NOT QUITE UP TO SCRATCH: AN EXAMINATION OF FAILURE, PERSISTENCE, AND 'LIVING DEAD' OUTCOMES FOR WIRELESS START-UPS

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ABSTRACT

NOT QUITE UP TO SCRATCH: AN EXAMINATION OF FAILURE, PERSISTENCE, AND 'LIVING DEAD' OUTCOMES FOR WIRELESS START-UPS

Anindya Ghosh

Johannes Pennings

This dissertation analyzes why some VC-funded high-tech firms do not generate harvesting events for investors through a lucrative sale, either to another company or on the stock exchange. In other words, I seek to understand two performance outcomes: failure and persistence. Building on the technology strategy and imprinting literatures, I investigate the effects of three signals of quality on failure and persistence. In the first essay, hypotheses are developed on the unintended consequences of patenting. Disclosure, through patents, exposes new firms to undesired spillovers that harm their survival chances. The second essay exploits asymmetric effects of factors on success and failure to expose start-up persistence. It analyzes another signal of quality—technology breadth, the applicability of inventions across domains—and suggests that the hazards of disclosure also varies with this breadth. Finally, in the third essay I hypothesize on the effects of signals of quality related to founding team on a third outcome, 'living dead'—a transitory state to which a start-up shifts when it persists beyond the norm without harvest or failure. I tested these hypotheses on a hand-collected longitudinal dataset on 428 US

VC-backed wireless firms founded between 1990 and 2009 using event history analysis and matched case-control study.

I find that a start-up's failure rate increases as its inventions are cited at a higher rate by others; in addition the failure rate increases when the citing firms have a track record of litigiousness. I show that the effect of signaling a specific, rather than general, technology while experiencing high rate of knowledge diffusion diminishes both the likelihood of failure and success; uncovering persistence through negative effects on success and failure. Loss of members in founding teams comprised of entrepreneurs with prior founding experience is found to be a shock that increases the odds of marginal performance. Intriguingly, a team size of two increases the likelihood of 'living dead', signaling underlying coordination costs. Overall, this dissertation enriches our understanding of new venture performance by adding to existing theory, conceptualizing a third performance outcome, providing empirical evidence for persistence and unintended consequences of signaling, and indicating future research paths.

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Chapter 1: Introduction

This dissertation examines performance of new ventures, particularly why VC-backed high-tech firms do not experience harvest outcomes (or "success") through a sale, either on the stock market or to another company.[1] I focus on factors that are considered signals, broadly defined, by both the firm and their evaluators that may contribute to the lack of success of these firms. Thus, by "non-success" I imply two outcomes, either outright failure via bankruptcy, distressed sale, and dissolution, or persistence without harvest beyond a reasonable time horizon. Persistence results in what are called as 'living dead' firms by venture capitalists, as they generate no liquidity or liquidating events for investors, and hence are a drag on their resources.

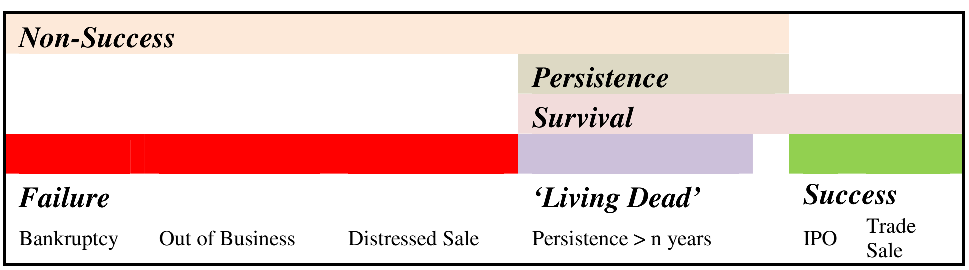
My reasons for studying non-success are three-fold. First, although performance is a central concept in entrepreneurship, strategy, and organization theory, research to date has focused more on success than outright failure, and even less on the middle ground of persistence between these two extremes. Enduring above-normal returns, the stated goal of strategy research, assumes a distribution of firms and implies the presence of consistent middle of the road performers too. Thus understanding failure and persistence in addition to success can provide us important insights into a facet of performance hitherto pushed to the background.

Second, making the important distinction that many start-ups neither achieve successful outcomes for investors nor fail allows me to demonstrate asymmetry between

[1] The scratch in the title refers to this expectation of achieving success through a lucrative sale when VC's and entrepreneurs unite. This success event is very much like a line or mark drawn as an indication of a boundary or starting-point in sports such as cricket and boxing and from where the phrase 'up to scratch' originated in 19th century England.

factors predicting success and failure. Asymmetric effects imply that a factor has the equivalent directional effect on both success and failure, which is the opposite of what is expected in a binary framing of performance outcomes. Current studies in entrepreneurship and organization theory often treat either failure or success as binary outcomes when analyzing new-venture performance (see Figure 1), thus implicitly assuming symmetric effects between the two[2]. Consequently, results on failure inform us about survival, that is, both persistence without liquidity events and success. Similarly, results on success enlighten us on failure and persistence together. Analyzing success and failure together therefore provides a useful empirical tool by exposing persistence and enabling the examination of how a variety of factors influence these three outcomes.

Figure 1. Performance Outcomes of Start-ups



Outcome	Negation
Success	Non-Success
Failure	Survival

Non-Success	Failure + Persistence
Survival	Persistence + Success
'Living Dead'	Persistence > n years

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[2] By symmetric effects I mean that if factor X increases the likelihood of success, its effect on failure will just be the opposite. In a binary framing where success is equal to not failing, such symmetric effects hold.

Finally, current studies have not paid much attention to those firms that persist without closure to investor expectations on harvest, the aforementioned middle-ground of performance. By conceptually and empirically defining a third outcome that is highly relevant to important stakeholders of new ventures, this dissertation tries to chart new territory, explored sparsely till now due to the conceptual, methodological and statistical difficulty of analyzing non-events such as persistence. By addressing these gaps, I contribute to understanding high-tech start-up performance as a phenomenon while also developing theoretical arguments that have broader consequence.

To explain the lack of success in new ventures I draw from two distinct streams of literature: intellectual property rights (IPR) strategy emerging from the broader technology strategy literature, and imprinting effects of founding teams originating in Stinchcombe's (1965) seminal work. The knot that ties these disparate bodies of work in this dissertation is their use as signals of quality (Podolny, 2005; Spence, 1973) to overcome classic adversities such as asymmetric information (Akerlof, 1970) and the liability of newness (Stinchcombe, 1965). Accumulated IPR, technology breadth as discovered by peers and prior experience and composition of founding team members are powerful signals that new ventures and their evaluators take advantage of as proxies for underlying quality. An important contribution of this study is to shed light on the unintended consequences these signals create besides the putative benefits underscored in the current literature.

New Venture Performance – Literature Review

Performance is a central concept in management. As the role of the manager is to plan, coordinate and appraise, any assessment needs some measure of performance (Chandler, 1962). Scholars in entrepreneurship, organization theory and strategy have extensively used performance as a key dependent variable in their research. Despite an impressive body of research reviewed briefly below, significant gaps in the understanding of new venture performance remain. First, there are relatively few studies on new firm performance and most of them model success or survival as a binary outcome. Research would be well served by recognizing and modeling the asymmetry that underlies different performance mechanisms. Another important contribution would be to understand survivors that persist in spite of unmet expectations. Second, while there are many studies on intellectual property, they usually focus on cooperative strategies with incumbents and knowledge flows in sectors characterized by high appropriability, namely the biotechnology industry. They also do not explicitly model the direct effects on performance, especially non-success. Third, an important source of imprinting, presence of entrepreneurs or managers with prior startup experience at founding, and its impact on performance has not been given much attention.

Within strategy both the Industrial Organization (IO) school, which links structure and conduct (strategy) to performance (Caves, 1980; Caves & Porter, 1977; Porter, 1980), and the Resource Based View (RBV) / Dynamic Capabilities school, which concerns achieving above normal rents from unique resources (Barney, 1991b; Eisenhardt & Martin, 2000; Penrose, 1995; Peteraf, 1993; Teece, Pisano, & Shuen, 1997;

Wernerfelt, 1984; Winter, 2003), embrace equilibrium and profit seeking assumptions and use continuous financial measures such as return on assets, return on equity and Tobin's q to proxy performance. However, for new ventures such data is rarely available such that use of firm survival and exit surface as the dominant measure of performance[3] among the few studies about startups with this framing (Acs & Audretsch, 1989; Gilbert, Audretsch, & McDougall, 2004; cf. Wetter, 2009).

Evolutionary theories, particularly population ecology and industry lifecycle perspectives, have contributed extensively to understand the phenomenon of new firms at an aggregate field level. Population ecology mainly deals with entry and exit of firms with environmental and inertial forces shaping competition and selection in populations of organizations (Hannan & Freeman, 1984). Mortality rates as captured through failures and acquisitions are the key events that are modeled to study survival within this body of literature (Baum & Oliver, 1991; Baum & Oliver, 1996; Brüderl & Schüssler, 1990; Carroll, Bigelow, Seidel, & Tsai, 1996; Delacroix & Carroll, 1983). Industry lifecycle theories also look at entry and exit patterns of firms; however the fundamental assumption is that knowledge as manifested in technology and technology cycles are the drivers of performance which is again mainly survival as in population ecology (Anderson & Tushman, 2001; Audretsch, 1991; Bayus & Agarwal, 2007; Christensen & Bower, 1996; Dosi, 1982; Dowell & Swaminathan, 2006; Jovanovic & MacDonald, 1994; Klepper & Graddy, 1990; Nerkar & Shane, 2003; Shane, 2001b, 2001a; Suarez & Utterback, 1995). The common thread in all the above research is causal symmetry with

[3] Few non-US studies in this category use sales growth as a measure of performance apart from survival.

survival a proxy for success, which is also prevalent in the literature specific to entrepreneurship.

Apart from the application of these general theories in strategy and organization theory, there is a long line of research in entrepreneurship which is germane to this dissertation. Assembling resources, human, financial, and network, are critical for a fledgling company. Literature on human resource assembly include studies on human resource practices (Baron, Burton, & Hannan, 1996, 1999a; Baron, Hannan, & Burton, 1999b, 2001; Henderson & Cockburn, 1994) and mobility of knowledge workers (Corredoira & Rosenkopf, 2010; Groysberg, Nanda, & Nohria, 2004; Marx, Strumsky, & Fleming, 2009). While these studies have important implications for firm performance they don't directly theorize about those outcomes.

The focal point in the literature on financial resources of start-ups emphasizes the extra-financial role of venture capitalists (VCs) (Gompers & Lerner, 2004; Hellman & Puri, 2000; Hellmann & Puri, 2002; Hsu, 2006b). While a stream of research originating in finance has drawn attention to the use of stringent contracts to screen entrepreneurial firms (Kaplan & Strömberg, 2004), another grounded in sociological theories has emphasized the importance of endorsements as signals of quality and legitimacy (Gulati & Higgins, 2003; Megginson & Weiss, 1991; Stuart, Hoang, & Hybels, 1999). Hsu (2004) also suggests that these certifications have associated costs, finding that entrepreneurs may willingly forego offers with higher valuation to affiliate with more reputed VC's. Other studies in this tradition have underscored the importance of network resources on startup performance (Baum, Calabrese, & Silverman, 2000b; Baum &

Silverman, 2004; Brüderl, Preisendörfer, & Ziegler, 1992; Lee, Lee, & Pennings, 2001; Stuart et al., 1999) with a focus primarily on success or survival.

