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Learning patterns in venture capital investing in new industries

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Using an organizational learning perspective, we link the decision by venture capital (VC) firms to invest early in a new high-technology industry to three experiential learning mechanisms: the familiarity associated with accumulation of early funding decisions, the shaping or imprinting effect of the firm's very first such decision, and the decay or "forgetting" associated with the dormancy of prior such decisions. We find support for these learning patterns using data on the investments made by US VC firms between 1962 and 2004.

JEL classification: D83, G24, L26, M13, O31.

1. Introduction

The second half of the 20th century has been characterized by awave of technological changes with profound social and economic impact (e.g. Mowery and Rosenberg, 1998). Among the many contributing conditions for the rapid increase in the extent and nature of technological innovation, we note the emergence and availability of venture capital (VC) to fund new ideas (Florida and Kenney, 1988b; Chesbrough, 1999; Kortum and Lerner, 2000; Hsu and Kenney, 2005). VC allows entrepreneurs to explore the merits of various technologies outside the sometimes rigid confines of large corporations (Florida and Kenney, 1988a), permitting uncertain but interesting ideas to be tested in practice. The "venture capital model," whereby risky ideas receive funds in exchange of ownership of the firm created to develop them has

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been largely successful (Gompers and Lerner, 2001), and consequently, the VC industry has expanded not only in scale, but also across borders, albeit with mixed intensity and success. In this regard, there is growing innovation policy attention toward understanding the mechanics of a healthy industry, and the promotion and development of active VC firms (Da Rin *et al.*, 2006).

Looming large in this historical co-evolution between VC and new high-technology opportunities are the early funding decisions that VC investors make in newly emerging sectors. These decisions have not only received little explicit attention in the literature, but also—due to their surrounding lack of objective benchmarks and converging narratives of industry evolution—do not easily fit within existing conceptions of VC decision making. Two observations can be made in this regard. First, while much research has operated with the implicit notion that there exist some archetypal selection criteria or cognitive processes (e.g. MacMillan *et al.*, 1985; Munari and Toschi, 2011), recent research suggests that there is systematic variation between investors' background and experience and the decisions they make (Dimov *et al.*, 2007; Patzelt *et al.*, 2009). Indeed, generic and relatively crude criteria such as "quality of the management team," "large market potential," and "strong competitive position" can be quite ambiguous in specific situations unless interpreted through the "lens" or depth of specific experience.

Second, as we illustrate in further detail below, qualitative accounts of the considerations associated with the early financial backing of pioneering companies vividly illustrate the tacit and ultimately admirable judgments that these early investors make (e.g. von Burg and Kenney, 2000), but also the messy reality behind these choices. These considerations raise the question of whether there exists any systematic pattern to the early investments made by VC firms beyond the prescient "gut" feelings (e.g. Hisrich and Jankowicz, 1990) featured in success anecdotes or the aura of inevitability that permeates most retrospective accounts of the birth of high-technology industries.

In this article, we look for such patterns in the context of VC investments in emerging high-technology industries over the past 50 years. Two main questions motivate our study: (i) what are the factors that make VC firms more likely to invest early in new industries? and (ii) how do these influences change over the life of the VC firms and in the context of their portfolio evolution? We examine these questions from an organizational learning perspective. Central in this perspective is the notion of behavior as rule-based, with rules emerging from the organization's experience to perpetuate certain desirable actions in response to particular problems (Cyert and March, 1963; Schulz, 1998), but also dissipating if organizational attention shifts away from such problems (Zhou, 1993). In that vein, we argue that a VC firm's decision to invest early in an emerging, yet unfamiliar industrial domain may have rule-like, experiential underpinnings, as a way of avoiding the painful deliberation associated with quantifying what cannot yet be quantified. Accordingly, we relate a VC firm's likelihood of making an early funding decision to three learning processes that affect the intensity and relevance of such rules: (i) accumulation which yields familiarity and momentum associated with prior early funding decisions; (ii) imprinting, stemming from the differential, shaping effect of the firm's first such decision; and (iii) the decay or "forgetting" associated with the dormancy of such prior decisions.

Observing these patterns requires examination of early funding decisions across an inclusive set of organizations and over time. Our data capture the evolution of the US VC industry from its early period in 1962 until 2004, as it unfolds. Over this period, 40 high-technology industry domains have emerged; some have ultimately become established, while others have borne no fruit at all for their investors. In our analyses, we identified 1764 "early" investments among 4446 VC firms active over that period; each investment was examined in the context of the VC firm's evolving portfolio, and was linked to the firm's prior investment experience as well as other characteristics of the firm and the investment environment.

We seek to make three contributions to our understanding of the "art" of VC investment decisions, with broader implications for the academic dialogue on organizational learning. First, observing the broad ecology of funding decisions—some early and others late in the lifecycle of the recipient industry—highlights the repeated nature of early funding decisions and their experiential origins. We identify several behavioral paths that can affect the occurrence of the subsequent such decision for a VC firm. Second, we extend the notion of organizational imprinting to the context of VC investments and elaborate on the long-term repercussions of a VC firm's very first investment in an emerging sector. The ability of organizations to differentiate and learn from their first such experience can affect the degree to which making such investments again is seen as an appropriate action in the future. Finally, we offer new insights into the learning decay associated with dormant experience and its undermining of future early funding decisions. We show that such dormancy is driven not so much by age-fueled decay as by the extent of subsequent, other investments made by the VC firm.

2. Overview of the US VC industry

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 (Sapienza, 1992; Hellman and Puri, 2002), and ultimately seek to sell their equity stakes in these companies to third-party investors, as is the case with initial public offerings (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 industries 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).

The development of the VC industry in the United States represents a gradual evolution of institutional arrangements that have enabled the emergence of VC intermediaries and the smooth operation of the VC cycle, in which funds flow from institutional investors through VC firms to entrepreneurial companies and back (Gompers and Lerner, 1999). In this regard, understanding the development of the US VC industry cannot be detached from its historical context and surrounding enabling conditions. One of the industry pioneers, Hambrecht (1984), outlines three catalytic events that have contributed to the technological leadership of the United States and the development of its VC industry: the emigration of prominent scientists and engineers from Europe in the 1930s, the massive investment in government research and development during the World War II, and the G.I. Bill. The emergence of the first VC company, American Research and Development Corporation (ARD), in 1946 reflected a growing strive for commercialization of the technologies developed in public research institutions.

Equally crucial for the industry development has been the presence of an active stock market, offering a lucrative exit route for VC-backed companies at critical junctions of the industry development, thereby spurring further VC fundraising and investing. Notably, ARD's success and iconic role in the VC industry is largely associated with its investment of $70,000 in Digital Equipment Corporation in 1957 that generated a gain of $355 million in 1971, raising the 25-year return of the entire ARD portfolio from 7.4% to 14.7% (Hsu and Kenney, 2005). The NASDAQ market has been the underpinning of the US VC industry, exemplifying its well-functioning exit mechanisms. Since, its creation in 1971, it has outpaced all other US markets in IPO listings and has been, so far, the most successful secondary market in the OECD. At its height in 1999, it listed nearly 5000 firms and had a market capitalization of over 50% of GDP (OECD, 2003).

Finally, the US VC market today reflects a learning and knowledge diffusion process that spans more than half a century and generates subsequent generations of investment managers. For example, the founders of some of the most prominent US VC firms can be traced back to the class on venture capitalism taught by one of ARD's founders, George Doriot, at Harvard Business School or to ARD itself. As Hsu and Kenney (2005) discuss, two class alumni, Arthur Rock and Thomas Davis, formed one of the earliest limited partnership funds (Davis and Rock) in 1961 that 9 years later turned a $3 million initial investment into a $100 million disbursement. Thomas Davis later founded the Mayfield fund, a prominent Silicon Valley VC firm with a track record of over 100 IPOs. Arthur Rock is another icon VC investor, credited with coining the term "venture capital." Continuing the ARD heritage, William Elfers left this firm to start Greylock Partners, another blue-chip firm, in 1965.

Throughout the industry's development, the US government has played a key role by providing incentives and support as well as changing regulations at key junctions. From the mid-1950s, with the passage of the Small Business Act in 1953, the attention of US policy was directed toward the financial needs of small businesses. The Small Business Investment Company (SBIC) program, launched in 1958, was designed "... to stimulate and supplement the flow of private equity capital and long-term funds which small-business concerns need for the sound financing of their business operations and for their growth, expansion, and modernization, and which are not available in adequate supply" (Widicus, 1966). It led to the establishment of SBICs designed to increase the availability of funds to new ventures.

Small Business Investment Companies (SBICs) were private corporations specially licensed to provide capital to risky ventures. SBICs were allowed to supplement their capital with special loans from the Small Business Administration (SBA) that were subject to certain tax benefits. In exchange for the loans, the SBA placed restrictions on the investment activity of the SBICs toward risky ventures. In the first 5 years of the program, 692 SBIC licenses were granted, leading to the management of $464 Million in VC (Fenn *et al*., 1995). Between 1958 and 1969, SBICs provided more than $3 Billion to small firms, over three times the amount of private VC over that period. Despite their gradual decline in importance by the late 1970s, the SBICs provided record amounts of capital to fast-growing companies and helped hone the craft of venture financing.

With the industry gaining momentum and the limited liability partnership emerging as a fundraising vehicle aligning the interests of investors and managers, several key legislations were enacted in the late 1970s that facilitated the flow of institutional funds to VC companies and unleashed unprecedented growth in the industry. First, a clarification by the US Department of Labor of the Employee Retirement Income Security Act's (ERISA) "prudent man" rule lifted barriers to the allocation of pension funds to venture capital or securities of small or young companies. This ruling initially revived the new-issues market for small company stocks and eventually provided a strong impetus for pension fund allocations to VC. The second piece of legislation pertains to a ruling in 1980 by the Department of Labor that granted VC partnerships a "safe harbor" exemption from plan asset regulations (Fenn *et al*., 1995). Finally, the Small Business Investment Incentive Act of 1980 redefined VC partnerships as business development companies, thereby making them exempt from the Investment Advisers Act.

Parallel with and feeding this development was the information technology revolution set in motion in the 1950s, spawning successive waves of entrepreneurial ventures in emerging sectors in need of financial backing. Such ventures are illustrative of the types of investments we study in this article. We focus on venture capitalists' decisions to financially back ventures at the frontier of new sectors, and seek to understand these decisions through the lenses of organizational learning.

