AND THE WHEELS JUST KEEP ON TURNING: IMPRINTING AND REPEATED EXPLORATION IN VENTURE CAPITAL FIRMS.[1]

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Abstract

In this paper, we study organizations' repeated engagement in exploration. Using an organizational learning perspective, we link repeated exploration to the existence and usage of exploration rules, and discuss two factors that affect exploration: the momentum of prior exploration(s) and the imprinting effect of early exploration(s). Our empirical work traces the investment decisions of US Venture Capital firms from 1962 to 2004, capturing the exploration of emerging, uncertain industries as they appear. We provide evidence that prior exploration increases the likelihood of future exploration, and that it decreases with the time elapsed since the last exploration. In addition, we find that VC firms that had explored early in their lives are more likely to do so again, and that this imprinting effect weakens as the number of prior explorations increases.

1. Introduction

Business organizations in uncertain environments strive to balance short-term performance with long-term survival: they need to consolidate and exploit their current competitive positions but they also need to explore new ones. Doing so, however, is particularly challenging as the latter can be detrimental to the former, and vice versa (March 1991; Tushman and O'Reilly 1996). Put more broadly, "the basic problem confronting an organization is to engage in sufficient exploitation to ensure its current viability and, at the same time, to devote enough energy to exploration to ensure its future viability" (Levinthal and March 1993: 105).

With its proximate goals, immediate returns, and well understood metrics, the pursuit of exploitation comes almost naturally to organizations. In contrast, the decision to engage in exploration is much more uncertain, requiring consideration of discontinuous paths with unclear payoff structures. Such decisions are interlaced with the organization's exploitation behavior (Brown and Eisenhardt 1997; Duncan 1976; Lavie and Rosenkopf 2006; Rothaermel and Deeds 2004) and are enabled by organizational structures or contexts that balance autonomy and integration (Gibson and Birkinshaw 2004; Puranam et al. 2006; Siggelkow and Levinthal 2003; Thomas et al. 2005). But beyond the structural facilitation of exploration decisions, their interspersed nature brings into focus the question of their magnitude and timing. This question is particularly relevant for researchers interested in exploration: we know that there is a tight link between an organization's past behavior and future actions (Argote and Greve 2007; Cyert and March 1963), and that raises the possibility that successive exploration decisions have behavioral underpinnings, that is, that they are enabled by prior behaviours or decision patterns.

In this paper we seek to understand the sequential and repeated nature of exploration. We do so by adopting a behavioral perspective, which understands present organizational decisions as the enactment of organizational rules. Rules emerge from both past decisions and their perceived consequences (Cyert and March 1963; Schulz 1998) and, as such, affect the organization's ability to perform complex collective activities such as exploration. Accordingly, a decision to explore can be seen as a function of the organization's pre-existing rules that inform and enable exploration; its existence and timing depends on whether these rules exist, and if they do, how they are developed and put to use. We identify two forces that shape the likelihood of engaging in (further) exploration: the learning associated with prior exploration and the imprinting effect of early exploration.

Our empirical examination traces the evolution of the US Venture Capital (VC) industry from its early period in 1962 until 2004, as it unfolds. Capturing the investment behavior of VC firms over time enables us to link their current investment decisions to prior ones and provides a rich context for studying learning and exploration. In addition, the controlled setting provided by a single industry and the structural simplicity of VC firms facilitate our theoretical inferences. VC firms provide financing and support to promising entrepreneurial companies, so their ongoing investment decisions capture well the exploration-exploitation dilemma: investing in companies that operate in familiar industries can bring known albeit smaller and diminishing returns, while trying out new and uncertain industries can bring unknown yet potentially higher returns. Over these forty-three years, some VC firms have been instrumental in financing emergent high technology industries such as semiconductors, personal computers, software, telecommunications, biotechnology, the internet, and more recently the web 2.0. As well, many VC firms have shied away from emergent industries, and many emergent, promising industries have borne no fruit, leaving their backers empty handed.

We seek to make two contributions to the current academic dialogue on exploration and organizational learning: (1) to increase our understanding of the nature of repetitive exploration by relating it to the rules that make it possible and to the triggers that make it happen; and (2) to develop the idea of imprinting as an important determinant of organizational learning and specifically, as a crucial factor in the development of rules that enable exploration. In the context of studies of the causes and consequences of organizational learning for flexibility, resilience, and other adaptive behaviors, we argue that early exploration can have long-lasting effect on the organization by making further exploration more likely, even in a distant future. In addition to these considerations, we show that such imprinting counter-weighs on the organization's cumulative exploration experience to prevent the organization from engaging in excessive exploration.

2. Theoretical Context

2.1. Organizational Learning, Rules, and the Exploration-Exploitation Dilemma

Organizational behaviour is purposefully patterned. These patterns reflect the logic of appropriateness, whereby the organization invokes a set of learned behaviours as the appropriate response to the situation it faces (Cyert and March 1963). Such rule-based action uses inferences from past behaviours (Levitt and March 1988), materialized in the assets, standard operating procedures (Cyert and March 1963), rules (Cyert and March 1963; March et al. 2000; Schulz 1998) and routines (Nelson and Winter 1982) of the organization.

An organization learns what to do or what not to do mostly from its own experience[2]. This generally happens through interactions with its proximate environment, which "produces a wealth of information about cause and effect, about the consequences of actions, and about what to do in order to achieve goals" (Sutton and Barto 1998: p. 3). This wealth of information usually takes the form of feedback, allowing the organization to adjust its behavior according to the information it receives from the environment. Through the positive reinforcement that arises out of feedback, organizations identify behaviours that have led to desired outcomes and seek to reproduce them through the development and application of rules, that is, the "explicit or implicit norms, regulations and expectations that regulate behaviours" (March et al. 2000: 5). This happens because rules define and limit the universe of acceptable behaviours, and consequently shape the repertoire of actions that firms can initiate in different situations (Miller and Chen 1996).

Lessons from the past are typically associated with local searches, refinements of current behaviours, or selection and reuse of routines that are adequate to the contextual demands the organization faces (Baum et al. 2000). Yet, current situations are imperfect reflection of past ones and rules often fall short of being a perfect bridge to the future. This tension between past and future is best represented by the exploration-exploitation dichotomy that arises in situations when prior actions guide current choices: "to obtain a lot of rewards, a reinforcement learning agent must prefer actions

[2] We acknowledge here that organizations also learn from the experience of others (Huber 1991), but we focus here on learning arising from own experience rather than vicarious learning. Although scholars have defined and discussed organizational learning in various ways (Easterby-Smith et al. 2000; Easterby-Smith and Lyles 2003), here we focus on behavioural learning (Miner and Anderson 1999)

that it has tried in the past and found to be effective in producing reward. But to discover such actions it has to try actions that it has not selected before. The agent has to *exploit* what it already knows in order to obtain reward, but it also has to *explore* to make better action selections in the future" (Sutton and Barto 1998: 4). Exploitation of current knowledge through existing rules produces optimal results in the short term, but exploration may produce higher rewards in the long term if it leads to the discovery of possibilities currently unknown to the agent (Siggelkow and Levinthal 2003), possibilities that can be crystallized into new rules that can produce better, more adapted behavior.

Learning in exploration comes through "concerted variation, planned experimentation and play" (Baum et al. 2000: 768), that is, from mindful exposure to novel situations. Since returns from exploration are uncertain, intractable, and, in addition, remote in time (March 1995), the appeal of specific exploration initiatives can be overpowered by their more readily perceived costs and suffer the "uncertain relevance of newness" (Schulz 2001). Since exploration cannot provide immediate remedies to current performance deficiencies, repeated, mindful engagement in exploration requires a set of rules that are distinct from those regulating exploitation. Thus, the different propensities to explore observed empirically can be explained by the development, refinement and usage of rules for exploration; rules that grew out of the learning arising from prior experiences.

2.2. Behavioral Antecedents of Repeated Exploration

To the extent that an organization's default course of action can be characterized as gradual, linear pursuit of alignment with its current context, we conceive of repeated exploration as a series of changes or "swerves" from that incremental behavior, whereby the organization redirects some of its attention to a new, uncertain area (Holmqvist 2004). Because change can be costly and disruptive (Amburgey et al. 1993; Hannan and Freeman 1984), it is not an activity that they can readily undertake. The mere prospect of change can create disruptions within the organization that make it more vulnerable to failure while the transition lasts (Barnett and Carroll 1995; Tushman and Romanelli 1985). The anticipation of such disruption in the absence of immediately visible benefits makes exploration difficult to initiate or repeat. But when such transition is formalized – guided through rules that lay out what to do and when, and that instill tolerance for the immediate lack of results and the higher failure rate– the disruption can be alleviated, consequently making the next exploration initiative easier and/or more likely.

2.2.1. The Repetitive Momentum of Prior Exploration. Learning helps organizations deal with recurring situations (Cyert and March 1963; Nelson and Winter 1982). Learning provides standard responses to standard problems, and cumulative exposure to repetitive problems helps develop and improve the set of rules that guide organizational behaviour in such situations. For example, when organizations undergo changes in response to exogenous factors, they develop rules that can be activated and drawn upon when similar concerns re-emerge. The occurrence of change, thus, makes the organization more malleable (Amburgey et al. 1993), and more deft at changing as change becomes part of its repertoire instead of being perceived as an unusual or painful event (Dougherty 1992; Dougherty and Hardy 1996) that needs to be ignored or minimized (Freeman 1999). Formalizing the change process solidifies the organization's perception of its appropriateness and thus creates a (repetitive) momentum for further change (Amburgey et al. 1993; Amburgey and Miner 1992) regardless of the organization's current performance (Greve 1998). As Amburgey and Miner argue, "… as an organization takes actions over time, it develops routines and competences which then become *independent engines* for further actions" (1992: 336, *emphasis added*).