Another fruitful avenue of research on new venture origins has been on a startup's initial technological endowment. A stream of literature in this vein exploits the variation in initial stock of knowledge to examine its impact on organizational behavior (Beckman, 2006; Eisenhardt & Schoonhoven, 1990). A second stream focuses on the local nature of search for knowledge and the mechanisms used to overcome the barrier (Hsu & Lim, 2008; Mowery, Oxley, & Silverman, 1996; Nelson & Winter, 1982; Rosenkopf & Almeida, 2003; Rosenkopf & Nerkar, 2001). A third stream following Cohen and Levinthal (1990) investigates effects of knowledge spillover due to imperfect nature of appropriablity (Breschi, Malerba, & Orsenigo, 2000; Cohen & Levinthal, 1989, 1990; Jaffe, Trajtenberg, & Henderson, 1993; Zucker, Darby, & Armstrong, 1998). Finally an extensive literature exists on intellectual property, especially licensing by startups and the benefits to both owners and licensees (Arora, Fosfuri, & Gambardella, 2004; Gans, Hsu, & Stern, 2002b; Nerkar & Shane, 2003; Rothaermel & Thursby, 2005; Shane, 2002; Shane & Stuart, 2002). A number of these studies are either based on the biotechnology sector, where patenting is the most important source of value appropriation, or investigates university based entrepreneurship.

Stinchcombe's (1965) analysis of organizational forms pointed to the salience of initial imprinting for the structure of an organization. Following this seminal piece scholars have investigated the prehistory of startups, especially the effect of established firms through spin-offs and prior experience (Boeker, 1989; Boeker & Karichalil, 2002;

Hannan, Burton, & Baron, 1996; Romanelli, 1989). Although mostly focused on the motivations of entrepreneurs to enter an industry and on transfer of "genetic" materials from established firms (Agarwal, Sarkar, & Echamebadi, 2002; Bhide, 1994; Burton, Sorensen, & Beckman, 2002; Gompers, Kovner, Lerner, Scharfstein, & Field, 2006; Phillips, 2002), a few studies highlight impact on performance through the distinction between *de-novo* and *de-alio entrants* (Klepper, 2002; Klepper & Simons, 2000). While Hsu (2007) finds that "serial entrepreneurs" help in speeding up financing and lower valuation received, the impact of serial entrepreneurs or founding executives, through the lens of imprinting, on performance is not explicitly investigated in the literature.

Signaling & Entrepreneurial Outcomes – Literature Review

Undertaking entrepreneurial venture requires mobilizing resources from scratch and is laden with uncertainty and unforeseen hazards (Stinchcombe, 1965). Start-ups need to attract financing, employees and partners. Thus external resource providers have to evaluate the quality of new ventures under considerable uncertainty across different criteria such as technology characteristic and economic viability. Furthermore, that quality is unknown ex-ante with considerable doubts about the venture's intrinsic value both at founding and through their infancy to adolescence (Brüderl & Schüssler, 1990). Besides, the information available to the start-up and evaluators are not distributed equally, not unlike the knowledge available to sellers and buyers of used cars in Akerlof's (1970) famous example of market for lemons. This information asymmetry can drive high quality firms out of the markets unless the new venture can signal their underlying quality to forestall this market failure. Thus mechanisms to signal start-up quality to overcome information asymmetry using different indicators have received a lot of attention in the entrepreneurship literature. We can classify this literature into two complementary streams, one grounded in economics and the other in sociology. In the following paragraphs I elaborate on the two perspectives and demonstrate their usefulness in this dissertation.

The economic perspective, exemplified by Hsu & Ziedonis (2008), is grounded in Spence's (1973) seminal piece on job market signaling. Analyzing the market for hiring employees, Spence defines signals as observable, unalterable characteristics attached to a jobseeking individual that can be manipulated by him. Using observable characteristics such as education as an indicator of productive capability, prospective employers can sort different applicants when making their hiring decision. The critical assumption is that costs to the individual to obtain the indicator are negatively correlated with productive capability. This concept of signal has been widely used in the economics and finance literature. Some notable examples germane to this dissertation include, Leland & Pyle (1977) examining insider information signals as manifested through investments by entrepreneurs, Megginson & Weiss (1991) demonstrating the positive effect of VC certification on IPO outcomes, and Hsu & Ziedonis (2008) using patents as signals of technological capability.

The sociological perspective, exemplified by Stuart et al., (1999), draws on the work by Podolny (2005) on status as signal of quality under uncertainty. Podolny argues that third party deference and association serve as useful indicators of underlying quality because high status partners may be subject to status leakage and have the incentive to associate with higher status alters. Building on this insight Stuart et al., (1999) show that characteristics of affiliates in inter-organizational exchange relationship are important indicators of underlying quality. Nascent firms that have been evaluated by prominent players send positive signals of their quality that increase the likelihood of IPO.

In this dissertation I examine both types of signals with the view that resource providers evaluate distinct aspects of quality with different indicators. First, patents, as argued by Hsu & Ziedonis (2008), closely adhere to the Spencian definition of signal, and provide information on the technological capabilities of the new venture. Further, besides solving the information asymmetry problem, patents are also an attempt to solve what has been termed as Arrow's information paradox (Arrow, 1962). This paradox states that products with strong information content such as a technology require a potential purchaser to know the technology and its working in sufficient detail to understand its capabilities and make the decision. Unfortunately, disseminating that knowledge reduces its value thus resulting in market failure. Patent protection avoids such market failures. However, patent enforcement is imperfect, especially in weak appropriability regimes leading to unintended hazards from such disclosures (Cohen, Nelson, & Walsh, 2000). Start-ups signaling their capabilities to investors due to such imperfections cannot exclude competitors from accessing the information disclosed while signaling thus exposing them to hazards such as designing around inventions.

Second, in the spirit of relational signals (Podolny, 2005; Stuart et al., 1999) I introduce a second signal based on technological capabilities, the possible opportunity set available to the start-up. Instead of using the prominence or status of the partner, I use the technological domains associated with the partners' inventions as an indicator of the applicability of a start-ups inventions to different technological areas. These domains may be scattered or clustered and by implication, become very informative to the entrepreneurs and outsiders alike since the applicability of technology is often unknown ex ante (Basalla, 1988). Further, the specificity of a technology and the magnitude of its diffusion indicate diminishing opportunities for strategic differentiation and could inform about a venture's "permanent failure" (Meyer & Zucker, 1989).

Finally, I examine founding team characteristics as signals. Prior experiences of founders are endowments disclosing information on the start-ups' entrepreneurial, managerial and industry related capabilities. This signal also conforms to the definition laid down by Spence (1973). While signals related to human capital and demography have been widely studied in the organization, strategy and economics literature (Baker, 1992; Baron et al., 1996; Baron et al., 2001; Beckman, 2006; Beckman & Burton, 2008; Beckman, Burton, & O'Reilly, 2007; Crutchley, Garner, & Marshall, 2002; Higgins & Gulati, 2006; Loderer & Sheehan, 1989; Pennings & Wezel, 2010; Zhang & Wiersema, 2009), there are few studies examining serial entrepreneurship (Gompers et al., 2006) and marginal performance (Gimeno, Folta, Cooper, & Woo, 1997). I therefore focus on prior founding experience of teams as an indicator of entrepreneurial capability and their effect on marginal performance. Besides teams at founding I investigate loss of members in those teams as a signal of underlying changes in shareholder expectations.

Dissertation Outline

My dissertation comprises three papers probing into entrepreneurial performance and indicators of a start-up's quality. On the one hand, I differentiate the new venture's outcome much further than mere failure or its opposite, by defining a transitory realm between success and failure, which I label "living dead." On the other hand, while the venture's quality is deemed essential for performance, quality is typically unobserved and surrounded by uncertainty. Therefore, I examine three ways through which entrepreneurs signal quality to external resource providers such as VCs: (1) intellectual property rights (patents), (2) the breadth of the venture's technological domain and (3) initial capabilities endowment as revealed by the founders' experience. The three papers that correspond to these three signals of quality provide fresh insights in to a startup's performance, including unintended negative consequences of using these signals that might lead to neither success nor failure.

Quality is regarded as multi-dimensional and hence a repertoire of signal is available to evaluators based on the dimension of quality under scrutiny. My concept of signal of quality is broad in that the signals examined encompass both endowments of the firm as well as its position with respect to others. In the former case, the signals strictly adhere to the definition espoused by Spence (1973). Patents and founding team characteristics are indicators that are partly manipulable by the actor and the difficulty of obtaining these indicators are inversely correlated to the firm's quality level in the aspect being evaluated. In the latter case, signals are more akin to the relational concept invoked by Podolny (2005) to conceptualize status as a quality signal. Technology breadth is therefore a signal similar, in the relational aspect, to status. However, it also satisfies the two criteria laid down by Spence. Therefore, the three indicators used in this dissertation are argued to represent signals of underlying quality under uncertainty for three different aspects: 1) technology capabilities, 2) technology opportunity set, and 3) start-up viability.

I start by analyzing *failure* due to concomitant risks of disclosure arising in conjunction with the role of patents as signals. In the next essay, I explore the phenomenon of *persistence* without liquidity events. To do so, I examine the effects of another patent related signal (technology breadth as revealed over time) on failure and success simultaneously. Finally, the third essay investigates persistence directly by analyzing the effects of another key signal, founding team characteristics, on a new venture's likelihood to persist without harvest or dissolution ('living dead').

Chapter 2: Unintended Hazards of Signaling: Patenting and Start-up Failure

High-technology new ventures employ patents to overcome adverse selection, signaling their underlying quality in the presence of uncertainty and information gap between them and investors (Hsu & Ziedonis, 2008). Hsu & Ziedonis (2008) argue that patents closely resemble Spence's (1973) original conceptualization of signals; they are costly to obtain and provide a mechanism to identify and sort a start-up's innovative capability. Furthermore, they show the benefits of signaling through increased chances of VC financing and higher IPO possibility. I build on their work to expose the possible hazards of patenting. Disclosure via patents provides information no only to investors but also to rivals. I contend that patents provide information about the technological position of the new venture along with proprietary knowledge that invite designing around and litigation threats as other firms use these inventions as building blocks of their own R&D program.

I test these assertions using all US wireless start-ups funded by venture capital between 1990 and 2009. I find that the failure rate of these firms increases as a function of the prior-art citations that their patents receive prior to failure. I further probe the mechanisms by examining the reputation of litigation of the firms that acknowledge the focal start-up's patents in their own inventions. Prior-art citations received from firms that have a reputation to enforce their intellectual property by initiating litigation are found to increase failure rates. Assuming that this reputation indicates a propensity of the citing firm to compete fiercely, resorting to designing around or even litigation, I conclude that patent disclosure erodes the benefits of secrecy and harms the prospects of a new venture.

The findings of this chapter contribute to the literature in the following ways. First, it highlights a counterintuitive mechanism of failure due to threats of designing around and litigation. Receiving citations to one's patents is usually deemed beneficial, providing licensing opportunity or implying deference. However, this view in the current literature may not be universally true as the results in this essay show; the benefits are eroded especially when contentious firms use the inventions. Second, I conceptually separate the stock (i.e., the endowment) and flow (i.e., the recent information) of the patents that a start-up receives. In this setting, the signaling benefits hold for the recent information (flow) while the knowledge stock translates to increased failure rate, again providing evidence of the hazards of disclosure. Finally, from a managerial point of view, this essay reinforces the significance of secrecy as well as technology conformity in settings akin to the wireless sector.

Chapter 3: A Glimpse at Persistence without Liquidity Events: Asymmetric Effects on Success and Failure

Findings in Chapter 2 show significant hazards to patent disclosure through its effect on failure. Disclosing one's inventions also provides additional information on the breadth of domains to which the patents are applicable, as revealed by their use by third-parties over time (Hall & Trajtenberg, 2004). Conceptualizing technology breadth as a signal of quality, I investigate its effect on success and failure simultaneously. Most of the research on new venture performance either analyzes failure or success. The framing is usually binary and symmetric with failure informing about survival and success focusing only on the likelihood of an IPO. By categorizing entrepreneurial performance consequences into success, failure and the continuum of non-events in between (see Figure 1) and examining the effects of the same factor on success and failure simultaneously, I am able to discover systematic, asymmetric forces that cause persistence.