3. Theoretical context

Organizational behavior is purposefully patterned (Mintzberg, 1978), and these patterns reflect the logic of appropriateness, whereby organizations invoke learned behaviors as appropriate responses to situations they face (Cyert and March, 1963). Such rule-based action relies on inferences from own past behaviors (Levitt and March, 1988) that are instilled in the assets, standard operating procedures (Cyert and March, 1963), rules (Schulz, 1998; March *et al.*, 2000) and routines (Nelson and Winter, 1982) of the organization.

Since organizations seek to reproduce rapidly and efficiently what they consider "useful" responses to recurring situations, they define and enact rules that limit the set of acceptable behaviors, and consequently shape their repertoire of actions in different situations (Miller and Chen, 1996). Rules, defined as the "explicit or implicit norms, regulations and expectations that regulate (sic) behaviors" (March *et al.*, 2000: 5), create significant efficiencies: they reduce the cost and effort spent on searching for solutions to problems, and this in turn increases the speed of reaction to opportunities. For example, on the basis of their experience, VC firms develop rules of thumb such as considering only investments that are referred through trusted sources, re-investing in previously successful entrepreneurs, or investing only in companies where they fully understand the market.

In the context of the widely discussed exploration–exploitation trade-off that organizations face (March, 1991), to the extent that organizations are prone to seek optimal solutions among their familiar choices (Sutton and Barto, 1998), exploration represents a conscious "swerve" into unfamiliar territory (Sidhu *et al.*, 2007), whereby the organization redirects some of its resources to a new, uncertain area (Holmqvist, 2004). In 1974, Eugene Kleiner and Tom Perkins, the two partners of 2-year old VC firm Kleiner Perkins, eventually to emerge as one of the blue-chip VC firms in Silicon Valley, hired Robert Swanson who was interested in the splicing of genes as a frontier of medical technology, but could not find investment deals (Ante, 2008). Kleiner and Perkins were ready to back him if he got "something going in this area." After numerous cold calls, Swanson met with Professor Herbert Boyer at University of California at San Francisco who at that time was working on drug development through DNA splicing. In April 1976, Swanson and Boyer incorporated Genentech, after investing $500 each. A month later, Kleiner Perkins bought a 25% stake in Genentech for $100,000. This 'swerve' proved to be an important marker in an emerging industry, as in 1980, Genetech was the first biotechnology company to go public.

Since change in general can be costly and disruptive (Hannan and Freeman, 1984; Amburgey *et al.*, 1993), it is not an activity that can be readily undertaken (Tushman and Romanelli, 1985; Barnett and Carroll, 1995): the absence of immediately visible benefits makes novel, uncertain decisions difficult to initiate or repeat. However, to the extent that the "pain" of such decisions is embedded in rules and standard operating procedures, the disruption and the uncertainty associated with the decisions can be alleviated, making their subsequent occurrence more likely. Learning, thus, can facilitate future exploratory decisions through the rules it creates and their enactment in future situations. The early history—as told by Ante (2008)—of Kleiner Perkins provides an interesting illustration of the emergence and importance of experience-based rules to make such exploratory decisions. The firm was founded in 1972 by Eugene Kleiner, from Fairchild semiconductor, and Tom Perkins, a former marketing and later general manager of Hewlett Packard's computer division. Given that their first few investments were not successful, the pair decided to be in control of things by being directly involved in the companies they backed or relying on people they knew and trusted. They brought in James Treybig, whom Perkins had earlier hired at Hewlett Packard, to start and run a computer systems company. Tandem Computers was founded in 1974 with James Treybig as CEO and Tom Perkins as chairman. The company was a spectacular success, going public in 1977 and ranked by *Inc.* magazine in 1980 as the fastest growing public company. The approach was later repeated with Genentech. As Eugene Kleiner later recalled, "In the case of Bob Swanson, we relied on the promise. We didn't have a lot of technical experience in the area, no one did. We turned to high-school biology for help but that didn't help us very much either. We got Steve Packard on the board and he too didn't know much about biotech."[1] Kleiner and Perkins honed this approach further and used it successfully in the backing of future pioneering businesses such as Sun Microsystems, Amazon, and Google.

Learning allows organizations to produce knowledge from their experiences[2] (Huber, 1991). Learning to explore comes through "concerted variation, planned experimentation, and play" (Baum *et al.*,2000: 768) with domains or activities that are unfamiliar to the organization, that is, from mindful exposure to novel situations. Yet, in each exposure, the organization needs to overcome the perceived costs and "uncertain relevance of newness" (Schulz, 2001). In the absence of the assuring certainty of rules, these factors can overpower the appeal of new endeavors. Indeed, because desirability of such endeavors often becomes evident only in the long run, they can be easily pushed aside in the short term, unless rules define them as appropriate at the particular moment. Therefore, different propensities to engage in exploratory behavior can be attributed to the existence and usage of rules that affirm the appropriateness of such behavior. The sustenance of such rules is inherently linked to the organization's experience (Zhou, 1993). We explore this idea below in the context of VC investment decisions.

[1]Interview with Eugene Kleiner in Udayan Gupta (2000)

[2]We acknowledge here that organizations also learn vicariously from the experience of others (Huber, 1991). Our explicit focus in this article is on their learning from own experience.

3.1. Early investments by VC firms

Although they do not bear the bulk of the financial risk associated with their investments, VC firms need to raise new capital on a regular basis, often from the same investors (Gompers and Lerner, 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). In this regard, VC firms continuously face an exploration–exploitation trade-off: investing in companies that operate in familiar industries can bring known albeit smaller and/or diminishing returns, while trying out new and uncertain industries can bring unknown yet potentially higher returns.

Among VC firms, the pursuit of investment opportunities in a particular industry generally follows a pattern with two discernible periods: (i) a slow initial period of uncertainty about the industry, in which only a limited number of companies in the industry receive VC investments from a limited number of VC firms; (ii) as the promise of the industry becomes positively revealed, more and more VC firms start investing in the industry, initiating a period of rapid increase in the number of companies receiving VC investment. It is in the first period that a VC firm's investment in the industry can be deemed *early*, as the nascent industry is novel both to the focal VC firm and the population of VC firms, and poses significant uncertainty in regard to the nature and viability of its investment opportunities.[3] For prospective investors, companies that spur the gestation of new industries and could become the next generation of industry leaders represent non-tractable bets as they may open up currently unknown possibilities, but cannot be justified or even fully understood on the basis of existing knowledge. Indeed, it is easy to admire today the backing of such prominent successes as DEC, Apple Computer, Microsoft, Sun Microsystems, Intel, 3Com, E-Bay, Google, and You Tube; yet, the merits of these investments when originally made were not immediately evident. Each winner has left behind a multitude of losers, including some of their peers who had also received VC but had failed to produce such admirable results. Notably, as von Burg and Kenney (2000: 1139) 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."

Early, exploratory investments and their behavioral antecedents are well illustrated in the context of the US VC industry, which has developed over the past 50 years in unison with the accelerating pace of technology development and commercialization. VC firms have been intimately involved in the emergence and development of new, high-technology industries, backing many of their progenitors. But, in what makes

[3]We note here that prior to receiving funding from VC firms, entrepreneurial companies can be funded by business angels or various other forms of seed capital. Our interest lies in the involvement of VC firms as a more formal community of investors.

this context particularly interesting for a systematic study, VC firms have not been equally prone to make such exploratory moves. Over time and across the population of VC firms and high-technology industries, it is possible to observe whether and when VC firms invest early in these industries and, if so, whether they do so repeatedly.

In early investments, VC investors can play an essential role in constructing the new company or even a whole new industry (von Burg and Kenney, 2000), with their own investment but also by lending legitimacy to an otherwise unproven idea or concept. However, such investments may require paradigmatic shifts in how they are to be identified, appraised, and pursued as the knowledge derived from previous investments may be inappropriate for judging 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. In the absence of objective parameters or indicators, many VC investors would be cautious about backing the companies in question(Eckhardt *et al.*, 2006).

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 with the aim 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 (2000: 1142) observe, "not surprisingly, most venture capitalists could not envision the economic space and could not believe that a startup could construct such a market." 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'' (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). More generally, VC investors can have a significant effect on the commercialization direction of the ventures they back (Hsu, 2006).

Therefore, in considering early investments, VC firms need to foresee and evaluate the commercial potential of new technologies, often within very short timeframes and with partial, incomplete and sometimes faulty information. In doing so, they often seek new sources of information, establish relationships with different sets of experts, and engage with a different set of partners (e.g. law, recruitment, consulting, other VC or even old portfolio firms) to support the new venture. In this regard, their informal and formal network of relationships serves as an important backbone to investment decisions and forms part of their accumulated investment experience that in turn shapes the way in which VC firms identify, evaluate, and manage their investments(e.g. Guler, 2007; De Clercq and Dimov, 2008). In this regard, to the extent that investing early in an unfamiliar industry is regarded not as blind rolling of the dice but as purposeful opportunity seeking, it can be related to certain enabling patterns in the VC firm's investment experience, i.e. an enactment of a different set of investment rules that have emerged in response to previously faced investment situations. Therefore, due to different investment experiences, VC firms may differ in their ability to develop, sustain, and use such rules.

3.2 Accumulation and familiarity of early investments

The occurrence of unusual events during the history of the organization, and the change that grows out of them, increase and refine the repertoire of rules that the organization has at a point in time, making it more malleable, resilient, and deft at changing (Amburgey *et al.*, 1993). Formalizing the process by which an organization undertakes certain actions solidifies the perception of its appropriateness and thus creates a (repetitive) momentum for further such actions (Amburgey and Miner, 1992; Amburgey *et al.*, 1993), regardless of the organization's current circumstances (Greve, 1998). As Amburgey and Miner (1992: 336, emphasis added) argue, "... as an organization takes actions over time, it develops routines and competences which then become *independent engines* for further actions." The implication of this general premise for our theoretical development is that familiarity with certain actions not only makes new actions of the same type less intimidating, but also provides valuable learning experience that enables the organization to create a set of rules to facilitate their consideration and execution. The above is illustrated in the reflections of Richard Kramlich of New Enterprise Associates regarding the process of development of investment skills: "the challenges were to try to bring these people up to date in experience. We had to train the operating people and attune them to the venture capital cycle. It was a problem. It takes about a half-dozen years to really learn this business. It doesn't seem like it's very complicated in certain ways, but there are a lot of subtleties involved" (Gupta, 2000: 196).