Applied to the context of exploration, the repetitive momentum logic strongly suggests that exploration is more likely for organizations that have explored more extensively in the past (Lavie and Rosenkopf 2006): previous exploration not only makes new exploration less intimidating, but also provides valuable learning experience that enables the organization to create a set of rules to facilitate the consideration and execution of future exploration initiatives. Extensive prior exploration makes rules more readily available and increases the likelihood of their usage. Yet, the knowledge incorporated in organizational rules is not eternal, and it tends to dissipate, sometimes rapidly and involuntarily (Argote 1999; Argote et al. 1990; Benkard 2000; Darr et al. 1995; Martin de Holan and Phillips 2004). If not used, then, rules can deteriorate and gradually disappear (Amburgey et al. 1993). Therefore, although prior exploration enables the organization to engage in exploration anew, foregoing exploration for a long time can make exploration rules dormant and difficult to re-activate.

2.2.2. The Imprinting Effect of Early Exploration. The disruptive effect of change varies with age (e.g. Amburgey et al. 1993). Organizational ageing, through the sustained focus on reliability and accountability, fuels rigidities and consequently creates structural inertia (Hannan and Freeman 1984; Miller 1994) that makes change difficult, and much more costly when it happens. Age tends to consolidate the worldview ("cosmogony") of the organization (Weick 1994) around dominant logics (Bettis and Prahalad 1995) and grammars of action (Pentland and Rueter 1994) that become dominant and unquestioned.

But we can trace the ageing process backward. When we do so, we see that engaging in exploration early in an organization's life can affect the organization's future worldview and subsequent perception of exploration. Early actions have a strong imprinting effect by creating and shaping the vested interests of the organization and its orientation, and also influencing the agenda of future decisions (Stinchcombe 1965). Thus, over time, as managers economize on the cognitive components of their decisions by looking at prior decisions (March and Simon 1958), early actions can become templates for future actions. In addition to rules, the overarching values that founders instil in the organization have a long-lasting influence on subsequent decision-making processes within the organization (Boeker 1989). Accordingly, early embracement of uncertainty and experimentation can become a distilled component of future decisions. These arguments suggest that early exposure to exploration can facilitate the emergence of exploration rules and make such rules easier to invoke, in turn making the organization more open to new initiatives and, as a result, more likely to consider and engage in new but uncertain opportunities.

Increased openness to exploration poses the challenge of containing the organization's exploration momentum. An increased propensity to explore may instill "impatience", preventing the organization from following through and revealing the full potential of its exploration initiatives. As a result, organizations may abandon such initiatives before being able to exploit them, and start pursuing newer, more promising ideas (Levinthal and March 1993), more promising because newer. Thus, a more thoughtful invocation of exploration rules means that more time can be devoted to exploitation and to profiting from prior exploratory moves, an essential feature of the exploration-exploitation dilemma (March 1991). In the absence of such containment, exploration could become an end in itself and potentially drive out exploitation.

Breaking a tendency to over-explore requires effective learning of the conditions, circumstances, and idiosyncrasies of the new domain, as this facilitates its successful exploitation. In this regard, organizations that explore early in their lives may be more apt to do so, as they have been exposed both to exploration and exploitation during their formative periods. Consequently, they understand in a better way how to manage the translation between exploitation and exploration: having undergone multiple exploration initiatives and having learned from them, these organizations are more likely to update their exploration rules to distinguish situations in which it is appropriate to explore and situations in which it is not. For each exploratory initiative, these organizations can distinguish between features that are specific to the domain and its circumstances, and those that are general and applicable in other contexts. In contrast, organizations that come to exploration late in their lives may not have learned such lessons and honed their rules to the same extent, resulting in different and possibly inferior behaviors while faced with the same opportunities for exploration. As such, the interaction of early exposure to exploration, cumulative experience with it, and learning teaches the organization to use exploration more judiciously. This suggests to us that as the number of explorations increases, the imprinting effect of early exploration will become more subdued.

3. Exploration in the Venture Capital Industry

The notion of repeated exploration and its behavioral antecedents are well illustrated in the context of the U.S. venture capital (VC) industry, which developed over the past 50 years in unison with the accelerating pace of technology development and commercialization. VC firms typically raise funds from institutional investors to make risky equity investments in entrepreneurial companies. They help develop these companies through active managerial involvement, strategic oversight, and corporate governance, seeking ultimately to sell their equity stakes in these companies to third-party investors, as is the case with IPOs or strategic acquirers (Gompers and Lerner 1999). For each investment, the result can range from a substantial capital gain for investments in companies that become successful and emerge as important players in their industry to total loss for the companies that fail to launch, or do so but face mediocre prospects. As such, VC firms perform an important interface role: they provide vital early-stage financing to startups that mainstream, institutional sources of finance find too risky (Fenn et al. 1995). Because they mostly spend "other people's money", they do not bear themselves most of the financial risk associated with their investments. Yet, VC firms need to raise new capital on a regular basis, often from the same investors (Gompers et al. 1998; Lerner and Schoar 2004), and thus stand to benefit from a proven track record of effective fund stewardship and the delivery of superior financial returns (Cumming et al. 2005).

Superior returns have been associated with backing such prominent successes as DEC, Apple Computer, Microsoft, Sun Microsystems, Intel, 3Com, E-Bay, Google, and You Tube that have marked technology changes over the past 50 years. But because of the necessary lag between the moment when the investment is made and the moment when the company launches its product or service, the full potential of these companies is enshrined in uncertainty, and is subject to strong skepticism: each winner has left behind a multitude of losers, including some of their peers who had also received VC but had failed to produce results. Also, there are many companies that received VC financing but produced mediocre results and, of course, there were many others who could not attract VC investors at all. For prospective investors, then, companies that introduce significant product, market, or process innovations – and that could spur the gestation of new industries and become the next generation of industry leaders; the next "killer app" – represent substantial bets that are consistent with the logic of exploration as they may open up currently unknown possibilities but cannot be justified on the basis of existing knowledge. Indeed, as von Burg and Kenney argue, "the greatest successes are almost always those in which the market growth is unforeseen by most investors, because if the success was foreseen the true value of the firm could have been judged" (2000: 1139). Therefore, backing emerging industries is likely to produce returns that have higher mean but also higher variance, while backing established industries involves lower risk at the expense of a lower mean. In line with the exploration-exploitation dilemma discussed in the previous section, continuing to invest in the same industries, while likely to produce higher returns in the short-term, is also likely to undermine the VC firm's long-term performance. It is thus important for VC firms to make timely exploratory investments in order to uncover promising new industry sectors that can produce a stream of returns in the future.

VC firms have been intimately involved in the emergence and development of new, high-technology industries, mostly by backing many of their progenitors. But not all VCs are the same: at the gestation stages of these industries some VC firms stepped forth while many others stayed away from them. Over time and across the population of VC firms, it is possible to observe whether and when VC firms make exploratory investments and whether they do so repeatedly. But why should there be variation in the VC firm's propensity to explore? After all, an exploration is just another investment. To understand this, it is helpful to contrast VC managers with traditional investment fund managers. The latter are passive investors: they select target companies and monitor their performance to determine whether and when they should sell their stakes. Essentially, for these investors performance is treated as a series of exogenous, stochastic events. In contrast, venture capitalists are active investors: they not only focus on selecting companies by careful "scouting" (Baum and Silverman 2004), but also are instrumental in making these companies successful (Hellman and Puri 2002; Sapienza 1992). Once a venture capital firm invests in a portfolio company, it often assumes an active role in monitoring and managing the investment (Lerner 1995). Venture capitalists support their companies by providing access to a broad network of customers, suppliers, and other potential investors, as well as strategic and operational assistance. At the same time, they monitor the company's progress by serving on the board, and providing capital in multiple stages over the company's life. Over time, they develop deep knowledge that enables them to carry out their selection, monitoring and value adding activities more efficiently (e.g. Amit et al. 1998; DeClercq and Dimov 2008; Sapienza 1992).

When making exploratory investments, VC investors can play an essential role in constructing the new company or even a new industry (von Burg and Kenney 2000). In this sense, they play an endogenous role in the ultimate success or failure of these investments. However, in line with the disruption that engaging in exploration may bring, such investments may require paradigmatic shifts in how they are to be identified, appraised, and pursued. In this regard, the knowledge that the venture capitalist possesses may not be easily flexed to appreciate emerging trends or promising new developments. Typically, there is no clear market and no benchmarks or other similar companies, thereby making the valuation of such companies extremely difficult. This difficulty is related not only to the fact that most entrepreneurial ventures are at very early stages of development and have limited track record to show, but also to the fact that there may be limited understanding of the economics of the industries, markets and even the business models of these ventures. For example, an internet start-up clearly represents an uncertain investment: there is much uncertainty about the market needs it may fulfill and about its ability to compete effectively with other firms in fulfilling these needs. In addition, it may be difficult to appraise the qualities of the management team if none of them has proven successful in similar domains. Yet, for a potential investor, the project would be much more uncertain if undertaken in 1995 than if undertaken in 2007 because in the earlier period there was much uncertainty about the potential of the internet for facilitating market transactions and about the nature of the business models that would make internet-based businesses sustainable. Therefore, in making exploratory investments, VC firms need to tap new sources of information, establish relationships with different sets of experts, and engage with a different set of partners (e.g. law, recruitment or consulting firms) to support the new venture.