I theorize that a signal of high technology breadth, conveying the presence of an underlying general purpose technology, is beneficial for survival; however it does not inform us much about success. To achieve success start-ups have to surmount two significant challenges: 1) Rent dissipation due to knowledge diffusion that comes with patent disclosure, and 2) commercialization of the technology through collaborations in a high growth market. I theorize that possessing a very specific technology (i.e., low technology breadth) while at the same time experiencing high knowledge spillover, as captured through citations received, increase survival chances; however, it also reduces success probability due to the limited growth possibilities of such technologies when compared to general technologies that can potentially be applied to many markets. I also hypothesize that a collaboration strategy that involves partners from diverse markets benefits both survival and success when the venture is endowed with a general technology (i.e., high technology breadth).

I test the theory in a sub-sample of VC-backed US wireless firms that patent their technology during the years 1990-2009. Findings suggest strong asymmetry in the effects on success and failure. Firms whose inventions signal specific (rather than general) technology and at the same time are highly cited as prior art, demonstrate a propensity to persist, i.e., survive without liquidity or liquidation events. Other systematic forces that inhibit both success (i.e., harvest possibilities) and failures are also uncovered. For example, longer gestation periods as measured through the time taken to receive first round of venture financing increases the likelihood of persistence, indicating inertia due to established routines and capabilities that help survival but impede harvest. In addition, alliance rate of start-ups have asymmetric effects on the two outcomes, i.e., it decreases failure as well as success, perhaps indicating the substitutability of alliance with acquisition.

The major contribution of this essay is to provide an empirical tool to reveal persistence. It provides compelling evidence on systematic forces that inhibit success and failure at the same time, leading us to the 'living dead' firms, the focus of Chapter 4. Other contributions include the usefulness of technology breadth as a signal of quality and some empirical clarification on patent citations as measures of knowledge diffusion, deference and competition (Jaffe et al., 1993; Podolny & Stuart, 1995; Podolny, Stuart, & Hannan, 1996).

Chapter 4: Neither Success nor Failure: Effects of Founding team Imprinting and Subsequent Disruption on the 'Living Dead' Outcome

In Chapter 3, I uncovered the presence of systematic forces that drive start-ups to persist. A subset of such firms, identified in the literature and practice as 'living dead' firms, is the subject of the third essay. 'Living dead' firms are marginal performers, between the two extremes of success and failure, who experience no liquidity events for "extended" periods of time, i.e., much beyond putative expectations (see Figure 1). Following clues from the existing literature on the phenomenon I investigate the effect of still another set of signals of quality—founding team characteristics. I hypothesize beneficial effects of founders' prior experience as entrepreneurs, predicting a lower likelihood of entering this transitory state of 'living dead.' Founding team comprising two members are speculated to indicate an inability to manage the paradoxical needs of fast but rigorous and consensual decision making that set successful firms apart from 'living dead' firms (Bourgeois & Eisenhardt, 1987). I further argue that turnovers in founding team with entrepreneurial experience, whether voluntary or imposed, is a shock that increases the odds of the new firm experiencing the transitory state of 'living dead' due to loss of high-level routines and capabilities or aggravating an already bad situation.

I test the theory using a matched case-control approach on the same population of US wireless ventures as in Chapter 2. A case-control approach is called for because cases are identified using the dependent variable. These cases are matched to similar firms from a control group that includes successful and failed firms. Results indicate that prior entrepreneurial experience, a signal of quality that is frequently used by investors, decreases the likelihood of ending up as a 'living dead' firm. The odds of finding a team with two founders are indeed higher in 'living dead' firms when compared to successful firms, probably signifying two leadership foci or decision making deadlocks that increase coordination costs. Finally, the odds of ending up as a 'living dead' are highly increased when founding teams with previous start-up experience lose members.

This study contributes to the understanding of marginally performing new ventures. It conceptually defines 'living dead' as a transitory state when persistence lasts beyond a threshold defined by industry expectations on time to exit and investment horizons of venture capitalists. Theoretically, it helps understand underlying mechanisms involving founding team characteristics as signals of venture quality. Having entrepreneurs with previous founding experience suggests the presence of higher-order start-up related routines and capabilities acquired through founding multiple ventures that help decrease the chances of persistence and increases the chances of dissolution. On practical insights, the findings suggest that teams with habitual entrepreneurs present a good bet if closure on investments through liquidity or liquidation events is desired. In addition, they suggest that VC interventions to team composition can be counterproductive, especially when founding teams are endowed with entrepreneurial experience.

Empirical Setting and Data

This dissertation is set in the wireless industry which presents three conditions that are especially suitable to test the theories developed in the three essays. First, it is characterized by a weak appropriability regime. Therefore it provides a contrasting setting, where unanticipated costs of disclosing one's proprietary information are significantly higher. Second, this sector has witnessed rapid technological changes managed by large generalist incumbents typically over a ten-year period. Niche partitioning along the periphery of the core technology markets presented entrepreneurial opportunities that spurred VC investments over the past two decades. Finally, the product cycles are short enough to provide start-ups with growth and "harvest" opportunities. In fact the average time to produce such exits in the population of start-ups is less than six years. Therefore, wireless provides a novel setting that contrasts with the biotechnology setting, which has been a major focus in much of extant research on start-ups and is characterized by a strong appropriability regime and long product development cycles.

Using VentureXpert (Thomson Financial) as the primary source of information on VC funding, I assembled a rich longitudinal dataset on 428 VC-backed wireless firms based in the US and founded between 1990 and 2009. Patent data were sourced from Derwent and the USPTO, while the Intellectual Property Litigation Clearinghouse (IPLC) database (also called Lex Machina) provided all intellectual property related litigations in the US. Alliance data was collected using three sources, SDC Platinum, Factiva, and the historical websites of start-ups accessed through the Wayback machine (http://web.archive.org). Product market related data came from Compustat, Hoovers, Corptech and Orbis. Mergers & Acquisitions and IPO events were obtained from SDC Platinum and Zephyr. Finally, historical information on management teams and changes in them was gathered using the Wayback machine and executive search websites such as LinkedIn and ZoomInfo.

Scope and Limitations

The scope of concepts and theory developed are defined by three important factors. First, the performance concepts are specific to the VC context. As such they do not apply to new ventures founded with objectives other than high-growth and eventual sale. Parallels could be drawn to other settings, however, where organizations persist in spite of unmet expectations of key stakeholders[4]. Second, Chapters 2 and 3 pertain mostly to high technology firms in environments where patent-seeking is prevalent. In contexts that discourage patenting, our findings may not be applicable. However, the general signaling mechanisms involved with disclosing proprietary knowledge might still hold. Finally, the conceptualization of marginal performance is driven by a lack of accounting related financial data, quite common with new ventures and more generally with private firms. In situations where data on sales, revenues and profits are available a more appropriate definition of marginal performance using their distribution would make sense.

[4] Examples include family-owned firms with mixed ownership, banks that are funded from institutional source rather than capital markets, and many non-profit organizations such as educational institutions.

In the following chapters I elaborate on the essays outlined above and finally conclude with a chapter that integrates the findings and provides a road-map for future research opportunities arising from this dissertation.

Chapter 2: Unintended Hazards of Signaling: Patenting and Start-up Failure

> *'Intellectual property portfolios are the lifeblood of many wireless tech firms. But patent disputes can cost millions of dollars to defend and take years to resolve.'*[5]

New ventures face significant challenges when securing resources (Stinchcombe, 1965). They have neither an established track record nor tangible assets. But while they possess more information about their technology, products, and people than their potential investors, customers, and employees, they lack the incentives to reveal their true quality because of risks of increased competition and imitation (Amit, Brander, & Zott, 1998; Shane & Cable, 2002; Shane & Stuart, 2002; Stuart et al., 1999). The asymmetric difference in available information between new ventures and potential external stakeholders may lead to adverse selection and market failure. The effects of this information asymmetry have been well-described by Akerlof (1970) in the 'market for lemons,' where uncertainty regarding underlying quality drives superior products out of the market.

Prior studies have investigated a variety of signaling mechanisms to bridge this information gap, including founders' demographic backgrounds (Burton et al., 2002; Eisenhardt & Schoonhoven, 1990), endorsements by reputable third parties (Baron et al., 1999b; Fitza, Matusik, & Mosakowski, 2009; Gulati & Higgins, 2003; Hsu, 2004; Megginson & Weiss, 1991; Stuart et al., 1999), and patents (Hsu & Ziedonis, 2008). For example, Eisenhardt and Schoonhoven (1990) established the positive effects of demographic factors such as founding team size, joint experience, and functional

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[5] Healing the Patent Process (cover story) by Sue Marek in Wireless Week, August 15, 2005, Vol. 11, Issue 17, pp. 6-7

heterogeneity on growth in a sample of semiconductor firms. Other studies have documented the effect of prior experience of founders in prominent companies resulting in increased likelihood of VC funding (Burton *et al.*, 2002), in financial success (Hsu, 2004), and in working with venture capitalists (Shane & Stuart, 2002). Researchers have also found that endorsement by prestigious alliance partners in the biotechnology sector boosts performance of start-ups (Baum, Calabrese, & Silverman, 2000a; Stuart et al., 1999). Likewise, securing early round financing from a prominent VC with representation on the venture's board, increases the venture's odds of survival (Hochberg, Ljungqvist, & Lu, 2007), successful product development (Hellmann & Puri, 2002), and higher IPO valuation (Gulati & Higgins, 2003). Finally, increased odds of IPO are observed when start-ups have a large number of patent applications (Hsu & Ziedonis, 2008; Mann & Sager, 2007; Stuart et al., 1999).

While the literature has extensively covered the benefits of these signals, both for entrepreneurial (Gulati & Higgins, 2003; Higgins & Gulati, 2006; Hsu & Ziedonis, 2008; Stuart et al., 1999) and established firms (Arikan & Capron, 2010; Levitas & McFadyen, 2009; Zhang & Wiersema, 2009), their hazards have been largely ignored. Indeed, studies to date have been slanted towards explaining successful outcomes such as raising finance, achieving IPO, or getting acquired. We believe it is important to study failure in order to avoid biases in learning that result from an over-abundance of success-centered investigations (Denrell, 2003).

Start-ups utilize patents to signal their quality to current and potential resource providers (Hsu & Ziedonis, 2008). The mere act of filing a patent inevitably results in simultaneous disclosure of proprietary knowledge to competitors. Hence, new firms must manage the strong need to signal their worth to resource providers while at the same time avoid revealing too much to competitors. Signaling is a double-edged sword with both benefits and hazards. We specifically address some of these hazards in a setting where patenting is fraught with dangers of value appropriation (Burgelman & Hitt, 2007).

We develop a simple framework to theorize about the benefits and hazards of patenting. We argue that the annual count of patents granted to a start-up serves as signal of underlying and possibly changing quality under uncertainty to resource providers such as VC firms and thus positively affects their prospects of survival. However, patenting is also harmful because it not only reveals information about inventions but also about the technological position of a firm vis-à-vis its peers. It also exposes their technologies to existing firms competing in the same arena. While the acknowledgement of inventions of new ventures by other firms is potentially beneficial due to possible licensing opportunities as well as implied deference legitimizing the start-ups activities, there is also a downside, especially if done by firms with a history of initiating lawsuits (Agarwal, Ganco, & Ziedonis, 2009). We assume that this history implies an underlying propensity to compete aggressively, including designing around inventions.

