377	1134

Notes. This table reports the descriptive statistics of 3,885 fundraising observations of 616 bio-pharmaceutical start-ups between 1985 and 2006. Panel A reports the mean and standard deviation (S.D.) of variables used in the following analyses. The column of all observations includes all the fundraising observations in the sample. The column of internal (external) financing includes the observations in which start-ups finance their projects internally (through CVCs or IVCs). The column of IVC (CVC) includes the observations in which start-ups finance their projects through IVCs (CVCs). Syndicated investments made by both IVCs and CVCs are categorized by the natures of leading investors (i.e., CVCs or IVCs). Panel B reports the yearly information of internal financing, IVCs, CVCs, acquisitions, and IPOs included in the sample. Amount is calculated in millions of U.S. dollars. Panel C reports correlation coefficients among the variables of interest. Panel D reports the means of variables between two groups of start-ups financed by IVCs and CVCs. Standard errors are presented in parentheses. The test statistic is defined by the t-statistic because the population mean and standard deviation are unknown. For the definitions of variables, please see Appendix B. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

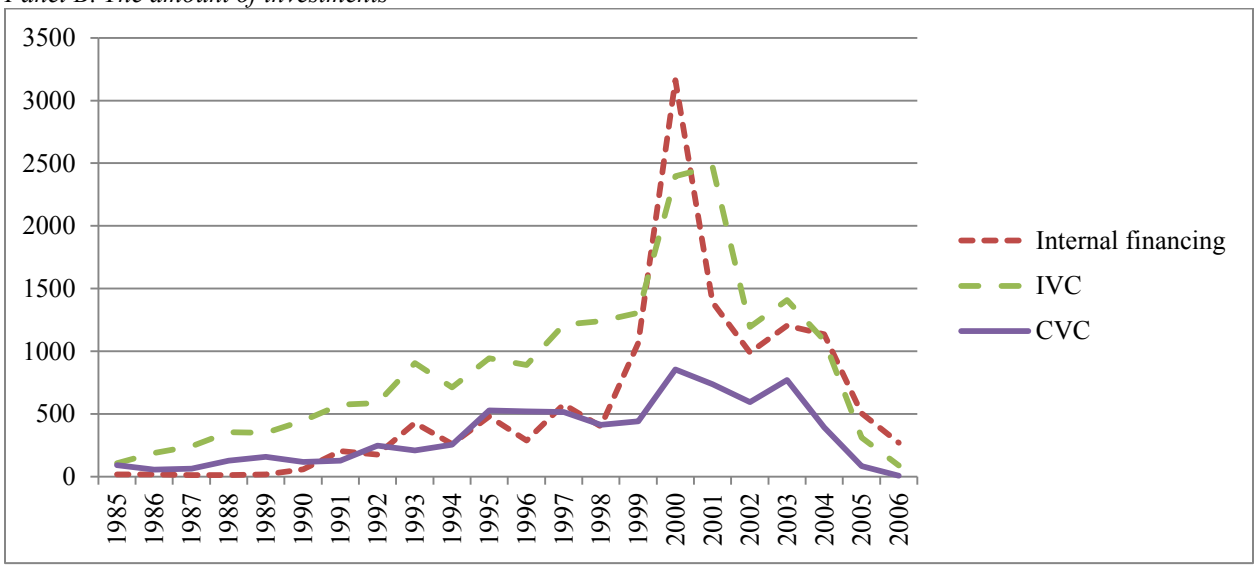
Panel B reports the yearly information of internal financing, IVCs, and CVCs included in the sample. The last two columns (i.e., acquisition and IPO) are presented to provide bench-mark statistics. This table indicates that start-ups finance $18,936 million (49% of total financing in the sample) from IVCs and $7,404 million (18% of total financing in the sample) from CVCs for their projects. The rest of the financing is internal. This finding is consistent with the results of recent surveys (e.g., MacMillan et al., 2008; National Venture Capital Association, 2010) that suggest that IVCs make significantly greater investments in start-ups than CVCs do. A possible explanation for this finding is that IVCs and CVCs have been guided by their own nature and motivation in their investments. More specifically, IVCs that primarily pursue capital gains should make large investments because their capital gains are commensurate with the amount of investments. In contrast, CVCs do not necessarily make large investments because their strategic motivations do not require a large amount of investment.

Figure 4.3 illustrates the number and amount of internal financing, IVCs, and CVCs through time presented in Panel B. This figure is important because it allows me to investigate whether or not IVCs and CVCs have been available financing sources for start-ups through time. If either IVCs or CVCs were extremely scarce during a particular time period and not readily available, start-ups' financing choice would be heavily impacted by the availability of financing sources rather than the contextual factors I study. If this concern is not the case, we should see a notable pattern that the amounts of financing from IVCs and CVCs move together over time. This figure indicates that the number and amount of financing from IVCs and CVCs together gradually increased in the 1990s, peaked in the early 2000s, and gradually decreased afterward.

Panel A. The number of investments



Panel B. The amount of investments



Notes. This figure illustrates the yearly information of internal financing, IVCs, and CVCs in the sample. Amount is calculated in millions of U.S. dollars. Syndicated investments made by both IVCs and CVCs are categorized by the natures of leading investors (i.e., CVCs or IVCs).

Figure 4.3. Sample distribution through time

Panel C reports correlation coefficients among the variables of interest. Interestingly, the variables of interest, including chosen, investor number, funding amount, IP protection, and future product, are significantly correlated with each other. This finding suggests that the variables of interest may be important factors in

determining start-ups' financing choice between IVCs and CVCs and thus should be included in the analysis. It is also noteworthy that investor number and funding amount indicate a significant and positive correlation coefficient at the 1% level. This correlation suggests that these two measures of T have a convergent validity that is the degree to which an operation is similar to other operations that theoretically should also be similar. This concept of convergent validity is widely used in various fields to examine the effectiveness of multiple measures that estimate a single construct. By the same token, it is not surprising that IP protection and future product indicate a significant and positive correlation coefficient at the 1% level because both q and δ are nondecreasing in C.

Panel D reports the means of the variables of interest between two groups of start-ups financed by IVCs and CVCs. Consistent with my prediction made in Hypothesis 1, the mean of investor number in the group of start-ups financed from IVCs is significantly greater than that in the group of start-ups financed from CVCs. In contrast, the mean of funding amount in the group of start-ups financed from IVCs is not significantly different from that in the group of start-ups financed through CVCs. These contrasting results should be examined with better elaborated econometric approaches because a t-test does not provide robust results to the omitted variable bias. The means of IP protection and future product in the group of start-ups financed from CVCs are significantly greater than those in the group of start-ups financed from IVCs. These statistics support my predictions made in Hypotheses 2 and 3, respectively.