Von Burg and Kenney (2000) provide a rich account of the financing of the early players in the local area networking industry that exemplifies the difficulties of making exploratory investments and the important role of early VC investors. In 1979 Ungermann-Bass (UB) was established aiming to create local access between terminals and minicomputers. Skepticism of the company's objectives was widespread, as attested by the almost universal negative responses to the founders' request for VC financing. As von Burg and Kenney observe, "not surprisingly, most venture capitalists could not envision the economic space and could not believe that a startup could construct such a market" (2000: 1142). Notably, as one of the early backers, James Schwartz of Adler and Co. when asked about the role of experts in the established large companies at the time in judging the feasibility of UB's business plan, commented, "if I had tried to do that kind of due diligence, I would have been absolutely convinced that [the UB investment] was something I should not do.'' (cited in von Burg and Kenney 2000: 1144). Similarly, 3Com, the first Ethernet-dedicated start-up, turned away potential investors with its vague business plan and lack of clear market. Yet, in their long quest for financing, both UB and 3Com were eventually backed by investors who had participated in earlier technology commercialization: James Schwartz was involved with Amdex, a pioneer in the broadband technology field, while Richard Kramlich of New Enterprise Associates had been involved with Apple Computer. In addition, one of UB's early backers, Neill Brownstein of Bessemer Ventures was intimately involved in the preparation of UB's business plan. And the early backers of 3Com were instrumental for its success: they recruited a seasoned CEO to lead the company and advocated a change in strategy in response to IBM's introduction of the personal computer, a move that proved critical for the company's spectacular growth (von Burg and Kenney 2000).

Exploration by VC firms requires an ability to identify and evaluate new technologies with promising commercialization potential. Because there is no consensus on the potential of emerging fields, the VC firm relies on its prior investment experience to make its judgments about the future marketability of a yet-untested technology. VC firms are organizations with relatively "simple" structures, comprising a team of general partners – which serve as principals in the funds that the VC firm raises – and a supporting group of investment officers. This structure has remained relatively stable over time, particularly since the emergence of the limited liability partnership in the late 1970s as the dominant form of structuring investment funds. Although investment opportunities are typically sourced by the individual partners or investment officers in the form of initial screening, much of the evaluation and decision elaboration takes place at an investment committee level (Fried and Hisrich 1994) which, given the flat structure of VC firms, essentially represents the firm as a whole. Such homogeneity in the structure of VC firms allows us to attribute shifts towards (or away from) exploration to the prior investment decisions made by the firm.

In summary, although venture capital firms are important in their own right, they also represent an adequate universe for the study of the dynamics of repeated exploration. While some of them invest early – when the contours of the new industry are still invisible, uncertain or downright fuzzy – others do so late riding on the accelerating excitement derived from the "proven" promise of the new industry. In this regard, to the extent that investing early is not regarded as random decision but a purposeful one, it can be attributed to decision rules that allow the VC firm to recognize certain patterns in the exploration domain and justify it in the eyes of the firm and its backers.

3.1. Learning from prior exploratory investments

Retrospective accounts of the emergence of new industries or the success of pioneering investments often emphasize the inevitability of these events and reinforce the notion that they could have been reliably foretold by a lucid analyst. And yet, when the next exploration looms on the horizon, the dilemma of errors of omission (not investing when one should) and errors of commission (investing when one should not) re-emerges in full force; to most, bubbles in a market are understood in retrospect but are seldom foretold. Without "before" and "after" insights of what is eventually regarded as obvious and inevitable, one would be more inclined to avoid the latter and, as result, commit the former. VC firms who have made exploratory investments in the past are able to observe how initial, uncertain expectations eventually play out and thereby develop a broader, more abstract understanding of the nature and dynamics. In contrast, those who have not made such investments have no direct experience of the uncertainties preceding the eventual hits or flops and are thus more malleable by the post hoc reconstruction and explanation of events.

Prior exploration experience alerts the VC firm to possible sources of new deals and the circumstances in which the potential deals originating from such sources have the right timing. In addition, in the due diligence process surrounding such potential deals, VC firms with prior exploration experience learn to seek, underplay or avoid the advice and opinions of particular experts or insiders entrenched in the existing order. In the cacophony of viewpoints inherent to emerging investment opportunities, what eventually turns out to be valuable opinions are often obscure, offered with lower intensity, and held by a small and often eccentric minority of observers. To weight such opinions more heavily requires decision rules reinforced by prior experience. Finally, prior exploration enables the VC firm to use valuation approaches that, although less orthodox at the time, allow it to suspend final judgment of the emerging opportunity until the understanding of the economics of the new industry becomes more solidified. These considerations lead to the following hypothesis:

Hypothesis 1a: *The likelihood of exploration increases with the number of prior explorations.*

Over time, if not reinforced through subsequent exploration decisions, many of these fragile decision heuristics may be overpowered by the knowledge and insights, and consequently the rules, emerging from more recent investments. As market moods swing and investor attention shifts to new areas, not seeking our alternative deal sources or interacting with experts at the sidelines can gradually tip the consideration of novel investments toward caution and avoidance of errors of commission. In addition, to the extent that exploration decisions have been driven by particular VC executives, the suppression of their voice through declining to back some of the deals they propose may lead to their exit from the firm (often to run their own VC firm) and thus further diminishing of the firm's propensity to consider and make exploratory investments.

Hypothesis 1b: *The likelihood of exploration decreases with the time elapsed since the last exploration.*

3.2. The lasting effect of early exploration

The early investment decisions of VC firms send important signals about the skills of their founding partners and about the firm's role and position in the investment community. In many cases, VC firms are founded by people who leave other VC firms – sometimes to pursue a stream of investments that did not fit with the previous firm's philosophy. In other cases, they are founded by technology savvy entrepreneurs who had been involved with pioneering start-ups or who have strong relationships with the R&D community. Such firms are well equipped from the start to engage in exploration and are thus more likely to do so early in their lives.

When VC firms do so, the decision process they use can become a template for habituation and is thus likely to have a lasting effect on subsequent investment decisions. Early exploration can reinforce and worldviews of the founders and ingrain exploration in the investment philosophy of the firm. In addition, as initial stakeholders or social network contacts, those offering investment referrals or expert opinion to the new firm will likely remain influential and actively sought as the firms identifies and evaluates new investment opportunities. In addition, to the extent that the focal VC firms beings other VC firms as investment partners for its exploration deals, these partners are more likely to recognize the focal VC firm as originator of novel investment deals, and look more favorably at its future deal flow. These considerations lead to the following hypothesis:

Hypothesis 2a: *Exploring when young increases the likelihood of engaging in future exploration.*

Because VC firms need to raise new capital on a regular basis, often from the same investors (Gompers et al. 1998; Lerner and Schoar 2004), and because successful fundraising depends on the VC firm's track record (Cumming et al. 2005), VC firms need to be judicious in their making of exploratory investments. VC firms imprinted by early exploration may develop a tendency to over-explore if their exploration propensity is not reigned in: having too many investments that may take long time to produce returns and that are subject to higher likelihoods of both success and failure, can endanger the return prospects of the VC firms. As the number of such investments increases, more time should be devoted to exploitation and to profiting from the newly opened domains by backing new ventures in those domains. Such not only allows the VC firms to capitalize on its newly developed knowledge but also increases the likelihood that a venture in backs will become part of the dominant design in the emerging industry.

Therefore, in order to balance its short- and long-term performance and consequently its sustainability, a VC firm needs to maintain a certain level of exploration: too much endangers the VC firm's immediate fundraising, while too little of it may subdue its long-term performance and thus dampen its long-term fundraising prospects. As a result, we expect that VC firms that explore early – and thus exhibit higher propensity to explore – to regress gradually towards that level of exploration. In other words, as their exploration experience accumulates, their propensity to explore may decrease. In contrast, VC firms who approach that level of exploration from below – by exhibiting low initial propensity – are likely to intensify their exploration propensity as they engage in more exploration.

Hypothesis 2b: *Cumulative exploration experience weakens the imprinting effect of early exploration.*

4. Method

4.1. Data

We collected data from the *VentureXpert* database published by Thomson Financial on all investment transactions executed by U.S. VC firms over the period 1962-2004. Full data were available on 185,085 transactions. Constituting a quasi-census, this database is the most comprehensive source on venture capital deals, stretching back to the beginning of the industry. Such longitudinal data enables us to track how VC firms develop their portfolios over time and thus balance exploration and exploitation in their investment activities.

To manage their financial risk, VCFs normally stage investments in each company across different investment rounds; a new (follow-on) round of investment usually requires that the portfolio company meet certain development milestones (Sahlman 1990). Thus, after its initial investment in a portfolio company, a VC firm may decide to invest further in that company if the performance prospects of the company remain satisfactory. Because each investment round is recorded in the database as a separate transaction, we identified the portfolio of each VC firm by selecting the *initial* investments made by each VC firm in each of its portfolio companies. There were a total of 84,237 initial investments made by 4,446 VC firms over the above 43-year period. These investments represented a relatively homogeneous set of decisions—adding a company to the VC firm's portfolio—and excluded the qualitatively different decision to continue to invest in a company already in the portfolio. We used this set of initial investments to represent the chronological development of each VC firm's investment portfolio, from investing in its first portfolio company until investing in its last. For each investment, we recorded the characteristics of both the VC firm and portfolio company, as detailed below.

As we were interested in *whether* and *when* VC firms invested in new industries, we organized the data in an event history format. That is, we represented the investment history of each VC firm as a sequence of time periods (spells) ending with the occurrence (or lack thereof) of particular events (Morita et al. 1993). In our case, the event of interest was a VC firm's making an investment in a newly emerging industry. To construct the spells and capture the time-varying characteristics of the VC firm's portfolio, we identified all the time points at which a particular VC firm's portfolio changed, i.e. new companies were added to it. Because the exact dates of the investments were not precisely recorded in the database but the months were, we chose the month of the investment as our time variable. In this way, each investment spell began in the month after a VC firm had last added new companies to its investment portfolio and ended in the month in which the VC firm made its next addition to the portfolio. At the end of each spell, VC firms were coded as making an exploratory investment or as right censored. For each spell, we recorded not only the new investment activity, but also kept a running total of the VC firm's cumulative investment activity to date. This initial event history data structure yielded 57,475 firm-spell observations. By allowing multiple events (i.e. explorations) to occur for each VC firm, we ensured that the duration information from each right-censored spell (except for the last spell) was carried over to the following spell. Compared to other methods of studying binary decisions, the event history format allowed us to make full use of the information contained in the right-censored observations. Because our data covered the entire life span of the VC industry, they did not suffer from left censoring, i.e. there was no investment activity prior to the observation period.