We test our framework using the population of U.S. VC–funded wireless new ventures founded in the period 1990-2009. Unlike discrete product industries such as chemical and pharmaceuticals (Cohen et al., 2000), appropriating gains from patents in the wireless industry is often challenging because of the complex nature of wireless innovations that involve both products and processes. The threats of ‘inventing around’ and patent litigations are much stronger in such contexts (Cohen *et al.*, 2000), leading to increased hazards to signaling using patents. Our setting is novel in that the majority of prior research on entrepreneurial firms has been conducted on the biotechnology and semiconductor industries, thus allowing us to triangulate some of these earlier findings in a different context.

We contribute to the literature in the following ways. First, we conceptually differentiate between the *stock* and the *flow* of patents and consider the episodic disclosure—the flow—to be the relevant signal of quality. Arguably, the existing stock of patents contains older inventions whose quality is less uncertain and which are less relevant in assessing current innovation efforts. While benefits from the stock of patents in raising finance, attracting prestigious investors, and achieving IPO are well established (Hsu & Ziedonis, 2008), the marginal benefit of receiving an additional patent has not been investigated. Therefore, we contend that recent patents carry more weight as signals to resource providers such as VC firms. Second, we highlight failure, a vastly under-researched aspect of entrepreneurship. Extant entrepreneurship research has indirectly studied failure by centering on survival. In this paper, we theorize directly about failure rather than survival. Third, we provide a fresh perspective on the tension and strategic balance between conformity and differentiation (Deephouse, 1999). Conformity is evident through similarity in technological platforms as revealed by shared technologies, while crowding through overlap in prior art challenges niche occupants to stand out. Last and most important, we show that a patent's forward citations, often conceptualized as 'deference' with positive connotations, are harmful rather than beneficial to the owner of the invention, especially if citations originate from contentious firms.

Finally, this paper has important managerial implications. First of all, our study reinforces the importance of secrecy. Second, while the benefits of patents as signals outweigh the costs, entrepreneurs must manage the dilemma of disclosure. Our research shows that excessive patenting is counterproductive and entrepreneurs should be judicious in selecting which of their valuable inventions to patent. Furthermore, they should monitor not only on the acknowledgements their patents receive, but also on the propensity of these acknowledging firms to litigate.

THEORETICAL FRAMEWORK

Benefits of using patents as signal of quality

> *'Start-ups aggressively seek patent awards so that they can present 'a bouquet of roses' to existing or future investors to prove their technological mettle.'*[6]

The markets where start-ups acquire vital resources for survival and growth such as financing are characterized by uncertainty and asymmetric information (Amit *et al.*, 1998; Gompers & Lerner, 2004). These markets very much resemble the 'market for lemons' (Akerlof, 1970) as resource providers lack the ability to sort new ventures according to their quality in the absence of established past performance or valuable tangible assets, creating the problem of adverse selection. To overcome such adversity and bridge this information gap, start-ups signal their quality to potential investors and other resource providers.

[6] The Relentless Pursuit of Patents. By Margo McCall, Wireless Week, October 14, 2002, p. 20.

Hsu and Ziedonis (2008) conceptualize patents as one of the many signals used by new ventures and examine the relative efficacy of different signals across the life of a new firm. In their semiconductor industry study, they show that the stock of patents significantly determines venture valuations, ceteris paribus, and fosters the likelihood of sourcing from a prominent VC in the first funding round. Their findings also highlight sector-specific practices, because endorsements in their industry are not associated with higher IPO probabilities, unlike the positive endorsement effects observed in biotechnology (Stuart *et al.*, 1999). Like the wireless sector in this study, the semiconductor sector exhibits an unfavorable appropriability regime where lead-times and secrecy trump patenting as mechanisms for protecting and appropriating gains from innovation. If the filing and granting of patents confers such positive signaling benefits in the semiconductor setting, we should expect, likewise, patents to perform an important signaling function in the wireless sector to attract new investors and convince existing promoters of the firm's viability. We go further, however, and ask whether there are limits to these benefits.

Limits to the benefits of signaling: Stock versus flow

We build on Hsu and Ziedonis (2008), making the important distinction between the stock and flow of patents in order to isolate endowment effects from signaling effects respectively. In other words, a firm's accumulation of patents during the course of its history can be viewed as the aggregate or stock, while the current increment represents the flow increasing that stock of knowledge. Using this distinction, we investigate the marginal benefits of receiving an additional patent as signal. We contend that this periodic addition is a powerful signal to distinguish between novel and existing information. Furthermore, this reasoning reinforces the relevance of recent over temporally distant and potentially outdated information.

New information might reduce existing uncertainty about the quality of the focal firm; however, since firms face the dilemma of revealing too much, the benefit of additional signaling cannot be monotonically increasing. Thus, while stock (endowment) is associated with positive outcomes, flow (signal) may be associated with decreasing returns. In other words, the benefits of the signal might decrease with increasing number of patents. Investors and other stakeholders update their evaluation of quality as start-ups are granted more patents. Additional patents could be superfluous in contributing to quality evaluation, if not counterproductive, in revealing the firm's technology endowment and ultimately its survival prospects. Resource providers might even interpret excessive patenting as a smokescreen or as exploitation of technology rather than innovation.

Therefore:

H1. The yearly flow of patents granted to a start-up has a curvilinear relationship to its failure rate.

As highlighted above, existing literature has paid considerable attention to the benefits of signaling without addressing its negative effects. Since the act of patenting not only confers benefits but also exposes the start-up to costs or liabilities, we next hypothesize about the harmful effects of disclosure through patenting. We argue that start-ups are exposed to two kinds of hazards when they patent— 1) revealing their position in the technology arena, and 2) negative spillovers, especially designing around and threats of litigation.

Hazards of using patents as signal of quality

In the following sections we analyze the two hazards that patenting entails. In order to capture the hazards of revealing the start-ups technology position we theorize about the new ventures location in two networks formed as they receive patents. First, the network formed through similarity in technology functions, i.e., ties defined through patents belonging to the same technology domains. Second, the network formed through a start-up using other new firms' inventions, a finer measure of similarity through shared technological inputs. Negative spillovers through disclosure are indirectly tracked through the acknowledgement of the focal start-up's inventions by other firms. Further, the reputation of litigation of the firms citing the start-up's patents is used tease out the competitive mechanism of designing around.

Nonconformity in start-up technology space

Start-ups face 'the liability of newness' (Stinchcombe, 1965). Because of their novelty and distinctiveness (Aldrich & Fiol, 1994), new ventures confront costs due to the lack of both legitimacy (Low & Abrahamson, 1997) as well as external validation (Stone & Brush, 1996). Start-ups that are considered legitimate get access to both firm-specific resource capital and institutional-level capital (Lounsbury & Glynn, 2001). Conformity gives access to institutional-level capital and comprises three components: industry legitimacy, industry norms and rules, and industry infrastructure (Lounsbury & Glynn, 2001; Oliver, 1997).

Industry legitimacy refers to the degree to which the products and services offered by a firm are accepted as appropriate and useful by the consumer (Hannan & Freeman, 1984; Scott, 1995; Suchman, 1995). Industry norms and rules demarcate the kinds of economic behaviors that are socially appropriate (Scott, 1995). Industry infrastructure encompasses the broader set of generalized industry resources, as well as market opportunities that allow incumbents and entrants to develop and grow their businesses. The hazards of nonconformity in our case refer to this third component, industry infrastructure, specifically the broad technological activities that are considered legitimate and incur diminished demand uncertainty. We use the concept of the industry's technology space to investigate that institutional-level capital.

Technology space comprises the arena where an organization invents and develops new technologies (Pontikes, 2009). To capture the hazards of nonconformity, we conceptualize the start-up's technology space as the cumulative network formed among new firms (nodes) through sharing general technology activities (ties), that is the functional domains to which a patent is attached, over the course of the sector's history (here called the *start-up technology activity network*). We define the network ties at a broad technology activity level and use a single cumulative network to define this space because the pressures to conform to technologies sanctioned by the industry only unfold over time, as new ventures with both legitimate and unsanctioned technologies enter the technology space and build on each other's inventions. As an analogy, we can compare the *start-up technology activity network* to the trajectories of smaller planetary objects such as asteroids, which are strongly influenced by the gravitational pulls of larger planets. Asteroids can orbit without being destroyed only in specific locations determined by the forces exerted by larger planetary objects.

The context where this technology activity network evolves is marked by two salient characteristics: managed standardization of technologies and their life cycles, and control of complementary assets by incumbents. Industry incumbents control the technology trajectory through managed evolution approximately over a ten-year cycle. Powerful telecom vendors such as Nokia and Qualcomm and telecom carriers such as Verizon and T-Mobile dominate standards bodies. Carriers also own the most important complementary asset, access to customers with mobile devices, which drive demand. This vice-like grip is further strengthened through the ownership by incumbent carriers of critical scarce resources, frequency spectrum in this case (Sabat, 2002) and by high investments in infrastructure. While carriers control that scarce resource and act as gatekeepers to customers, vendors control the technology development by exploiting established resources, capabilities, and market power (Leiponen, 2008).

The threats from powerful incumbents are multiplied when a start-up's technology deviates from established standards as they seek to maintain the status quo. These factors are especially detrimental to small firms, which exhibit a particularly strong need for access to the industry infrastructure. Therefore start-ups have a strong incentive to innovate in technology domains that are sanctioned by the incumbents, placing them along a core-periphery continuum. Firms attempting nonconforming innovations reside at the periphery, while those which are technologically proximate to major incumbents or congruent with their standards will occupy central positions. A space characterized by a core-periphery structure rewards start-ups that innovate in the core technologies of the sector through access to complementary assets, increased legitimacy, and increased demand.

Nonconformity to sanctioned technologies and standards, as denoted by the firm's peripheral position, could be fatal, as illustrated by the case of ComSpace Corp, a Texas-based company that received $26 million in equity financing from such prestigious sources as Sevin Rosen Funds and Noro-Moseley Partners. ComSpace owned about 20 patents on a technology that allowed an eightfold amount of traffic to be carried over existing radio channels. Called Digital Multicarrier Architecture—DCMA for short—the technology also handled data, meaning it could be used for wireless access of the Internet, short-text messaging, e-mail, and video. However, DCMA, despite sharing a nearly identical acronym with Code Division Multiplex Access (CDMA), one of the core technologies standardized by industry incumbents, quickly vanished from the sector because it did not conform to existing industry standards and thus could not access the markets controlled by incumbent carriers.

Hence, the second hypothesis:

H2. The closer to the core of the start-up technology activity network a firm is, the lower its failure rate.

Having reviewed the similarity of start-ups at the broad technology-activity level to hypothesize about their need for legitimacy, we next consider the pressures to 'stand out' in order to compete in the technology space, consistent with previous research on strategic balance between conformity and differentiation (Deephouse, 1999; Porac, Thomas, & Baden-Fuller, 1989).

Competitive crowding in the start-up technology space

Similarity (or difference) among firms is an important issue both in strategic management and organization theory (DiMaggio & Powell, 1983; Hannan & Freeman, 1977; Porter, 1980; Rumelt, Schendel, & Teece, 1994). By being similar, a firm gains legitimacy benefits (DiMaggio & Powell, 1983; Meyer & Rowan, 1977; Pfeffer & Salancik, 1978; Suchman, 1995), while by being different, it can build a competitive advantage (Barney, 1991a; Baum & Mezias, 1992; Porter, 1991). Scholars have pointed out the need to balance these conflicting requirements, showing the benefits of moderate levels of similarity in the market space demonstrated by Deephouse (1999) in his study of U.S. banks. By recasting the technology space at a more granular level of resolution, we parse the location of new entrants in terms of their technological distinctiveness.

