Venture Capital Influence on Innovation: A Fund-Level Perspective

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ABSTRACT

This paper investigates the dynamic relationship between the finite duration of the VC fund and the exploratory nature of innovation pursued by the portfolio ventures and whether the relationship is contingent on fund performance relative to its expected performance (reference point). The paper draws on the theoretical framework of exploration-exploitation and provides an illustrative two-arm bandit model to analyze the investment tradeoff between exploration of uncertain innovation that may generate higher innovation impact and exploitation of known innovation. The empirical analysis based on VC-backed biotechnology ventures provide evidence that VCs invest in more exploration type innovation at the start of fund that generate a higher innovation impact but progressively the degree of exploration and the innovation impact declines over the finite duration of the fund. However, when the fund performance falls below expectations, VCs exhibit risk seeking behavior and continue to pursue exploration projects that generate a higher innovation impact.

Key words: Innovation, Venture Capital, Patent, Exploration, Prospect Theory

1.0 Introduction

Innovation is an important driver for economic growth and over the past three decades venture capital investments have played a significant role in financing radical innovations in the U.S economy. Extant research has established that value-added benefits of venture capital investment facilitate innovation in technology ventures (e.g., Hellmann and Puri, 2000; Kortum and Lerner, 2000). Such benefits are derived partly from the VC endorsement effect that signals quality of the venture and VCs efforts in monitoring and governance in the early stages of the venture. Innovation, especially those that are exploratory in nature, however, is a time intensive task and financing such innovation demands an appetite to experiment, and requires patience to nurture radical innovations (Holmstrom, 1989). Despite considerable investigation into the role of venture capital on value creation, there is little understanding on how the time oriented facet of venture capital financing has a significant economic impact on the type of innovation pursued by technology ventures.

A central feature of the VC financing process is the predetermined duration of the fund, typically for 10 years (Gompers, 1996; Sahlman, 1990). Prior research investigating the role of finite fund duration highlights sub-optimal decisions made by VCs that reflect myopic behavior. For example, Gompers (1996) showed the effect of grandstanding in the VC industry that forces VCs to consider premature exit from the portfolio ventures and this phenomenon is more pronounced for less experienced VCs yet to establish their credibility. In similar lines, Guler (2007) analyzed psychological, institutional, and political factors that may create systematic challenges in VCs' decision to terminate sequential investments. In this paper I extend this stream of research to examine the influence of finite time duration of the VC fund on the value added benefits derived from VC investments. Specifically, the research question ascertains the dynamic relationship between the finite duration of the VC fund and the exploratory nature of innovation pursued by the portfolio ventures and whether the relationship is contingent on fund performance relative to its expected performance (reference point).

To do so, I draw upon the theoretical framework of exploration-exploitation originally introduced by March (1991) in organization learning processes that identifies the need to allocate resources across both the exploitation of the known and exploration of the novel as a central strategic trade-off. Balancing the task of exploration and exploitation is central to firm performance and there is a near consensus in the literature that organizations must excel at both tasks (Gupta et al., 2006). This paper theoretically contributes to the literature by examining how the critical factor of finite time duration affects the appropriate balance of exploration and exploitation in the context of innovation development process and how such innovation is recognized by other firms and integrated into future technological developments. In addition, this paper advances the application of prospect theory (Kahneman and Tversky, 1979) to the exploration-exploitation literature by investigating whether the balancing act of exploring and exploiting innovation and the innovation impact is influenced by the behavioral contingency of the dynamic change in performance relative to the reference target.

March (1991: 85) notes, "The essence of exploitation is the refinement and extension of existing competencies, technologies, and paradigms....The essence of exploration is experimentation with new alternatives". An essential attribute of exploring novel innovation is the willingness to invest in the uncertain project in order to learn over time the quality of the innovation. This option value of learning by investing in uncertain projects over time gradually reduces the project uncertainty and increases the ex-post value of a project as long as the updated belief from learning about the project continues to remain positive (Manso, 2011). In keeping with March (1991), in the context of financing innovation, exploration is defined as innovation projects that are uncertain but over time investors learn and update information about the projects value as the quality of the innovation unfolds. In contrast, exploitation is defined as innovation projects that have a known outcome and the amount of learning is relatively lower than exploration projects. In other words, exploitation project signals an established quality and the outcome of such projects is somewhat definitive in nature which makes them less risky compared to exploration projects. Given VC investments are time bound, a central tradeoff lies in the decision to invest in exploration of novel innovation that is initially uncertain but ex-post may yield higher innovation impact or invest in exploitation of known innovation that has a high certainty but may prevent the discovery of 'big ticket' radical innovations.

To understand the dynamic nature of financing innovation over finite time duration of the VC fund, I apply an illustrative two arm bandit Bayesian learning model that has been a canonical representation of the exploration–exploitation dilemma. The two arms of the model illustrate the tension between exploration of uncertain and potentially superior projects and exploitation of existing projects with known return.[1] The paper argues that it is optimal for investors to focus more on exploration type innovation in early periods of the fund. Since the amount of learning is greater in exploration compared to exploitation (Gupta et al., 2006), investing in exploration type innovation in early periods of the fund provides a longer time window to accrue the option value of learning from exploration projects. Moreover, VCs willingness to experiment may reduce when the available duration of the fund shrinks because

[1] In economics and finance literature there has been a significant work modeling the decision on exploration and exploitation that has used some form of the two armed bandit problem. Early applications of the bandit model include Rothschild (1974)'s model of firms' experimentation with prices to learn about uncertain demand and Weitzman (1979)'s analysis of optimal sequencing of research projects.

the pressure to liquidate the fund is high in the later periods of the fund (Gompers, 1996; Lerner and Schoar, 2004).

The empirical analyses conducted on the innovations pursued by VC-backed biotechnology ventures suggest that the finite time duration of the VC fund has a profound impact on the degree of exploration projects pursued by the VC. In the early stages of the fund duration VCs adopt an exploration strategy by investing in innovation projects that create new knowledge through recombination of knowledge across different technological domains and such projects have a widespread impact that influences subsequent innovations in a variety of technological domains. As the time duration of the fund shrinks VCs tend to deviate from exploration strategy and focus on projects that exploit known innovation that lowers their impact on subsequent innovation. This result is consistent with the idea that both exploration and exploitation tasks are associated with learning and innovation, but the factor of finite time duration affects the critical balance between the two tasks. Further, investigating the contingent effect of fund performance relative to the reference level reveals that the negative impact of shorter time duration on exploration is dampened if VC fund performance is perceived to be in a loss domain (below its expected performance). In other words, the impetus on exploration type innovation is greater if a fund’s performance is below its expectation.

2.0 Background Literature

Innovation projects involve a high probability of failure and it is challenging to effectively ascertain the future contingencies under high uncertainty. An important issue in financing innovation that originates from information asymmetry, and the one that financial intermediaries like venture capitalists attempt to solve, is to connect entrepreneurs who have innovative ideas with investors who have the capital but lack the information to find innovative ideas. To do so, VCs raise private equity funds from limited partners, conduct due diligence to invest in innovative ventures, and monitor the venture growth (Kaplan and Strömberg, 2001). Literature on value-added benefits of VC investment confirms that VCs have a positive treatment effect on venture development. For example, Kortum and Lerner (2000) showed VC investments generate a positive impact on venture innovation and Hellmann and Puri (2000) showed that VCs are more likely to invest in projects that are more radical in nature compared to simple imitative projects and VC investments expedite the commercialization process of such innovation.

Another stream of literature in the venture capital domain has drawn some attention towards the behavioral facets that influence VC investments (e.g., Gompers, 1996; Guler, 2007). Gompers (1996) grandstanding hypothesis and the following work by Lee and Wahal (2004) confirm a myopic behavior of premature exit in VC investments decisions. Guler (2007) qualitative and empirical study suggests psychological and cognitive factors that create systematic challenges in VCs' decision to terminate sequential investments. This finding is consistent with the behavioral theory proposition that escalation of commitment makes it difficult for the decision maker to abandon the course of action (Staw, 1976). A recent work by Kandel et al. (2011) models the relationship of the finite life of the fund on the VCs sub-optimal decision to terminate its investment in a venture as the time of the fund come to an end. This paper contributes to the venture capital literature by connecting the exploration-exploitation dilemma to the VC investments in innovation projects made over the stipulated time duration of the VC fund and examining the contingency effect of fund performance relative to its expectation drawn from the behavioral constructs of prospect theory.