In the VC context, retrospective accounts of the emergence of new industries or the success of early, pioneering investments often emphasize the inevitability of these events and reinforce the mythical notion that they could have been reliably foretold by a lucid analyst. And yet, when the next nascent technology 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 a result, commit the former. VC firms who have made early, 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 of a nascent industrial domain. In this regard, direct experience of the previous uncertainties can serve as an important anchor in dealing with new uncertainties. For example, Donald Valentine, the founder of Sequoia Capital, another blue chip VC firm in Silicon Valley, had learned from his experience as head of sales and marketing at Fairchild Semiconductor and National Semiconductor to assess the attractiveness of new ideas by whether they had a strong marketing team behind them (Ante, 2008). Thus, he agreed to back the fledgling minicomputer company started by Steve Jobs and Steve Wozniak on the condition that they hire a sales and marketing executive. A. C. Markulla, a former colleague of Valentine'sat Fairchild Semiconductors joined the company as chairman. Jobs, Wozniak, and Markulla launched Apple Computer in January 1977; the company went public in December 1980.

Familiarity with the reality of early investments and the ambiguity that surrounds them can alert the VC firm to possible sources of new deals and enable them to make a more informed choice on whether such deals have the right timing. In addition, in the due diligence process surrounding such potential deals, VC firms that are more experienced with early investments learn to seek, underplay or avoid the advice and opinions of particular experts or insiders entrenched in the existing order and understand the boundaries of the deal outside of which a seemingly "good" deal is no longer such. 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, with a great deal of noise, and held by a small and often eccentric minority of observers. To weigh such opinions more heavily requires decision rules of thumb that have been derived and reinforced by prior experience. Finally, a more seasoned VC firm may be more comfortable with using 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 1: The likelihood of making early investments increases with the VC firm's early investment experience.*

3.3 Imprinting of first early investment

To the extent that each subsequent early investment appears more familiar and less difficult to enact, the VC firms very first such investment requires special consideration. It lies among the most unusual events for the organization and so the experiential context in which it occurs may be particularly relevant. Organizations can learn much from unusual events (Marcus and Nichols, 1999). Yet, in learning from experience, paucity of experience can be a particular impediment to organizational intelligence (Levitt and March, 1988) because, by definition, an unusual event requires a background of "usualness" against which its peculiarities can emerge and be contrasted. In this sense, when an organization has little or no experience, any new event is unusual by default. This suggests that a VC firm may have a limited ability to learn from (e.g. make sense of) its first early investment when that investment occurs in the context of limited experience. The firm may lack the ability to discriminate between different investment approaches and their consequences, and thus fail to derive inferences that it can effectively use the next time it faces the prospect of an early investment. In contrast, when evaluated against a backdrop of abundant "usual" investing experiences, learning from the first early investment is likely to be more powerful, and leave a stronger "imprint" on subsequent decisions. Thus, the first early investment experience can become the basis of decision rules only when it is sufficiently differentiated; and differentiation can occur only in the context of more extensive experience. Indeed, by the time they made their investment in Tandem Computers, Kleiner Perkins had made several unsuccessful investments through which they inferred the importance of hands-on involvement and reliance on trusted managers. These considerations lead to the following hypothesis:

> *Hypothesis 2: The likelihood of making early investments increases with the extent of VC firm's investing experience at the time of its first early investment.*

3.4. Decay of early investment experience

Beyond the putative benefits derived from learning (Miner ana Mezias, 1996; Argote, 1999; Miner and Anderson, 1999), organizations can forget, too (Argote *et al.*, 1990; Darr *et al.*, 1995; Benkard, 2000; Martin de Holan and Phillips, 2004). Forgetting has been documented in intermittent production settings when, due to run changeovers and other interruptions, learning is followed by forgetting followed by re-learning (Carlson and Rowe, 1976). Such decay has been attributed, among other factors, to the deterioration of the rules that the organization created from experience (Darr *et al.*, 1995): when they are not used regularly, they tend to deteriorate (Martin de Holan and Phillips, 2004). Rules, then, are not eternal and they tend to dissipate, sometimes rapidly and involuntarily, even to the point of disappearing. As Day (1994: 44) vividly says, "Organizations without practical mechanisms to remember what has worked and why will have to repeat their failures and rediscover their success formulas over and over again."

In the context of early investments as requiring some deviation from more "mainstream" investment approaches, the relevant rules that enable such investments can be rendered dormant if the VC firm focuses its attention on mainstream deals over extended periods of time. More broadly, shifting the organizational attention away from particular actions can demote such actions from the agenda of relevant issues (Ocasio, 1997) and, as a consequence, exclude their underlying rules from the set of appropriate solutions (Zhou, 1993). This suggests that foregoing early investments for a long time can make their associated rules difficult to activate, reconstruct or adapt to the present situation.

For VC firms, many of the fragile decision heuristics associated with early investments, if not reinforced or used in subsequent investment decisions, may be with time overpowered by the knowledge and insights and, consequently, the rules emerging from more recent mainstream investments. As market moods swing and investor attention shifts to new areas, not seeking out 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 early investments are advocated by particular VC firm 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 diminish the firm's propensity to consider and make early investments.

Hypothesis 3: *The likelihood of making early investments decreases with the dormancy of the VC firm's early investment experience.*

4. Methods

In terms of their organization, VC firms have relatively "simple" structures, comprising a team of general partners—who serve as principals in the funds that the VC firm raises—and a supporting group of investment officers. Although a VC firm makes its individual investments through separate investment funds, the investment decisions, monitoring and value adding activities are essentially performed by the firm's investment team. Typically, the VC firm's management team changes gradually over time, creating a relatively stable collective experience. Beyond the personal experience that the partners may bring to the management team, their collective experience carries substantial weight in investment decisions, and is thus the explicit focus of our empirical examination.

4.1 Data

We collected data from the *VentureXpert* database published by Thomson Financial on all investment transactions executed by US VC firms over the 1962–2004 period. The dataset is widely used in the VC literature (e.g. Megginson and Weiss, 1991; Lerner, 1994, 1995; Sorenson and Stuart, 2001; Hochberg *et al.*, 2007;) and is perhaps the earliest and largest (most comprehensive) source of VC data.[4] While we collect the data starting with 1962 in order to capture the earliest developments in the VC industry, we acknowledge that the data coverage before 1980 may be sparser (Lerner, 1995). However, while many studies use data from 1980 onwards due to the watershed effect that the regulatory changes introduced in the late 1970s had on the development of the VC industry in the USA, it is difficult to tease out the difference between the pre-1980 and post-1980 periods that could be exclusively attributed to data coverage issues. We elaborate further on this issue in the "Limitations" section of this article.

To manage their financial risk, VC firms typically spread investments in each company across different investment rounds; a new (follow-on) round of investment is usually disbursed when the portfolio company meets 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 or cease investing if the prospects are bleak. Since each investment round is recorded in the database as a separate transaction, we captured the evolving portfolio composition of each VC firm by selecting the *initial* investments made by each VC firm in each of its portfolio companies. Over the 43-year period, 4446 VC firms made a total of 84,237 initial investments, which we tracked in chronological order.

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 non-occurrence of particular events (Morita *et al.*, 1993). In our case, the event of interest was a VC firm's early investment in a newly emerging industry. To construct the spells and capture the time-varying characteristics of the

[4]When comparing our data set to another recently used data set (Woodward and Hall, 2007, 2010), we find that *VentureXpert* has a broader coverage in terms of the number of venture-backed companies identified. Specifically, while Woodward and Hall (2007, 2010) identify 19,434 venture-backed companies funded over the period 1987-–2003 (of which 13,049 were first funded before 2001), for the same periods, the *VentureXpert* data set contains, respectively, 22,540 and 18,460 companies.

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. Since 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 either as making an early 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. early investments) 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. Left censoring in the data is possible due to the non-inclusion in the data of transactions made prior to 1962, but as we discuss in the limitations section, it should not have a material effect on our estimations.

4.2 Identifying the early investments

The *VenureXpert* database uses 5 main high-technology industry categories (communications and media, computer related, semiconductors and electronics, biotechnology, and medical and pharmaceutical) and 40 sub-categories. We identified early investments for each of the 40 sub-categories. Since the threshold between "early" and "late" investments could not be determined a priori, we sought to triangulate it from the data by combining two different approaches.

First, we estimated the rate of new investments in a given industry sub-category and looked for its acceleration point. To do so, we recorded the total number of new companies in an industry sub-category receiving VC investments in a given year. We then estimated a negative binomial model of the number of new investments in each sub-industry based on the time elapsed (in years) since the very first VC investment made in that industry. In order to account for the different starting point of each sub-industry and different duration dependence for each sub-industry, we used a dummy variable for each sub-industry and interacted that dummy with the time variable. We used these estimation results to plot for each sub-industry the (cumulative) number of companies receiving VC financing in relation to the number of years since the onset of the industry. As expected, the pattern of development varied across industries, with some industries accelerating rapidly and others "lingering" for extended periods of time. Our inspection of the plots and the estimated marginal rates of new investments revealed that a rate of 10 new investments per year represented a good approximation of the threshold. We illustrate this in Figure 1, using as