Whereas the *start-up technology activity network* defined above is an attempt to infer conformity pressures, shifting the network tie to a more fine-grained level through the actual inventions on which new firms build their patents, that is, backward citations, can be viewed as an attempt to infer differentiation amongst start-ups. We therefore define another time-evolving technological network using patent citations (here called the *start-up technology citation network*) to capture this strategic imperative to stand apart amid competition

Podolny, Stuart, and Hannan (1996) define organizational niche in terms of technological ties among firms, where a tie forms a link between an antecedent and consequent invention between two organizations. The tie reflects the points of contact in research and development between them. We capture the competitive crowding that a firm faces consistent with this concept of niche overlap (Podolny *et al.*, 1996). Niche overlap entails the common dependence of two organizations on a finite resource, in our case the set of prior inventions that have already been disclosed. These overlaps are asymmetric and greater the dependence, the stronger the competitive effect of one firm over the other. That is, one firm's pursuit of technology possibilities (specific inventions it owns that become antecedents to others' inventions) affects the ability of the other organization to pursue its opportunities. Greater niche overlap implies similarity and even redundancy in technological efforts. Consequently, the market opportunities of an entry-seeking firm are inversely proportional to the extent of its overlap with all other entrants, all else equal.

Technological crowding around a focal new firm (a node in the network) is the aggregate of all its niche overlaps with all other start-ups. Crowded technology areas often imply continuous duplication of effort as undifferentiated firms invest in development of closely related technologies (Stuart, 1998). The implication of similarity and even redundancy in technological sourcing implies increased probability of failure given similar demand on the output side. We therefore posit our third hypothesis:

H3. The greater the technological crowding of a firm in the start-up technology citation network, the higher its failure rate.

We now transition our theorizing from the *start-up technology activity* and *start-up technology citation networks*—collectively the start-up technology space—to the technology space that comprises both start-ups and other established firms in the sector, broadly defined. We theorize about the hazards to start-ups as they disclose their newly developed technology and as other firms build on these inventions.

Disclosure: Negative spillovers and litigation reputation

The effectiveness of patent protection varies across industries. In their survey of R&D managers, Cohen et al. (2000) highlighted the perils of patenting, including the difficulty in demonstrating an invention's novelty, the risk of disclosing too much information in a patent, the cost of applying, the cost of defending a patent in court, and the ease of legally inventing around a patent for competitors. The most common reasons given for not filing a patent were ease of inventing around it and concerns over disclosure. Smaller firms were also dissuaded from patenting by the cost of litigation.

Cohen et al. (2000) distinguish between 'discrete' and 'complex' product industries. Complex product industries are those where products and processes are protected by numerous patents (for example, computers and communications equipment). Discrete product industries are those where a product is typically protected by relatively few patents (for example, drugs and chemicals). Discrete product industries, compared to complex ones, enjoy far more favorable appropriability conditions. The wireless telecommunication industry, with mostly complex products is known for the preferential use of secrecy and rapid time-to-market over patents (Bekkers, Duysters, & Verspagen, 2002; Bekkers & West, 2009; Leiponen, 2008). Patenting as a signal has unwanted side effects, including harmful spillovers and imitation, not to mention the threat of litigation, as captured by the opening quote of this paper.

The hazards of disclosure and negative spillovers for a focal firm cannot be directly observed. However, other firms that build on the start-up's inventions can be tracked using prior-art citations (forward citations) received by the focal firm's patents.

Further, we can characterize the behavior of these citing firms in enforcing their patents through litigations. For example, extant research finds that firms which aggressively protect their intellectual property build a reputation that deters employees who move to other companies from disclosing valuable knowledge (Agarwal *et al.*, 2009). We therefore combine forward citations with the litigation reputation of those firms that acknowledge the R&D output of the start-up to conjecture about the hazards of disclosure.

Forward citations have been conceptualized by researchers in a number of ways. The cumulative forward citations received over time are often imputed as a patent's value. (Hall, Jaffe, & Trajtenberg, 2005). Moreover, forward citations have been used as paper trail for knowledge spillover (Jaffe et al., 1993) and as indicators of likelihood of patent litigation (Lanjouw & Schankerman, 2001). As flows, they have been construed as direct ties between organizations revealing the reliance on the focal invention for the citing firm's proprietary research (Podolny & Stuart, 1995; Podolny *et al.*, 1996; Stuart & Podolny, 1996). Forward citations as direct ties have been conventionally interpreted as 'deference' or respect to the cited firm's contributions (Podolny & Stuart, 1995; Podolny *et al.*, 1996; Stuart, 1998). While acknowledging that such direct ties could harm the firm's prospects because they signal increased competition resulting from similarity of inventions, existing literature has mostly shown the benefits of forward cites, both with or without considering the status of the firm that expresses implied deference (Podolny *et al.*, 1996; Stuart, 1998; Stuart *et al.*, 1999). The net effect of the forward citation as a direct tie on average remains an empirical question. We therefore, examine the firms citing the start-up's patents and their litigiousness to hypothesize about negative spillovers.

Given that entrepreneurial firms are typically small, fledgling organizations, and therefore extremely vulnerable to the litigious threats of large incumbents, we further extend the hypothesized argument by considering the patent litigation record of firms that build on their inventions. We distinguish between the reputation to initiate lawsuits and to receive them. We contend that a firm competes aggressively if on average it initiates more litigations than it receives. In other words, these firms actively enforce their intellectual property rather than just defend. We argue that such firms display a higher propensity to aggressively contest start-ups that encroach into their technology niche. Instead of expressing deference, we contend that these competitors may choose to invent around and leverage their reputation as tough litigators. Such a threat may be a powerful deterrent to small firms as litigations are costly, undesirable, if not outright hazardous (Koen, 1991; Lanjouw & Schankerman, 2004; Lerner, 1995). C*eteris paribus*, the more litigious the firm that builds on the start-up's patents, the lower the survival prospects of the start-up. Thus:

> *H4. The greater the reputation of enforcing patent litigations of forward-citing firms, the higher the start-up's failure rate.*

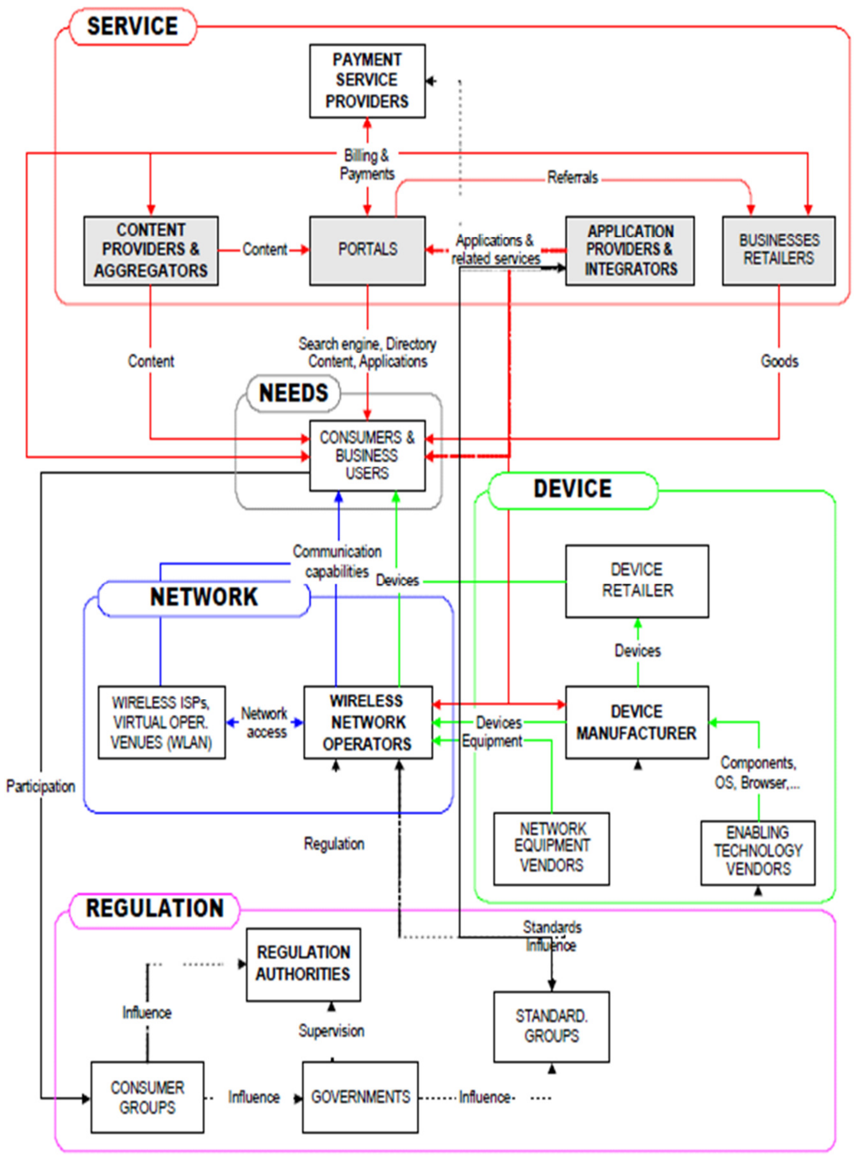
EMPIRICAL SETTING AND METHODOLOGY

Industry Context

Our study is based in the wireless sector during the period 1990-2009. We selected this context because wireless is a 'complex product' industry with both product and process innovation, which results in a stronger concern regarding the hazards of patenting (He, Lim, & Wong, 2006). Further, access to complementary assets such as manufacturing capability, distribution, branding, and marketing is of paramount importance in this setting (He *et al.*, 2006; Teece, 2006). During the period of investigation, the sector is marked by successive generations of standards-based technologies, starting with the second-generation (2G) voice-based technologies and followed by the data-oriented third-generation and fourth-generation (3G & 4G) technologies (Ansari & Garud, 2009).

The wireless sector exhibits a very complex 'ecosystem' with a variety of players, as illustrated in Figure 2 (Camponovo & Pigneur, 2003). This implies that the industry cannot be conceived using a simple SIC code classification. This vertically disaggregated industry 'value network' is dominated by firms that are vendors of equipment and handsets (for example, Nokia, Ericsson, Apple, Qualcomm, Samsung, and Motorola) and network operators (or carriers) (for example, T-Mobile, Verizon, and Vodafone) through control of important complementary assets. Costly infrastructure and technologies together with ownership of important complementary assets exert strong conformity pressures on new entrants seeking a foothold. For example, a start-up with a novel antenna technology that improves the capacity of mobile networks needs to be compatible with the incumbent technologies already deployed. Without conforming to prevailing technology standards, new firms can neither license nor implement their innovations. Further, the evolution of the wireless sector is marked with several instances of challenges to existing standards – for example, Wi-Fi (Christensen & Raynor, 2003) and more recently WiMax (Teece & Pisano, 2007) as substitutes for third generation (3G) technologies, that have so far succumbed to conformity pressures.

Figure 2. Wireless Actors Map



The influence of powerful incumbents, however, has not been a deterrent to venture capital funding. High growth potential and a variety of opportunities resulting from deregulation and technological discontinuities have spurred entrepreneurial activity. New firms not only introduced new wireless technologies such as Wi-Fi, WiMax, Bluetooth, ultra-wideband (UWB), ZigBee, global positioning system (GPS), and radio-frequency identification (RFID), but have also spawned new software, applications, and content. The gradual shift in emphasis from voice to data has also been a key determinant in opening up these opportunities. For example, push e-mail (popularized by Research in Motion [RIM] through its Blackberry device and service) has diffused widely as wireless data technologies have increased in speed, creating opportunities in smart-phone devices, service management, servers, software applications, and peripherals.