4.4.2 Start-ups' Financing Choice between CVCs and IVCs

Table 4.3 reports ordinary least squares (OLS) regressions predicting the linear probabilities that start-ups finance their projects from CVCs and IVCs. I estimate the

following models: $y_i = u_0 + \Pi_i u_1 + e_i$, where y_i is an indicator variable that equals one (zero) if a start-up finances its project from CVCs (IVCs). The independent variables of interest are investor number, funding amount, IP protection, and future product. Models 1 and 2 indicate that investor number and funding amount are associated with 24% and 15% decreases in the probability that start-ups finance their projects from CVCs rather than IVCs, respectively. This finding supports Hypothesis 1. Models 3 and 4 indicate that IP protection and future product are associated with 23% and 2% increases in the probability that start-ups finance their projects from CVCs rather than IVCs, respectively. These findings support Hypotheses 2 and 3. Firm size and location (U.S.) indicate positive and significant coefficients across models. These results suggest that start-ups financed from CVCs tend to be larger and headquartered in the United States than do start-ups financed from IVCs. Major investor also indicates positive and significant coefficient across models. This finding suggests that start-ups financed from CVCs tend to more strongly want to finance their projects from major investors than do start-ups financed from IVCs.

Table 4.3. Hypothesis test using linear probability regressions

	OLS				
Model	(1)	(2)	(3)	(4)	(5)
y_s	CVC	CVC	CVC	CVC	CVC
Investor number	-0.244***				-0.202***
	(0.025)				(0.028)
Funding amount		-0.151***			-0.068***
		(0.023)			(0.024)
IP protection			0.226***		0.096*
			(0.058)		(0.055)
Future product				0.015***	0.011**
				(0.006)	(0.005)
Firm size	0.076***	0.142***	0.087***	0.083***	0.084***
	(0.026)	(0.028)	(0.028)	(0.028)	(0.027)
Internal R&D	0.002	0.019	-0.007	-0.009	0.000
	(0.030)	(0.032)	(0.032)	(0.033)	(0.030)
Patent stock	-0.020	-0.004	-0.011	-0.006	-0.020
	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)

Table 4.3. continued

International business	0.015	0.009	0.043	0.072	0.020
	(0.078)	(0.082)	(0.083)	(0.085)	(0.077)
Location (U.S.)	0.250**	0.337***	0.287**	0.301***	0.235**
	(0.104)	(0.108)	(0.112)	(0.112)	(0.103)
Prior IVC	-0.099	-0.127*	-0.181**	-0.108	-0.164**
	(0.072)	(0.077)	(0.080)	(0.078)	(0.075)
Prior CVC	0.020	0.028	0.052	0.080*	-0.018
	(0.040)	(0.043)	(0.044)	(0.043)	(0.041)
Major investor	0.321***	0.301***	0.350***	0.320***	0.291***
	(0.044)	(0.046)	(0.047)	(0.048)	(0.044)
Constant	-0.260	0.585**	-0.782*	0.601**	0.806***
	(0.441)	(0.270)	(0.469)	(0.248)	(0.260)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	554	552	554	553	551
F	9.827	7.431	6.227	6.045	10.070
Prob>F	0.000	0.000	0.000	0.000	0.000
R^2	0.360	0.300	0.263	0.251	0.384

Notes. This table reports ordinary least squares (OLS) regressions predicting the linear probabilities of start-ups' financing through corporate investors (CVCs) and independent venture capitalists (IVCs). I estimate the following models: $y_i = u_0 + \Pi_i u_1 + e_i$, where y_i is an indicator variable that equals one (zero) if a start-up finances its project through CVCs (IVCs). The independent variables of interest are investor number, funding amount, IP protection, and future product. Control variables are firm size, internal R&D, patent stock, international business, location (U.S.), prior IVC, prior CVC, major investor, and year fixed effects. For the definitions of variables, please see Appendix B. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

To consider internal financing as an alternative financing source, I estimate multinomial logit (MNL) regressions predicting the probabilities that start-ups finance their projects from internal financing ($y_s = 0$), IVCs ($y_s = 1$), and CVCs ($y_s = 2$). Specifically, I estimate the following models: $(y_s = j) = \frac{\exp(Z_i \delta_j)}{\sum_{k=1}^{3} \exp(Z_i \delta_k)}, j \in \{0,1,2\}$, where Z_i are categorical or continuous explanatory variables. In Table 4.4, Panel A reports MNL regressions estimated with all the observations in the sample. The observations of $y_s = 1$ are set to a base group to ensure model identification. Models 1 and 2 indicate that investor number and funding amount have negative and significant coefficients for the probability of $y_s = 2$ at the 1% level. These results suggest that investor number and funding amount are associated with significant decreases in the

probability of start-ups' financing from CVCs with respect to IVCs, supporting Hypothesis 1. In contrast, Models 3 and 4 indicate that IP protection and future product have positive and significant coefficients for the probability of $y_s = 2$ at the 1% level. These results suggest that IP protection and future product are associated with significant increases in the probability of start-ups' financing from CVCs with respect to IVCs, supporting Hypotheses 2 and 3.

Table 4.4. Hypothesis test using multinomial logit (MNL) regressions

Panel A. MNL regressions with the full sample

	MNL regression									
Model	(1)		(2)		(3)		(4)		(5)	
y_s	Internal financing	CVC	Internal financing	CVC	Internal financing	CVC	Internal financing	CVC	Internal financing	CVC
Investor number	-3.105***	-1.529***							-3.254***	-1.273***
	(0.451)	(0.262)							(0.500)	(0.264)
Funding amount			0.111	-0.884***					0.818***	-0.396**
			(0.151)	(0.172)					(0.192)	(0.187)
IP protection					2.394***	1.263***			1.347***	0.534
					(0.365)	(0.357)			(0.462)	(0.400)
Future product							0.120***	0.113***	0.059	0.081**
							(0.039)	(0.034)	(0.042)	(0.035)
Firm size	-0.022	0.428**	-0.025	0.841***	0.014	0.511***	0.074	0.563***	-0.365*	0.535***
	(0.184)	(0.172)	(0.167)	(0.163)	(0.152)	(0.149)	(0.154)	(0.155)	(0.205)	(0.201)
Internal R&D	-0.042	0.036	-0.050	0.113	-0.154	-0.047	-0.188	-0.107	-0.186	0.024
	(0.178)	(0.195)	(0.160)	(0.179)	(0.159)	(0.169)	(0.149)	(0.169)	(0.201)	(0.220)
Patent stock	-0.078	-0.096	0.143	0.032	0.024	-0.024	0.114	0.017	-0.115	-0.121
	(0.087)	(0.083)	(0.088)	(0.082)	(0.081)	(0.076)	(0.089)	(0.080)	(0.088)	(0.092)
International business	0.743	0.174	1.082**	0.091	1.057**	0.423	1.002**	0.369	1.079**	0.084
	(0.466)	(0.421)	(0.481)	(0.448)	(0.520)	(0.467)	(0.418)	(0.387)	(0.513)	(0.479)
Location (U.S.)	0.808	1.303**	1.098	1.757*	0.820	1.404**	1.224*	1.529**	0.596	1.273*
	(0.671)	(0.617)	(0.719)	(0.897)	(0.700)	(0.703)	(0.685)	(0.604)	(0.689)	(0.680)
Prior IVC	-1.606***	-0.714	-1.511***	-0.785*	-2.089***	-1.132***	-1.599***	-0.763*	-1.865***	-1.032*
	(0.500)	(0.561)	(0.391)	(0.437)	(0.416)	(0.434)	(0.373)	(0.393)	(0.556)	(0.598)
Prior CVC	0.126	0.143	0.554**	0.347	0.312	0.313	0.517**	0.456**	-0.044	-0.048
	(0.249)	(0.234)	(0.248)	(0.221)	(0.236)	(0.217)	(0.241)	(0.218)	(0.275)	(0.257)
Major investor	-36.909***	2.120***	-37.226***	1.797***	-40.133***	1.971***	-33.391***	1.780***	-37.666***	2.052***
	(0.327)	(0.312)	(0.307)	(0.309)	(0.310)	(0.280)	(0.319)	(0.286)	(0.365)	(0.333)
Constant	27.414***	23.879***	23.618***	22.732***	23.075***	22.404***	23.666***	22.618***	25.891***	24.001***
	(1.649)	(1.198)	(1.615)	(1.414)	(1.151)	(1.412)	(1.035)	(1.215)	(1.770)	(1.256)
Year fixed effects	Yes		Yes		Yes		Yes		Yes	
N	950		943		950		939		932	