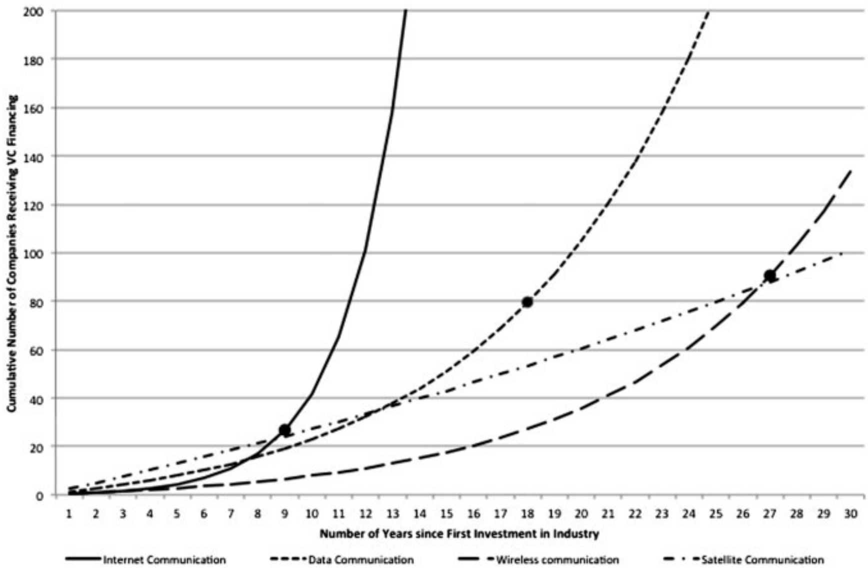

Figure 1 Illustration of different rates of VC investments across industries. The markers designate the threshold of 10 new companies per year receiving VC financing. This threshold has not been reached for Satellite Communication.

examples four sub-industries from the Communications and Media category: (Internet Communication, Data Communication, Wireless Communication, and Satellite Communication). The marker on each line shows the time at which the industry reaches the rate of 10 investments per year, after respectively 9, 18, 27, and 39 years (in the case of Satellite Communication that rate is not yet reached and the time is right-censored at the end of our observation period, i.e. end of 2004). It represents the end of the initial period for that industry. As the figure shows, the rate of investment gradually picks up in the cases of Internet, Data, and Wireless Communication, and rapidly increases after the estimated thresholds, while it remains steady in the case of Satellite Communication. In the latter case, more and more companies receive VC backing over time, but the intensity of investment does not change and so the industry does not really "take off" as an investment opportunity. For the 40 sub-industries in our data, the duration of this early period varied between 9 and 39 years. There is thus sufficient diversity in investment patterns across these industries.

Second, since IPOs can represent watershed events in the development of an industry (Stuart and Sorenson, 2003) and spur further entrepreneurial and investment activity, we tracked the VC-backed IPOs occurring in each sub-industry and marked the year in which three such IPOs had already occurred. Arguably, at that

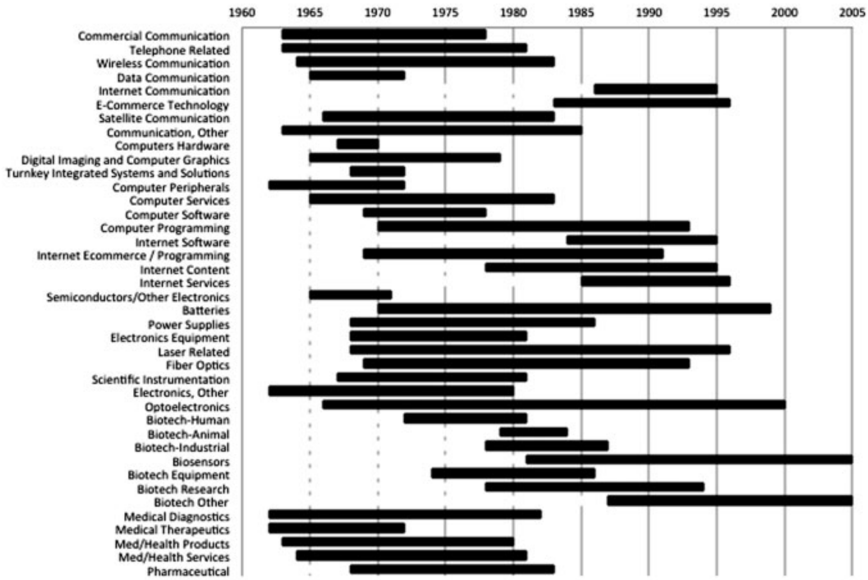

Figure 2 The early periods among the 40 sub-industries.

point the industry can be considered legitimized in the eyes of prospective VC investors and subsequent investments can be deemed no longer "early."

With these two criteria in hand, we chose the earlier of the two time markers as the threshold between the "early" and "late" periods for each sub-industry. Thus, all investments occurring before that threshold were recorded as "early." Figure 2 shows the early period of each of the 40 sub-industries, covering the time from the first investment in the industry until the threshold as identified based on the two criteria above. Again, the investment patterns vary both across time and across industry. Table 1 shows some descriptive statistics for the estimated early period thresholds in terms of the year in which they occur, the number of years elapsed since the very first VC investment in the industry, and the number of VC-backed companies. Two of the 40 industries were still in their early period at the time of the data collection. Based on our criteria, there were 1653 early investment events in our data experienced by 633 VC firms.[5] Table 2 shows the summary characteristics of these events, in terms of the time of their occurrence, duration, and characteristics of the VC firms

[5]There were a total of 1764 early investments in the data, of which 111 occurred in the same period as other early investments by the same VC firm, resulting in 1653 firm-periods in which early investments occurred. We treated multiple early investments by the same VC firm in the same period as one event, while counting the actual number of early investments in the experience of the VC firm.

Table 1 Descriptive statistics for the "early" period thresholds

Characteristics	*n* (%)
Threshold year	
1970–1975	6 (15.0)
1976–1980	5 (12.5)
1981–1985	12 (30.0)
1986–1990	3 (7.5)
1991–1995	7 (17.5)
1996–2000	5 (12.5)
2001–2004	0 (0.0)
Still in "early" period	2 (5.0)
Number of years until threshold	
1–5	3 (7.5)
6–10	8 (20.0)
11–15	9 (22.5)
16–20	12 (30.0)
21–25	5 (12.5)
≥25	3 (7.5)
Number of VC-backed companies at threshold	
1–10	2 (5.0)
11–20	17 (42.5)
21–30	10 (25.0)
31–40	7 (17.5)
41–51	4 (10.0)

experiencing them. In addition, to illustrate the evolution of early events over time, Figure 3 shows, for each year from 1962 until 2004, the number of VC firms experiencing such events and the number of industries in their early period. The figure shows that there were early investments in all years of observation. Finally, Figure 4 provides a summary of the companies backed in the early periods, across time (in each decade of the data) and in terms of their location. California, Massachusetts, New York, and Texas were the states with the most companies receiving early VC investments, although their dominance decreases over time: 57% in the 1960s, 47% in the 1970s, 48% in the 1980s, 41% in the 1990s, and 33% in the 2000s (with the caveat that 2000s in our data include only the first 4 years of this decade).

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 early

Table 2 Descriptive statistics for the early investment events

Characteristics	Early investment number				
	1	2	3	4	≥5
Number of events	633	275	171	116	458
Year of occurrence	1983.4	1982.1	1981.5	1980.3	1981.7
Time elapsed since prior event (years)		3.7	2.7	2.7	2.2
VC firm characteristics					
VC firm age (years)	2.5	5.8	6.9	7.9	12.7
Number of industries in early period at VC firm founding	17.7	20.0	20.7	20.2	19.7
Private VC (%)	49.8	51.6	53.8	55.2	57.4
Corporate VC (%)	14.7	9.8	8.8	6.9	4.4
Affiliates of financial institutions (%)	16.1	20.0	18.7	20.7	28.4
VC firm portfolio characteristics					
Number of companies in VC firm's portfolio	7.8	19.0	24.9	25.6	70.2
Number of companies added to portfolio since last event		12.6	12.3	12.4	18.9
Portfolio concentration index (Herfindahl)	0.33	0.43	0.33	0.28	0.22

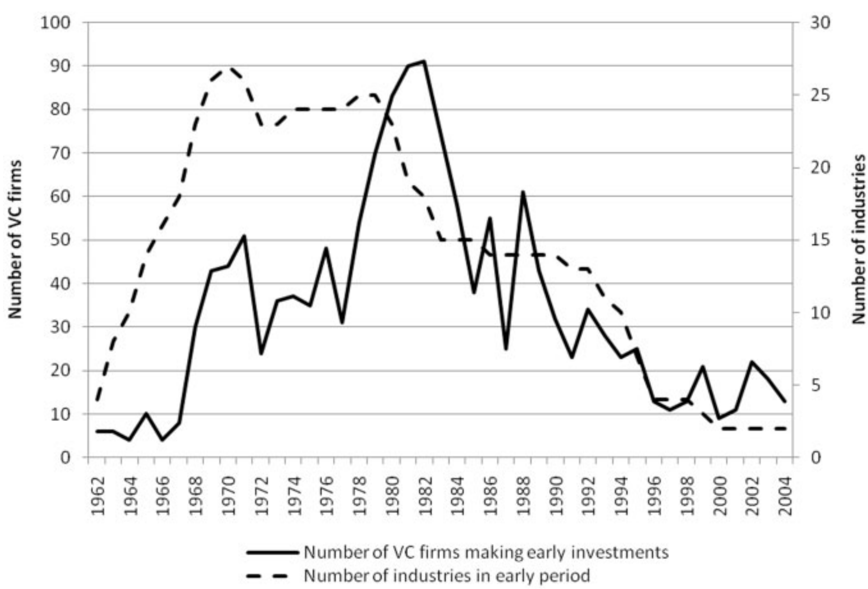

Figure 3 Early investments in the US VC industry over time.

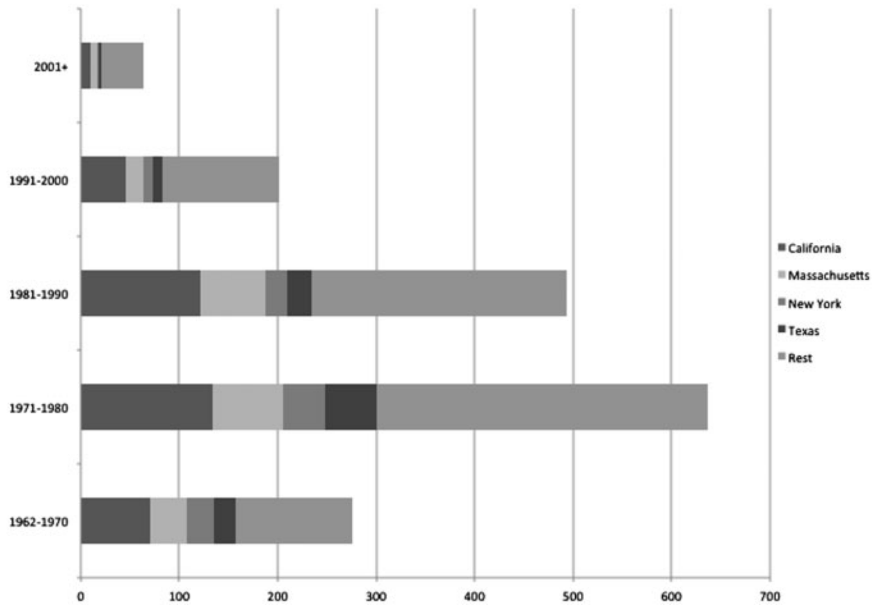

Figure 4 Companies receiving VC investments during the early periods.

investment event. Defining and designating the time at risk required some further consideration in preparing our data for analysis. Specifically, 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 early, choosing an arbitrary founding point and using that point as the onset of risk would lead to biased estimation of the firms' first events. This issue was particularly potent given that 86% of the VC firms did not make early investments. In view of these considerations, we chose each firm's first investment as the onset of the firm's risk of making early investments. 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 243, to 1410. Additionally, 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 600 (18%) experienced one event and were at risk of experiencing second event and only 116 (3.5%) were at risk of experiencing five or more events.