Financing innovation demands management of the underlying risk and a failure tolerant policy that requires a longer time to learn about the potential quality of the innovation. The tradeoff in such time bound investment is whether to *explore* novel but uncertain innovation projects or *exploit* existing projects with known outcomes. The framework of exploration and exploitation, initially coined by March (1991) in the context of organizational learning, is well suited to explain the differences in the investment strategies of financing innovation that has some prior precedence in the literature. Before developing the hypotheses, I employ a two arm bandit framework which belongs to the class of Bayesian decision model, to illustrate how the finite time duration influences the balance between exploration and exploitation tasks. Early work by Weitzman (1979) applies the bandit problem framework to study the innovation process and Manso (2011) adapted the two-arm bandit framework to model the incentive structure to motivate exploration type innovation. A key takeaway from prior work is that exploration projects take a longer time to mature and if successful, generates a higher value compared to exploitation. In an economy with an infinite time period, it may be optimal to invest in exploration as long as learning from the updated information gathered from each time period reveals positive outcome about the project (Roberts and Weitzman, 1981). However, real world investments have finite time duration and as the time window shrinks the option value of learning from investing in exploration projects is reduced.

2.1 Illustrative Two-armed Bandit Model

The model assumes an investor (VC) is a Bayes rational agent and choices are made under uncertainty. As the information about the innovation quality flows in each period, the investor updates her belief about the prospects of the project. The evolution of the posterior belief of eventual project success represents the learning process that follows Bayes' rule. The VC investment demonstrates the tradeoff between exploration and exploitation, the two arms of a bandit model. This model helps to illustrate why VCs may prefer to invest in exploration in the early period of the fund when the available evaluation time window is long and switch to exploitation as the evaluation time window shrinks. The switch between exploration and exploitation over the finite duration of the fund suggests a higher VC impact on innovation at the beginning of the fund's life that declines as the fund ages.

Consider an economy where the investor has two possible technology projects in the space $I = \{A, B\}$. Project (A) is the exploitation arm of the bandit process with a known probability of return, and project (B) is the exploration arm of the bandit process with uncertain return. The payoffs from projects (A) and (B) are independent of each other. The finite time duration of the fund is T_f. Assume the investor has per period utility function, updates her beliefs about the project quality (μ_t) in a Bayesian fashion, discounts returns by the factor δ ($\delta < 1$), and seeks to maximize discounted expected utility. The basic condition I model is that the investor at each point in time decides whether to exploit project (A) or explore project (B).

---------------------- Insert Figure 1 here ----------------------

Figure 1 depicts the investment sequence for a simple two period extensive form setting where in every period, the VC has the option to invest in project (A) or project (B). At t_0 the investor decides to invest in a project based on some prior belief (μ_0) about the quality of the project. The innovation outcome of an investment in each period is either success (S) or failure (F). If the innovation outcome for exploration project (B) reveals success, it generates a higher return compared to exploitation project (A).

Let $\mu_1 = E(p_b)$ denote the expected probability of innovation success for project B in period-1. Conditional on observing the innovation outcome in period-1, $\mu_2 = E(p_b|S)$, and $\gamma_2 = E(p_b|F)$ are the updated probabilistic beliefs i.e. the expected probability of innovation success in period-2. If project (B) reveals success in period-1, the updated belief of achieving success in period-2 increases and if it reveals failure in period-1, the updated belief of success in period-2 decreases. Therefore, $\mu_2 > \mu_1 > \gamma_2$.

Let p_a denote the known probability of innovation success for project *A* (exploitation arm) for all the periods. For simplicity, I assume no switching cost is incurred to switch between projects. Innovation success in a given period for project *B* generates a return of V_b and for project *A* generates a return of V_a and zero if the outcome of the project is a failure.[2] I assume $V_b > V_a$ or else there would be no option value to explore. Also, I assume the ex-ante expected one period return in time t_0 is equal for project *A* and *B.*

$$\mu_2 * V_b > \mu_1 * V_b = p_a * V_a > \gamma_2 * V_b \tag{1}$$

Given the temporal stationary of the above decision problem, there is an optimal stationary investment strategy for the investor that depends on her current belief about the different arms (explore or exploit). This stationary can equivalently be thought of as a particular type of path independence, in that any two paths of reward realizations leading to the same updated belief should generate the same action by an optimizing agent.

As a baseline condition, I relax the finite time duration constraint and consider a simple discrete-time Markov bandit processes with an infinite sequence of periods $t = 0, 1, 2. . .$ This assumption serves to simplify the initial exposition of the main idea that exploration projects generate a higher return but at the cost of uncertainty of eventual failure. In an infinite period process, it is optimal to continue investing in exploration project *B* if the updated belief in each period is above a critical threshold. Designed in the infinite time setting, based on investor's initial belief μ_0 at time t_0, her maximal discounted payoff from project *A* and *B* will be:

[2] Although the actual return from investment is realized at the termination of the project, the returns in each period can be assumed to be the average per period return. Basically the potential return can be viewed as a sum of independent random variables normally distributed over a large number of component development stages and averaged at V_b and V_a for project *B* and project *A*.

$$R_a = p_a V_a + \delta p_a^2 V_a + \delta^2 p_a^3 V_a + \delta^3 p_a^4 V_a + ... = \frac{p_a V_a}{(1-\delta p_a)} \tag{2}$$

$$R_b(t) = \sup_{\mu_t} E[\sum_{t=0}^{\infty} \delta^t V_b \mu_t \mid \mu_0 = \mu] \tag{3}$$

Formulated as a dynamic programming problem for multiple time period the Bellman equation for the supremum value of R_b is:

$R_b(t) = \max_t E[V_b \mu_t] + \delta E[V_b \mu_{t+1}]$; μ_{t+1} is determined by μ_t using Bayes' theorem. (4)

The investor should continue investing in exploration project *B* as long as $R_b(t) > R_a$ for the updated belief greater than some critical belief cut point (μ^*) for which $R_b(t) = R_a$ .The optimizing decision at time t_0 is a numerically challenging dynamic problem. Gittins and Jones (1974) transformed the optimization decision problem into the form of an index policy - Gittins index. The index theorem states the optimal decision in each time period is to select the project that has the highest index value. The idea is to find for each project the optimal time τ that results in the maximum discounted expected payoff. The economic interpretation of the index is equivalent to a reservation value (or the rent) an investor at the margin is willing to incur to earn the expected discounted payoff from the project.

Consider, $t=\tau$ is the optimal time for the exploration project (*B*) to generate the maximum payoff. The expected payoff for project (*B*) is then:

$$R_b(\tau) = \sup_{\tau>0} E[\sum_{t=0}^{\tau-1} \delta^t V_b \mu_t \mid \mu_0 = \mu] \tag{5}$$

The Gittins index (γ) is the supremum value of the expected discounted payoff over τ periods divided by the expected total discounted time over τ periods.

$$\gamma_b(t) = \sup_{\tau>0} \frac{E[\sum_{t=0}^{\tau-1} \delta^t V_b \mu_t \mid \mu_0 = \mu]}{E[\sum_{t=0}^{\tau-1} \delta^t \mid \mu_0 = \mu]} \tag{6}$$

Following the Gittins index, the decision choice to invest in exploration project *B* at time period *t* in the infinite time sequence reduces to the condition: $\gamma_b(t) > p_a V_a$. (7)

Alternatively, consider imposing finite time duration (T_f) after which both project *A* and *B* have zero payoff. At time $t < T_f$ it is optimal to invest in the exploration project (*B*) iff

$$\gamma_b(t) > p_a V_a \mid T_f - t \geq \tau \text{ ; where } 0 \leq t < T_f \text{ and } \tau > 0. \tag{8}$$

Eqn. (8) shows as the time *t* approaches T_f, the available time (τ) to generate the maximum payoff from exploration project reduces. This suggests that investors should be less likely to invest in exploration projects when the available evaluation time period is short.

3.0 Research Hypotheses

Scholars have argued the benefit of balancing exploration and exploitation (March, 1991; Levinthal and March, 1993; Benner and Tushman, 2003) and empirical work has supported this proposition (e.g., Katila and Ahuja, 2002). The theoretical considerations underlying the exploration-exploitation problem discussed above suggest that specific features of the context within which venture capitalists decide influences the balance between exploration-exploitation. In examining the factors that influence the strategic trade-off between exploration-exploitation, literature has focused on the role of changes in the external environment and organizations ability and willingness to adapt (e.g., Levinthal and March, 1993; Benner and Tushman, 2003). For example, some research suggests availability of financial slack facilitates exploration by investing in radical innovation (O'Brien, 2003) while some research provide an opposing view that slack resources leads to risk aversion that results in low exploration and increased focus on exploitation (Katila and Shane, 2005). VCs face substantial uncertainty when investing in innovation projects and the context of finite time duration in which they evaluate an innovation project can determine their decision to pursue an exploration versus an exploitation opportunity. I draw on the theoretical antecedents of exploration-exploitation and prospect theory to investigate how VCs' influence on innovation varies over the finite duration of the fund with particular characteristics of the investment setting. The hypotheses outlined below tests the direct relationship between funds' elapsed time duration and the degree of exploratory type innovation and its impact, and how the degree of innovation exploration and its impact alters contingent on fund performance relative to the reference target.