4.2. The Exploration Events

To specify the exploration investments, we focused on the VC firms' investment activity in high tech industries. The *VenureXpert* database uses 5 main categories – communications and media, computer related, semiconductors and electronics, biotechnology, and medical and pharmaceutical – and 40 sub-categories for designating high-tech industries. We focused on the 40 sub-categories as the set of industries that a VC firm could potentially explore. When investing in a high tech industry, a VC firm faces highest uncertainty not only when it first invests in that industry but also when relatively few other VC firms have previously invested in that industry. To capture such situations, we recorded the chronological order of each VC firm's investment in each of the 40 high-tech industries. We derived this order by time sorting all the investments made in each industry over the observation period and assigning a sequence number to each investment. We then selected the first-time investments made by each VC firm in each of these industries and considered each such investment *exploration* by the particular VC firm if it was among the first 50 investments made in the particular industry sub-category[3]. Thus, our event marker for each VC firm and investment period

[3] The choice of fifty investments as a cut-off point, while *prima facie* arbitrary, reflects a trade-off between the true novelty of an investment and the statistical power needed to detect a particular effect. Choosing a lower cut-off point reduces the number of exploration events. On the other hand, choosing a higher cut-off point reduces the "explorative" appeal of the investment. We note nevertheless that slight variations to the selected cut-off point produces results consistent with the ones reported below. In addition, because *ex post* updating of industry codes could change the chronological order of a particular investment and thus its exploration designation, a sensitivity analysis revealed that our results were robust to the exclusion of exploration events occurring in "high-drift" industries as well as in industries that were most prone to changes in exploration designation.

(spell) indicated whether an exploration "event" occurred in that period. There were 1,602 periods in which exploration occurred. If a VC firm made more that one exploratory investment in a given period, we used the actual number of such investments in deriving the count of prior explorations. In order to verify that the so chosen cut-off points indeed captured the "embryo" period for each of the industries, we examined the number of VC firms investing in an industry by the cut-off point as a proportion of the number of VC firms ever investing in that industry. A low proportion would indicate not enough institutional momentum for the industry to be considered legitimate enough, thereby reflecting higher uncertainty and an exploratory environment. Across the industries, the average proportion was 6.5% (s.d. 11.3%) and 91% of the proportions were below 20%. Figure 1 illustrates the number of VC firms experiencing exploration events in each year over the 1962-2004 period. The figure shows that explorations occurred in all years of the observation period prior to 2003. In addition, the figure shows the fluctuations associated with the well documented technology "bubbles" of the mid-1980s and late-1990s.

Insert Figure 1 about here

4.3. Time at Risk

The validity of an estimation based on event history analysis depends on an accurate definition of the time in which a VC firm is at risk of experiencing an exploration event. Defining and designating the time at risk required two further considerations in preparing our data for analysis. First, given that each VC firm came under observation at the end of its first spell – i.e. when it made its very first investment(s) – we had no data concurrent with that investment period and thus lacked predictors for the nature of the firm's first investment. In addition, because the exact time of the founding of the VC firm was not reliably provided in the data, to the extent that a firm's first investment was exploratory, choosing an arbitrary founding point and using that point as the onset of risk would lead to biased estimation of the first exploration events. This issue was particularly potent given that 86% of the VC firms did not engage in exploration. In view of these considerations, we chose each firm's first investment as the point of origin of the firm's risk of engaging in exploration. As a result, each firm's first investment period was excluded from the analysis, reducing the number of spells by 4446 and the number of exploration events by 255, to 1347. 1104 firms made no investments beyond their first investment period and were thus excluded from further consideration, bringing the number of "active" firms to 3342. Of these, only 585 (17.5%) were at risk of experiencing a second exploration event and only 124 (3.7%) were at risk of experiencing five or more exploration events.

Second, we considered that, given our definition of the exploration events, once there were 50 investments made in all 40 sub-industries, firms were no longer at risk of engaging in exploration. As the "last" exploration occurred in December 2002, we removed from consideration all spells that started after that date, bringing the number of spells used in the analysis to 49,134 and the number of firms to 3256.

As the VC firms in our data experienced multiple events and each event consisted of multiple spells – reflecting each change in the composition of the VC firm's portfolio – we used a *counting process* formulation to define the risk intervals in our data (Ezell et al. 2003). In this formulation, the time at risk represents the time elapsed since the event marking the onset of risk (the firm's very first investment), with the left time of each risk interval reflecting the beginning of each spell. This formulation is appropriate for data in which few firms experience two or more events and when the substantive interest of the estimation is in whether the hazard rate increases or decreases with the number of previous events (Ezell et al. 2003; Therneau and Grambsch 2000).

4.4. Independent Variables

We measured *early exploration* by an indicator, showing if a given VC firm had engaged in exploration in or within two years of its first investment period. To reflect the fact that this variable became effective after this initial two-year period, it was recoded to zero for all spells ending within the initial two-year period. We measured the *number of prior explorations* as the number of explorations made by a VC firm prior to the particular investment period. We also constructed a clock to record the time elapsed since the previous exploration event. It started "ticking" after the first exploration event – i.e. it had a value of 0 until that event – and was then re-set to 0 at each subsequent exploration event.

4.5. Control Variables

We included an extensive set of control variables in our analysis in order to eliminate various possible alternative explanations for the VC firms' exploration of new high-tech industry domains. First, we included an indicator for whether a spell ended during the VC firm's initial two-year period. This variable accounted for the possibility that newly-established firms were qualitatively different in their likelihood to enter new domains.[4] In addition, it served to partial out the initial-period effect from the coding of early exploration.

Second, for each investment period, we controlled for the number of companies in the VC firm's portfolio at the beginning of the period to partial out differences in resource munificence as well as accounted for the investment stage and industry preferences of the VC firms. Naturally, VC firms that were oriented towards early-stage investments would be more likely to invest early in new technology domains, while those not investing in high-technology sectors would be less likely to do so. Therefore, for the investments made by the VC firm prior to the current period, we calculated and controlled for the proportion of them made in early-stage companies (seed, start-up or other early stage) as well as the proportion of them made in non-high-technology industries (industry categories 6, 7, 8, and 9 above).

Third, to account for the fact that VC firms specializing in particular industry sectors may be less open to engaging in exploration, we controlled for each VC firm's industry specialization for each period, measured as a Herfindahl Hirschman Index (HHI) on the industry distribution of the VC firm's investments made prior to the current period. To calculate the index, we used formula $\sum p_i^2$, where p_i represents the proportion of investments made in a particular industry category during the period from the founding of the VC firm up to the period in question. The HHI thus reflected how concentrated the VC firm's previous investments were across industries as it was making new

[4] We note here that in the context of VC firms it is common for investment managers trained and experienced in one firm to leave to found their own VC firms. In this sense, the effect for new firm captures the possibility that people who wish to pursue new technological opportunities and who do not find the necessary support within their existing firms (e.g. due to the ageing and reduced decision making flexibility of these firms) leave to pursue these opportunities through new investment firms.

investments in the given period.[5] In addition, considering the possibility that recently raised funds may change the focus or intensity of the VC firm's investment efforts, we controlled for whether the VC firm had raised new funds within the 2 years preceding the investment period.

Fourth, we controlled for various characteristics of the VC firms that could affect their exposure to and consideration of investment opportunities in new industries. To account for the possibility that independent VC firms had more strategic freedom, while corporate subsidiaries or affiliates of financial institutions could operate under additional strategic or liquidity constraints (Manigart et al. 2002; Mayer et al. 2005), we controlled for the ownership structure of the VC firms by including indicator variables for each of these types of VC firm. In addition, to account for location effects associated with proximity to technology innovation clusters, from which many of the high-tech industries had emerged (Saxenian 1994), we included indicators for whether a VC firm was located in California or Massachusetts. Finally, to account for the fact that VC firms founded in different time periods had different possibilities to invest early in some of the high-technology sectors, as well as to capture the differences in investment environment and resource munificence across periods, we controlled for whether the VC firm was established in the 1962-1970, 1971-1975, 1976-1980, 1981-1985, 1986-1990, 1991-1995, 1996-2000, or 2001-2004 period.

Finally, we controlled for the effects of two technology "bubble" periods by including indicators for whether a VC firm's current investments were made in these periods. The first period covered the time from the end of 1980 (i.e. after the IPOs of Apple Computer and Genentech) until the end of 1985. The second period covered the time from September 1995 (following the IPO of Netscape Communications) until the end of 2001. We expected that VC firms that had not previously invested in emerging high-technology domains might exhibit a herding tendency to (not to) do so in these particular periods.

[5] The index varies between 0.11 and 1, with a higher score representing higher concentration. Because the initial investment periods were excluded from the analysis, there was a positive number of prior investments for all spells in the data. The minimum value is obtained when the VC firm has invested previously in all nine industries in equal proportions.