Data and Sample

We test our hypotheses using the population of all VC-funded firms in the U.S. wireless sector that were founded between the years 1990 and 2009. We include those new firms that received at least one round of early-stage VC funding, consistent with our earlier discussion regarding the problem of information asymmetry (Gompers, 1995). Firms that seek venture capital must signal their quality, making the use of secrecy difficult. We limit ourselves to U.S.-based ventures for three reasons. First, the majority of the start-up activity was concentrated in the United States (53% of all start-ups, compared to 9% in Sweden, the next ranking country). Second, the venture capital segment of private equity is more developed in the United States, both in numbers and in terms of well-established practices that encourage entrepreneurs to choose this financing route over alternatives (Jeng & Wells, 2000). Third, it allows us to hold constant idiosyncratic country-level factors including government subsidies and political risk, among others. Although we confine the start-up sample to U.S. firms, we investigate their inventions in the global technological environment.

Our sample consists of 428 firms as documented by VentureXpert, the leading source of information about venture capital from Thomson Research, commonly viewed as the most comprehensive and widely used database for research on venture-funded companies (Kaplan & Schoar, 2005). We classify start-ups as wireless firms using the Venture Economics Industry Classification (VEIC) (Dushnitsky & Lenox, 2005) system of Thomson. We consider new ventures assigned to primary VEIC codes in the range of 1300 to 1399 as wireless firms. We supplement these codes with Standard Industry Classification (SIC) codes from SDC Platinum, Hoovers, Orbis, and CorpTech.

A major source of data on the sampled firms' patents is Derwent, a database of global patents maintained by Thomson since 1969 and frequently used in strategic management research (Eggers, 2008; Henderson & Cockburn, 1994). The Derwent database provided higher coverage for our sample of firms because of its global reach. Since wireless is a global industry, firms also seek intellectual property protection outside the United States, thus making Derwent a better choice for our inquiry.

We collected patent litigation data using the Intellectual Property Litigation Clearinghouse (IPLC) database (also called Lex Machina) at Stanford University. It was created by the Stanford Program in Law, Science and Technology to make intellectual property litigation data more widely available. It covers all (1) patent infringement, (2) manifest copyright, (3) manifest trademark, (4) manifest antitrust, and (5) certain trade secret lawsuits filed in the U.S. District Courts from January 1, 2000, to the present. We obtained all patent-related cases involving our focal firms as well as firms that cite their patents for the ten-year period available.

Data related to alliances were collected from three sources: SDC Platinum, Factiva, and the historical Web sites of firms in our sample using the Wayback machine (http://web.archive.org).[7] For merger and acquisition and IPO information we relied on SDC, Zephyr, Factiva, and Hoovers. Finally, COMPUSTAT was accessed for segment data on publicly listed wireless firms.

Dependent Variable and Estimation Method

Table 1 provides definitions of the variables used in our analysis. We conduct an event history study of failure rate. We categorize failed firms as those that were liquidated due to outright bankruptcy or those that were acquired in a distressed sale. These modes of dissolution were primarily determined through VentureXpert, which maintains this information in the 'Company Current Situation' field. For those firms involved in a distressed sale, the information came from SDC and Zephyr, which captures this status in the deal description. *Failure,* the dependent variable, is set to 1 in the year that the focal firm failed and 0 in all other years from founding. We identified 109 failed outcomes and created firm-year spells from founding to failure or to the end of 2009 when the data are censored. Firms that achieve Initial Public Offerings (IPO) and firms that are acquired were also identified and added to the dataset. All the remaining

[7] We used three sources to ensure completeness of data. Standard sources like SDC and Factiva under report alliances from smaller firms; therefore we used multiple sources and triangulated the information.

firm-observations were censored at the end of the study period. We model the hazard rate using the time to failure experienced by the firm from birth.

Right-censoring and the presence of both time-varying and time-invariant covariates make the choice of the Cox proportional hazard model appropriate for this study (Allison, 1984). The main set of regressions estimates the hazard rate of failure h(t) using the following equation:

$$\log(h(t)) = \alpha(t) + \beta_1 * (\textit{Patent Grant Flow}(t)) + \beta_2 * (\textit{Patent Grant Flow}(t))^2 + \beta_3 * (\textit{Closeness Centrality in Technology Activity Network}) + \beta_4 * (\textit{Crowding in Technology Citation Network}(t)) + \beta_5 * (\textit{Patent Cite Flow by Firms}(t)) + \beta_6 * (\textit{Reputation Patent Litigation of Citing Firms}) + \beta_7 * (\textit{Controls}) + \varepsilon \quad (1)$$

Using this equation the test of H1—that is, the diminishing rate of returns to patent flow—consists of verifying if $\beta_1 < 0$ and $\beta_2 > 0$. The nonconformity hypothesis, H2, is tested by estimating whether $\beta_3 < 0$, while the crowding or technological overlap hypothesis, H3, is deemed valid if $\beta_4 > 0$. For the competing hypotheses, H4, we use β_5 to determine which of the two prevails. H5 is tested using β_6 (>0) and additional analysis described below. The regressions were computed using the stcox procedure of Stata.

Table 1. Variable Definitions (Chapter 2)

Variables	Description
Dependent Variables	
(1) Failure	A dummy indicating that the firm had experienced a distressed sale or had become defunct in a given year
Independent Variables	
(2) Patent Grant Flow	Number of new patents granted to the firm in a given year
(3) Closeness Centrality in Technology Activity Network	Closeness centrality of the firm in the network defined through shared IPC
(4) Crowding in Technology Citation Network	Sum of niche overlap in the network defined by backward citations
(5) Patent Cite Flow by Firms	Number of new cites received from other organizations by the firm in a year
(6) Cumulative Litigation Initiated	Forward cite flow weighted by count of lawsuits initiated
(7) Cumulative Litigation Received	Forward cite flow weighted by count of lawsuits received
Control Variables	
Patenting Related	
(8) Self-Citations	Total number of self-cites received by the firm in a year
(9) Patent Grant Stock at t-1	Stock of the firm's patents at the start of a year
(10) Total Forward Cite Stock at t-1	Stock of forward cites received by the firm at the start of a year
Exit Market Conditions	
(11) IPO Heat	Intensity of IPO activity in the firm's primary SIC code in a given year
(12) Number of Targets in SIC	Number of targets acquired in the SIC in a given year
Investor Characteristics	
(13) Total Number of Investors	Number of distinct investors that invested in the firm over all rounds
(14) Number of Investors Investing in All Rounds	Number of investors that invest in all rounds
(15) Prominent Investor	Indicator of presence of investor that was in the Forbes Midas list
Financing Related	
(16) Number of Rounds Received	Number of rounds of funding received by the firm till the end of study
(17) Time to First Round	Time in days from founding to receiving first round
Initial Firm Quality	
(18) Founding Team Start-up Experience	Sum of wireless start-ups founding team worked in prior to the focal firm
Firm Strategic Action	
(19) Number of Alliances	Number of alliances by the firm in a year
(20) Number of Acquisitions	Number of acquisitions by the firm in a year
Others	
(21) Business Segment Sales in Wireless	Total sales of all public wireless companies in a given SIC code
(22) Number of Public Competitors	Number of public competitors
(23) Entry Year	Year of entry of the firm in the risk set

We perform robustness checks using a shared frailty model to allay concerns of unobserved heterogeneity (Gutierrez, 2002) and further address endogeneity concerns in the Results section below. Frailty models assume that the dependence is created by unobserved heterogeneity, and correct for bias in both coefficient estimates and standard error estimates by treating the unobserved heterogeneity term as a random variable with a specified probability distribution (gamma-distributed in our case) using an equation of the following type:

$$log\,(h_i\,(t\,)) = \alpha\,(t\,) + \beta * x_i(t) + \varepsilon_i, \qquad (2)$$

Here $h_i(t)$ is the hazard for the i-th firm and ε_i represents the unobserved heterogeneity of the i-th firm.

Independent Variables

Benefits of Signaling

Patent Grant Flow

We distinguish between the stock and flow of the patents granted to a start-up. *Patent Grant Flow* captures the number of patents granted to a firm in a given year. We use the grant year to construct the stock and flow because patent grant is arguably a more powerful signal to resource providers than the mere act of applying.[8] This time-varying flow of new patents allows us to distinguish between fresh information, that is, the signal, and the endowment, that is, the stock accumulated up to the start of a given year. It ranges from 0 to 41 with a mean of 1.

[8] Robustness checks using application dates are also performed and give consistent results

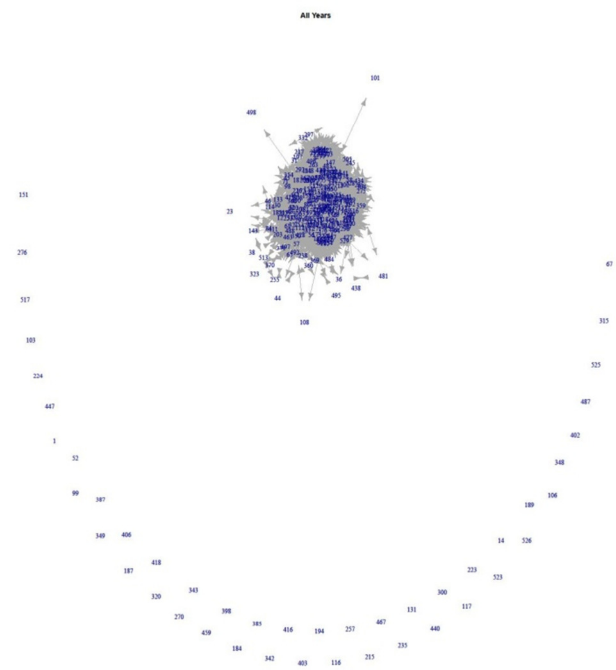
Hazards of Signaling

Start-up Technology Activity Network: Nonconformity

The technology activity network is the affiliation network formed among start-ups through sharing broad technology activities. We use the International Patent Classification (IPC) subclass (4 alphanumeric symbols denoting the third hierarchical level of the classification) to proxy technology activity. For example, the IPC subclass G06F, which refers to all activities related to electronic digital processing, is shared by 193 of our focal firms, while G06E, which covers optical computing devices, is present in the patents of only one company. Thus the two sets of vertices in our affiliation network are the focal new ventures and the IPC subclass to which their patents belong.

Following our theory, we construct a single affiliation network spanning 1990-2009 to capture the prevailing conformity pressures that incumbents exert, especially in the start-up technology space. The assumption is that incumbents shape the incentives to innovate in their preferred activities, as reflected in the network formed among new ventures through shared IPC subclasses. Using the start-ups as nodes, we transform this bipartite graph into a 1-mode network to define similarities in technology activity between start-ups as revealed by shared IPC subclasses (Wasserman & Faust, 1994). This start-up network (Figure 3) displays an expected core-peripheral structure.

Figure 3. Wireless Start-up Technology Activity Network, 1990-2009



To measure the degree to which firms conform, we calculate the closeness centrality in this network. Essentially, we seek to ascertain how close a start-up is to its peers along the core-periphery continuum (Freeman, 1979). The variable *Closeness Centrality in Technology Activity Network ($C(n_i)$)* which measures this closeness between a start-up and other new ventures is defined by the following formula:

$$C(n_i) = (n-1)/[\Sigma_j \; d(n_i,n_j)] \tag{3}$$

where n_j is the jth node and n is the total number of nodes. The function *d(x,y)* is a distance function measuring the number of hops in the shortest path linking nodes n_i and n_j. The closeness centrality variable ranges between 0 and 1, with unity indicating that a firm is maximally close to all other firms. The higher this value, the closer a start-up is to the core. It ranges from 0 to 0.02 with average value 0.01.