3.1 Effect of evaluation period on the degree of exploration and innovation impact

The first hypothesis considers the dynamic shift in the degree of exploration and the innovation impact as the fund ages from its launch to closure. Exploration type innovation as defined earlier are experimental in nature and involves a higher risk (Rosenkopf and Nerkar, 2001; Benner and Tushman, 2003) that calls for a longer time to develop compared to exploitation type innovation (Manso, 2011). However, contingent on being successful exploratory innovation which is considered to be radical in nature has a higher innovative impact compared to exploitation type innovation which is considered to be incremental in nature built on prior art (Rosenkopf and Nerkar, 2001; Greve, 2007). As mentioned earlier, a VC fund typically possesses a defined tenure after which the VC liquidates the fund and returns the proceeds to the investors. The two-arm bandit model clearly elucidates that the option value of learning from exploration projects is high when the evaluation time duration is long. It is therefore rational for an investor to have an increased focus on exploration activities in the early period of the fund. Moreover, since VCs are fund managers whose performance is linked to the returns generated from the fund, the available time duration of the fund is an important factor that influence VCs risk behavior. Accordingly, the manager of a fund of recent vintage evaluates riskiness of the innovation opportunities presented to it with a long investment horizon in mind that suits exploration type projects, whereas the manager of a fund of earlier vintage would evaluate the same risk profile of innovation opportunities under the shadow cast by the impending liquidation of the fund and therefore avoid undertaking the riskiness of exploration type projects.

The finite fund duration bestows immense pressure on VCs to optimally balance the risk of exploration as the fund duration shrinks. Since it is beneficial for the VC to emphasize on exploration in the early period of the fund when the available evaluation time window is longer, it is expected that innovation projects in the early period of the fund will tend to be more exploratory compared to the later period of the fund. Since exploration projects tend to have a higher impact, therefore, we should expect a higher innovation impact for projects funded in the early periods of the fund. The first set of hypotheses posits that innovation pursued in the early periods of the fund are more exploratory in nature that generates a higher innovation impact and the degree of exploration and innovation impact declines as the fund duration is elapsed

Hypothesis 1a: The degree of exploration in innovation projects invested by a VC fund is negatively related to the elapsed evaluation period.

Hypothesis 1b: The impact of the innovation projects invested by a VC fund is negatively related to the elapsed evaluation period.

3.2 Contingent effect of expected fund performance

In order to describe and explain willingness to take risk, behavioral models of choice commonly draw on the fundamental predicate that individuals assess alternatives relative to a reference state (Simon, 1955). Specifically, Prospect theory postulates that individuals define the value of an alternative by comparing it to a reference point. Based on their position with respect to the reference point, individuals exhibit risk seeking behavior when the current state lies below the reference point and exhibit risk averse behavior when the current state lies above the reference point (Kahneman and Tversky, 1979), an observation that has been supported by study of decision makers in many contexts (March, 1988). Evidence from the field shows that managers consider fewer risks when performance exceeds their targets (March and Shapira, 1987), and high risk taking is found when performance relative to the reference target is low (Miller and Chen, 2004; Bromiley, 1991; Bolton, 1993). In the context of investments by VC fund manager(s) who have to deliver acceptable returns to the investors, the past performance of the fund manager(s) provides a valid basis not only to form their own expectations but also shape the expectations of investor of the VC fund and make any promises about target returns. The historical performance of the fund manager thus serves as a useful reference point to compare the ongoing performance of the investment portfolio of the focal fund.

Espousing the prospect theory analogy, I posit that the state of the investment portfolio of the VC fund relative to the historical performance levels of fund manager (VC firm) affects the extent to which fund managers exhibit preference towards exploration over the duration of the fund when evaluating innovation projects. Prospect theory suggests that decision makers that lie in the loss domain with respect to the reference point tend to prefer a prospect with a probability of high loss/gain (risk taking) compared to a prospect with a certainty of a smaller loss/gain (Kahneman and Tversky, 1979).[3] This implies that when the performance of the VC fund falls below the historical performance of the fund manager, the fund manager is likely to view a risky

[3] In other words, individuals make choices under uncertainty by maximizing a value function that evaluates their position with respected to a reference level (gain/loss domain), rather than an expected utility function that ranks choices according to the level of expected utility. The value function is positive and concave in the gain domain (relative to the reference level) and negative and convex in the loss domain.

exploration project in more favorable terms. Although in a shorter evaluation period a fund manager tends to avoid experimenting with risky exploration projects, however, fund performance below expectations can induce the fund manager to seek risky alternatives even when facing shorter investment horizons and continue to have a higher innovation impact. Accordingly, I argue that the performance of the VC fund relative to previous performance of the fund manager will mitigate the extent to which aging of the fund (elapsed evaluation period) negatively impacts the degree of exploration and the impact of innovation.

Hypothesis 2a: The negative effect of the elapsed evaluation period of the fund on the degree of exploration in innovation projects will be attenuated for funds whose performance is below its expectation.

Hypothesis 2b: The negative effect of the elapsed evaluation period of the fund on the impact of innovation projects will be attenuated for funds whose performance is below its expectation.

4.0 Data and Measures

To test the hypotheses I construct a longitudinal sample of VC-backed biotechnology ventures (SIC 2833, 2834, 2835, and 2836) funded by VC funds started in the United States in the twenty year period between 1985 and 2004 and tracked until it experiences an exit through IPO or acquisition or goes bankrupt or until year 2012, whichever comes earlier using data from Thomson One VentureXpert database. Given the objective of the paper is to understand the relationship between fund duration and venture innovation, I focus on VC funds with a stipulated tenure. In order to limit the confounding impact of heterogeneous institutional features and mandates of investment funds, I concentrate on the class of VC funds that invest in new ventures. Accordingly, I do not include evergreen funds, acquisition and buyout funds, corporate venture capital funds, fund of funds, bank affiliated funds, and private investments in public entities (PIPEs). A second desirable dimension of homogeneity in the study concerns the selection of biotechnology as the industry context. The relevance of innovation through patenting is particularly important in biotechnology sector relative to other sectors (e.g., Levin et al., 1987) and VC investments in biotechnology give emphasis to patenting as a potential signal of innovation and venture quality. Also, the venture development cycle in the biotechnology sector is much longer than other sectors like software and telecommunication and thus demands a longer investment time compared to other industries (e.g., Lerner and Schoar, 2004). The information on industry SIC, investment round dates, investment amount, development stage, and exits through IPO or acquisition, was obtained from *VentureXpert*, combined with data from *Thomson One Banker*, *SEC filings*, *Corptech Directory of Technology Companies (1995 – 2006)*, and company websites. *VentureXpert* database was consulted for all VC firm level and VC fund level information. For each unique VC fund-venture pair, the time when the VC fund has first invested in a venture is considered for the analyses. The dataset includes investments made by 515 VC funds (managed by 265 VC firms) in 335 biotech ventures.

Innovation measures are based on patent information sourced from *IQSS Patent Network database* (see Lai et al., 2011 for a description), and *USPTO database*. Patent information was collected by matching the assignee names in the sample and USPTO was used to verify the patents obtained for each assignee and the grant date. For each patent, I obtained information on forward citation (future patents citing the focal patent), backward citations (patents cited by the focal patent), and primary class and sub-class information for the focal, citing and cited patents. A total of 5290 patents were filed and granted in the sample between 1985 and December 2012.

Dependent variables. The innovation measures are the key dependent variables used in the empirical analysis. To examine the hypotheses, I categorize and measure exploration type innovation and its impact by using patent data. This follows precedent of prior research that have used patent citations as a measure of innovation exploration and its impact (e.g., Jaffe et al., 1993; Katila and Ahuja, 2001; Rosenkopf and Nerkar, 2001). Every patent is assigned to a three-digit technical class, which is used for the purpose of identifying distinct technical domains being developed by the ventures in the sample. In the USPTO classification there are currently 400 such technical three-digit classes. I began the data collection by establishing the patent classes that circumscribe biotechnology industry.[4] The set of classes and their description can be found in Table 1.[5]

----------------------- Insert Table 1 here -----------------------

Each patent cites (backward citation) previous patents ('prior art') that provide credible information of built-upon knowledge. Each backward citation to another patent was traced to determine if the built-upon patent was classified under the same class as the focal patent, and whether the built-upon patent was belongs to the biotechnology classes. Patents that cite previous patents in a broader array of technology classes outside its technological domain are often viewed as exploratory (Rosenkopf and Nerkar, 2001) and considered to be more "original" (Hall et al., 2001, 2005). By considering the backward citations, two variables are used that reflect

[4] The complexity and rapidly developing nature of biotechnology field that involves natural and synthetic biological molecules, cells, tissues, organs, and even whole organisms makes it challenging to identify the scope of patent classes and sub-classes. At the sub-class level, the classification for biotechnology patents is highly diffuse and the variable scope of sub-classes suggest there is an overlap between sub-class categories and does not align well with the structure of biotechnology research (Adelman and DeAngelis, 2007). Therefore, as a conservative approach, innovation variables are measure at the three-digit class level.