Table 4.4. continued

Log likelihood	-690.862	-772.162	-783.793	-802.531	-628.522
Prob>χ^2	0.000	0.000	0.000	0.000	0.000
pseudo R^2	0.329	0.245	0.238	0.213	0.379

Panel B. MNL regressions with a limited sample excluding syndicated investments

	MNL regression							
	(1)		(2)		(3)		(4)	
y_s	IVC	CVC	IVC	CVC	IVC	CVC	IVC	CVC
Funding amount	-0.832***	-1.247***					-0.814***	-1.253***
	(0.208)	(0.170)					(0.212)	(0.171)
IP protection			-1.214***	-0.585			-1.610***	-0.926
			(0.448)	(0.514)			(0.539)	(0.579)
Future product					-0.095**	0.006	-0.072	0.026
					(0.048)	(0.033)	(0.050)	(0.036)
Control variables	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
N	770		777		766		759	
Log likelihood	-542.455		-587.524		-584.618		-526.640	
Prob>χ^2	0.000		0.000		0.000		0.000	
pseudo R^2	0.305		0.254		0.249		0.318	

Panel C. Post estimation of MNL regressions

Panel C-1. Joint tests

	χ^2	Pr>χ^2
Investor number	66.13	0.00
Funding amount	48.98	0.00
IP protection	48.43	0.00
Future product	12.94	0.00
All the above variables	122.19	0.00

Panel C-2. Predicted probabilities

	Mean	S.D.

Table 4.4. continued

Internal financing	0.41	0.33
IVC	0.30	0.29
CVC	0.29	0.27

Panel C-3. Small-Hsiao tests of IIA assumption

Omitted	Log likelihood (full)	Log likelihood (omit)	χ^2	Pr>χ^2
$y_s = 0$	-215.94	-125.50	180.89	0.00
$y_s = 1$	-182.98	-121.97	122.02	0.00
$y_s = 2$	-251.01	-112.30	277.42	0.00

Notes. This table reports MNL regressions predicting the probabilities of start-ups' financing through internal financing, independent venture capitalists (IVCs), and corporate investors (CVCs). I estimate the following models: $(y_s = j) = \frac{\exp(Z_i\delta_j)}{\sum_{k=1}^{3}\exp(Z_i\delta_k)}$, $j \in \{0,1,2\}$, where Z_i are categorical or continuous explanatory variables. Panel A reports MNL regressions estimated with the full sample. IVC ($y_s = 1$) is set to a base group to ensure model identification. The independent variables of interest are investor number, funding amount, IP protection, and future products. Control variables are firm size, internal R&D, patent stock, international business, location (U.S.), prior IVC, prior CVC, major investor, and year fixed effects. Panel B reports MNL regressions estimated with a limited sample excluding syndicated investments (i.e., investor number>1). Internal financing ($y_s = 0$) is set to a base group. Investor number is excluded from the analyses because it has insufficient variance. Panel C reports the post estimation of MNL regressions. Panel C-1 reports joint tests that examine whether or not the independent variables of interest are statistically significant in determining the probabilities of financing through internal financing ($y_s = 0$), IVCs ($y_s = 1$), and CVCs ($y_s = 2$). For example, the significance of funding amount varies across alternatives (i.e., internal financing and CVC) in Model 2 presented in Panel A. The basic idea of this test is that, if this variable is significant in determining the probabilities of financing through the alternatives, adding or deleting it will significantly affect the log likelihood of the models. The significant value of test statistic (Prob>χ^2) indicates that this variable significantly affects the log likelihood of the models. Panel C-2 reports the predicted probabilities of financing through internal financing, IVCs, and CVCs. Panel C-3 reports Small-Hsiao tests that examine the validity of independent of irrelevant alternatives (IIA) assumption. The basic idea of this test is that, if the IIA assumption is satisfied, adding or deleting an alternative does not significantly affect the odds among the remaining alternatives. The significant value of test statistic (Prob>χ^2) indicates that the IIA assumption has been violated. For the definitions of variables, please see Appendix B. Robust and clustered standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel B reports MNL regressions estimated with the limited sample that excludes the observations of syndicated investments (i.e., investor number>1). Investor number is excluded in this estimation because it has insufficient variance. The observations of $y_s = 0$ is set to a base group to ensure model identification. Model 1 shows that funding amount indicates greater coefficient for the probability of $y_s = 1$ than that of $y_s = 2$. In contrast, IP protection and future product indicate greater coefficients for the probability of $y_s = 2$ than that of $y_s = 1$. These results are consistent with the results presented in Panel A, suggesting that my findings are robust regardless of the existence of syndicated investments in the sample.

Panel C reports the post estimations of MNL regressions. Panel C-1 reports joint tests that examine whether or not the independent variables of interest are statistically significant in determining the probabilities of start-ups' financing from internal financing, IVCs, and CVCs. For example, the significance of funding amount varies across alternatives (i.e., internal financing and CVC) in Model 2, as presented in Panel A. The basic idea of this test is that, if a focal variable is significant in determining the probabilities of financing through the alternatives, adding or deleting it will significantly affect the log likelihood of the models. The significant value of test statistic (i.e., Prob>χ^2) indicates that the focal variable significantly affects the log likelihood of the models. The test statistics indicate that all the variables of interest are important in determining the start-ups' financing sources because the test statistics are significant at the 1% level.

Panel C-2 reports the predicted probabilities of start-ups' financing from internal financing, IVCs, and CVCs. These predicted probabilities indicate that internal financing

(41%) is the financing source that is the most often used by start-ups, followed by IVCs (30%) and CVCs (29%). These results are consistent with the concern discussed with Figure 4.3 that start-ups can finance their projects from more diverse sources other than IVCs and CVCs. Furthermore, I need to investigate whether or not this internal financing impacts the probabilities of start-ups' choice between IVCs and CVCs because MNL regressions assume the IIA condition.

Panel C-3 reports Small-Hsiao tests that examine the validity of IIA assumption. The basic idea of this test is that, if the IIA assumption is satisfied, adding or deleting an alternative does not significantly affect the odds among the remaining alternatives. The significant value of test statistic (i.e., Prob>χ^2) indicates that the IIA assumption has been violated. The test statistics are significant at the 1% level, suggesting that the IIA assumption is violated. As a result, I should refine and improve my search for more definitive evidence by using the sequential logit regression.