4.6. Model and Analysis

In all estimations, taking into consideration the multiple observations per VC firm, we clustered the data by VC firm, thereby adjusting the standard errors for the non-independence of these observations. In choosing a model for estimating the hazard rate of VC firms' making exploration investments, a test of the proportional hazard assumption – based on the existence of nonzero slopes in a regression of the (scaled) Schoenfeld residuals on functions of time (Grambsch and Therneau 1994) – revealed that it was violated, thereby rendering a semi-parametric, proportional hazard model inappropriate (Cox 1972). We therefore looked for a parametric form of the baseline hazard rate. Considering that in the context of VC exploration the hazard rate of investing early monotonically decreases with time as the exploration window gradually closes and the technology / industry becomes more established, we estimated the hazard rate using a Weibull model[6] with the following hazard rate function:

$$h_i(t) = pt^{p-1}\exp[\mathbf{BX_i}]$$

where $h_i(t)$ is the hazard rate for a VC firm (i) to enter a new industry at time (t) given that it hasn't done so previously, $\mathbf{X_i}$ is a vector of covariates for firm (i), $\mathbf{B}$ is the vector of the coefficients that need to be estimated for these covariates, and *p* is a Weibull distribution parameter estimated from the data. It was estimated to be less than one in all models, indicating that there was indeed a negative duration dependence effect.

Event history estimation results critically depend on the precise compilation of risk sets, i.e. the set of firms at time *t* that are considered at risk of experiencing a particular event at time *t* (Ezell et al. 2003; Therneau and Grambsch 2000). In analyzing data with repeated events, the essential choice is between the Andersen-Gill counting process model and the Prentice, Williams and Petersen conditional risk models, with the actual choice depending on the theoretical considerations underlying the estimation (Ezell et al. 2003). The former approach does not distinguish between events of different order, uses unrestricted risk sets, and thus models the baseline hazard as shared by all events

[6] To verify the appropriateness of the Weibull specification, we made a non-parametric estimation of the survivor function [s(.)] using the product limit estimator and derived a transformation [ln(-ln(s(.)))] that would make a Weibull survival function linearly dependent on the log of time. Plotting the transformed non-parametric survivor function against the log of time revealed a linear relationship, thereby confirming the validity of the Weibull specification (Blossfeld et al. 2007).

(Andersen and Gill 1982). The latter approach allows the baseline hazard to vary for higher-order events and restricts the set of firms at risk of experiencing the k^{th} exploration only to those firms that have the $(k-1)^{th}$ exploration (Prentice et al. 1981). As Ezell, Land, and Cohen comment, "The Anderson-Gill model is the preferred model when the substantive interest surrounds the overall rate of recurrence through the effect of common parameter estimate, especially when few subjects experience two or more events and when there is a substantive interest in knowing whether the hazard rate is increasing/decreasing with the unfolding of the event process" (2003: 138). Given our interest in repetitive momentum and the nature of our data, we used the Anderson-Gill model[7].

5. Results

5.1. Main analysis

Table 1 shows the descriptive statistics for the variables used in the analyses. The estimation results for the counting process Weibull model are shown in Table 2. Model 1 includes only the control variables; Model 2 adds the main effects of the number of prior explorations and time since prior exploration; Model 3 adds the main effect of early exploration; Model 4 adds the interaction effect of early exploration and the number of prior explorations. In Model 5, we re-estimated the full model after excluding the early period of each VC firm. As the models were estimated with proportional hazard formulation, the exponentials of the reported coefficients provide the hazard ratio (HR) for each variable, i.e. the multiplier of the hazard rate for a unit increase in the particular variables, all other factors being equal. All models are significant and the addition of both the main and interaction effects improves the model fit. The full model has the best fit, attesting to the importance of all the included variables. In addition, the exclusion of the early periods did not change the pattern or the significance of the results.

[7] To examine the sensitivity of our results to the usage of unrestricted risk sets, in a separate analysis we estimated the hazard of exploration using a conditional risk set model, whereby we stratified the estimation based on the sequential number of the exploration event that a firm was at risk of experiencing, e.g. 3rd exploration if the firm had experienced 2 exploration events previously (Prentice, Williams and Peterson 1981). In this method, the effect of prior exploration is subsumed in the variation of the baseline hazard rate across strata. Because there was a significant drop in the number of firms experiencing more than 4 explorations, we put all such cases in one stratum. The effects for early exploration and time since last exploration were consistent with those reported below. In addition, the interaction effects reported below were corroborated by variations of the effect of early exploration across strata. The results of this estimation are not shown here due to space limitations but are available from the first author upon request.

Hypotheses 1a and 1b predicted a momentum effect for prior exploration, with the likelihood of exploration decreasing with the time elapsed since the last exploration. The main effect for the number of prior explorations was not significant in Models 2 and 3, but was positive and significant in Models 4 and 5 ($\beta = 0.131$ and 0.147, $p < .001$). These results suggest that the effect of the number of prior exploration depends on the VC firm's early exploration: it is positive only for the subset of firms that have not explored early. These findings provide qualified support for Hypothesis 1a and discuss the contingent effect of the number of prior explorations in the context of Hypothesis 2b below. The effect for the time elapsed since the last exploration is negative and significant in all models ($p < .001$). As the coefficient in Model 4 implies, one year following an exploration event the hazard of exploring decreases by 17% ($e^{-0.015*12}$). This finding provides support for Hypothesis 1b.

Hypothesis 2a predicted a positive effect of early exploration on the hazard of exploration in a given period. The coefficients for early exploration were positive and significant ($p < .001$) in all models, suggesting a strong positive effect for early exploration. The hazard ratio for the main effect of early exploration in Model 3 is 1.9 ($e^{0.643}$), implying that VC firms that had explored early were almost twice more likely to explore again. This finding provides strong support for Hypothesis 2a. In addition, Hypothesis 2b predicted that VC firms that explore early will exhibit a lower propensity to explore as the number of prior explorations increases. The interaction effect of early exploration and the number of prior explorations was negative and significant in both Models 4 and 5 ($p < .001$). Figure 2 illustrates this interaction effect by showing the hazard rate multipliers across different levels of prior exploration for VC firms that had explored early in their lives and for those that had not. As the plot shows, cumulative exploration subdues the imprinting effect of early exploration: initially, firms that had engaged in early exploration were overall more likely to explore again – attesting to the lasting effect of early exploration – but that edge disappeared as the number of prior explorations increases. This result provides support for Hypothesis 2b. In addition, consistent with hypothesis 1a, cumulative exploration increases the exploration hazard for VC firms that had not explored early.

Insert Tables 1, 2 and Figure 2 about here

5.2. Robustness Analyses

We performed several additional analyses to examine the robustness of our results. First, because many VC investments are syndicated, the involvement of a particular VC firm may vary based on whether or not the firm is a lead investor in that specific investment. In addition, non-lead investors may be invited to participate in investments and thus engage in exploration for reasons other than those espoused in this paper. To examine the possibility that exploration could be affected by the lead vs. non-lead status of the VC firm, we re-estimated Model 4 from Table 2 using only the cases in which the VC firm explored as a lead investor. Because the exact amounts invested by each VC firm in each portfolio company were not reliably provided in the data, we inferred the firm's lead status in two ways: (1) by its being a first-round investor, i.e. when no other VC firms had invested in the company previously and, further, (2) by there being no more than 3 investors involved in that first round. The results of these re-estimations, based on these two specifications of the set of explorations in which the VC firm was a lead investor, are provided in Models 1 and 2 of Table 3. They are consistent with the results in Table 2 and thus rule out lead status as an interfering explanation.

Second, because it is plausible to argue that VC firms are more likely to explore sub-industries that are closer to their existing portfolios – i.e. when the VC firms has invested extensively in other areas of the same main industry category – we sought to determine whether our results held in cases where the sub-industries were unfamiliar to the VC firms. We thus re-estimated Model 4 from Table 2 using only the cases in which the VC firm explored into sub-industries for which (1) it had made no more than two investments in the respective main industry and, further, (2) the exploration was made as a first-round investment. The results are provided in Models 3 and 4 of Table 3. They are consistent with the results in Table 3 and thus further reinforce our main results.

Finally, a potent rival explanation for our repetitive momentum and early exploration results concerns the existence of unobservable heterogeneity among the VC firms, whereby they have constant but unequal probabilities of exploring due to factors not captured in our models (Ezell et al. 2003), such as the prior experience, and/or the social networks of their general partners. Although our correction of the standard errors for the dependence of repeated observation helped alleviate such concerns (Allison 2005), we sought to rule out such rival explanation by re-estimating Model 5 of

Table 2 with a fixed-effects specification. This approach stratifies the estimation, with each VC firm assigned to a separate stratum, whereby all firm-specific, time-invariant effects are subsumed in the baseline hazard rate of each stratum (Allison 2005). Because such estimation is more readily made in a Cox proportional hazard model and requires a gaptime formulation of the risk intervals, we modified our data by aggregating the spells within each exploration event and re-set the time clock to zero at each exploration event. This modification ensured that there were no multiple spells within each exploration event that would cause overlap in the gap times. The estimation results are presented in Model 5 of Table 3[8]. They are consistent with those in Table 2 and thus further reinforce our main findings. We note that the fixed-effects specification captures only within-firm variability and thus essentially excludes the firms that have not engaged in exploration.

Insert Table 3 about here
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6. Discussion and Conclusion

Engaging in both exploration and exploitation is essential for short and long term performance. Yet, a common consequence of the reinforcement logic inherent to organizational learning is that exploitation can drive out exploration, as organizations' continuous mastery of their existing domains offers familiar, short-term choices with lower average returns but also with lower standard deviations, in contrast to the uncertainty associated with the exploration of new domains, with bigger payoffs for bigger risks. In this context, we examine the conditions under which firms engage repeatedly in exploration. Using an organizational learning perspective, we linked repeated exploration to the existence and usage of exploration rules, and discussed two factors that affect exploration at a given point in time: the momentum of prior exploration and the imprinting effect of early exploration rules.

Our study of investment decisions made by US VC firms over the period 1962-2004 allowed us to examine how different firms responded to the emerging investment opportunities in high technology sectors, given their previous investment choices. Consistent with the behavioral learning

[8] As a precursor to this analysis, a re-estimation of our main model using a Cox proportional hazard model and a gaptime formulation revealed results consistent with those reported in Table 2.

rationale, we provide evidence that prior exploration increases the likelihood of future exploration, and that this likelihood decreases with the time elapsed since the last exploration. In addition, we found that VC firms that had explored early in their lives were more likely to do so again later on. More significantly, we found that this imprinting effect weakens as the number of prior explorations increases. In the paragraphs below we discuss the contribution of our work to the literatures on exploration and organizational learning.