[5] The three digit classifications for biotechnology patents was identified through consultation of USPTO manual of patent classification, technical sources (Linton et al., 2008; http://patentclassifier.com/; patent sequence data on www.lens.org/), and patent portfolios of established biotechnology companies (Amgen, Genentech, Gilead, Genzyme, Biogen Idec, Celgene, Medimmune, Chiron, Millennium, Genencor). Next, I compared the set of three digit classes to those identified by Adelman and DeAngelis (2007) in their extensive analysis of the biotechnology patent classification system. All the classes that I identified as biotechnology classes were similarly designated by Adelman and DeAngelis (2007); I also added four other classes – 047, 119, 800, and 930.

exploration innovation - *external citation* is defined as the proportion of backward citations that are not in the biotechnology classification area, and *patent originality* is defined as 1 minus the Herfindahl concentration index of patent classes (excluding the patent class of the focal patent) associated with cited patents; a higher (lower) value of originality thus suggests that the focal patents build on a broader (narrower) set of technological areas external to its technological area. I apply the bias correction of the Herfindahl measures associated with small numbers of backward and forward citation counts, described in Hall and Trajtenberg (2005).

The impact of patents in year on subsequent technological development was measured by tracking all patents that cited the focal patents. Patents that are more cited are typically interpreted as having greater impact or as being more important than less cited patents (e.g., Trajtenberg, 1990). In line with the literature, I scale the citation counts to account for truncation effect and use two patent citation based measures that reflect the impact of innovation on subsequent innovations in different technological domains - *forward 4-year citation* is defined as the number of forward citations within a four-year post-issue time window to patents applied (and subsequently granted) by a venture in a given year, and *patent generality* is defined as 1 minus the Herfindahl concentration index of patent classes associated with citing patents. A higher (lower) value of generality suggests that the focal patent impacts future innovation in a broader (narrower) set of technological domains.[6]

***Independent variables*.** The primary theoretical variable is the evaluation time period available to the VC fund to garner returns from the investment. *Elapsed fund duration* is the elapsed time since the fund was started measured in months between the fund vintage year and the first investment round date in a venture. Since this measure exhibited positive skewness, the

[6] Self-citations were excluded from the innovation measures. Since the distribution of patent citations is highly right skewed, logarithmic transformation is employed for the innovation measures.

count measure is transformed by taking the log of 1 plus the number of months. This measure captures the reduction in the finite time duration available to the VC fund - longer the elapsed fund duration the shorter is the available time left for the VC fund. As mentioned in VentureXpert database, fund vintage year is the year of fund formation and first takedown of capital or the year the fund made its first investment into a portfolio venture. A similar measure was employed by Guler (2007).

The second theoretical variable considers the situation of the VC fund in relation to a reference point during the finite fund duration. The measure portrays the relative position of the VC fund based on the performance differential with the expected performance. *Delta performance* is defined as a dummy variable equal to '1'if the realized performance rate at time t in a fund's duration is below its expected performance rate (the reference point) and '0' otherwise. The expected performance rate (R_t^e) is calculated based on the historical percentage of successful exits (IPOs and acquisition deals) achieved by prior funds managed by the VC firm normalized by the amount invested by prior funds and is defined as: $R_t^e = \left(\frac{\sum_{i=1}^{j-1} s / \sum_{i=1}^{j-1} N}{\sum_{i=1}^{j-1} K}\right) K_j \frac{t}{T_j}$; where s is the count of number of successful exits achieved by the VC firm for funds $i = 1,\ldots,j\text{-}1$ prior to the start of the focal fund j, N is the count of number of investments made by j-1 funds prior to the start of focal fund j, and K is the investment size of $i = 1,\ldots,j\text{-}1$prior funds. K_j is the fund size of jth fund and T_j is the fund duration for jth fund (i.e. the time between fund vintage year and maturity date).[7]

The realized performance rate (R_t^r) for fund j is defined as: $R_t^r = s_t / N_t$; where s_t is the count of number of investments (that eventually had a successful exit) until time t and N_t is the count of number of investments made by fund j until time t. A key challenge for the

[7] If fund j is the first fund, the expected performance of the fund is taken as the average of the expected performance of all funds started in the same fund year.

econometrician is to quantify investments at time *t* that will eventually have a successful exit. While successful exits are generally observed at the end of a fund's life, it is established that VCs stage their investments in a venture that allows them to gather information and periodically update their belief about the likelihood of a successful exit. A simple Bayesian updating of VC's posterior belief suggests that increase in the rounds of capital infusion in a venture increases the likelihood of a successful exit (Gompers, 1995). Put differently, the ex-ante realization of a successful investment resides on the rounds of VC funding received by the venture. Accordingly, a venture in the fund's portfolio is considered to be a successful investment if it meets the following two criteria – a) the venture has received at least three rounds of VC investment by time *t*, and b) the venture eventually realized an exit through IPO or acquisition.[8]

The fund performance measure is similar in spirit to the VC success rate measure applied by Gompers et al. (2008). Fund performance in terms of financial returns or cash flow is difficult to observe and is generally kept secret. To the extent that financial performance of a fund cannot be completely ascertained, the expected and the realized fund performance is operationalized based on successful exits (IPO and acquisition). IPOs and acquisitions generate most of the returns on VC investment and are considered as a key metric to evaluate VC performance (Gompers and Lerner, 1999).[9]

Controls. Fund level measures used as control variables include *fund size* measured as the natural log of amount of committed capital available to the fund in US dollar million and adjusted for 2012 US dollar terms, *fund portfolio* is the natural log of count of number of ventures in which the fund has invested until time *t*, *round amount* is the amount of investment

[8] In the sample a venture on average received four rounds of VC investment. Semi-structured interviews with 15 VC partners located in the east coast suggest VCs generally are able to comprehend whether an investment will be a success after the third round of funding. The following statement by a VC illustrates the point: "It is not until the third round of financing that we can make a fair assessment whether we will have a successful exit from the investment".

[9] In an unreported test, an alternative measure of performance based on only IPO exits was considered and the results remain qualitatively similar to those reported in the paper.

made by the fund in the focal venture in its first round in US dollar million and adjusted for 2012 US dollar terms, and *first fund* which is a dummy variable equal to one if the fund is the first fund managed by the VC firm. At the VC firm level, *running funds* is the natural log of count of other active funds simultaneously managed by the VC firm at time *t*. The estimation also controls for VC investment experience and biotechnology industry expertise - *VC investment share* is the total amount of investment in US dollar million made by the VC firm from 1980 until the previous calendar year of starting a particular fund, normalized by the overall aggregate investment in the VC industry in those years (e.g., Nahata, 2008). Next, I measured the number of biotechnology investments made by the VC firm until the previous calendar year of starting the particular fund, normalized by the average of the number of biotechnology investments made by all VC firms in those years (e.g., Gompers et al., 2008). A VC firm is identified as an experienced biotech investor if the VC firm was above the median of biotech investments for all VCs during that time period. *VC Biotech expertise* is defined as a dummy variable equal to '1' if the VC associated with the fund was on the list of experienced biotech VCs, and '0' otherwise. *VC-CA, VC-MA, VC-NY, VC-PA* are indicator variables if the VC firm is located in California, Massachusetts, New York and Pennsylvania. The estimation also controls for venture characteristics - *venture age* is the natural log of age (in months) of the venture at the time of the investment event, *venture early stage* is coded as '1' for investments that happen in the seed stage or early stage of the venture or else it is '0', *patent stock* is the natural log of the count of total patents filed by a venture until year *t*-1. *SIC2833*, *SIC 2834*, *SIC 2835,* and *SIC2836* are indicator variables to control for sub-industry effects. Finally, the estimation controls for time fixed effects, VC firm fixed effects, and fund fixed effects.

Statistical methods. The dependent variables are log transformed citation based measures portraying innovation exploration and innovation impact. The key independent variable(s) is the elapsed fund duration for each year in the post investment four year time period. I employ fixed effects OLS estimation using year fixed effects, fund fixed effects, and VC firm fixed effects to estimate the following regression models:

$$Y_{i,k} = \alpha + \beta_1 D_{j,t} + \sum_{k=t+1}^{t+4} \beta_k (Time_{i,t}^k) + \sum_{k=t+1}^{t+4} \eta_k (Time_{i,t}^k * D_{j,t}) + \beta_2' X_{j,t} + \beta_3' M_{m,t} + \beta_4' S_{i,t} + \sum_{k=t+1}^{t+4} \partial_k (Time_{i,t}^k * X_{j,t}) + \sum_{k=t+1}^{t+4} \varphi_k (Time_{i,t}^k * M_{m,t}) + \sum_{k=t+1}^{t+4} \omega_k (Time_{i,t}^k * S_{i,t}) + \mu_t Year(t) + \delta_j Fund(j) + \gamma_m VC\ Firm(m) + \varepsilon_{i,j,t} \quad (1)$$

$$Y_{i,k} = \alpha + \beta_1 D_{j,t} + \beta_2 P_{j,t} + \beta_3 (D_{j,t} * P_{j,t}) + \sum_{k=t+1}^{t+4} \beta_k (Time_{i,t}^k) + \sum_{k=t+1}^{t+4} (\eta_k (Time_{i,t}^k) * D_{j,t}) + \sum_{k=t+1}^{t+4} (\vartheta_k (Time_{i,t}^k)(D_{j,t} * P_{j,t}) + \sum_{k=t+1}^{t+4} (\theta_k (Time_{i,t}^k) * P_{j,t}) + \beta_2' X_{j,t} + \beta_3' M_{m,t} + \beta_4' S_{i,t} + \sum_{k=t+1}^{t+4} \partial_k (Time_{i,t}^k * X_{j,t}) + \sum_{k=t+1}^{t+4} \varphi_k (Time_{i,t}^k * M_{m,t}) + \sum_{k=t+1}^{t+4} \omega_k (Time_{i,t}^k * S_{i,t}) + \mu_t Year(t) + \delta_j Fund(j) + \gamma_m VC\ Firm(m) + \varepsilon_{i,j,t} \quad (2)$$