Table 4.5 reports sequential logit regressions that predict the probabilities of start-ups' financing from internal financing and external financing (i.e., IVCs or CVCs) at the first transition and the probabilities of start-ups' financing from IVCs and CVCs at the second transition. Transitions denote the choice nodes presented in Figure 4.2. The transition of interest is the second transition. Panel A reports bench-mark results and the sequential logit regressions discussed in Section 3. Models 1 and 2 indicate that investor number and funding amount have negative and significant coefficients for the probability of $y_s = 2$ (CVC) at the second transition. These results provide evidence that start-ups with better evaluated technology tend to raise funds for their projects from IVCs rather than CVCs, thus alleviating the IIA concern and supporting Hypothesis 1. In contrast,

Models 3 and 4 indicate that IP protection and future product have positive and significant coefficients for the probability of $y_s = 2$ at the second transition. These results provide evidence that start-ups tend to finance their projects through CVCs rather than IVCs when their intellectual property is effectively protected and their research pipelines contain multiple products, supporting Hypotheses 2 and 3.

Table 4.5. Hypothesis test using sequential logit regressions: Bench-mark results

Panel A. Sequential logit regression: Bench-mark results

	Sequential logit regression									
Model	(1)		(2)		(3)		(4)		(5)	
Transition	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
y_s	IVC or CVC	CVC	IVC or CVC	CVC	IVC or CVC	CVC	IVC or CVC	CVC	IVC or CVC	CVC
Investor number	2.402***	-1.519***							2.712***	-1.282***
	(0.416)	(0.238)							(0.434)	(0.248)
Funding amount			-0.564***	-0.800***					-1.062***	-0.367**
			(0.117)	(0.152)					(0.150)	(0.155)
IP protection					-1.775***	1.398***			-1.184**	0.634*
					(0.311)	(0.329)			(0.461)	(0.364)
Future product							-0.048	0.106***	-0.015	0.081**
							(0.032)	(0.032)	(0.037)	(0.035)
Firm size	0.199	0.327**	0.334**	0.698***	0.165	0.388***	0.114	0.431***	0.605***	0.405**
	(0.141)	(0.166)	(0.147)	(0.150)	(0.131)	(0.144)	(0.134)	(0.147)	(0.163)	(0.188)
Internal R&D	-0.161	0.075	-0.026	0.059	-0.059	-0.082	-0.025	-0.168	-0.004	0.057
	(0.134)	(0.169)	(0.145)	(0.157)	(0.137)	(0.149)	(0.130)	(0.147)	(0.159)	(0.182)
Patent stock	-0.124*	-0.108	-0.183**	-0.025	-0.152**	-0.068	-0.175**	-0.058	-0.074	-0.105
	(0.071)	(0.081)	(0.074)	(0.083)	(0.068)	(0.076)	(0.073)	(0.080)	(0.074)	(0.086)
International business	-0.559	-0.129	-0.952**	-0.051	-0.732*	0.203	-0.720*	0.409	-0.995**	-0.103
	(0.403)	(0.439)	(0.420)	(0.414)	(0.428)	(0.470)	(0.389)	(0.449)	(0.409)	(0.468)
Location (U.S.)	-0.536	1.063*	-0.705	1.491*	-0.442	1.167	-0.732	1.243*	-0.526	1.009
	(0.485)	(0.628)	(0.568)	(0.883)	(0.555)	(0.768)	(0.542)	(0.709)	(0.458)	(0.636)
Prior IVC	1.299***	-0.710	1.218***	-0.767	1.590***	-1.097**	1.260***	-0.587	1.397***	-1.090*
	(0.336)	(0.600)	(0.354)	(0.467)	(0.326)	(0.442)	(0.324)	(0.375)	(0.387)	(0.614)
Prior CVC	-0.188	0.095	-0.478**	0.163	-0.222	0.299	-0.337	0.451**	-0.104	-0.116
	(0.225)	(0.238)	(0.233)	(0.225)	(0.212)	(0.209)	(0.215)	(0.211)	(0.261)	(0.258)
Major investor	17.266***	1.969***	17.094***	1.610***	17.907***	1.808***	16.908***	1.617***	16.685***	1.863***
	(0.206)	(0.266)	(0.202)	(0.266)	(0.204)	(0.259)	(0.219)	(0.263)	(0.233)	(0.284)
Constant	-3.223***	0.136	0.645	-1.928**	0.730	-2.907***	0.049	-2.546***	-1.914**	0.208
	(0.820)	(0.770)	(0.650)	(0.923)	(0.616)	(0.802)	(0.619)	(0.763)	(0.831)	(0.763)
Year fixed effects	Yes		Yes		Yes		Yes		Yes	

Table 4.5. continued

N	950	943	950	939	932
Log likelihood	-757.837	-834.455	-848.570	-864.680	-683.204
Prob>χ^2	0.000	0.000	0.000	0.000	0.000

Panel B. Sequential logit regression with hypothetical confounding variables

	Sequential logit regression							
Model	(1)		(2)		(3)		(4)	
Transition	1st	2nd	1st	2nd	1st	2nd	1st	2nd
y_s	IVC or CVC	CVC	IVC or CVC	CVC	IVC or CVC	CVC	IVC or CVC	CVC
Investor number	2.563***	-1.701***						
	(0.366)	(0.205)						
Funding amount			-0.774***	-1.113***				
			(0.114)	(0.146)				
IP protection					-2.369***	1.097***		
					(0.352)	(0.367)		
Future product							-0.084***	0.091**
							(0.027)	(0.039)
Control variables	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
N	950		943		950		939	
Log likelihood	-760.498		-834.852		-849.317		-864.780	
Prob>χ^2	0.000		0.000		0.000		0.000	

Notes. This table reports sequential logit regressions predicting the probabilities of start-ups' financing through internal financing and external financing (i.e., IVCs or CVCs) at the first transition and the probabilities of start-ups' financing through IVCs and CVCs at the second transition. Transitions denote the choice nodes presented in Figure 4.2. The transition of interest is the second transition. Panel A reports bench-mark results and the sequential logit regressions discussed in Section 3. The independent variables of interest are investor number, funding amount, IP protection, and future product. Control variables are firm size, internal R&D, patent stock, international business, location (U.S.), prior IVC, prior CVC, major investor, and year fixed effects. Panel B reports sequential logit regressions with hypothetical confounding variables. This estimation investigates how a confounding variable (i.e., an unobserved variable that is extraneous and correlates with both the dependent and independent variables) impacts the estimated results presented in Panel A. I use hypothetical confounding variables with correlation and standard deviation at 0.1. These four models demonstrate what can happen if the hypothetical confounding variable is correlated with investor

number (Model 1), funding amount (Model 2), IP protection (Model 3), and future product (Model 4). For the definitions of variables, please see Appendix B. Robust and clustered standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel B reports sequential logit regressions with hypothetical confounding variables. This estimation investigates how a confounding variable (i.e., an unobserved variable that is extraneous and correlates with both the dependent and independent variables) impacts the estimated results presented in Panel A. I use hypothetical confounding variables with correlation and standard deviation fixed at 0.1. These four models demonstrate what can happen if the hypothetical confounding variable is correlated with investor number (Model 1), funding amount (Model 2), IP protection (Model 3), and future product (Model 4). Consistent with the results presented in Panel A, Models 1 and 2 indicate that investor number and funding amount have negative and significant coefficients for the probability of $y_s = 2$ at the second transition. In Models 3 and 4, IP protection and future product indicate positive and significant coefficients for the probability of $y_s = 2$ at the second transition. These results alleviate the concerns about the existence of the potential confounding variable, suggesting that my findings presented in Panel A are robust to the potential confounding variable problem.