Studying organizational actions and cumulative learning longitudinally allowed us to add theoretical depth to the understanding of the drivers of exploratory behavior. Our results extend previous work on the sequencing of exploration and exploitation (e.g. Lavie and Rosenkopf 2006), by providing evidence that such sequencing varies across firms, and by identifying the behavioral conditions that are conducive to its occurrence. Indeed, whereas Lavie and Rosenkopf (2006) inferred the sequence from observed increases or decreases of exploration tendencies over time (given their initial levels), we related such variations to the interaction between prior exploration and imprinting. In addition, we see the pattern of exploration behavior over time not necessarily as monotonic decrease or increase in intensity, but as periodic, not incessant repetition. Figure 3 illustrates this notion using the predicted values of the hazard of exploration for the VC firm in our sample that has engaged in the highest number of explorations. The spikes in the graph correspond to the exploration events and the initial spike illustrates the effect of imprinting. Despite the overall suppressing effect of time, each exploration flexes and refreshes the exploration rules within the firm, thereby preventing their lapse into oblivion.

Insert Figure 3 about here

Reflection on this pattern allows us to engage in the conversation on the nature and determinants of organizational ambidexterity (e.g. Raisch and Birkinshaw 2008), of which exploration is an essential component. Because exploitation is a mode that is more naturally inherent to organizations given their focus on efficiency, incremental improvement, and short-term metrics, ambidexterity is enacted over time through repeated exploration. In addition, because of the lag between exploration and its outcomes, engaging in exploration is not necessarily performance-driven.

Instead, it results from the existence, emergence and usage of exploration rules that become honed with practice. An interesting analogy can be drawn with human ambidexterity. Although human ambidexterity is rare at birth, it can be developed with adequate training. Curiously, it is more common to find ambidextrous people that were originally left-handed: because of the wide-spread focus on right-hand ergonomics, such people have better opportunities to practice their weaker hands. From an organizational perspective, we can draw the analogy that organizations are not born ambidextrous and that their current demonstrations of ambidexterity can be traced back through their experience and learning to prior "handedness". We can further speculate – in line with the revealed importance of early imprinting – that organizations have a preferred mode at birth, and that they can develop and refine it well beyond its usefulness, or they can learn a complementary skill. When they do so, they become temporally ambidextrous, invoking each skill as it becomes needed.

We also introduce the idea of organizational imprinting to the context of exploration activities. Engaging in novel activities early in the organization's life – as opposed to doing and copying what other organizations do – develops and ingrains exploration rules in the organization's repertoire. Just as founder characteristics or founding moments have a persistent effect on the values and processes associated with organizational decisions (Boeker 1988, 1989; Swaminathan 1996), so do early rules and behavior. While this insight is not particularly novel in the context of human or organizational behavior, it does expand the theoretical domain of organizational learning, because organizational learning scholars – concerned with how particular learning routines affect the organization's future adaptations – have tended to downplay the importance of the organization's set of initial learning conditions. For young organizations, exploration may become a vested interest (Stinchcombe 1965) and thus a potent agenda for informing future decisions. In contrast, for older organizations not used to exploration, engaging in it may be quite upsetting to their routines, so much so in fact that it may take a long time before they can become outward looking again. This latter view is consistent with interpretive and social constructionist views that argue that innovation in large, established organizations often is an illegitimate activity that creates so many disruptions for the organization that some large organizations chose to forgo innovations rather than face the difficulties inherent to it (Dougherty 1992; Dougherty and Heller 1994).

As a third contribution, we elaborate of the notion of exploration momentum or path dependence. Unlike prior studies that have found a positive relationship between prior exploration and future exploration (Lavie and Rosenkopf 2006) or, more generally, between prior changes and future changes (Amburgey et al. 1993), our results in this regard were more nuanced. Whereas exploration can be encoded into rules that make the organization more likely to engage in further exploration and more adept at it, there is a significant element of organizational learning associated with when such rules should be used. In addition, if unused these rules tend to dissipate with time.

As the organization's exploration experience increases and the organization becomes well versed in the "grammar" of exploration (Pentland and Rueter 1994), determining the appropriateness of engaging in further exploration becomes an important learning hurdle. Too much exploration too soon may render it ineffective whereas too little of it too late may render it forgotten. In this regard, our results show that particular organizations are better positioned to experience and learn the intricacies of sequencing exploration and exploitation over time. Organizations engaging in early exploration can learn to use their exploration rules judiciously. Accordingly, we found that compared to their counterparts such organizations, while initially more likely to explore, become more subdued in their exploration propensity as their exploration experience increases. In other words, exploration imprinting not only entrenches exploration in the worldview of the organization, but also facilitates the refinement of exploration rules.

Inevitably, there are limitations to our study. First, even though we used the concept of organizational rules to derive predictions about the relationship between past behavior and exploration, our data did not allow us to properly capture this intermediary mechanism; rather we attributed the firms' consistency in behavior over time to the enactment of relevant rules: we attributed purposes to the patters we observed. We note that this limitation is typical for empirical studies using an organizational learning logic in that there is significant complexity associated with directly measuring learning mechanisms. Second, our exploration inferences were based on an *ex post,* and possibly changing, industry classification and not on the contemporaneous perceptions of the decision makers. With time, as different sense is being made and recorded of the decision makers' original considerations and actions, the degree of novelty attributed to each decision may change.

While we sought to address this deficiency of our data by conducting certain sensitivity analyses, we also acknowledge that difficulty of studying exploration after much of the original uncertainty surrounding it has been resolved.

Third, while we found the VC context appropriate for examining the organizational behavior associated with repeated exploration, generalizations beyond our context should be made with care, as is the case with any generalization. It is obviously possible that exploration in the VC industry is different from exploration in other industries. After all, simply put, VC firms invest "other people's money" instead of their own, but that is also common in publicly owned firms in a variety of industries. We used the structural simplicity of VC firms to focus on the behavioral dynamics of exploration, yet, the counter-weight to our choice lies in the external validity of our results. In particular, given the nature of VC activity and the discrete nature of their investment projects, exploration and exploitation can effectively co-exist, with limited disturbance of one another. Because such features may be particularly conducive to the behavioral factors driving exploration, straight application of this logic may not be possible to settings where exploratory activities potentially disturb core activities, and thus need to be de-coupled from the core organizational processes. Naturally, such limitation suggests that a more elaborate examination of the mutual inter-dependency between organizational structure and learning processes in their determination of repeated exploration represents a promising avenue for future research.

In conclusion, a considerable amount of organizational literature, both academic and practitioner-oriented, is devoted to examining the benefits of exploration and distinguishing organizations that "balance" efficiency and flexibility. The nature of organizational learning and the role that attention plays in guiding current actions make organizations susceptible to simplicity in behavior (Miller 1993), particularly towards behavior that maintains stability and improves efficiency. Our study has taken a small but decisive step in uncovering the dynamics of exploration and its relationship to prior decisions and evolving organizational characteristics.

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Table 1 Descriptive Statistics and Correlations [a]

		Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Early exploration	0.29	0.45	1.00														
2	Number of prior explorations	2.19	4.19	0.62	1.00													
3	Time since prior exploration	27.37	52.10	0.49	0.26	1.00												
4	VC firm less than 2 years old	0.21	0.40	-0.32	-0.25	-0.26	1.00											
5	Number of portfolio companies	51.28	82.50	0.37	0.71	0.31	-0.28	1.00										
6	Early-stage investments	0.41	0.26	0.11	0.09	0.00	0.01	0.08	1.00									
7	Non-high-tech investments	0.25	0.26	0.02	0.04	0.06	-0.10	-0.04	-0.38	1.00								
8	Industry specialization	0.40	0.25	-0.36	-0.36	-0.29	0.51	-0.34	0.04	-0.19	1.00							
9	New fund raised in last 2 years	0.70	0.46	-0.09	-0.01	-0.11	0.22	0.11	0.07	-0.11	0.07	1.00						
10	Private firm	0.61	0.49	0.02	0.00	-0.08	-0.01	0.04	0.20	-0.08	-0.02	0.16	1.00					
11	Corporate subsidiary	0.09	0.28	-0.06	-0.10	-0.04	0.06	-0.11	-0.04	-0.18	0.21	-0.06	-0.39	1.00				
12	Affiliate of fin. Institution	0.17	0.37	0.03	0.13	0.07	-0.05	0.09	-0.15	0.16	-0.11	-0.06	-0.56	-0.14	1.00			
13	Located in California	0.29	0.45	0.04	0.02	-0.04	0.00	0.05	0.19	-0.23	0.04	0.07	0.13	-0.01	-0.11	1.00		
14	Located in Massachusetts	0.12	0.33	0.06	0.08	0.10	-0.06	0.08	0.01	-0.03	-0.06	0.04	0.07	-0.05	-0.06	-0.24	1.00	
15	Period Jan-81 - Dec-85	0.13	0.33	0.15	0.11	-0.05	0.08	-0.11	0.01	0.11	-0.05	0.00	-0.04	-0.03	0.05	-0.01	0.00	1.00
16	Period Sep-95 - Dec-01	0.42	0.49	-0.17	-0.11	0.04	0.06	0.05	-0.04	-0.10	0.12	0.13	0.03	0.06	-0.05	0.02	0.00	-0.33

[a] N = 49,134. All correlations with absolute value greater than .009 are significant at $p < .05$.