Equation (1) tests hypotheses 1a and 1b and equation (2) tests hypotheses 2a and 2b. $Y_{i,k}$ denotes the innovation measures for venture *i* in time *k* that is the four year period post investment time ($k = t+1$, $t+2$, $t+3$, $t+4$), D_{jt} is the elapsed fund duration and P_{jt} is the delta performance for fund *j* at the time of investment *t*. The variable $Time^k_{i,t}$ is equal to '1' if the observation is *k* years after the fund investment time *t*, and '0' otherwise. Vector ***X*** includes the fund control variables (fund size, fund portfolio, round amount, first fund), vector ***M*** includes the VC firm control variables (running funds, VC investment share, VC Biotech expertise, location dummies), and vector ***S*** includes the venture control variables (venture age, patent stock until time *t*-1, seed early stage, sub-industry dummies). *Year(t), Fund(j), and VC Firm(m)* captures year, fund, and firm fixed effects, $\varepsilon_{i,j,t}$ is the error term.

As a robustness check, instead of fixed effect OLS regression, I employ a quasi-maximum likelihood estimation using generalized linear model with a logit link and the binomial family (Papke and Wooldridge, 1996) for the fractional dependent variables (external citation, patent originality, patent generality) and negative binomial specification for the count dependent variable (forward 4-year citation). For brevity, I do not present the results but are qualitatively similar to the results reported below.

4.0 Results

Table 2 reports the descriptive statistics of the variables used in the analysis. The average fund age was 30.9 months (*elapsed fund duration* = 2.93) and 30 percent of the funds were first funds (*first fund* = 0.30). The average fund size is US dollar 214.65 mn (*fund size* = 4.41), managed around 16 ventures at a given time in the fund duration (*fund portfolio* = 4.41), and made an average investment of US $1.73 mn in the first round (*round amount* = 0.84). Majority of the VC firms are headquartered in California or Massachusetts. The average investment share by a VC firm in a given year is around two percent and nearly 90 percent of the VC firms in the sample had expertise in biotechnology industry. Of the sampled ventures, 67 percent of the biotech ventures were in the seed or early stage of development (*venture early stage* = 0.67), and the average venture age at the time of investment was 39.6 months (*venture age* = 3.23). On average 25 percent of the citations referenced to prior art in a patent are external to the biotechnology domain (*external citation* = 0.19) and the average Herfindahl originality measure of a patent was 0.31 (*patent originality* =0.23). The patents received on average 2.17 forward citation in the four year post application time window (*forward 4-year citation* = 0.67) and the average Herfindahl originality measure of a patent was 0.24 (*patent originality* =0.23).

---------------------- Insert Table 2 here ----------------------

Table 3a presents the regression results for testing Hypotheses 1a. The dependent variables in models I - III is *external citation* and in models IV - VI is *patent originality*. Model I and IV is the baseline specification with year fixed effects, models II and V include firm fixed effects, and models III and VI include fund fixed effects. Hypothesis 1a predicts that VC funds with greater elapsed fund duration will show a decline in the degree of exploration for innovation projects funded by the VC fund. The coefficient estimates of elapsed fund duration (post investment year *k*) are negative and significant for all the four years post investment across all the model specifications using the two dependent variables, providing support for Hypothesis 1a.

----------------------- Insert Tables 3a and 3b here -----------------------

Similarly, Table 3b presents the regression results for testing Hypotheses 1b. The dependent variables in models I - III is *forward 4-year citation* and in models IV - VI is *patent generality*. Hypothesis 1b predicts that the innovation impact of the projects funded by the VC fund will show a decline for VC funds with greater elapsed fund duration. The coefficient estimates of elapsed fund duration (post investment year *k*) are negative and significant for all the four years post investment across all the model specifications using the two dependent variables, providing support for Hypothesis 1b.

Table 4a presents the result for hypothesis 2a by adding the second theoretical variable - *delta performance* and the interaction term of *Elapsed fund duration* and *delta performance* for each year in the post investment four year time period. The dependent variables in models I - III is *external citation* and in models IV - VI is *patent originality*. Model I and IV is the baseline specification with year fixed effects, models II and V include firm fixed effects, and models III and VI include fund fixed effects. Hypothesis 2a posits that the negative effect of elapsed fund duration (predicted in hypothesis 1a) on the degree of exploration is weakened for funds with performance below expected target. The positive and significant interaction of delta performance variable with elapsed fund duration in the four years post investment across all models provides strong support for this hypothesis.

---------------------- Insert Tables 4a and 4b here ----------------------

Similarly, Table 4b reports the result for hypothesis 2b. The dependent variables in models I - III is *forward 4-year citation* and in models IV - VI is *patent generality*. The central proposition stated in hypothesis 2b that the negative effect of elapsed fund duration (predicted in hypothesis 2a) on the innovation impact is weakened for funds with performance below expected target. The positive and significant interaction of delta performance variable with elapsed fund duration in the four years post investment across all models provides support for this hypothesis.

Figures 2 (a), (b), (c), and (d) visually depicts the results of the interaction effect of elapsed fund duration and delta performance for the four dependent variables – external citation, patent originality, forward 4-year citation, and patent generality, supporting Hypotheses 2a and 2b. The slopes of the dependent variables are plotted on the independent variable (elapsed fund duration) when the moderator variable (delta performance) equals '1' and '0'. The values of other explanatory variables in the function are taken at their means. The dash line indicates funds where the delta performance equals '1' (fund performance below its expected target) and the solid line indicates funds where delta performance equals '0' (fund performance equal or above its expected target). In all the four plots, the solid line has a steeper downward slope compared to the dash line that suggests when the fund performance is below its expected performance, VCs continue to invest in exploration type innovation that results in a more gradual decline in innovation impact over the duration of the fund.

------------------ Insert Figures 2 (a), (b), (c), and (d) here ---------------

Supplementary Analysis. VC funds typically syndicate their investments along with other VCs, and the lead investor is the most active investor who extensively helps in monitoring the venture development, and generally plays a dominant role in the governance and critical decisions of the venture that may have a more direct effect on the innovations pursued by a venture. Accordingly, I sought to investigate the robustness of the results for VC funds managed by the lead VC firm. As per convention, I identify the lead VC firm as the VC firm that participated in the first round and made the largest total investment in the venture across all rounds of funding (e.g., Nahata, 2008) and 59 percent of the investments in the sample were made by the lead investor. Sub-sample analyses conducted on investments made by a lead VC firm reveal similar results to those reported in the paper.

5.0 Discussion and Conclusion

In high-technology industries like biotechnology, firm success depends on the ability to innovate consistently. Indeed the delicate balance between exploration and exploitation in innovation has a long term effect on firm performance. The paper highlights the effect of finite time duration of venture capital investments on the type of innovation pursued by the portfolio ventures and the impact of such innovation on subsequent technological developments. The findings provide evidence that VCs rationally reduce their attention on exploration projects as the VC fund approaches maturity. Investments made by the venture capitalist at the early periods of the fund life are more exploratory in nature that generates a higher innovation impact compared to investments made in the later period of fund. However, when the fund performance relative to the expected reference level is in the loss domain, VCs tend to continue investing in riskier projects that result in a more gradual decline in risk preference over the finite fund duration. This behavioral alteration over time shows the temporal dynamic attribute of risk preferences that supports the theoretical arguments of prospect theory (Kahneman & Tversky, 1979). Our first hypothesis pertains to this strategic shift in the investment strategy and posits that investments made by the venture capitalist at the early periods of the fund life will be more exploratory in nature that generates a higher VC impact on venture innovation compared to investments made in the later period of fund. However, when the fund performance relative to the expected reference level is in the loss domain, VCs tend to continue focusing on exploration projects that are deemed to be riskier. As a result the decline in innovation impact is more gradual over the finite fund duration. This behavioral alteration over time shows the temporal dynamic attribute of risk preferences that supports the theoretical arguments of prospect theory (Kahneman and Tversky, 1979).

Some limitations are worth discussing that may present fruitful avenues for future research. The results present compelling evidence that VCs' focus on exploration type innovation changes over the fund duration and are subjected to behavioral considerations of fund performance in the gain/loss domain, but the paper does not measure the effect on the performance outcome of the biotech ventures. Future research may attempt to more directly relate the type of innovation to the potential performance metrics such as the likelihood of commercialization or the time to new product development and show whether the change in exploration projects benefits the venture capital firm.