Table 4.6 reports two-stage probit regressions that predict the probabilities of start-ups' financing from CVCs and IVCs. Four models include the first-stage regressions of investor number (Model 1), funding amount (Model 2), IP protection (Model 3), and future product (Model 4). These four variables are instrumented by industry IPO, industry acquisition, and industry funding amount. For the definitions of these variables, please see Appendix B. The stage of interest is the second stage. In this stage, a dependent variable is the indicator variable that equals one (zero) if a start-up finances its project from CVCs (IVCs). Models 1 and 2 indicate that investor number and funding amount have negative and significant coefficients for the probability of $y_s = 2$ at the 1% level.

Models 3 and 4 indicate that IP protection and future product have positive and significant coefficients for the probability of $y_s = 2$ at the 1% level. These findings reduce concerns about endogeneity problem and are consistent with the findings presented in the sequential logit regressions. As a post estimation of two-stage probit regression, the Wald test of exogeneity is included. The significant Wald test statistic of exogeneity indicates that the null hypothesis (i.e., no correlation between the errors in the first- and second-stage regressions) is rejected, and thus the use of two-stage probit regression is supported. These test statistics are significant at the 1% level across models and thus my estimation using two-stage probit regression is supported.

Table 4.6. Hypothesis test using two-stage probit regressions

	Two-stage probit regression							
Model	(1)		(2)		(3)		(4)	
Stage	1st	2nd	1st	2nd	1st	2nd	1st	2nd
Dependent variable	Investor number	CVC	Funding amount	CVC	IP protection	CVC	Future product	CVC
Investor number		-1.546***						
		(0.074)						
Funding amount				-1.277***				
				(0.053)				
IP protection						3.065***		
						(0.139)		
Future product								0.293***
								(0.033)
Firm size	-0.067	-0.055	0.318***	0.424***	0.042*	-0.101	0.623	-0.169*
	(0.051)	(0.080)	(0.044)	(0.055)	(0.024)	(0.074)	(0.390)	(0.098)
Internal R&D	0.060	0.175**	0.144***	0.215***	0.013	-0.002	0.869***	-0.243***
	(0.055)	(0.076)	(0.055)	(0.072)	(0.026)	(0.079)	(0.303)	(0.080)
Patent stock	-0.063***	-0.077**	0.004	0.012	0.024**	-0.064*	0.189	-0.051
	(0.024)	(0.037)	(0.037)	(0.046)	(0.012)	(0.035)	(0.215)	(0.065)
International business	-0.224**	-0.376**	-0.310	-0.413	0.014	-0.062	-2.199**	0.630***
	(0.098)	(0.176)	(0.243)	(0.281)	(0.080)	(0.250)	(0.890)	(0.240)
Location (U.S.)	-0.233	-0.014	0.059	0.176	0.139	-0.281	0.904	-0.216
	(0.172)	(0.287)	(0.226)	(0.293)	(0.109)	(0.333)	(0.755)	(0.211)
Prior IVC	-0.075	-0.276	-0.132	-0.230	0.338***	-1.105***	0.056	-0.042
	(0.172)	(0.292)	(0.140)	(0.190)	(0.091)	(0.298)	(0.505)	(0.149)
Prior CVC	-0.279***	-0.362***	-0.408***	-0.495***	0.165***	-0.472***	0.387	-0.104
	(0.083)	(0.130)	(0.083)	(0.108)	(0.036)	(0.107)	(0.346)	(0.102)
Major investor	0.030	0.324***	-0.224***	-0.182*	-0.048	0.272**	1.397**	-0.365**
	(0.072)	(0.113)	(0.084)	(0.108)	(0.035)	(0.112)	(0.618)	(0.170)
Industry IPO	-0.017		-0.009		0.004		0.017	
	(0.017)		(0.008)		(0.004)		(0.018)	
Industry acquisition	-0.086*		-0.052*		0.024*		0.139	
	(0.045)		(0.027)		(0.013)		(0.095)	
Industry funding amount	0.412***		0.191***		-0.100***		-0.429	
	(0.047)		(0.061)		(0.022)		(0.261)	

Table 4.6. continued

Constant	-0.314	2.571***	0.020	1.187***	0.655***	-0.556	-0.793	0.812**
	(0.388)	(0.405)	(0.430)	(0.366)	(0.179)	(0.396)	(1.796)	(0.378)
Wald test of exogeneity	73.78		81.83		105.40		40.93	
	(0.000)		(0.000)		(0.000)		(0.000)	
N	554		552		554		553	
Log likelihood	-750.676		-834.497		-351.698		-1.6e+03	
Prob>χ^2	0.000		0.000		0.000		0.000	

Notes. This table reports two-stage probit regressions predicting the probabilities of start-ups' financing through corporate investors (CVCs) and independent venture capitalists (IVCs). Four models include the first-stage regressions of investor number (Model 1), funding amount (Model 2), IP protection (Model 3), and future product (Model 4). These four variables are instrumented by industry IPO, industry acquisition, and industry funding amount. The stage of interest is the second stage. In this stage, a dependent variable is the indicator variable that equals one (zero) if a start-up finances its project through CVCs (IVCs). The independent variables of interest are investor number, funding amount, IP protection, and future product. Control variables are firm size, internal R&D, patent stock, international business, location (U.S.), prior IVC, prior CVC, and major investor. As a post estimation of two-stage probit regression, the Wald test of exogeneity is included. The significant Wald test statistic of exogeneity indicates that the null hypothesis (i.e., no correlation between the errors in the first and second stage regressions) is rejected, and thus the use of two-stage probit regression is supported. For the definitions of variables, please see Appendix B. Robust and clustered standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 4.7 examines the robustness of my findings thus far and reports survival analysis regressions that predict the hazard (the intensity with which the event occurs) of start-ups' financing through IVCs and CVCs. In Panel A, I estimate the following models: $h_i(t) = (\alpha_i + Z_i\beta)t$, where h_i is the hazard for i $(i = 1, \ldots, N)$, β is the slope parameter, and Z_i are categorical or continuous explanatory variables. Specifically, I use the Cox proportional hazard models, which assume that the covariates multiplicatively shift the baseline hazard function, in the analysis. These models make no assumption about the shape of hazard over time. The event (failure) is defined as start-ups' financing from IVCs ($y_s = 1$) in Models 1 through 5 and CVCs ($y_s = 2$) in Models 6 through 10. Prior IVC, prior CVC, and major investor are excluded from the analysis because they have insufficient variances. The coefficients are the log hazard ratios. Models 1, 2, 6, and 7 show that investor number and funding amount indicate greater coefficients for the hazard of $y_s = 1$ than that of $y_s = 2$. In contrast, IP protection and future product indicate smaller coefficients for the hazard of $y_s = 1$ than that of $y_s = 2$. Hence, my results thus far are robust. The corollary and unreported test for multiple coefficients indicates $\chi^2(4)=52.74$ (prob>χ^2=0.00) and $\chi^2(4)=16.45$ (prob>χ^2=0.00), which suggests that the effects of these variables are significant at the 1% level in Models 1 through 5 and Models 6 through 10, respectively.