The record of each VC firm consisted of multiple spells—reflecting each change in the composition of the VC firm's portfolio—and each spell was marked by whether the event of interest occurred at the end of it. Given our interest in the learning processes connecting successive events, we used a *gaptime* 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 last event occurrence. For firms that have not yet experienced the event, the time at risk represents the time elapsed since the onset of risk (i.e. the firm's very first investment). 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 (Therneau and Grambsch, 2000; Ezell *et al.*, 2003).

4.4 Independent variables

We measured each VC firm's *early investment experience* as the log [ln(1 + N)] of the number of early investments made by the VC firm prior to the particular investment period. The use of the logged value of the number of prior early investments was dictated by the skewed distribution of that variable, with very few firms making large numbers of early investments. In addition, given that the vast majority of VC firms did not make early investments, we used an indicator for whether a VC firm has made at least one early investment in order to partial out the mere making of an early investment from the learning momentum associated with an increasing number of early investments. We measured the extent of VC firm's investing *experience at the time of its first early investment* as the log of the number of companies in the firm's portfolio prior to that investment. By default, this measure had a value of zero until the VC firm made its first early investment. Finally, we measured the *dormancy* of each VC firm's early investment experience as the log of the number of companies added to the VC firm's portfolio since the firm's last early investment. By default, this variable has a value of zero until after the VC firm makes its first exploration.[6]

4.5 Control variables

We included an extensive set of control variables in our analysis in order to eliminate various possible alternative explanations for why some VC firms might invest early in new industry domains. First, to account for the fact that VC firms founded in different time periods may face different (larger or smaller) sets of industries in early periods, we controlled for the number of industries "available" to a VC firm, i.e. still in their early periods at the time of the firm's founding. Second, for each investment period, we controlled for the number (logged) of companies in the VC firm's portfolio at the beginning of the period to partial out differences in resource munificence.

[6]In follow-up analyses, we replaced the measures of experience at first early investment and dormancy of early investment experience with, respectively, the firm's age at first early investment and time elapsed since the last early investment. The results were fully consistent with those reported below. But, when both sets of measures were used simultaneously, the age effects were no longer significant.

We also considered that VC firms oriented toward 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 investments made in early stage companies (seed, start-up or other early stage) as well as the proportion of investments made in non-high-technology industries.

Third, to account for the fact that VC firms specializing in particular industry sectors may be less open to making early investments, we controlled for each VC firm's industry specialization for each period, measured as a Herfindahl Hirschman Index (HHI) of 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 represented 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 investments in the given period.[7] Fourth, 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.

Fifth, 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, 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) do so in these particular periods.

[7]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 were positive numbers 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 early investments, a test of the proportional hazard assumption—based on the existence of non-zero 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 estimated the hazard rate using a Weibull model[8] with the following hazard rate function:

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

where $h_{\mathrm{i}}(t)$ is the hazard rate for a VC firm (i) to make an early investment at time (t) given that it has not done so previously, $\mathbf{X_i}$ is a vector of covariates for firm (i), **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 <1 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 (Therneau and Grambsch, 2000; Ezell *et al.*, 2003). 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 (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 event only to those firms that have experienced the $(k-1)$th event(Prentice *et al.*, 1981). As Ezell *et al.* (2003: 138) 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." Given our interest in the link

[8]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).

between early investments and the VC firm's evolving experience, we used the Anderson–Gill model.[9]

5. Results

5.1. Main analysis

Table 3 shows the descriptive statistics for the variables used in the analyses. The estimation results for the Weibull model are shown in Table 4. Model 1 includes only the control variables; Model 2 adds the indicator for prior early investments; Model 3 adds the main effects for early investment experience, investment experience at the time of the first early investment, and dormancy of early investment experience. In addition, in order to ensure that our results were not sensitive to the fact that the vast majority of the VC firms do not make early investments, in Model 4 we re-estimate the model by focusing only on the subset of observations in which firms have made at least one early investment previously. In all models, the exponentials of the reported coefficients provide the hazard ratio 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 the main effects significantly improves model fit.

Hypothesis 1 predicted a momentum effect based on the firm's familiarity with early investments, i.e. we suggested that the hazard of exploration increases with the firm's early investment experience. We tested this hypothesis in two ways. First, we found that the effect for the indicator for prior early investments was positive and significant ($\beta = 1.20$, $P < 0.001$), suggesting that firms that have made early investments in the past are on average 3.3 times ($e^{1.2}$) more likely to do so again. Second, we found that the effect for early investment experience was positive and significant ($\beta = 1.62$, $P < 0.001$), suggesting that the hazard of making early investments increases with the number of prior early investments, a fivefold increase ($e^{1.62}$) for each unit increase in the log of the number of prior early investments. In addition, the effect for early investment experience holds when estimated on the subset of firms that have made at least one early investment previously (Model 4). These findings provide support for Hypothesis 1.

[9]To examine the sensitivity of our results to the usage of unrestricted risk sets, in a separate analysis, we estimated the hazard of making early investments using a conditional risk set model, whereby we stratified the estimation based on the sequential number of the event that a firm was at risk of experiencing, e.g. third if the firm had experienced two events previously (Prentice et al., 1981). In this method, the effect of early investment experience 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 four events, we put all such cases in one stratum. The results of this estimation are fully consistent with those reported below and are available from the first author upon request.

Table 3 Descriptive statistics and correlations[a]

Variable	Mean (SD)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Prior early investment indicator	0.43 (0.50)	1.00															
Early investment experience	0.65 (0.88)	0.84	1.00														
Experience at first early investment	0.78 (1.10)	0.81	0.57	1.00													
Dormancy of early inv. experience	1.34 (1.73)	0.89	0.80	0.76	1.00												
Number of available industries	13.89 (8.02)	0.59	0.54	0.43	0.53	1.00											
Number of portfolio companies	3.13 (1.37)	0.58	0.65	0.54	0.70	0.42	1.00										
Early-stage investments	0.41 (0.26)	0.12	0.12	0.08	0.11	0.06	0.09	1.00									
Non-high-tech investments	0.24 (0.26)	0.05	0.07	0.03	0.03	0.21	−0.04	−0.38	1.00								
Industry specialization	0.39 (0.24)	−0.47	−0.47	−0.39	−0.46	−0.42	−0.64	0.04	−0.19	1.00							
New fund raised in last 2 years	0.68 (0.47)	−0.05	−0.03	0.02	0.01	−0.09	0.04	0.07	−0.09	0.07	1.00						
Private firm	0.61 (0.49)	−0.01	0.00	0.03	0.02	−0.01	0.09	0.20	−0.08	−0.02	0.15	1.00					
Corporate subsidiary	0.09 (0.28)	−0.10	−0.12	−0.11	−0.11	−0.10	−0.15	−0.05	−0.18	0.21	−0.06	−0.39	1.00				
Affiliate of financial institution	0.16 (0.37)	0.06	0.11	0.03	0.06	0.05	0.06	−0.16	0.17	−0.11	−0.05	−0.56	−0.14	1.00			
Located in California	0.29 (0.45)	0.00	0.02	−0.02	0.02	0.01	0.09	0.18	−0.23	0.04	0.05	0.12	0.00	−0.11	1.00		
Located in Massachusetts	0.12 (0.33)	0.07	0.07	0.08	0.09	0.05	0.11	0.01	−0.03	−0.06	0.04	0.07	−0.05	−0.06	−0.24	1.00	
Period January 1981–December 1985	0.12 (0.32)	0.18	0.17	0.05	0.05	0.32	−0.09	0.01	0.11	−0.05	0.01	−0.04	−0.03	0.05	−0.01	0.00	1.00
Period September 1995–December 2001	0.39 (0.49)	−0.17	−0.15	−0.08	−0.08	−0.23	−0.03	−0.04	−0.07	0.12	0.15	0.02	0.06	−0.04	0.01	0.00	−0.29

[a]*N* = 53,029. *All correlations with absolute value > 0.009 are significant at P < 0.05.*

Table 4 Weibull regression **e**stimation of the VC firm's hazard of making an early investment

Independent variables	Model 1	Model 2	Model 3	Model 4
Prior early investment indicator		1.795***	1.199***	
Early investment experience			1.620***	1.210***
Experience at first early investment			0.621***	0.391***
Dormancy of early investment experience			−0.963***	−1.210***
Number of available industries	0.064***	0.014	0.015*	−0.005
Number of portfolio companies	−0.643***	−0.846***	−0.833***	−0.478***
Early-stage investments	0.585**	0.376*	0.253	0.019
Non-high-tech investments	−0.041	0.391*	0.311*	0.143
Industry specialization	−1.038***	−0.539*	−0.293	−0.840*
New fund raised in last 2 years	0.333**	0.402***	0.645***	0.560***
Private firm	0.084	0.229	0.070	0.235
Corporate subsidiary	−0.176	−0.099	−0.234	−0.037
Affiliate of financial institution	0.255	0.336	0.053	0.188
Located in California	−0.038	0.069	0.119	0.187
Located in Massachusetts	0.146	0.135	0.055	0.082
Period January 1981–December 1985	0.462***	0.303**	0.196*	0.047
Period September 1995–December 2001	−2.221***	−2.151***	−2.098***	−2.376***
Constant	−5.907***	−6.011***	−6.988***	−4.843***
Weibull parameter [ln(p)]	−0.16***	−0.11***	0.11***	0.14***
Log likelihood	−6993.05	−6665.75	−6103.75	−4014.94
Chi-square	903.31***	1191.48***	2035.90***	1325.22***
Chi-square, LL change		654.61***	1124.00***	
N	53,029	53,029	53,029	23,032
Number of exploration events	1410	1410	1410	1020

$^{***}P<0.001$, $^{**}P<0.01$, $^{*}P<0.05$

Hypothesis 2 predicted that the hazard of making an early investment will be higher for firms who had greater investing experience at the time of their first early investment. The coefficient for experience at first early investment is positive and significant ($\beta = 0.62$, $P < 0.001$), suggesting that the hazard of making an early investment is higher for firms with greater experience at their first early investment. Each unit increase in the log of that experience makes subsequent early investments 86% more likely. This effect holds in Model 4 as well and provides support for Hypothesis 2.