A second limitation is that, although patents continue to play a central role in research on innovation, there is a great deal of heterogeneity across industries and firms in the way in which innovation is pursued and patents may not be a comprehensive measure of innovation. Since firms strategically choose whether or not to pursue patents, patent acquisition is endogenous to the firm's decision, and causality claims linking patents to innovation should be viewed more conservatively. The paper attempts to alleviate this concern by sampling the biotechnology industry where the importance of patenting to the appropriation and valuation of innovations is particularly relevant and is considered important by the venture capital firms (e.g., Levin et al., 1987). As a conservative approach, the exploration and impact measures consider the USPTO patent classifications as a calibrated scope of technology boundaries to identify innovations that build on prior knowledge spanning beyond the boundaries of biotechnology field and subsequently impact innovation in other technology domains. It should be noted that, although the USPTO classification provides a systematic approach to classify technological taxonomies, the multidimensional nature of science prevents a rigid calibrated approach. As a result some USPTO classifications may have enormous scope and not necessarily unique to any particular area of biotechnology (Adelman and DeAngelis, 2007). A promising direction for future research would be to analyze innovation classified by biochemical pathway, organ, or disease. While this study provides insight in the context of the biotechnology sector that is rich in pursuing radical innovation through patenting, future work may consider a study involving other technology industries like medical devices, software, electronics, and telecommunication.

Finally, the expected performance target of a VC fund may be driven by multiple expectations (e.g., market driven expectation) that can act as a reference point for performance. While the paper considers performance expectations derived from the historic performance of a VC firm which is consistent with the prospect theory (Lant, 1992), future efforts may incorporate other measures of reference points.

Prior research has established the value-added effect of venture capital investment in nurturing innovation through active monitoring and governance and through venture capital endorsement that signals the quality of the innovation (e.g., Kortum and Lerner, 2000; Hellman and Puri, 2000). This paper therefore complements prior venture capital research by documenting the variance in the type of innovation and the subsequent innovation impact in fund-level investments that provides a more granular insight on the investment strategies adopted by the venture capital firms. Second, this study also contributes to the research stream on application of prospect theory. This research has suggested and shown that risk preferences change depending on firm's performance relative to the reference level (Bromiley, 1991; Miller and Chen, 2004). The temporal perspective we develop complements prior research by empirically showing that the dynamic shift in pursuing exploration activities relative to the reference level. Finally, the normative arguments from the results appeal to both private equity investors and to technology entrepreneurs seeking venture capital investment. The skills to nurture radical innovation in a finite time frame requires an investor to continue to have an impetus to pursue exploration type innovation, yet generate returns in a stipulated time. For technology entrepreneurs seeking venture capital funding, the results indicate the importance of fund age on the type of innovation may develop.

References

Adelman, D. E., DeAngelis, K. L. 2007. Patent metrics: the mismeasure of innovation in the biotech patent debate. *Texas Law Review*, *85*, 1677.

Benner, M. J., Tushman, M. L. 2003. Exploitation, exploration, and process management: The productivity dilemma revisited. *Academy of Management Review*, 28(2): 238-256.

Bolton, M. K. 1993. Organizational innovation and substandard performance: when is necessity the mother of innovation?. *Organization science*, 4(1): 57-75.

Bromiley, P. 1991. Testing a causal model of corporate risk taking and performance. *Academy of Management Journal*, 34(1): 37-59.

Gittins, J., Jones, D. 1974. A Dynamic Allocation Index for the Sequential Allocation of Experiments, in *Progress in Statistics*, ed. By J. Gani, pp. 241–266. North-Holland, Amsterdam.

Gompers, P. A. 1995. Optimal investment, monitoring, and the staging of venture capital. *Journal of Finance*, 50(5): 1461-1489.

Gompers, P. 1996. Grandstanding in the venture capital industry. *Journal of Financial economics*, 42(1): 133-156.

Gompers, P., Kovner, A., Lerner, J., Scharfstein, D. 2008. Venture capital investment cycles: The impact of public markets. *Journal of Financial Economics*, 87(1): 1-23.

Gompers, P., Lerner, J. 1996. Use of Covenants: An Empirical Analysis of Venture Partnership Agreements, *The. JL & Econ.*, 39: 463.

Gompers, P., Lerner, J. 1999. An analysis of compensation in the US venture capital partnership. *Journal of Financial Economics*, 51(1): 3-44.

Greve, H. R. 2007. Exploration and exploitation in product innovation. *Industrial and Corporate Change*, 16(5): 945-975.

Guler, I. 2007. Throwing good money after bad? Political and institutional influences on sequential decision making in the venture capital industry. *Administrative Science Quarterly*, 52(2): 248-285.

Gupta, A. K., Smith, K. G., Shalley, C. E. 2006. The interplay between exploration and exploitation. *Academy of Management Journal*, 49(4): 693-706.

Hall, B. H., Jaffe, A. B., Trajtenberg, M. 2001. The NBER patent citation data file: Lessons, insights and methodological tools (No. w8498). National Bureau of Economic Research.

Hall, B. H., Jaffe, A., Trajtenberg, M. 2005. Market value and patent citations. *RAND Journal of Economics*, 16-38.

Hellman, T., Puri, M. 2000. The interaction between product market and financing strategy: The role of venture capital. *Review of Financial studies*, 13(4): 959-984.

Holmstrom, B. 1989. Agency costs and innovation. *Journal of Economic Behavior & Organization*, 12(3): 305-327.

Jaffe, A. B., Trajtenberg, M., Henderson, R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* (August): 577–675.

Kandel, E., Leshchinskii, D., Yuklea, H. 2011. VC funds: aging brings myopia. *Journal of Financial and Quantitative Analysis*, 46(2): 431.

Kahneman, D., Tversky, A. 1979. Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the Econometric Society*, 263-291.

Kaplan, S., Strömberg, P. 2001. Venture Capitalists as Principals: Contracting, Screening, and Monitoring. *American Economic Review*, 91: 426-430.

Katila, R., Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. *Academy of management journal*, 45(6): 1183-1194.

Katila, R., Shane, S. 2005. When does lack of resources make new firms innovative?. *Academy of Management Journal*, 48(5): 814-829.

Kortum, S., Lerner, J. 2000. Assessing the contribution of venture capital to innovation. *RAND Journal of Economics*, 674-692.

Lai, R., D’Amour, A., Yu, A., Sun, Y., Torvik, V., Fleming, L. 2011. Disambiguation and co-authorship networks of the US Patent Inventor Database. Harvard Institute for Quantitative Social Science, Cambridge, MA, 2138.

Lant, T. K. 1992. Aspiration level adaptation: An empirical exploration. *Management science*, 38(5): 623-644.

Lee, P. M., Wahal, S. 2004. Grandstanding, certification and the underpricing of venture capital backed IPOs. *Journal of Financial Economics*, 73(2): 375-407.

Lerner, J., Schoar, A. 2004. The illiquidity puzzle: theory and evidence from private equity. *Journal of Financial Economics*, 72(1): 3-40.

Levin, R. C., Klevorick, A. K., Nelson, R. R., Winter, S. G., Gilbert, R., Griliches, Z. 1987. Appropriating the returns from industrial research and development. *Brookings papers on economic activity*, (3): 783-831.

Levinthal, D. A., March, J. G. 1993. The myopia of learning. *Strategic Management Journal*, 14(S2): 95-112.
Linton, K., Stone, P., Wise, J. 2008. Patenting trends and innovation in industrial biotechnology. Office of Industries US International Trade Commission Report. (Website link: https://www.bio.org/articles/patenting-trends-and-innovation-industrial-biotechnology)
Manso, G. 2011. Motivating innovation. *The Journal of Finance*, 66(5): 1823-1860.
March, J. G. 1988. Variable risk preferences and adaptive aspirations. *Journal of Economic Behavior & Organization*, 9(1): 5-24.
March, J. G. 1991. Exploration and exploitation in organizational learning. *Organization science*, 2(1): 71-87.
March, J. G., Shapira, Z. 1987. Managerial perspectives on risk and risk taking. *Management Science*, 33(11): 1404-1418.
Miller, K. D., Chen, W. R. 2004. Variable organizational risk preferences: Tests of the March-Shapira model. *Academy of Management Journal*, 47(1): 105-115.
Nahata, R. 2008. Venture capital reputation and investment performance. *Journal of Financial Economics*, 90(2): 127-151.
O'brien, Jonathan P. 2003. The capital structure implications of pursuing a strategy of innovation. *Strategic Management Journal*, 24(5): 415-431.
Papke, L.E., Wooldridge, J.M. 1996. Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics*, 11: 619–632.
Roberts, K., Weitzman, M. L. 1981. Funding criteria for research, development, and exploration projects. *Econometrica: Journal of the Econometric Society*, 1261-1288.
Rosenkopf, L., Nerkar, A. 2001. Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*, 22(4), 287-306.
Rothschild, M. 1974. A two-armed bandit theory of market pricing. *Journal of Economic Theory*, 9(2): 185-202.
Sahlman, W. A. 1990. The structure and governance of venture-capital organizations. *Journal of financial economics*, 27(2): 473-521.
Simon, H. 1955. A behavioral model of rational choice. *Quarterly Journal of Economics*, 99-118.
Staw, B. M. 1976. Knee-deep in the big muddy: A study of escalating commitment to a chosen course of action. *Organizational behavior and human performance*, 16(1): 27-44.
Trajtenberg, M. 1990. A penny for your quotes: patent citations and the value of innovations. *RAND Journal of Economics*, 172-187.
Weitzman, M. L. 1979. Optimal search for the best alternative. *Econometrica: Journal of the Econometric Society*, 641-654.