Table 4.7. Hypothesis test using survival analysis regressions

Panel A. Cox proportional hazard regressions

	Cox proportional hazard regressions									
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Event	IVC ($y_s = 1$)					CVC ($y_s = 2$)				
Investor number	0.374***				0.327***	-0.172				-0.132
	(0.102)				(0.127)	(0.144)				(0.159)
Funding amount		-0.138			-0.375***		-0.233**			-0.233**
		(0.104)			(0.113)		(0.095)			(0.102)
IP protection			-1.198***		-1.192***			-0.583**		-0.769***
			(0.210)		(0.223)			(0.268)		(0.293)
Future product				-0.070**	-0.060**				0.044***	0.044**
				(0.029)	(0.030)				(0.017)	(0.017)
Firm size	-0.247*	-0.238*	-0.224	-0.246*	-0.083	0.023	0.080	0.047	-0.029	0.027
	(0.135)	(0.141)	(0.141)	(0.139)	(0.145)	(0.118)	(0.120)	(0.117)	(0.118)	(0.124)
Internal R&D	0.247	0.280	0.357**	0.298*	0.461**	0.446***	0.521***	0.492***	0.399***	0.517***
	(0.175)	(0.173)	(0.178)	(0.176)	(0.181)	(0.146)	(0.143)	(0.148)	(0.148)	(0.144)
Patent stock	-0.122*	-0.133*	-0.077	-0.129*	-0.062	-0.027	-0.026	-0.010	-0.024	-0.009
	(0.073)	(0.074)	(0.072)	(0.074)	(0.073)	(0.055)	(0.054)	(0.055)	(0.055)	(0.054)
International business	-0.703	-0.671	-0.600	-0.621	-0.623	-0.133	-0.158	-0.151	-0.073	-0.034
	(0.440)	(0.415)	(0.417)	(0.405)	(0.382)	(0.314)	(0.301)	(0.311)	(0.323)	(0.300)
Location (U.S.)	-1.074***	-1.097***	-0.977**	-1.115***	-0.861**	0.513	0.475	0.547	0.515	0.569
	(0.374)	(0.404)	(0.427)	(0.392)	(0.363)	(0.667)	(0.640)	(0.645)	(0.634)	(0.594)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	757	751	757	757	751	757	751	757	757	751
Log likelihood	-938.338	-926.710	-927.020	-941.441	-898.816	-1098.140	-1082.188	-1096.316	-1096.340	-1075.048
pseudo R^2	0.124	0.121	0.135	0.121	0.147	0.145	0.148	0.147	0.147	0.154

Panel B. Post estimation of Cox proportional hazard regressions using seemingly unrelated regression (SUR)

	χ^2	$Pr > \chi^2$
Investor number	4.31	0.04
Funding amount	0.16	0.69
IP protection	3.99	0.05

Table 4.7. continued

Future product	3.61	0.06

Notes. This table reports survival analysis regressions predicting the hazard (the intensity with which the event occurs) of start-ups' financing through independent venture capitalists (IVCs) and corporate investors (CVCs). In Panel A, I estimate the following models: $h_i(t) = (\alpha_i + Z_i\beta)t$, where h_i is the hazard for i $(i = 1, \dots, N)$, β is the slope parameter, and Z_i are categorical or continuous explanatory variables. Specifically, I use the Cox proportional hazard models, which assume that the covariates multiplicatively shift the baseline hazard function, in the analyses. These models make no assumption about the shape of hazard over time. The event (failure) is defined as start-ups' financing through IVCs ($y_s = 1$) in Models 1 through 5 and CVCs ($y_s = 2$) in Models 6 through 10. The independent variables of interest are investor number, funding amount, IP protection, and future product. The corollary and unreported test for multiple coefficients indicates $\chi^2(4)=52.74$ (prob>χ^2=0.00) and $\chi^2(4)=16.45$ (prob>χ^2=0.00), which suggests that the effects of these variables are significant at the 1% level in Models 1 through 5 and Models 6 through 10, respectively. Prior IVC, prior CVC, and major investor are excluded from the analyses because they have insufficient variances. The coefficients are the log hazard ratios. Panel B reports test statistics that examine whether or not the coefficients of the independent variables of interest estimated in Panel A are significantly different across two groups in which the events (failures) are defined as $y_s = 1$ and $y_s = 2$. For example, the coefficients of investor number in Models 1 and 6 are estimated in independent equations. As a result, it is not clear whether or not these two coefficients are significantly different. To investigate this issue, I estimate seemingly unrelated regression (SUR) models of the number of days from founding to the first financing by IVCs and CVCs, respectively. These SUR models are used to test and impose cross-equation constraints that are impossible in independent equation-by-equation hazard models used in Panel A. The significant value of the test statistic, Prob>χ^2, indicates that the coefficients are significantly different. For the definitions of variables, please see Appendix B. Robust standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel B reports test statistics that examine whether or not the coefficients of the independent variables of interest estimated in Panel A are significantly different across two groups in which the events (failures) are defined as $y_s = 1$ and $y_s = 2$. For example, the coefficients of investor number in Models 1 and 6 are estimated in independent equations. As a result, it is not testable whether or not these two coefficients are significantly different. To investigate this issue, I estimate seemingly unrelated regression (SUR) models of the number of days from founding to the first financing by IVCs and CVCs, respectively. These SUR models are used to test and impose cross-equation constraints that are impossible in independent equation-by-equation hazard models used in Panel A. The significant value of the test statistic, Prob>χ^2, indicates that the coefficients are significantly different. The test statistics indicate that the coefficients of investor number, IP protection, and future product are significantly different across the two groups, by contrast with those for funding amount.

4.4.3 Performance Metrics

To estimate the performance metrics created by start-ups' financing from CVCs and IVCs, I use a simple econometric approach that uses the predicted values of performance metrics, including Tobin's q, valuation, and patent citation. Specifically, I estimate the following ordinary least squares (OLS) regression models: $y_i = u_0 + \Pi_i u_1 + e_i$, where y_i is a set of performance metrics and Π_i is a set of variables that may impact the performance metrics. These regressions are presented in Table 4.8. I predict base $\hat{y}$ in the base regressions that do not include funding amount as an independent variable (i.e., Models 1, 3, and 5). I also predict treated $\hat{y}$ in the treated regressions that do include funding amount as an independent variable (i.e., Models 2, 4, and 6). I then

calculate the differences between treated ŷ and base ŷ (i.e., treated ŷ-base ŷ) and use these differences as a proxy for the effects of IVC and CVC financing on the performance metrics. Because treated ŷ can be viewed as a projection onto the linear space spanned by funding amount, which is not projected in base ŷ, along with Π_i, the differences between treated ŷ and base ŷ can be understood as the effects of IVC and CVC financing separated from those of other factors (i.e., Π_i) on the performance metrics.