Hypothesis 3 predicted that the hazard of making early investments will decrease with the dormancy of the firm's early investment experience. The coefficient for this predictor is negative and significant ($\beta = -0.96$, $P < 0.001$), suggesting that this hazard indeed decreases as the firm makes more investments since its last early investment. Each unit increase in the log of the number of companies added to the firm's portfolio since its last early investment makes subsequent future early investments 62% less likely. This effect holds in Model 4 as well and provides support for Hypothesis 3.

5.2 Robustness analyses

We performed several additional analyses to examine the robustness of our results, shown in Table 5. 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, also reflecting the lead VC firm's access to industry network resources (e.g. Dimov and Milanov, 2010). In addition, non-lead investors may be invited to participate in investments and thus make early investments for reasons other than those espoused in this article. To examine the possibility that making early investments could be affected by the lead versus non-lead status of the VC firm, we re-estimated Model 3 from Table 4 using only the cases in which the VC firm was a lead investor when making its early investments. Since 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. In Model 1, we limited our analysis to first-round investors; in Model 2, we further limited the analysis to the first-round investors who have participated in the most financing rounds for each company (e.g. Sorenson and Stuart, 2008). In both cases, the results are fully consistent with those reported in Table 4.

Second, because it is plausible that VC firms are more likely to invest early in 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 made early investments in sub-industries for which it had made no more than two investments in the respective main industry (Model 3) and, further, such early investment was made as a first-round investment (Model 4). The results are fully consistent with those reported in Table 4 and thus further reinforce our main findings.

Finally, we sought to examine whether our results could be affected by the existence of unobservable heterogeneity among the VC firms, whereby they have constant but unequal probabilities of making early investments due to factors not captured in our models (Ezell *et al.*, 2003), such as their general partners' prior experience, and/or their social networks. Accordingly, we re-estimated Model 3 of Table 4 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). Such estimation is more readily made with a Cox proportional hazard

Table 5 Robustness estimations of the VC firm's hazard of making an early investment

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Prior early investment indicator	1.779***	2.317***	1.250***	1.305***	1.870***
Early investment experience	1.824***	1.708***	2.191***	2.387***	0.462**
Experience at first early investment	0.476***	0.362***	0.553***	0.627***	
Dormancy of early investment experience	−1.038***	−1.085***	−1.130***	−1.111***	−1.222***
Number of available industries	0.018*	0.010	0.019*	0.016	
Number of portfolio companies	−0.816***	−0.768***	−1.321***	−1.441***	0.135
Early-stage investments	0.407*	0.452*	0.003	0.102	0.147
Non-high-tech investments	0.578**	0.635**	0.731***	0.948***	0.288
Industry specialization	−0.262	−0.272	−0.730***	−0.969***	0.496
New fund raised in last 2 years	0.699***	0.713***	0.745***	0.740***	0.924***
Private firm	0.335**	0.342*	0.082	0.252	
Corporate subsidiary	−0.075	0.029	−0.175	−0.037	
Affiliate of financial institution	0.287	0.381*	0.042	0.276	
Located in California	0.071	0.023	0.033	0.008	
Located in Massachusetts	0.137	0.041	0.195	0.248	
Period January 1981–December 1985	0.187	0.017	0.128	0.115	0.639***
Period September 1995–December 2001	−2.049***	−1.887***	−2.314***	−2.410***	−1.334***
Constant	−7.935***	−8.169***	−6.000***	−6.305***	
Weibull parameter [ln(p)]	0.12***	0.12***	0.06*	0.06*	
Log likelihood	−4302.40	−3665.86	−3813.54	−2716.92	−1257.32
Chi-square	2124.41***	1894.55***	1797.19***	1782.12***	657.79***
N	53,029	53,029	53,029	53,029	4722
Number of exploration events	920	755	874	583	1410

Note: The estimation in Model 5 uses a Cox proportional hazard model and single spell per early investment event.

***$P<0.001$, **$P<0.01$, *$P<0.05$, $^{+}P<0.10$.

model[10] and necessitated aggregation of the spells within each early investment event in order to avoid overlap in the gap times; in this way, each spell ends in early investment or is right censored at the firm's last investment. Therefore, because such fixed-effects specification captures only within-firm variability, it essentially excludes the firms that have not made early investments. In addition, due to its overlapping with the indicator for prior early investments in this within-firm setting,

[10]As a precursor to this analysis, a re-estimation of our main model using a Cox proportional hazard model revealed results fully consistent with those reported in Table 4.

experience at first early investment was excluded from this estimation. The results of this estimation are presented in Model 5 of Table 5 and are fully consistent with those in Table 4. Specifically, beyond the differences in the baseline hazard across firms, for each firm the hazard of making an early investment increases with its early investment experience and decreases with the dormancy of that experience. Overall, these supplementary analyses affirm the robustness of our findings.

6. Discussion and conclusion

Adopting an organizational learning perspective, we theorize about the mechanisms that link VC firms' decisions to invest early in newly emerging high-technology industries to the VC firm's prior experience. Specifically, we identify three learning mechanisms that affect a firm's likelihood of making an early investment at a given moment: the momentum derived from the familiarity of making early investments, the lasting significance—imprinting—of learning from the first early investment, and the decay associated with dormancy of early investment experience. We provide evidence for these learning patterns by studying the investments made by US VC firms in high-technology industries between 1962 and 2004. We discuss these findings and their scholarly contribution as follows.

6.1. Implications for VC decision making

Our work provides a dynamic conception of the VC investment process. Specifically, we analyze how investment choices are guided by the evolving nature of the VC firm's experience, and the particular considerations associated with investing in new and unfamiliar industry sectors. There is an increasing recognition in the VC investment literature that experience matters (e.g. Dimov *et al.*, 2007; De Clercq and Dimov, 2008; Patzelt *et al.*, 2009), but implicit in this view is a relatively simplistic, automatic link between experience and learning: more experience always leads to more learning and thus to better performance. Departing from that view, we highlight in this article, three experiential processes—accumulation, imprinting, and forgetting—which underlie the evolution of a VC firm's experience and which, as we show, have different implications for the types of investment decision that a VC firm might make next. These processes allow us to read different things into the "experience" of a particular VC firm: on one hand, accumulated experience with particular types of investment breeds familiarity that can facilitate further investment decisions of the same type. On the other hand, such experience can form a basis for differentiating and learning from unusual investments, such as those associated with the first investment into a newly emerging industry. But equally, new experience can be "plastered" over previous experience and render previous investment insights forgotten. These insights suggest that investment experience cannot be considered

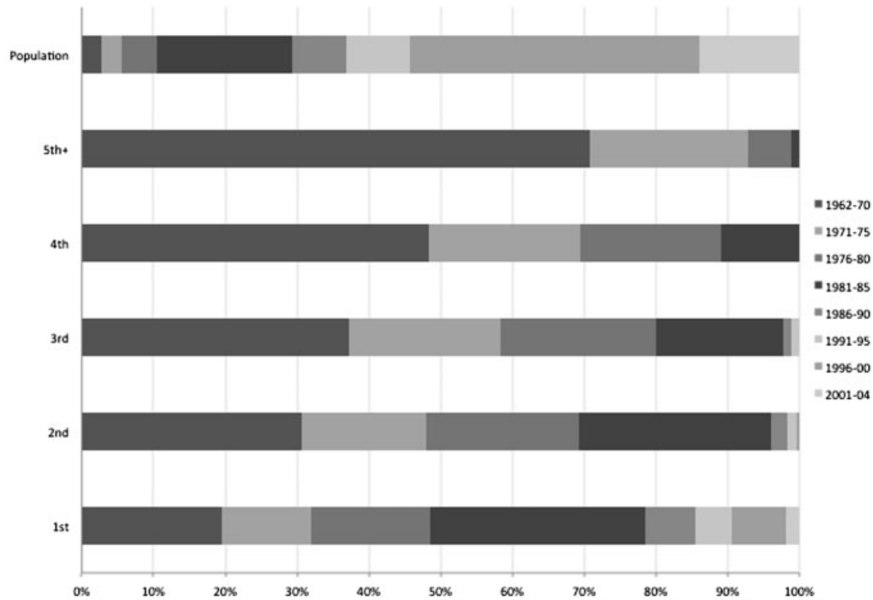

Figure 5 Pioneering investments by order and founding year of the VC firm.

in static terms or as a permanent label; it is constantly evolving and opens (or closes) the VC firm to (or away from) new investment opportunities.

The historical depth of our data allows to observe the broad ecology of VC funding decisions in newly emerging industries and, particularly, the repeated nature of those made early in the life of those industries. In addition to the quantitative regularities outlined above, we were also able to make some observations into the early investments by VC firms, which open up interesting research questions. Notably, 71% of fifth and later pioneering investments by a single VC firm were made by firms founded in the 1960s. Further 22% were made by firms founded between 1971 and 1975. Thus, this early cohort of 245 VC firms—several of whom were mentioned in our anecdotal examples above—accounts for the vast majority of repeated early investments, even though historically they only represent 5.5% of the VC firms ever active over the period of the study. This pattern is illustrated in Figure 5. In the context of our analysis, these firms represent a cohort that has been in the beneficial position of being exposed to the early stages of information, communication, and biotech revolution of the past 50 years. By virtue of such historical circumstances, these firms have been in a position to make a large number of early, pioneering investments and thereby affirm their industry leadership as well as in a position to have been shaped or imprinted (Stinchcombe, 1965) by their association with the early periods of the technology revolution. It is therefore important for researchers not to overlook the path-dependence and distinct period effects in the development of a VC industry and explore how a relatively small set of firms are able to exhibit a persistent pioneering role in the funding of new industries. This issue is particularly potent when considering the desire and efforts of policy makers in other countries to replicate the scale and impact of the US VC industry, which has so far proved to be elusive.