Table 2 Weibull Regression Estimation of the VC Firms' Hazard of Exploration*

Independent variables	**Model 1**			**Model 2**			**Model 3**			**Model 4**			**Model 5**		
Number of prior explorations				0.02		(0.01)	-0.015		(0.01)	0.131	***	(0.03)	0.147	***	(0.03)
Time since prior exploration				-0.01	***	(0.00)	-0.013	***	(0.00)	-0.015	***	(0.00)	-0.013	***	(0.00)
Early exploration							0.643	***	(0.14)	1.074	***	(0.14)	0.935	***	(0.15)
Early expl X Prior explorations										-0.165	***	(0.03)	-0.171	***	(0.03)
VC firm less than 2 years old	0.821	***	(0.10)	0.854	***	(0.10)	1.169	***	(0.14)	1.222	***	(0.14)			
Number of portfolio companies	0.000		(0.00)	-0.001		(0.00)	0.000		(0.00)	0.000		(0.00)	0.000		(0.00)
Early-stage investments	0.147		(0.13)	0.155		(0.12)	0.130		(0.11)	0.121		(0.11)	0.258	+	(0.15)
Non-high-tech investments	-0.681	***	(0.13)	-0.846	***	(0.13)	-0.691	***	(0.13)	-0.576	***	(0.12)	-0.605	***	(0.16)
Industry specialization	-2.395	***	(0.17)	-2.203	***	(0.17)	-2.055	***	(0.17)	-1.810	***	(0.17)	-2.604	***	(0.26)
New fund raised in last 2 years	0.509	***	(0.08)	0.411	***	(0.07)	0.383	***	(0.07)	0.359	***	(0.07)	0.374	***	(0.08)
Private firm	0.203	+	(0.10)	0.093		(0.10)	0.081		(0.10)	0.081		(0.09)	0.128		(0.11)
Corporate subsidiary	-0.046		(0.16)	-0.074		(0.14)	-0.074		(0.14)	-0.063		(0.14)	-0.034		(0.17)
Affiliate of fin. Institution	0.136		(0.13)	0.035		(0.11)	0.053		(0.12)	0.049		(0.11)	0.054		(0.12)
Located in California	0.098		(0.09)	0.048		(0.08)	0.028		(0.08)	0.070		(0.08)	0.161	+	(0.09)
Located in Massachusetts	0.081		(0.11)	0.104		(0.09)	0.124		(0.09)	0.130		(0.09)	0.209	*	(0.10)
Period Jan-81 - Dec-85	0.061		(0.07)	0.036		(0.07)	0.005		(0.07)	0.005		(0.07)	0.046		(0.08)
Period Sep-95 - Dec-01	-1.120	***	(0.10)	-0.808	***	(0.09)	-0.748	***	(0.09)	-0.699	***	(0.09)	-0.640	***	(0.10)
Constant	-1.694	***	(0.28)	-1.785	***	(0.28)	-2.396	***	(0.31)	-2.958	***	(0.32)	-1.498	***	(0.41)
Weibull parameter [ln(p)]	-0.37	***	(0.04)	-0.23	***	(0.04)	-0.17	***	(0.04)	-0.13	**	(0.04)	-0.43	***	(0.07)
	-			-			-			-			-		
Log likelihood	2,079.25			1,941.93			1,918.53			1,889.96			1,111.97		
Chi square	1,542.50	***		2,087.56	***		1,945.42	***		2,148.99	***		1,552.55	***	
Chi square, LL change				274.64	***		46.80	***		57.14	***				
N	49,134			49,134			49,134			49,134			39,041		
Number of exloration events	1,347			1,347			1,347			1,347			1,064		

*Note: Controls for VC firm founding period are included in the models but not reported in the table. In Model 5, the spells covering the early period (first 2 years) of each VC firm have been excluded from the estimation. Robust standard errors adjusted for within-cluster correlation reported in parentheses.
*** $p < .001$, ** $p < .01$, * $p < .05$, + $p < .10$.

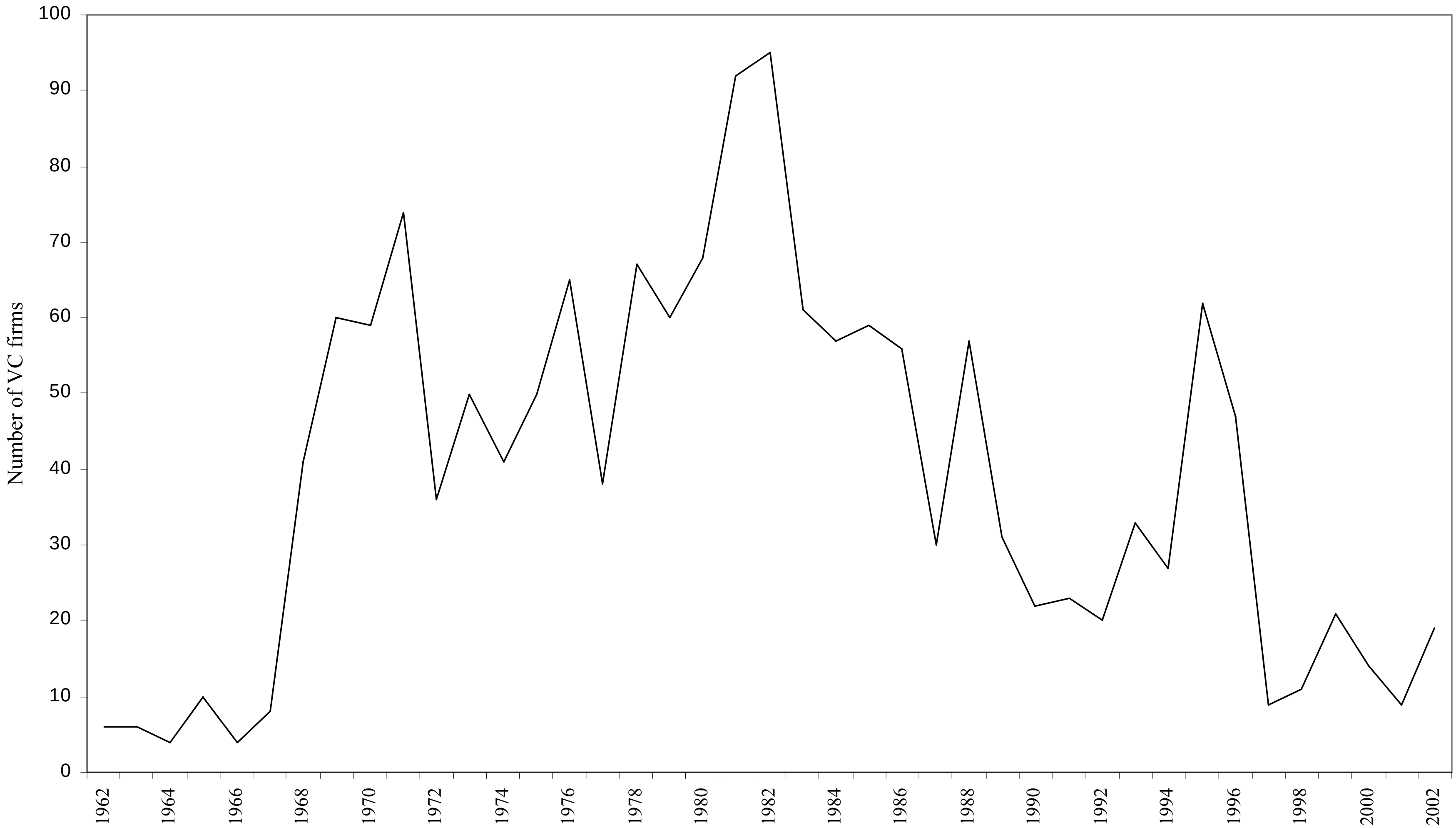
Table 3 Robustness Estimations of the VC Firms' Hazard of Exploration*

Independent variables	Model 1			Model 2			Model 3			Model 4			Model 5*		
Number of prior explorations	0.144	***	(0.03)	0.129	***	(0.03)	0.165	***	(0.03)	0.191	***	(0.05)	0.532	***	(0.07)
Time since prior exploration	-0.015	***	(0.00)	-0.015	***	(0.00)	-0.019	***	(0.00)	-0.020	***	(0.00)	-0.113	***	(0.01)
Early exploration	1.174	***	(0.17)	1.209	***	(0.19)	1.558	***	(0.18)	1.676	***	(0.22)	1.282	***	(0.27)
Early expl X Prior explorations	-0.183	***	(0.03)	-0.180	***	(0.04)	-0.212	***	(0.04)	-0.242	***	(0.05)	-0.540	***	(0.07)
VC firm less than 2 years old	1.193	***	(0.16)	1.227	***	(0.17)	1.770	***	(0.17)	1.751	***	(0.20)	0.411	+	(0.21)
Number of portfolio companies	0.000		(0.00)	0.000		(0.00)	-0.015	**	(0.01)	-0.020	***	(0.00)	-0.003	**	(0.00)
Early-stage investments	0.329	*	(0.15)	0.339	*	(0.15)	-0.044		(0.12)	0.102		(0.16)	-0.001		(0.33)
Non-high-tech investments	-0.320	*	(0.15)	-0.293	+	(0.16)	-0.274	*	(0.13)	-0.020		(0.16)	-1.088	**	(0.40)
Industry specialization	-1.637	***	(0.19)	-1.648	***	(0.20)	-1.425	***	(0.18)	-1.422	***	(0.21)	-0.896	*	(0.38)
New fund raised in last 2 years	0.390	***	(0.09)	0.416	***	(0.09)	0.279	**	(0.10)	0.251	*	(0.11)	-0.068		(0.14)
Private firm	0.245	*	(0.12)	0.270	+	(0.14)	-0.001		(0.10)	0.172		(0.14)			
Corporate subsidiary	-0.094		(0.17)	0.002		(0.19)	-0.044		(0.15)	-0.076		(0.20)			
Affiliate of fin. Institution	0.152		(0.15)	0.179		(0.16)	-0.001		(0.12)	0.128		(0.15)			
Located in California	0.089		(0.09)	0.089		(0.10)	-0.078		(0.09)	-0.089		(0.11)			
Located in Massachusetts	0.191	+	(0.11)	0.292	*	(0.12)	0.043		(0.11)	0.099		(0.13)			
Period Jan-81 - Dec-85	0.088		(0.08)	-0.118		(0.10)	0.057		(0.08)	0.229	*	(0.09)	-0.127		(0.15)
Period Sep-95 - Dec-01	-0.583	***	(0.11)	-0.419	***	(0.11)	-0.983	***	(0.15)	-1.027	***	(0.19)	1.571	***	(0.30)
Constant	-3.694	***	(0.37)	-3.727	***	(0.39)	-3.809	***	(0.35)	-4.334	***	(0.40)			
Weibull parameter [ln(p)]	-0.15	**	(0.05)	-0.17	**	(0.06)	-0.01		(0.05)	-0.03		(0.05)			
Log likelihood	- 1,580.16			- 1,500.00			- 1,631.59			-1,263.23			-810.32		
Chi square	1,698.49	***		9,348.92	***		1,940.54	***		1,370.11	***		1,761.03	***	
Chi square, LL change															
N	49,134			49,134			40,379			40,379			3,467		
Number of exloration events	880			755			859			573			1,347		