Table 4.8. Ordinary least squares (OLS) regressions for estimating predicted values

	OLS regressions					
Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Tobin's q		Valuation		Patent citation	
Funding amount (dollar value)		0.341***		7.616***		-0.570*
		(0.099)		(0.509)		(0.336)
Investor number	-10.900	-8.650	-2.175	-36.691	8.713	13.308
	(13.276)	(13.264)	(37.337)	(33.864)	(22.119)	(22.361)
IP protection	-1.674	13.033	-117.236	-67.377	-72.948	-68.553
	(34.623)	(36.424)	(76.101)	(69.467)	(45.083)	(45.869)
Future product	7.253***	6.985***	58.636***	52.650***	-6.971*	-6.549*
	(1.367)	(1.354)	(6.397)	(5.767)	(3.790)	(3.808)
Firm size	67.016***	64.439***	247.595***	178.100***	27.955	33.302*
	(8.144)	(8.282)	(31.523)	(29.079)	(18.674)	(19.201)
Internal R&D	-12.661	-16.100*	33.516	10.148	1.633	3.354
	(9.156)	(9.185)	(35.940)	(33.200)	(21.291)	(21.922)
Patent stock	-11.764***	-11.440***	-26.606	-24.091	206.397***	205.752***
	(3.647)	(3.608)	(16.815)	(15.138)	(9.961)	(9.995)
International business	9.586	6.458	48.705	-3.052	384.185***	388.897***
	(17.093)	(16.923)	(81.883)	(73.708)	(48.508)	(48.670)
Location (U.S.)	37.650	30.959	242.770*	178.544	-69.622	-65.983
	(44.386)	(44.039)	(130.607)	(117.607)	(77.373)	(77.657)
Prior IVC	-23.528	-18.626	-150.825**	-116.910*	-34.796	-34.351
	(20.654)	(20.597)	(70.605)	(64.388)	(41.827)	(42.516)
Prior CVC	1.795	2.888	-32.270	-14.581	-12.335	-12.725
	(11.742)	(11.614)	(48.005)	(43.471)	(28.439)	(28.704)
Major investor	-24.044	-18.763	-101.484	-23.530	12.632	7.676
	(14.948)	(14.853)	(66.245)	(59.768)	(39.244)	(39.465)
Constant	-73.910	-66.997	-405.243	-277.601	109.379	90.211
	(127.180)	(101.817)	(296.665)	(267.362)	(175.747)	(176.540)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	495	493	939	932	939	932
F	8.461	8.818	12.723	22.242	19.509	18.849
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.362	0.380	0.303	0.442	0.400	0.402

Notes. This table reports OLS regressions predicting performance metrics including Tobin's q, valuation, and patent citation. I estimate the following models: $y_i = u_0 + \Pi_i u_1 + e_i$, where y_i is a set of performance metrics and Π_i is a set of variables that may impact the performance metrics. I predict base ŷ in the base regressions that do not include funding amount as an independent variable (i.e., Models 1, 3, and 5). I also predict treated ŷ in the treated regressions that do include funding amount as an independent variable (i.e., Models 2, 4, and 6). I then calculate the differences between treated ŷ and base ŷ (i.e., treated ŷ-base ŷ) and use these differences as a proxy for the effects of IVC and CVC financing on the performance metrics. Because treated ŷ can be viewed as a projection onto the linear space spanned by funding amount, which is not projected in base ŷ, along with Π_i, the differences between treated ŷ and base ŷ can be understood as the effects of IVC and CVC financing separated from those of other factors (i.e., Π_i) on the performance metrics. For the definitions of variables, please see Appendix B. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 4.9 reports start-ups' performance metrics associated with financing through IVCs and CVCs. Panel A reports two-sample t-tests that examine whether or not the means of performance metrics, which are calculated from two groups of start-ups financed from IVCs and CVCs, are significantly different. This approach is a naïve approach that simply compares the means of performance metrics without separating and estimating the effects of IVC and CVC financing on the performance metrics. As a result, it is not clear whether the differences between the means of performance metrics are attributable to IVC and CVC financing or other factors that may impact the performance metrics. This table indicates that start-ups have significantly greater Tobin's q, valuation, and patent citation when they finance their projects from CVCs than IVCs.

Table 4.9. Hypothesis test using several performance metrics

Panel A. Means of several performance metrics between two groups of start-ups: Naïve approach

	IVC	CVC	Difference
Tobin's q	52.384	82.873	-30.488**
	(7.666)	(11.459)	(15.796)
N	106	172	
Valuation	64.846	210.560	-145.713***
	(8.987)	(29.057)	(23.108)
N	1880	719	
Patent citation	73.267	152.976	-79.709***
	(5.709)	(15.951)	(13.509)
N	1880	719	

Panel B. Means of several performance metrics generated from predicted values: Better approach

	IVC	CVC	Difference

Table 4.9. continued

Tobin's q	1.490	-1.780	3.271**
	(1.265)	(0.457)	(1.350)
N	277	274	
Valuation	18.783	-40.058	58.841**
	(26.929)	(7.659)	(28.127)
N	277	274	
Patent citation	-2.193	2.757	-4.951**
	(2.031)	(0.600)	(2.128)
N	277	274	

Notes. This table reports start-ups' performance metrics associated with financing through independent venture capitalists (IVCs) and corporate investors (CVCs). These performance metrics include Tobin's q, valuation, and patent citations. Panel A reports two-sample t-tests that examine whether or not the means of performance metrics, which are calculated from two groups of start-ups financed through IVCs and CVCs, are significantly different. This approach simply compares the means of performance metrics without separating and estimating the effects of IVC and CVC financing on the performance metrics. As a result, it is not clear whether the differences between the means of performance metrics come from IVCs and CVCs financing or other factors that may impact the performance metrics. Panel B reports two-sample t-tests that examine whether or not the means of new performance metrics, which are estimated by using the regressions presented in Table 4.8 and thus separate and estimate the effects of IVC and CVC financing on the performance metrics, are significantly different. For the definitions of variables, please see Appendix B. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel B reports two-sample t-tests that examine whether or not the means of new performance metrics, which are estimated using the regressions presented in Table 4.8 and thus separate and estimate the effects of IVC and CVC financing on the performance metrics, are significantly different. Interestingly, inconsistent with the results presented in Panel A, start-ups indicate significantly greater Tobin's q and valuation when they finance their projects from IVCs than CVCs. In contrast, start-ups indicate significantly greater patent citation when they raise funds from CVCs than IVCs. These mixed results suggest that it is hard to determine which financing source is absolutely more beneficial for start-ups than other sources. Rather, these results suggest that, while IVCs tend to create greater managerial value (i.e., Tobin's q and valuation) for start-ups, CVCs tend to create greater technological value (e.g., patent citation) for start-ups. These results support Hypothesis 4.

4.5 Conclusions

In this paper I present an analytical framework and empirical evidence to address the issues regarding start-ups' financing choice between IVCs and CVCs and its performance implications by highlighting the contextual factors that may impact the choice. My theoretical and empirical investigation suggests that start-ups that possess better evaluated technology tend to finance their projects from IVCs rather than CVCs. In contrast, start-ups tend to finance their projects from CVCs rather than IVCs when their technology is effectively protected and their research pipelines contain multiple products. While financing from IVCs contributes to increasing start-ups' Tobin's q and valuation, financing from CVCs contributes to enhancing start-ups' forward patent citations.