Start-up Technology Citation Network: Competitive Crowding

Consistent with existing literature, the start-up technology citation network is constructed as a time-variant network of all the patents that the focal start-ups cite, using a five-year moving window, prior to and including the year in consideration (Podolny *et al.*, 1996). Thus, each prior art that firms cite in their inventions is construed to form a tie between firms. Following Podolny et al. (1996), we first define the niche overlap, $Ov(n_{ijt})$, for a focal firm i with another start-up, j, as the proportion of the common backward citations between the two firms to the total number of backward citations ($BC(n_{it})$) of the focal firm at a given time t, over the window $t-4$ to t.

$$Ov(n_{ijt}) = (BC(n_{it}) \cap BC(n_{jt}) / BC(n_{it}) \tag{4}$$

$$Ov(n_{jit}) = (BC(n_{it}) \cap BC(n_{jt}) / BC(n_{jt}) \tag{5}$$

$$Ov(n_{ijt}) \neq Ov(n_{jit}) \tag{6}$$

We thus create an asymmetric matrix of these niche overlaps for each firm pair and then create the variable *Crowding in Technology Citation Network,* $Cr(n_{it})$, for each start-up, as the sum of all such niche overlaps across the set of other start-up firms.

$$Cr(n_{it}) = \Sigma_j \, Ov(n_{ijt}) \tag{7}$$

This construct that measures similarities of ties based on actual inventions, is conceptually similar to structural equivalence and represents the competitive costs due to crowding. The more start-ups cluster together, the more they experience competitive pressure. This variable takes on values from 0 to 9 with a mean of 0.12. It's correlation with the closeness centrality in start-up activity network is 0.14.

Disclosure: Negative Spillovers and Litigation

To calibrate the costs of disclosure, we use the yearly flow of forward citations (as prior art) that the focal start-up receives from other firms (excluding self-citations). We calculate this variable annually from the focal firm's founding till either failure or censoring. This variable, *Patent Cite Flow by Firms*, thus measures 'deference' by calculating the annual, unweighted forward citations from peer organizations in a given year.

We create two additional variables, *Cumulative Litigation Initiated* and *Cumulative Litigation Received*, by weighting the flow of forward citations by the patent litigation reputation of the citing firms. To measure this reputation, we obtained 27,457 patent-related cases from the Lex Machina database during the time frame 2000-2009.[9] We matched the names of start-ups in our sample and the names of all the organizations that cite the focal new ventures to the names of firms that either initiate patent lawsuits or act as defendants in such cases.[10] The reputations were constructed by cumulating the count of lawsuits in which firms were involved in these roles over the ten-year period that the database covers. *Cumulative Litigation Initiated* is the forward citation flow weighted by the reputation of the citing firm as plaintiff, while *Cumulative Litigation Received* is the forward citation flow weighted by the reputation of the citing firm as defendant. For example, if focal start-up i receives citations FC_{jit} and FC_{kit} from firms j and k at time t,

[9] Lex Machina starts coverage in 2000, so we do not have data on patent litigation from 1990-99.
[10] We used a combination of automated and manual matching. As a first step we matched the names using Soundex and then manually went through the list to get the exact matches.

and the reputations for litigation as plaintiff and defendant are RLI_j (and RLI_k) and RLD_j, (RLD_k), then:

$$Patent\ Cite\ Flow\ by\ Firms_{\,it} = FC_{jit} + FC_{kit} \tag{8}$$

$$Cumulative\ Litigation\ Initiated_{\,it} = FC_{jit} * RLI_j + FC_{kit} * RLI_k \tag{9}$$

$$Cumulative\ Litigation\ Received_{\,it} = FC_{jit} * RLD_j + FC_{kit} * RLD_k \tag{10}$$

Since these two measures are highly correlated (those who sue are likely to be counter-sued), in our analysis we use the net effect obtained through the residuals of regressing *Cumulative Litigation Initiated* over *Cumulative Litigation Received*.

Control Variables

Prior studies have identified many factors that influence new venture survival. We therefore include controls in seven broad categories. In the first category, related to patents, we include the stock of patents granted (Hsu & Ziedonis, 2008) as well as the stock of forward citations received (to capture the value of the patents (Hall *et al.*, 2005)) in the previous years. Prior studies have also shown significant positive effects for self-citation (Hall *et al.*, 2005); we therefore use self-citation flow as a control. These could signify attempts by firms to create patent thickets or a technology trajectory that might be beneficial for survival.

The second category controls for market conditions that are important drivers for liquidity events (Sorenson & Stuart, 2008; Stuart & Sorenson, 2003). The intensity of annual IPO activity in a start-up's four-digit SIC industry and the annual incidence of merger and acquisition activity in that industry are both computed as yearly counts and included as controls in the models. The third group of variables controls for investor characteristics. We include a measure of investor quality (Hochberg *et al.*, 2007) using the count of VCs that invest in a start-up and that were also featured in the Forbes Midas list between 2000 and 2009. The Midas list provides an annual ranking by *Forbes Magazine,* of the best dealmakers in high-technology and life sciences venture capital. We also control for investor confidence and expectations in the start-up using two variables: the count of all the VCs that invest, and the count of investors who commit funds in all rounds of financing (Sorenson & Stuart, 2008).

Fourth, new ventures need resources to survive (Lee et al., 2001). Therefore we control for the number of rounds of financing received and time from founding to the first VC financing. In the fifth group, we include the start-up experience of the founding team - another signal of quality - to account for variations in initial quality among the start-ups (Burton et al., 2002; Eisenhardt & Schoonhoven, 1990). The sixth category includes corporate development actions, that is, strategic alliances and acquisitions. We thus control for endorsement effects that have been shown to be significant predictors of a new venture's success (Stuart *et al.*, 1999). Last, we include product market competition and growth at the sector level (Covin & Slevin, 1989), using the number of public companies and total sales per year in all business segments in which publicly quoted wireless operators (SIC 4812) and vendors (SIC 3663) operate. Finally, we include the start-up entry year to account for potential violation of the non-informative censoring assumption.

Descriptive Statistics

Table 2 presents the correlations and descriptive statistics for the variables in the analysis. Given the high correlations between some of our variables, we performed diagnostics for multicollinearity using the Variance Inflation Factor (vif) procedure after running an OLS regression in Stata. No significant issues were found (Allison, 1984).

On average, a start-up receives four rounds of financing, with an average of roughly one million dollars invested per round. It takes six years on average to generate an exit via IPO, while acquisition events take five and a half years, similar to the time it takes to become defunct. A new venture is granted a mean of 12 patents, with considerable variation between firms (ranging from 0 to 143). This translates into a yearly flow of one patent, again with substantial heterogeneity (0 to 41). These patents cover 146 IPC subclasses. The top ten IPC subclasses are responsible for 60% of the ties between firms (Table 3). Interestingly, the IPC subclass specifically dedicated to wireless communication (H04W) occupies only the tenth position. The firms in our sample receive about four forward citations per year, but again there is a large dispersion in this statistic. Table 4 lists the top ten firms that build on the patents of the focal new ventures.

Regarding patent infringements, we found that only 15 out of the 428 new ventures were involved in any lawsuit (8 initiated litigation, while 11 were defendants). Of the 15, only 3 firms experienced an IPO or acquisition, and in those cases the lawsuits occurred after the liquidity event. Table 5 lists the count of litigations initiated and received by the top 10 firms which cite patents owned by the ventures in our sample.

Many of these firms are well-known organizations; they are the targets of litigation more often than plaintiffs–the two counts are highly correlated.

Table 2. Summary Statistics and Correlations (Chapter 2)

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	0.04	0.19	0.00	1.00	1.000									
(2)	0.98	3.14	0.00	41.00	-0.005	1.000								
(3)	0.01	0.01	0.00	0.02	-0.057	0.223	1.000							
(4)	0.12	0.42	0.00	9.00	0.039	0.071	0.141	1.000						
(5)	3.52	11.41	0.00	155.00	0.061	0.527	0.225	0.128	1.000					
(6)	23.43	114.46	0.00	2203.00	0.021	0.226	0.147	0.064	0.606	1.000				
(7)	102.90	506.01	0.00	8312.00	0.010	0.195	0.146	0.062	0.556	0.962	1.000			
(8)	0.21	1.07	0.00	23.00	0.013	0.693	0.150	0.056	0.645	0.375	0.315	1.000		
(9)	2.69	8.83	0.00	112.00	0.043	0.414	0.213	0.070	0.584	0.739	0.664	0.411	1.000	
(10)	12.36	64.76	0.00	1364.00	0.014	0.216	0.139	0.061	0.559	0.956	0.882	0.367	0.764	1.000
(11)	0.04	0.05	0.00	0.28	-0.060	-0.057	0.000	-0.052	-0.058	-0.043	-0.037	-0.039	-0.067	-0.052
(12)	125.85	186.67	0.00	662.00	-0.029	-0.037	0.025	-0.007	-0.025	-0.020	-0.003	-0.040	-0.052	-0.038
(13)	6.11	4.72	1.00	29.00	-0.040	0.165	0.249	0.041	0.270	0.243	0.281	0.142	0.218	0.192
(14)	0.92	1.00	0.00	8.00	0.042	-0.045	-0.091	-0.025	-0.055	-0.060	-0.055	-0.028	-0.079	-0.057
(15)	0.62	0.49	0.00	1.00	-0.042	0.119	0.192	0.039	0.084	0.023	0.035	0.049	0.087	0.016
(16)	4.28	3.02	1.00	20.00	-0.058	0.063	0.123	0.017	0.127	0.115	0.128	0.060	0.118	0.082
(17)	680.27	769.08	0.00	4496.00	-0.037	-0.049	-0.074	-0.075	-0.037	0.006	-0.005	-0.023	-0.016	0.032
(18)	0.53	1.13	0.00	8.00	-0.067	0.024	0.083	0.056	-0.049	-0.052	-0.052	-0.008	-0.022	-0.052
(19)	0.34	0.94	0.00	13.00	-0.055	0.089	0.089	0.024	0.117	0.141	0.158	0.087	0.121	0.116
(20)	0.04	0.23	0.00	5.00	-0.023	-0.010	-0.005	-0.001	0.012	0.021	0.040	-0.021	0.002	0.022
(21)	1.89e+06	3.24e+06	0.00	1.06e+07	0.006	0.099	0.095	0.036	0.158	0.097	0.070	0.157	0.099	0.093
(22)	138.59	149.10	0.00	600.00	-0.026	-0.011	0.051	-0.023	-0.006	-0.039	-0.046	-0.001	-0.053	-0.043
(23)	1999.19	3.89	1990.00	2009.00	-0.042	-0.020	0.057	0.008	-0.143	-0.130	-0.123	-0.078	-0.087	-0.135

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(11)	1.000												
(12)	0.752	1.000											
(13)	0.096	0.058	1.000										
(14)	-0.018	0.020	-0.286	1.000									
(15)	0.055	0.071	0.419	-0.068	1.000								
(16)	0.037	0.017	0.685	-0.450	0.276	1.000							
(17)	-0.029	-0.077	-0.209	0.004	-0.233	-0.195	1.000						
(18)	-0.042	0.029	-0.008	0.071	0.156	0.037	-0.110	1.000					
(19)	0.056	0.149	0.170	-0.019	0.147	0.087	-0.099	0.054	1.000				
(20)	-0.008	0.031	0.090	-0.066	0.031	0.054	-0.027	0.002	0.056	1.000			
(21)	-0.204	-0.222	0.124	-0.068	-0.001	0.123	-0.005	0.021	-0.001	0.015	1.000		
(22)	0.806	0.836	0.076	-0.013	0.070	0.047	-0.059	-0.037	0.069	0.017	-0.076	1.000	
(23)	-0.069	0.096	-0.258	0.259	0.035	-0.228	-0.444	0.315	0.058	-0.029	-0.148	-0.046	1.000

Absolute correlations above 0.03 are significant at $p < .10$.