TABLE 1: Biotechnology Patent Classification

Three digit class	Description of the class
047	Plant husbandry
119	Animal husbandry
424	Drug, bio-affecting and body treating compositions
435	Chemistry: molecular biology and microbiology
514	Drug, bio-affecting and body treating compositions
530	Chemistry: natural resins or derivatives; peptides or proteins; lignins or reaction products
536	Organic compounds
800	Multicellular living organisms and unmodified parts thereof and related processes
930	Peptide or protein sequence

TABLE 2: Descriptive Statistics

	Mean	**Std. Dev.**	**Min**	**Max**
External citation	0.19	0.26	0	0.69
Patent originality	0.23	0.27	0	0.69
Forward 4-year citation	0.67	0.86	0	4.96
Patent generality	0.18	0.23	0	0.69
Elapsed fund duration	2.93	1.32	0	5.13
Delta performance	0.42	0.49	0	1
Fund size	4.41	1.42	-0.59	7.10
Fund portfolio	2.51	0.79	0.69	4.76
Round amount	0.84	0.53	0	3.13
First fund	0.30	0.46	0	1
Running funds	1.01	0.67	0	2.56
VC investment share	0.02	0.06	0.000018	0.90
VC Biotech expertise	0.90	0.22	0	1
VC - CA	0.36	0.48	0	1
VC - MA	0.17	0.38	0	1
VC - NY	0.08	0.26	0	1
VC - PA	0.03	0.16	0	1
Patent stock	1.10	1.21	0	4.54
Venture age	3.23	1.14	0	6.29
Venture early stage	0.67	0.47	0	1
N	8142			

Note. The unit of observation is firm-year. The sample includes investments made by 515 VC funds (managed by 265 VC firms) in 335 biotech ventures.

TABLE 3a: Direct effect of elapsed fund duration on exploration type innovation

Dependent variable	*External citation*			*Patent originality*		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Intercept	0.040 (0.047)	0.076 (0.084)	-0.173 (0.118)	0.117*** (0.044)	0.028 (0.067)	-0.128 (0.091)
Elapsed fund duration	0.005 (0.003)	0.002 (0.004)	0.018** (0.009)	0.005 (0.004)	0.001 (0.003)	0.015* (0.009)
Elapsed fund duration (post investment year 1)	-0.011* (0.005)	-0.012* (0.006)	-0.011* (0.006)	-0.019** (0.007)	-0.020*** (0.007)	-0.019** (0.007)
Elapsed fund duration (post investment year 2)	-0.021*** (0.008)	-0.021*** (0.008)	-0.019** (0.008)	-0.028*** (0.008)	-0.029*** (0.008)	-0.028*** (0.008)
Elapsed fund duration (post investment year 3)	-0.016** (0.008)	-0.016** (0.008)	-0.014* (0.008)	-0.015* (0.008)	-0.015* (0.008)	-0.014 (0.008)
Elapsed fund duration (post investment year 4)	-0.019** (0.009)	-0.018** (0.009)	-0.016* (0.009)	-0.022** (0.010)	-0.021** (0.010)	-0.020** (0.010)
Post investment year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Venture controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm fixed effects	No	Yes	No	No	Yes	No
Fund fixed effects	No	No	Yes	No	No	Yes
N	8142	8142	8142	8142	8142	8142
R-squared	0.22	0.27	0.30	0.14	0.18	0.20

Note. Fund controls include fund size, fund portfolio, round amount, and first fund; VC firm controls include running funds, VC investment share, VC Biotech expertise, and location dummies; venture controls include venture age, patent stock until time t-1, seed early stage, and sub-industry dummies. The unit of observation is firm-year. Heteroskedasticity -adjusted robust clustered errors at the fund level are reported in parenthesis. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

TABLE 3b: Direct effect of elapsed fund duration on innovation impact

Dependent variable	*Forward 4-year citation*			*Patent generality*		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Intercept	0.287 (0.231)	0.203 (0.336)	1.237** (0.500)	0.111* (0.065)	0.083 (0.088)	0.240* (0.150)
Elapsed fund duration	0.044** (0.018)	0.017 (0.018)	0.058 (0.042)	0.009* (0.004)	0.001 (0.004)	0.006 (0.010)
Elapsed fund duration (post investment year 1)	-0.040* (0.022)	-0.039* (0.021)	-0.039* (0.021)	-0.014** (0.006)	-0.014** (0.006)	-0.013** (0.006)
Elapsed fund duration (post investment year 2)	-0.058** (0.025)	-0.053** (0.025)	-0.050** (0.025)	-0.025*** (0.006)	-0.024*** (0.006)	-0.023*** (0.007)
Elapsed fund duration (post investment year 3)	-0.079*** (0.025)	-0.067*** (0.025)	-0.065*** (0.025)	-0.016** (0.007)	-0.014** (0.007)	-0.013* (0.007)
Elapsed fund duration (post investment year 4)	-0.047* (0.025)	-0.040* (0.022)	-0.041* (0.023)	-0.015** (0.007)	-0.014** (0.007)	-0.014** (0.007)
Post investment year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Venture controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm fixed effects	No	Yes	No	No	Yes	No
Fund fixed effects	No	No	Yes	No	No	Yes
N	8142	8142	8142	8142	8142	8142
R-squared	0.12	0.25	0.31	0.15	0.29	0.34

Note. Fund controls include fund size, fund portfolio, round amount, and first fund; VC firm controls include running funds, VC investment share, VC Biotech expertise, and location dummies; venture controls include venture age, patent stock until time t-1, seed early stage, and sub-industry dummies. The unit of observation is firm-year. Heteroskedasticity -adjusted robust clustered errors at the fund level are reported in parenthesis. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

TABLE 4a: Contingent Effect of Delta Performance on exploration type innovation

Dependent variable	*External citation*			*Patent originality*		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Intercept	0.006 (0.046)	0.083 (0.079)	0.192*** (0.070)	0.773*** (0.043)	0.723*** (0.065)	0.604*** (0.071)
Elapsed fund duration	0.003 (0.007)	-0.012 (0.008)	-0.020 (0.015)	-0.005 (0.008)	-0.019** (0.009)	-0.020 (0.015)
Delta performance	0.040* (0.022)	-0.001 (0.030)	0.018 (0.013)	0.005 (0.030)	-0.025 (0.029)	-0.039 (0.042)
Elapsed Fund Duration X delta performance (post investment year 1)	0.012** (0.006)	0.011* (0.007)	0.010* (0.006)	0.024*** (0.006)	0.022*** (0.006)	0.022*** (0.006)
Elapsed Fund Duration X delta performance (post investment year 2)	0.026*** (0.007)	0.025*** (0.007)	0.023*** (0.007)	0.030*** (0.007)	0.028*** (0.007)	0.027*** (0.007)
Elapsed Fund Duration X delta performance (post investment year 3)	0.027*** (0.006)	0.028*** (0.006)	0.026*** (0.006)	0.017** (0.007)	0.016** (0.007)	0.016** (0.008)
Elapsed Fund Duration X delta performance (post investment year 4)	0.013** (0.006)	0.013** (0.006)	0.011* (0.006)	0.018** (0.008)	0.017** (0.008)	0.018** (0.008)
Post investment year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Venture controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm fixed effects	No	Yes	No	No	Yes	No
Fund fixed effects	No	No	Yes	No	No	Yes
N	8142	8142	8142	8142	8142	8142
R-squared	0.17	0.23	0.26	0.10	0.15	0.19