Beyond providing a broad bench-mark for start-ups' financing choice and its performance implications, this study has important implications for start-ups and entrepreneurial investors. First, it implies that the risk of appropriation is an important factor that impacts start-ups' financing choice. This implication is important because much of the existing literature, with just a few exceptions, has emphasized CVCs as an alternative financing source without appropriate caution. Second, this study implies that each type of investor can fulfill different needs for start-ups. This implication can open a new avenue of future research that addresses what different types of investors do and how they interact with each other in the entrepreneurial finance market. This line of study can make it possible for start-ups to effectively pursue the ability to create synergies with different types of investors to capture managerial and technological resources as well as financial capital.

To conclude this paper, some limitations of the study are discussed. The first obvious limitation is that my findings are limited to the context of the bio-pharmaceutical industry. To the extent that the motivations and consequences of CVCs vary across industries, my findings should be interpreted with caution when they are applied in the contexts of other industries. Furthermore, due to the exploratory nature of this study, I had little theoretical and empirical guidance from the existing literature. As a result, my theoretical and empirical models might omit some important potential factors.

APPENDIX A

Variable	Description	Data sources
Cash flow	Net income after interest and taxes plus depreciation and amortization in year t	Compustat
CVC amount	Amount of CVC investments by firm *i* in year t	Deloitte Recap
CVC average amount	Yearly mean of CVC amount of all sample firms in year t	Deloitte Recap
CVC fraction	Number of firms making CVC investments in year t	Deloitte Recap
External R&D	Number of alliances stock, including licensing, strategic alliances, and acquisitions, in year t	Deloitte Recap
Financial return	Geometric average return. I construct this variable (g_n) as follows: $g_n = (1 + r_c)^{\frac{1}{n}} - 1$, where g_n is the geometric average return applicable on each subset period *n*, r_c is the cumulative return over the entire period, and *n* is the number of equal subset periods to average the return. For the sample in which CVC investments are made in pre-IPO portfolios that go public afterward, r_c is estimated by using IPO price per share. For the sample in which CVC investments are made in post-IPO portfolios or pre-IPO portfolios that do not go public afterward, r_c is estimated by using the last funding activity price. The last funding activity includes acquisition and other forms of fund-raising activities by portfolios. I finally calculated the weighted mean of g_n with amounts invested individual CVC investments for firm *i* in year t.	Deloitte Recap
Financial return rank	Ranking variable of financial return. The greater ranking denotes the greater financial return.	Deloitte Recap
Growth rate	Growth rate of revenue (e.g., [revenue (t)-revenue (t-1)]/ revenue (t-1))	Compustat
Headquarter (U.S.)	Indicator variable that equals one if firm *i* is headquartered in U.S. and zero otherwise	Compustat
Internal R&D (t)	R&D expenses in year t	Compustat
Internal R&D (t-1)	R&D expenses estimated in year t-1	Compustat
Leverage	Ratio of total debt to total assets in year t	Compustat
Multinationality	Indicator variable that equals one if firm i manages its business in more than one country and zero otherwise	Compustat
Number of products (pre-clinical)	Number of products within pre-clinical stage in year t	PharmaProjects
Number of products (total)	Total number of products within stage I, II, and III in year t	PharmaProjects
Number of products (weighted)	Number of products weighted by the probabilities of advancing to the next stage within stage I, II, and III in year t	PharmaProjects
Patents	Number of patents applied in year t	NBER
Post-IPO	Indicator variable that equals one if firm *i* makes CVC investments in post-IPO portfolios and zero otherwise	Deloitte Recap
R&D intensity (t)	R&D expenses divided by total assets (e.g., R&D expenses/total assets) in year t	Compustat
R&D intensity (t-1)	R&D intensity estimated in year t-1	Compustat
Return type	Sub-group I or IV. I split the sample between CVC investments generating technological and financial returns above and below the means, respectively. Group I represents CVC investments resulted in low technological return and low financial return; group II in low technological return and high financial return; group III in high technological return and low financial return; and group IV in high technological return and high financial return.	All sources
SIC (28)	Indicator variable that equals one if the first two digits of SIC code	Compustat

	are 28 and zero otherwise	
Size	Log of total assets in year t	Compustat
Technological diversity	1/(1+the number of patents that share first three digits of patent class between firm *i* and its portfolios)	NBER
Technological return (pre-clinical)	Differences between treated ŷ and base ŷ (e.g., treated ŷ-base ŷ) estimated from Models 5 and 6 in Table 3.1	All sources
Technological return (t)	Technological return (weighted) in year t	All sources
Technological return (t+1)	Technological return (weighted) in year t+1	All sources
Technological return (t+2)	Technological return (weighted) in year t+2	All sources
Technological return (total)	Differences between treated ŷ and base ŷ (e.g., treated ŷ-base ŷ) estimated from Models 3 and 4 in Table 3.1	All sources
Technological return (weighted)	Differences between treated ŷ and base ŷ (e.g., treated ŷ-base ŷ) estimated from Models 1 and 2 in Table 3.1	All sources
Technological return (t) rank	Ranking variable of technological return (t). The greater ranking denotes the greater technological return (t).	All sources

APPENDIX B

Variable	Description
Chosen (y_s)	A ternary variable that equals zero if a start-up finances its project through internal financing ($y_s = 0$), one if through IVCs ($y_s = 1$), and two if through CVCs ($y_s = 2$). Syndicated investments made by both IVCs and CVCs are categorized by the natures of leading investors (i.e., CVCs or IVCs).
Firm size	Log of total assets of start-up
Funding amount	Log of amount of investment calculated in millions of U.S. dollars
Funding amount (dollar value)	Amount of investment calculated in millions of U.S. dollars
Future product	Number of products (i.e., drugs) in pre-clinical stage
Industry acquisition	Number of acquisitions in the bio-pharmaceutical industry in a year
Industry funding amount	Amount of investments made by IVCs and CVCs in the bio-pharmaceutical industry in a year
Industry IPO	Number of IPOs in the bio-pharmaceutical industry in a year
Internal R&D	Log of R&D expenditures of start-up
International business	An indicator variable that equals one if a start-up is involved with international business and zero otherwise
Investor number	Number of investors in an investment
IP protection	An indicator variable that equals one if a start-up finances its project in the stages later than Series C (i.e., the median of financing stages in the sample) and zero otherwise
Location (U.S.)	An indicator variable that equals one if a start-up is headquartered in U.S. and zero otherwise
Major investor	An indicator variable that equals one if a start-up finances its project through major CVCs or IVCs listed in Table 4.1 and zero otherwise
Patent citation	Number of patents that cite a start-up's patents
Patent stock	Cumulative number of patents applied by a start-up (depreciated 15% annually)
Prior CVC	An indicator variable that equals one if a start-up has previously financed its project through CVCs and zero otherwise
Prior IVC	An indicator variable that equals one if a start-up has previously financed its project through IVCs and zero otherwise
Tobin's q	Tobin's q is approximated as follows: Approximate q = (MVE+PS+DEBT)/TA, where MVE is the product of a firm's share price and the number of common stock shares outstanding, PS is the liquidating value of the firm's outstanding preferred stock, DEBT is the value of the firm's short-term liabilities net of its short-term assets, plus the book value of the firm's long-term debt, and TA is the book value of the total assets of the firm.
Valuation	A start-up's implied value estimated by investor community

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