*Note: Controls for VC firm founding period are included in the models but not reported in the table. The estimation in Model 5 uses a Cox proportional hazard model, a gaptime formulation of risk internals, and single spell per exploration event. Robust standard errors adjusted for within-cluster correlation reported in parentheses.

*** $p < .001$, ** $p < .01$, * $p < .05$, + $p < .10$.

Figure 1 Exploration in the US VC Industry



Note: Vertical axis shows the number of VC firms making their first investment in a high-technology sector, which is also among the first 50 VC investments made in that sector.

Figure 2 Interaction Effect of Early Exploration and Number of Prior Explorations on the Hazard of Exploration

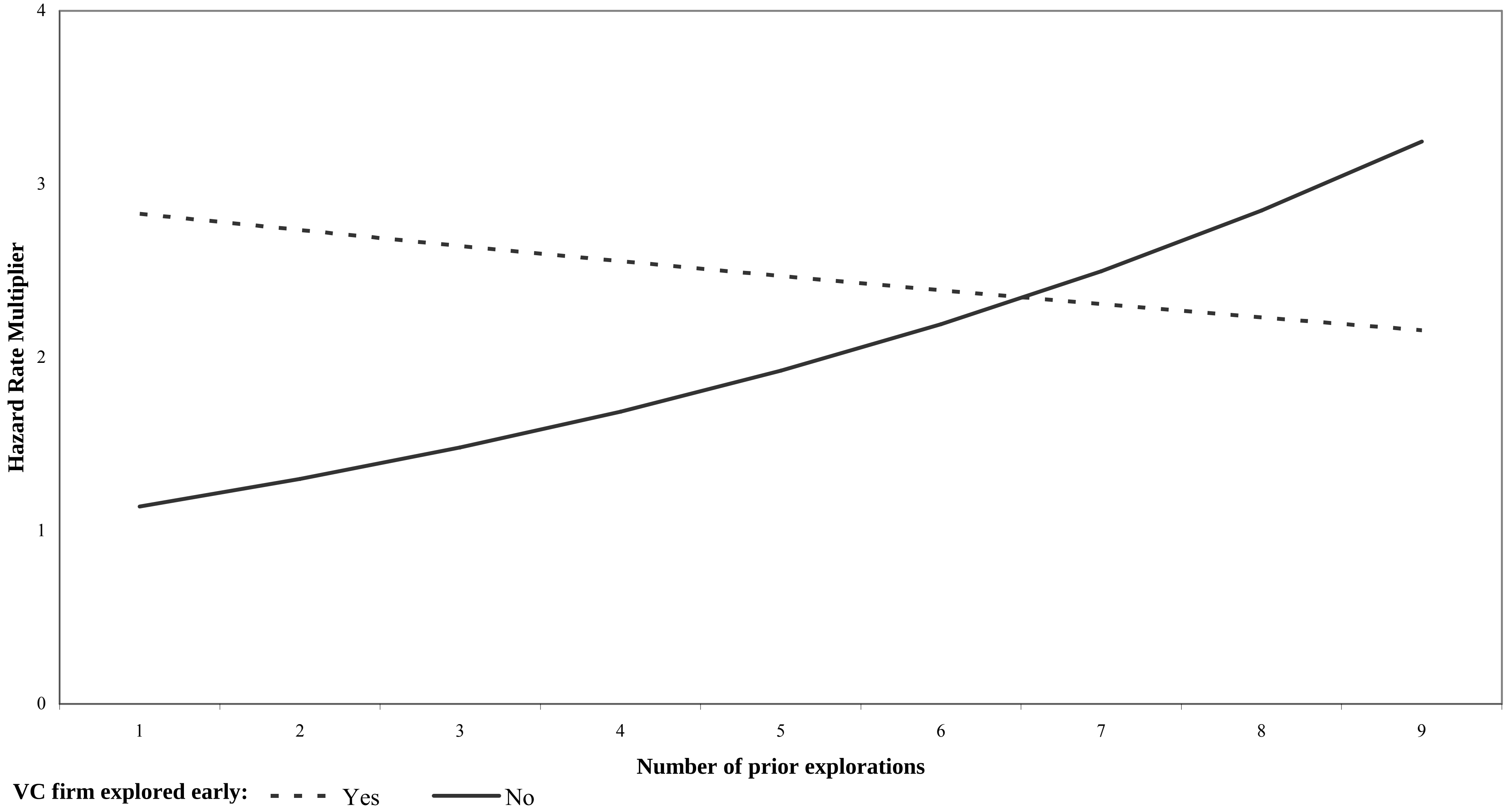
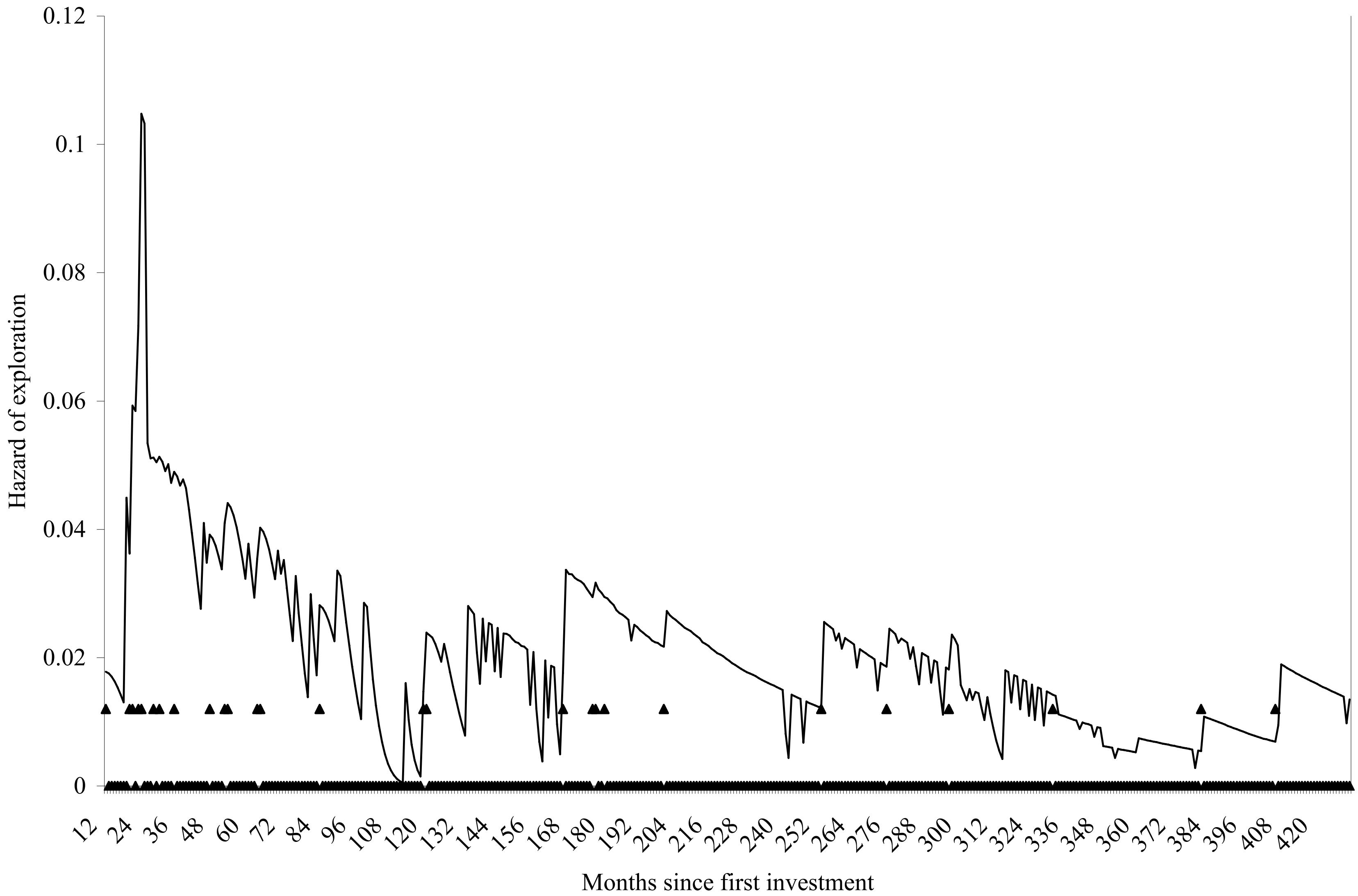


Figure 3 Illustration of the Hazard of Exploration over Time



Note: The triangles mark the occurrence of exploration events.