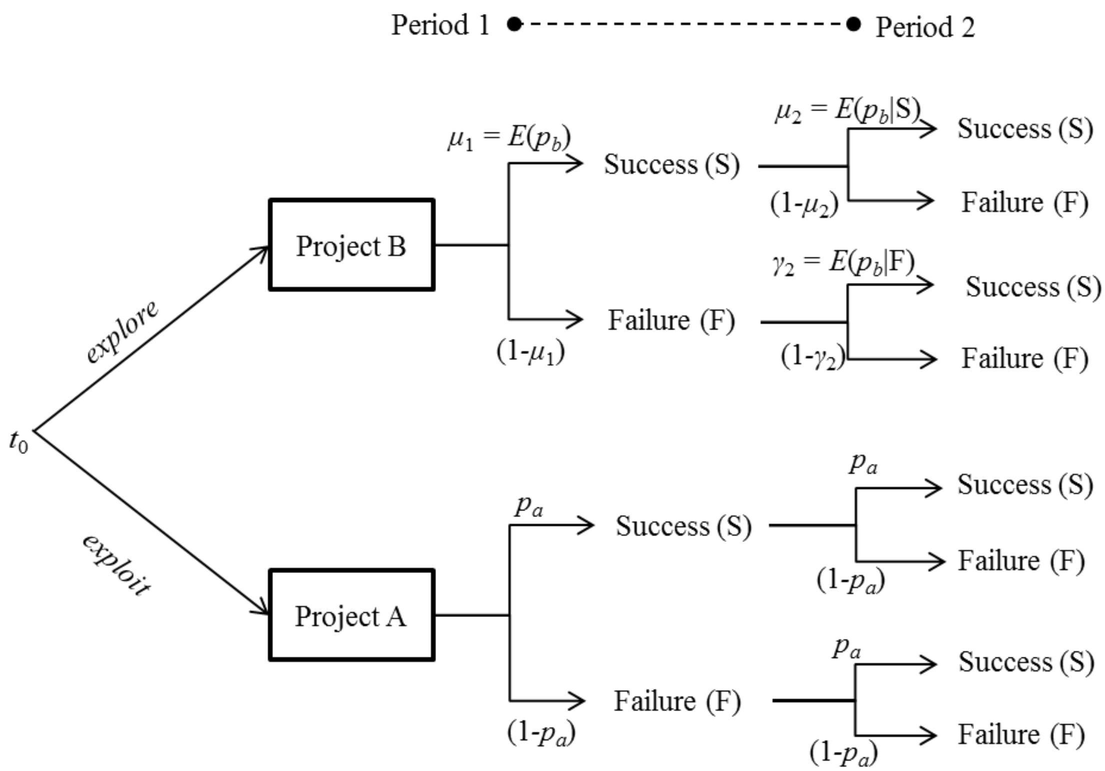
Note. Fund controls include fund size, fund portfolio, round amount, and first fund; VC firm controls include running funds, VC investment share, VC Biotech expertise, and location dummies; venture controls include venture age, patent stock until time t-1, seed early stage, and sub-industry dummies. The unit of observation is firm-year. Heteroskedasticity -adjusted robust clustered errors at the fund level are reported in parenthesis. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

TABLE 4b: Contingent Effect of Delta Performance on innovation impact

Dependent variable	*Forward 4-year citation*			*Patent generality*		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Intercept	1.021 (0.246)	0.857*** (0.329)	1.456*** (0.363)	0.391*** (0.062)	0.254*** (0.081)	0.509*** (0.088)
Elapsed fund duration	0.005 (0.039)	-0.092* (0.049)	-0.175* (0.104)	-0.004 (0.010)	-0.033*** (0.012)	-0.051** (0.025)
Delta performance	0.067 (0.138)	-0.190 (0.181)	-0.399 (0.334)	0.014 (0.037)	-0.066 (0.045)	-0.103 (0.076)
Elapsed Fund Duration X delta performance (post investment year 1)	0.046*** (0.017)	0.041*** (0.016)	0.033** (0.016)	0.019*** (0.005)	0.019*** (0.005)	0.016*** (0.004)
Elapsed Fund Duration X delta performance (post investment year 2)	0.078*** (0.021)	0.071*** (0.020)	0.057*** (0.019)	0.021*** (0.005)	0.018*** (0.005)	0.014*** (0.005)
Elapsed Fund Duration X delta performance (post investment year 3)	0.053*** (0.019)	0.056*** (0.019)	0.047*** (0.018)	0.018*** (0.005)	0.019*** (0.006)	0.015*** (0.005)
Elapsed Fund Duration X delta performance (post investment year 4)	0.052*** (0.020)	0.055*** (0.019)	0.048*** (0.018)	0.019*** (0.006)	0.019*** (0.008)	0.016** (0.005)
Post investment year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Venture controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
VC Firm fixed effects	No	Yes	No	No	Yes	No
Fund fixed effects	No	No	Yes	No	No	Yes
N	8142	8142	8142	8142	8142	8142
R-squared	0.16	0.28	0.37	0.16	0.31	0.39

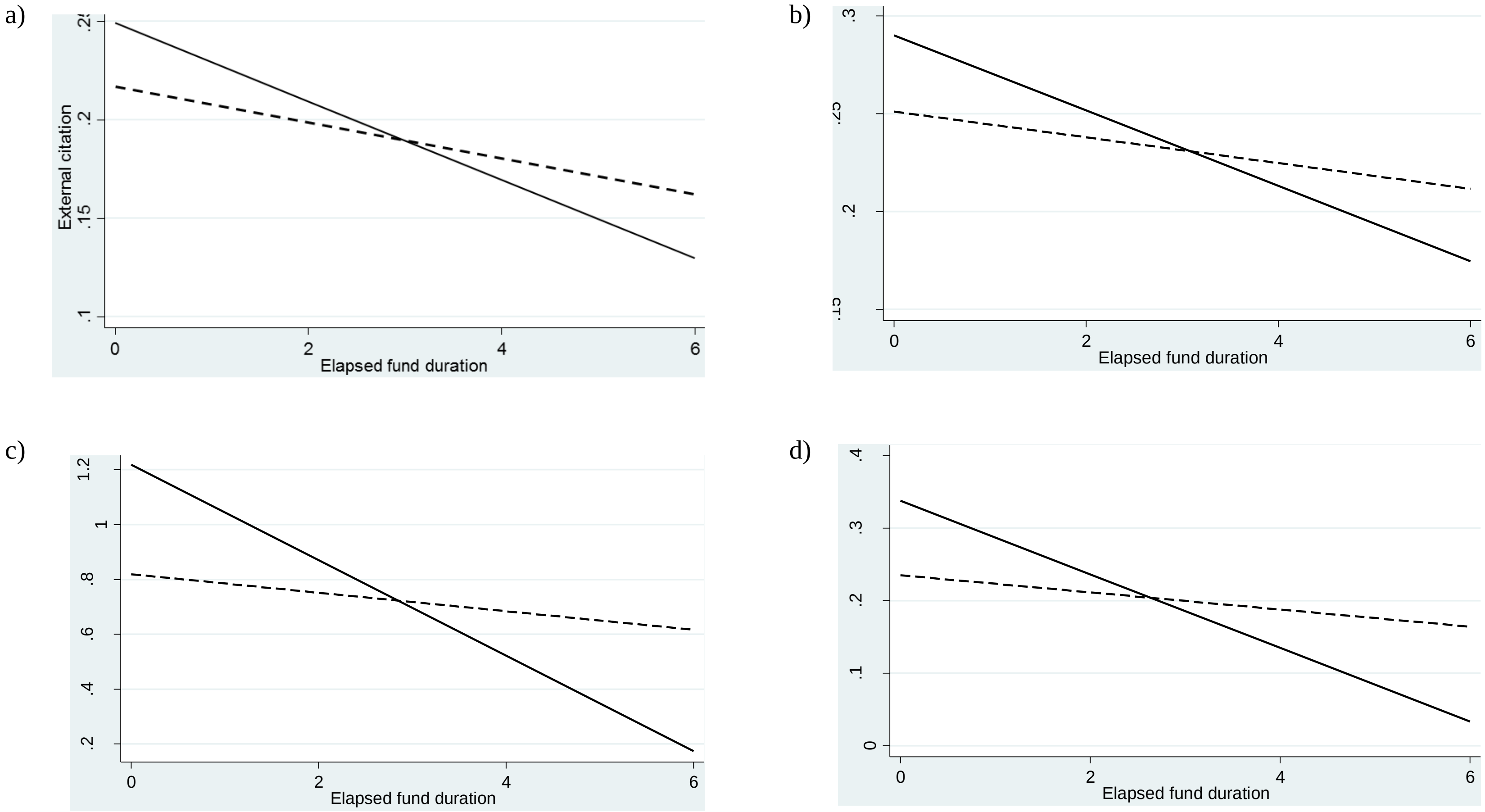
Note. Fund controls include fund size, fund portfolio, round amount, and first fund; VC firm controls include running funds, VC investment share, VC Biotech expertise, and location dummies; venture controls include venture age, patent stock until time t-1, seed early stage, and sub-industry dummies. The unit of observation is firm-year. Heteroskedasticity -adjusted robust clustered errors at the fund level are reported in parenthesis. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

FIGURE 1
Two-Period Extensive Form Investment Sequence



Note: The figure represents the flow of a two period investment sequence where project *A* is exploitation type with known probability of success and project *B* is exploration type with uncertain probability.

FIGURE 2
Interaction Effect of Delta Performance



Note: The figures plot the interaction effect of fund delta performance for each of the innovation success variables. The dashed line depicts mean fund age.
Source: Author's own tabulation.