Another logical extension of our work concerns the question of the occurrence of the VC firm's very first early investment. For some firms, it occurs upon their founding and for others much later. Given the importance of early investment experience, future research could examine the circumstances in which VC firms are founded and the experience and prior affiliations of their founders. Particularly, intriguing is the possibility that VC managers who are frustrated by their inability to pursue particular investment opportunities within the confines of their existing VC firms may leave these firms to pursue these opportunities by founding new investment firms.

6.2. *Implications for organizational learning*

More broadly, our paper can enrich the ongoing academic dialogue about exploration and organizational learning (e.g. March, 1991). Specifically, by viewing early investments as a form of exploration by VC firms, we advance our understanding of the factors that motivate or discourage exploration, and we do so by identifying several systematic patterns related to exploration decisions that evolve in unison with the organization's experience. In addition, we increase our understanding of the phenomenon by tracing organizational experience longitudinally as well as cross-sectionally, and by placing exploration decisions in specific experiential contexts.

The combination of learning-induced momentum and decay in rules helps illuminate the long-term dynamics of exploration. Although previous studies have discussed the issue of momentum in the context of exploratory (i.e. novel) alliances (Lavie and Rosenkopf, 2006) and organizational change (Amburgey *et al.*, 1993), our work elaborates on the behavioral paths that make exploration more or less likely to occur. Specifically, whereas Lavie and Rosenkopf (2006) observed that exploration tendencies in strategic alliances become self-reinforced over time, we suggest that the pattern of exploration behavior over time is not necessarily one of monotonic decrease or increase in intensity, but one of periodic, intermittent repetition. In a similar vein, Amburgey *et al.* (1993) focused on the intervening effects of ageing, a choice facilitated by the uncommonly smooth rate of experience gains of the firms they studied (newspapers). In our context, VC firms exhibit different rates of experience—i.e. investments are made in less regular intervals—and so ageing is probably a much less relevant indicator of the actual rate of experience. Accordingly, the dormancy of prior exploration is driven not so much by the mere passing of time as it is by the intensity with which the organization engages its attention in other non-exploratory activities.

Another broader contribution of our work pertains to elaboration of the role of first experiences on the organization's long-term (exploratory) behavior. Prior studies have emphasized the imprinting effect of early experience on the values and processes associated with subsequent organizational decisions (Boeker, 1988; Swaminathan, 1996). Our results suggest that firms may have limited ability to learn from (e.g. make sense of) its first exploration when it occurs in the context of limited experience. In such cases, the organization may well lack the ability to draw qualitative distinction between its different courses of action. This mechanism is consistent with the notion of paucity of experience as an impediment to organizational intelligence (Levitt and March, 1988), and represents an interesting path for additional research.

6.3 Limitations

Inevitably, there are limitations to our study. First, we could not directly observe the learning mechanisms that we discuss in this article; rather, we attributed certain purposes to the patterns 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 early investment inferences were based on an *ex post*, and possibly changing, industry classification and not on the contemporaneous, real-time perceptions of the decision makers. With time, as different sense is being made and recorded of their 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 the difficulty of studying decisions in emergent domains after much of their original uncertainty has been resolved. Third, given the nature of our data, our focus was on the firm-level experience and learning. Even though these processes become paramount as the VC firm becomes more established; for new VC firms, it is the personal experience of the founding partners that shapes their first investment decisions. Therefore, understanding these decisions through the lenses of the founders represents an important area for future research.

Fourth, when discussing our data source, we raised the possibility that the coverage of investments prior to 1980 is sparser. If *VentureXpert* indeed under-reported investments prior to 1980, one might expect that data gathered from earlier periods are more likely to overlook failed investments. However, our comparison of rates of failure—as indicated by "defunct" status in the database—of companies backed before and after 1980 revealed the two rates to be nearly identical (5.92% versus 5.96%). Although the rate of failure in our data as compared with another recent study is lower [Woodward and Hall (2010) report failure rates of 15.2%], it is important to note that Woodward and Hall (2010) focus on zero-value exits in their data, and their analysis was based on the cash distribution from the investment and not on the operating status of the company. Therefore, to the extent that the exclusion of VC transactions in the 1960s and 1970s is not systematic, such exclusion should not affect our estimation of early period thresholds in the data and thus should not change our findings substantively.

Finally, we note that generalizations of our results beyond our research context should be made with care. In particular, given the nature of VC activity and the discrete nature of their investment projects, early investments can be undertaken perhaps with less disturbance to the firm than in other contexts.

6.4 Conclusion

Venture capital is considered an integral part of an open innovation landscape, enabling ideas to be tested and commercialized outside the confines of existing business organizations. Beyond the visible attributes of VC firms lies the intangible, tacit reality of their investment decisions. By nature of their intermediary role in connecting institutional investors with budding entrepreneurs, VC investors make bets that are invariably deemed risky. But, when these bets involve entrepreneurs who operate at the avant-garde of the industrial landscape, and who will perhaps establish new industries and open new markets, their decision logic is hard to discern and articulate. In this article, we identified and discussed several patterns about such pioneering investments made by VC firms in the USA over the past 50 years, and underlying these patterns is the notion of organizational learning as a link between prior experience and future decisions. While all early, pioneering investments can be characterized by the impossibility of developing reliable forecasts or anticipating possible course of business development, those who have made such investments before can look beyond these dejecting characteristics and focus on searching for the most promising exploration paths. But such heightened intuition, when left idle, can be easily overwhelmed by the formality of more "normal" investments.

Looking at experience as the building block of the evolution and development of the VC industry highlights its historical, path-dependent nature. Recent policy discussions about developing national VC industries—often by seeking to reenact the development and prominence of the US VC industry—tend to focus on the replication of visible elements (such as fund structure, incentives, etc.) and overlook the tacit nature of the desired investment decisions. Recreating the structural elements without providing the experiential context in which certain investment decision skills have emerged cannot ensure that the same type of patient, forward-looking decisions will be made elsewhere in support of promising technologies.

References

Allison, P. D. (2005), *Fixed Effects Regression Methods for Longitudinal Data Using SAS*. SAS Institute: Cary, NC.

Amburgey, T. L. and A. S. Miner (1992), 'Strategic momentum: the effects of repetitive, positional and contextual momentum on merger activity,' *Strategic Management Journal*, **13**, 335–348.

Amburgey, T. L., D. Kelly and W. P. Barnett (1993), 'Resetting the clock: the dynamics of organizational change and failure,' *Administrative Science Quarterly*, **38**, 51.

Andersen, P. K. and R. D. Gill (1982), 'Cox's regression model for counting processes: a large sample study,' *Annals of Statistics*, **10**, 1100–1120.

Argote, L. (1999), *Organizational Learning: Creating, Retaining, and Transferring Knowledge*. Kluwer Academic: Boston.

Argote, L., S. L. Beckman and D. Epple (1990), 'The persistence and transfer of learning in industrial settings,' *Management Science*, **36**, 140–155.

Barnett, W. P. and G. R. Carroll (1995), 'Modeling internal organizational change,' *Annual Review of Sociology*, **21**, 217–236.

Baum, J. A. C., S. X. Li and J. M. Usher (2000), 'Making the next move: how experiential and vicarious learning shape the locations of chains' acquisitions,' *Administrative Science Quarterly*, **45**, 766–801.

Benkard, C. L. (2000), 'Learning and forgetting: the dynamics of aircraft production,' *American Economic Review*, **90**, 1034–1054.

Blossfeld, H. P., K. Golsch and G. Rohwer (2007), *Event History Analysis with Stata*. Lawrence Erlbaum Associates: Mahwah, NJ.

Boeker, W. (1988), 'Organizational origins: entrepreneurial and environmental imprinting at the time of founding,' in G. R. Carroll (ed.), *Ecological Models of Organizations*. Ballinger Publishing: Cambridge, MA, pp. 33–51.

Carlson, J. G. and A. J. Rowe (1976), 'How much does forgetting cost?' *Industrial Engineering*, **8**, 40.

Chesbrough, H. W. (1999), 'The organizational impact of technological change: a comparative theory of national institutional factors,' *Industrial and Corporate Change*, **8**, 447–485.

Cox, D. R. (1972), 'Regression models and life-tables,' *Journal of the Royal Statistical Society, Series B*, **34**, 187–220.

Cumming, D., G. Fleming and J. A. Suchard (2005), 'Venture capitalist value-added activities, fundraising and drawdowns,' *Journal of Banking and Finance*, **29**, 295–331.

Cyert, R. M. and J. G. March (1963), *A Behavioral Theory of the Firm*. Prentice-Hall: Englewood Cliffs, NJ.

Da Rin, M., G. Nicodano and A. Sembenelli (2006), 'Public policy and the creation of active venture capital markets,' *Journal of Public Economics*, **90**, 1699–1723.

Darr, E., L. Argote and D. Epple (1995), 'The acquisition, transfer and depreciation of knowledge in service organizations: productivity in franchises,' *Management Science*, **41**, 1750–1762.

Day, G. S. (1994), 'The capabilities of market-driven organizations,' *Journal of Marketing*, **58**, 37–52.

De Clercq, D. and D. Dimov (2008), 'Internal knowledge development and external knowledge access in venture capital investment performance,' *Journal of Management Studies*, **45**, 585–612.

Dimov, D. and H. Milanov (2010), 'The interplay of need and opportunity in venture capital syndication,' *Journal of Business Venturing*, **25**, 331–348.

Dimov, D., D. A. Shepherd and K. M. Sutcliffe (2007), 'Requisite expertise, firm reputation, and status in venture capital investment allocation decisions,' *Journal of Business Venturing*, **22**, 481–502.

Dougherty, D. (1992), 'Interpretive barriers to successful product innovation in large firms,' *Organization Science*, **3**, 179–202.

Dougherty, D. and C. Hardy (1996), 'Sustained product innovation in large, mature organizations: overcoming innovation-to-organization problems,' *Academy of Management Journal*, **39**, 1120–1153.

Eckhardt, J. T., S. Shane and F. Delmar (2006), 'Multistage selection and the financing of new ventures,' *Management Science*, **52**, 220–232.

Ezell, M. E., K. C. Land and L. E. Cohen (2003), 'Modeling multiple failure time data: a survey of variance-corrected proportional hazards models with empirical applications to arrest data,' *Sociological Methodology*, **33**, 111–167.

Fenn, G., N. Liang and S. Prowse (1995), *The Economics of the Private Equity Market*. Board of Governors of the Federal Reserve System: Washington, DC.

Florida, R. L. and M. Kenney (1988a), 'Venture capital and high technology entrepreneurship,' *Journal of Business Venturing*, **3**, 301–319.

Florida, R. L. and M. Kenney (1988b), 'Venture capital-financed innovation and technological change in the USA,' *Research Policy*, **17**, 119–137.

Freeman, S. (1999), 'Identity maintenance and adaptation: a multilevel analysis of response to loss,' *Research in Organizational Behavior*, **21**, 247–294.

Gompers, P. and J. Lerner (1998), 'What drives venture capital fundraising?' *Brookings Papers on Economic Activity: Microeconomics*, **1998**, 149–204.

Gompers, P. and J. Lerner (1999), *The Venture Capital Cycle*. MIT Press: Cambridge, MA.

Gompers, P. and J. Lerner (2001), 'The venture capital revolution,' *Journal of Economic Perspectives*, **15**, 145–168.

Grambsch, P. M. and T. M. Therneau (1994), 'Proportional hazards tests and diagnostics based on weighted residuals,' *Biometrika*, **81**, 515–526.

Greve, H. R. (1998), 'Performance, aspirations and risky organizational change,' *Administrative Science Quarterly*, **43**, 58.

Guler, I. (2007), 'Throwing good money after bad? A multi-level study of sequential decision making in the venture capital industry,' *Administrative Science Quarterly*, **52**, 248–285.

Gupta, U. (2000), *Done Deals: Venture Capitalists Tell Their Stories*. Harvard Business Press: Boston, MA, p. 105.

Hannan, M. T. and J. Freeman (1984), 'Structural inertia and organizational change,' *American Sociological Review*, **49**, 149–164.

Hellman, T. and M. Puri (2002), 'Venture capital and the professionalization of start-up firms: empirical evidence,' *Journal of Finance*, **57**, 169–197.

Hisrich, R. D. and A. D. Jankowicz (1990), 'Intuition in venture capital decisions: an exploratory study using a new technique,' *Journal of Business Venturing*, **5**, 49–62.

Hochberg, Y. V., A. Ljungqvist and Y. Lu (2007), 'Whom you know matters: venture capital networks and investment performance,' *Journal of Finance*, **62**, 251–302.

Holmqvist, M. (2004), 'Experiential learning processes of exploitation and exploration within and between organizations: an empirical study of product development,' *Organization Science*, **15**, 70–81.

Hsu, D. H. (2006), 'Venture capitalists and cooperative start-up commercialization strategy,' *Management Science*, **52**, 204–219.

Hsu, D. H. and M. Kenney (2005), 'Organizing venture capital: the rise and demise of American Research & Development Corporation, 1946–1973,' *Industrial and Corporate Change*, **14**, 579–616.

Huber, G. P. (1991), 'Organizational learning: the contributing processes and the literature,' *Organization Science*, **2**, 88–115.

Kortum, S. and J. Lerner (2000), 'Assessing the contribution of venture capital to innovation,' *RAND Journal of Economics*, **31**, 674–692.

Lavie, D. and L. Rosenkopf (2006), 'Balancing exploration and exploitation in alliance formation,' *Academy of Management Journal*, **49**, 797–818.

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

Levitt, B. and J. G. March (1988), 'Organizational learning,' *Annual Review of Sociology*, **14**, 319–340.

MacMillan, I., R. Siegel and P.N. Subbanarasimha (1985), 'Criteria used by venture capitalists to evaluate new venture proposals,' *Journal of Business Venturing*, **1**, 119–128.

Manigart, S., K. De Waele, M. Wright, K. Robbie, P. Desbrieres, H. Sapienza *et al.* (2002), 'Determinants of required return in venture capital investments: a five-country study,' *Journal of Business Venturing*, **17**, 291–312.

March, J. G. (1991), 'Exploration and exploitation in organizational learning,' *Organization Science*, **2**, 71–87.

March, J. G., M. Schulz and X. Zhou (2000), *The Dynamics of Rules: Change in Written Organizational Codes*. Stanford University Press: Stanford, CA.

Marcus, A. A. and M. L. Nichols (1999), 'On the edge: heeding the warnings of unusual events,' *Organization Science*, **10**, 482–499.

Martin de Holan, P. and N. Phillips (2004), 'Remembrance of things past? The dynamics of organizational forgetting,' *Management Science*, **50**, 1603–1613.

Mayer, C., K. Schoorsb and Y. Yafeh (2005), 'Sources of funds and investment activities of venture capital funds: evidence from Germany, Israel, Japan, and the United Kingdom,' *Journal of Corporate Finance*, **11**, 586–608.

Miller, D. and M.-J. Chen (1996), 'The simplicity of competitive repertoires: an empirical analysis,' *Strategic Management Journal*, **17**, 419–439.

Miner, A. S. and P. Anderson (1999), 'Industry and population-level learning: organizational, interorganizational and collective learning processes,' *Advances in Strategic Management*, **16**, 1–30.

Miner, A. S. and S. J. Mezias (1996), 'Ugly duckling no more: pasts and futures of organizational learning research,' *Organization Science*, **7**, 88–99.

Mintzberg, H. (1978), 'Patterns in strategy formation,' *Management Science*, **24**, 934–948.

Morita, J. G., T. W. Lee and R. T. Mowday (1993), 'The regression-analog to survival analysis: a selected application to turnover research,' *Academy of Managament Journal*, **36**, 1430–1465.

Mowery, D. C. and N. Rosenberg (1998), *Paths of Innovation: Technological Change in 20th Century America*. Cambridge University Press: Cambridge, UK.

Munari, F. and L. Toschi (2011), 'Do venture capitalists have a bias against investment in academic spin-offs? Evidence from the micro- and nanotechnology sector in the UK,' *Industrial and Corporate Change*, **20**, 397–432.

Nelson, R. R. and S. Winter (1982), *An Evolutionary Theory of Economic Change*. Harvard University Press: Cambridge, MA.

Nonaka, I. (1994), 'A dynamic theory of organizational knowledge creation,' *Organization Science*, **5**, 14–37.

Ocasio, W. (1997), 'Towards an attention-based view of the firm,' *Strategic Management Journal*, **18**, 187–206.

OECD (2003), Venture capital policy review: United States. *Directorate for Science, Technology and Industry*.

Patzelt, H., D. z. Knyphausen-Aufseß and H. T. Fischer (2009), 'Upper echelons and portfolio strategies of venture capital firms,' *Journal of Business Venturing*, **24**, 558–572.

Prentice, R. L., B. J. Williams and A. V. Peterson (1981), 'On the regression analysis of multivariate failure time data,' *Biometrika*, **68**, 373–379.

Sahlman, W. A. (1990), 'The structure and governance of venture-capital organizations,' *Journal of Financial Economics*, **27**, 473–521.

Sapienza, H. J. (1992), 'When do venture capitalists add value?' *Journal of Business Venturing*, **7**, 9.

Saxenian, A. L. (1994), *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Harvard University Press: Cambridge, MA.

Schulz, M. (1998), 'Limits to bureaucratic growth: the density dependence of organizational rule births,' *Administrative Science Quarterly*, **43**, 845–876.

Schulz, M. (2001), 'The uncertain relevance of newness: organizational learning and knowledge flows,' *Academy of Management Journal*, **44**, 661–681.

Sidhu, J. S., H. R. Commandeur and H. W. Volberda (2007), 'The multifaceted nature of exploration and exploitaiton: value of supply, demand, and spatial search for innovation,' *Organization Science*, **18**, 20–38.

Sorenson, O. and T. E. Stuart (2001), 'Syndication networks and the spatial distribution of venture capital investments,' *American Journal of Sociology*, **106**, 1546–1588.

Sorenson, O. and T. E. Stuart (2008), 'Bringing the context back in: settings and the search for syndicate partners in venture capital investment networks,' *Administrative Science Quarterly*, **53**, 266–294.

Stinchcombe, A. (1965), 'Social structure and organizations,' in J. G. March (ed.), *Handbook of Organizations*. Rand McNally: New York, pp. 142–193.

Stuart, T. and O. Sorenson (2003), 'Liquidity events and the geographic distribution of entrepreneurial activity,' *Administrative Science Quarterly*, **48**, 175–201.

Sutton, R. S. and A. G. Barto (1998), *Reinforcement Learning: An Introduction*. MIT Press: Cambridge, MA.

Swaminathan, A. (1996), 'Environmental conditions at founding and organizational mortality: a trial-by-fire model,' *Academy of Management Journal*, **39**, 1350–1377.

Therneau, T. M. and P. M. Grambsch (2000), *Modeling Survival Data: Extending the Cox Model*. Springer-Verlag: New York.

Tushman, M. E. and E. Romanelli (1985), 'Organizational evolution: a metamorphosis model of convergence and reorientation,' in B. Staw and L. Cummings (eds), *Research in Organizational Behavior*, Vol. 7, JAI Publishers: Greenwich, CT, pp. 171–222.

von Burg, U. and M. Kenney (2000), 'Venture capital and the birth of the local area networking industry,' *Research Policy*, **29**, 1135–1155.

Widicus, W. W. (1966), 'A Quantitative Analysis of the Small Business Investment Company Program,' *Journal of Financial and Quantitative Analysis*, **1**, 81–111.

Zhao, Z., J. Anand and W. Mitchell (2004), 'Transferring collective knowledge: teaching and learning in the Chinese auto industry,' *Strategic Organization*, **2**, 133–167.

Zhou, X. (1993), 'The dynamics of organizational rules,' *American Journal of Sociology*, **98**, 1134–1166.