Table 3. Top 10 IPC subclasses shared by new ventures

IPC Class	Number of Ties	IPC Description
G06F	193	Electric digital data processing
H04L	166	Transmission of digital information
H04Q	162	Selecting (switches, relays, etc.)
H04B	138	Transmission information-carrying signals
H04M	137	Telephonic communication
H04J	86	Multiplex communication
H04K	51	Secret communication; jamming of communication
H04N	50	Pictorial communication, e.g., television
G06Q	43	Data processing for commercial and financial purposes
H04W	43	Wireless communication

Table 4. Top 10 firms citing new venture patents

Forward-Citing Firms	
Nokia	504
Motorola	501
Ericsson	466
Qualcomm	403
Samsung	393
IBM	381
Intel	322
Microsoft	318
Cisco	272
Sony	272

Table 5. Top 10 litigation counts in 2000-2010 of firms citing new venture patents

Litigations Initiated			Litigations Received	
Hewlett-Packard	15		Microsoft	94
Yahoo	14		Google	62
Broadcom	10		Sony	54
Medtronic	10		Apple	51
Sony	10		Yahoo	48
Intel	9		Motorola	42
Microsoft	9		Medtronic	38
3M	9		Hewlett-Packard	37
Motorola	9		Amazon	31
Sandisk	9		Hitachi	30

RESULTS

The hypotheses were tested by fitting a Cox proportional hazard model to the data, as elaborated above. Table 6 presents the results for five different models, starting with a baseline model that includes only the controls and the *Patent Grant Flow* variable. Models 2 to 4 cover intermediate estimations wherein we successively add the explanatory variables corresponding to our hypotheses. Model 5 is the full model that is central to our analysis.

Hypothesis 1 posited a diminishing return of the flow of patents granted with the failure hazard rate. This is strongly supported in models 2 to 5, with a negative main effect and a positive effect for the quadratic term. The grant of a single patent from a baseline of zero patents decreases the hazard of failure by 28%. Thus our hypothesis about the value of patents as a signal is corroborated. Figure 4 plots the effect of the annual flow of patents that a start-up obtains on failure, illustrating the curvilinear effect due to diminishing returns. For high values of the flow of received patents, (which is rare since only 16 of the firms have more than 15 patents granted in any single year), the increased hazard reflects the potential costs of investors viewing the new venture as neglecting commercial objectives.

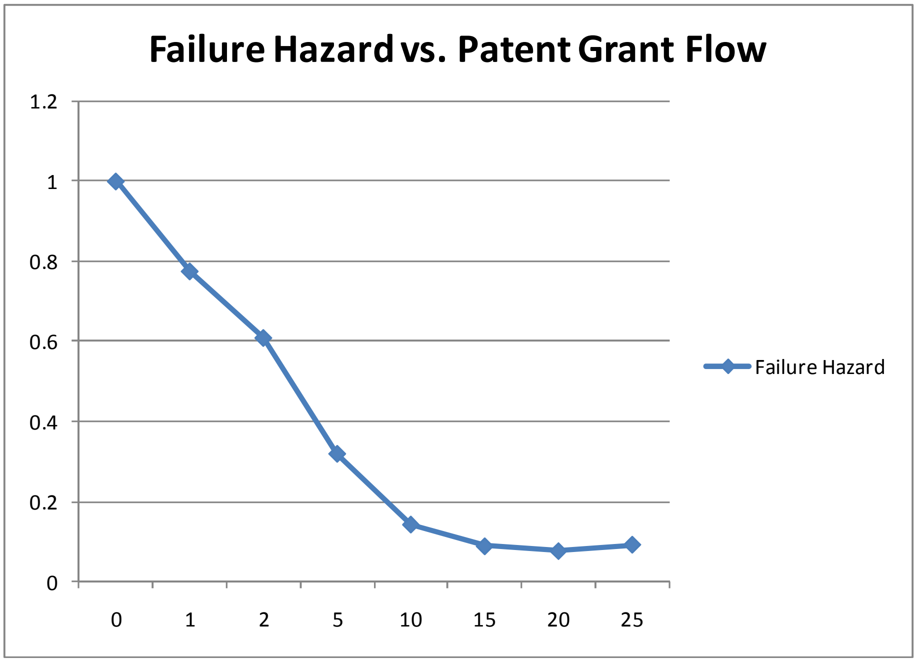
Hypothesis H2 regarding the cost of nonconformity is also supported in all models in Table 6, suggesting that start-ups that are central within the wireless start-up technology activity network fare better, while those located in the periphery face early exit. However, hypothesis H3 that discusses the costs of competitive crowding finds very weak support. The coefficient in the full model is not statistically significant, with a p-value of 13%.

Table 6. Cox Proportional Hazard Model for Failure: Results for H1-3 (Chapter 2)

Variables Models	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Patent Grant Flow	-0.107 (0.0700)	-0.261*** (0.0952)	-0.229** (0.0952)	-0.224** (0.0951)	-0.261*** (0.0978)
Patent Grant Flow Square		0.00644** (0.00251)	0.00571** (0.00253)	0.00559** (0.00253)	0.00664** (0.00276)
Closeness Centrality in Technology Activity Network			-18.84* (11.18)	-21.80* (11.44)	-25.04** (11.58)
Crowding in Technology Citation Network				0.251* (0.142)	0.227 (0.151)
Patent Cite Flow by Firms					0.0337*** (0.0116)
Self-Citations	0.160 (0.145)	0.0439 (0.116)	0.0333 (0.118)	0.0326 (0.118)	-0.145 (0.140)
Patent Grant Stock at t-1	0.0247** (0.0119)	0.0289** (0.0116)	0.0307*** (0.0115)	0.0311*** (0.0115)	0.0280** (0.0123)
Total Forward Cite Stock at t-1	-0.00188 (0.00263)	-0.00176 (0.00249)	-0.00138 (0.00242)	-0.00152 (0.00244)	-0.00437 (0.00341)
IPO Heat	-19.58*** (5.497)	-19.73*** (5.523)	-19.69*** (5.502)	-19.56*** (5.485)	-18.90*** (5.472)
Number of Targets in SIC	0.000863 (0.00122)	0.000574 (0.00124)	0.000678 (0.00123)	0.000656 (0.00124)	0.000575 (0.00125)
Total Number of Investors	0.00627 (0.0361)	0.0159 (0.0373)	0.0269 (0.0378)	0.0261 (0.0375)	-0.00164 (0.0371)
Number of Investors Investing in All Rounds	0.142 (0.103)	0.142 (0.102)	0.124 (0.103)	0.129 (0.103)	0.112 (0.105)
Prominent Investor	-0.266 (0.222)	-0.273 (0.222)	-0.278 (0.221)	-0.276 (0.221)	-0.275 (0.223)
Number of Rounds Received	-0.177*** (0.0626)	-0.181*** (0.0636)	-0.186*** (0.0638)	-0.181*** (0.0637)	-0.167*** (0.0622)
Time to First Round	-0.001*** (0.000206)	-0.00098*** (0.000206)	-0.00096*** (0.000207)	-0.00093*** (0.000207)	-0.00092*** (0.000206)
Founding Team Start-up Experience	-0.469** (0.206)	-0.446** (0.206)	-0.451** (0.209)	-0.525** (0.221)	-0.500** (0.219)
Number of Alliances	-0.872*** (0.312)	-0.838*** (0.311)	-0.822*** (0.310)	-0.814*** (0.310)	-0.854*** (0.312)
Number of Acquisitions	-1.038 (0.942)	-1.056 (0.941)	-1.074 (0.943)	-1.049 (0.943)	-1.023 (0.939)
Business Segment Sales in Wireless	-2.85e-08 (3.18e-08)	-2.72e-08 (3.24e-08)	-1.70e-08 (3.30e-08)	-1.67e-08 (3.30e-08)	-1.75e-08 (3.33e-08)
Number of Public Competitors	0.00278 (0.00173)	0.00325* (0.00173)	0.00316* (0.00172)	0.00318* (0.00172)	0.00318* (0.00173)
Entry Year	-0.101*** (0.0360)	-0.0970*** (0.0360)	-0.0847** (0.0361)	-0.0812** (0.0363)	-0.0747** (0.0366)
Observations	2958	2958	2958	2958	2958
Chi-square	115.5	122.2	125.1	127.3	136.4
Number of firms	428	428	428	428	428
Log likelihood	-350.4	-347.0	-345.6	-344.4	-339.9
Number of failures	109	109	109	109	109

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Figure 4. Diminishing Returns to Patent Grant Flow



We find strong evidence that the net costs of disclosure (measured through forward citations) dominate the net benefits. We had argued that the effects of such ‘deference’ could be two-sided and therefore not hypothesized about the effect of forward citations received annually. An additional forward citation from other firms increases the hazard of failure by 3.4% implying that deference may in fact be harmful to small entrepreneurial firms. The stock of patents granted prior to the current year (*Patent Grant Stock at t-1*, a control variable) has a positive and significant coefficient in all models, further bolstering our thesis regarding disclosure costs; patents granted in previous years that reflect old information are a net cost to the firm instead of serving as beneficial signals.

Finally, Table 7 presents the models for testing hypotheses 4 regarding the contentious role of incumbent firms and their defensive posture regarding possible encroachment into proprietary technological domains. The forward citation received weighted by cumulative count of lawsuits initiated by incumbent firms that cite the patents of focal ventures in our sample is significant (model 7). However, in model 6, which differs from model 7 in that it does not include the cumulative count of litigations received, the effect of the litigation-initiated variable is statistically insignificant. Since these two variables are highly correlated, the result could be thus spurious. To present a more robust test, we created a new variable by regressing *Cumulative Litigation Initiated* on *Cumulative Litigation Received* and then use the residuals shown in model 8. Theoretically this is the more accurate model, because by netting out the effects of being sued from the effects of suing for patent infringement, we account for the litigious reputation of incumbents. Again the coefficients are positive and significant at 5%, implying that being cited by incumbents with a history of legal enforcement harms entrepreneurial survival chances, accounting for an increase of 1.6% of failure rate for every unit of litigation-reputation weighted forward citation. We thus conclude that H4 is also supported.

Table 7. Cox Proportional Hazard Analysis for Failure: Results for H4 (Chapter 2)

Variables Models	(6)	(7)	(8)
Patent Grant Flow	-0.238** (0.0961)	-0.228** (0.0959)	-0.221** (0.0951)
Patent Grant Flow Square	0.00597** (0.00253)	0.00590** (0.00247)	0.00573** (0.00247)
Closeness Centrality in Technology Activity Network	-21.48* (11.45)	-21.30* (11.45)	-21.54* (11.43)
Crowding in Technology Citation Network	0.248* (0.141)	0.248* (0.142)	0.253* (0.141)
Cumulative Litigation Initiated	0.00506 (0.00308)	0.0150** (0.00649)	
Cumulative Litigation Received		-0.00226 (0.00160)	
Residual Cumulative Litigation Initiated Over Received			0.0163** (0.00747)
Self-Citations	0.0320 (0.118)	-0.00304 (0.116)	-0.0194 (0.115)
Patent Grant Stock at t-1	0.0325*** (0.0116)	0.0300** (0.0120)	0.0286** (0.0118)
Total Forward Cite Stock at t-1	-0.0106 (0.00699)	-0.0134* (0.00775)	-0.00666* (0.00398)
IPO Heat	-20.01*** (5.555)	-19.94*** (5.525)	-19.85*** (5.502)
Number of Targets in SIC	0.000465 (0.00125)	0.000750 (0.00123)	0.000834 (0.00123)
Total Number of Investors	0.0131 (0.0381)	0.0321 (0.0401)	0.0377 (0.0395)
Number of Investors Investing in All Rounds	0.128 (0.104)	0.120 (0.104)	0.116 (0.104)
Prominent Investor	-0.250 (0.222)	-0.277 (0.223)	-0.287 (0.223)
Number of Rounds Received	-0.180*** (0.0629)	-0.199*** (0.0653)	-0.194*** (0.0645)
Time to First Round	-0.000924*** (0.000207)	-0.000916*** (0.000206)	-0.000897*** (0.000204)
Founding Team Start-up Experience	-0.521** (0.222)	-0.521** (0.222)	-0.529** (0.222)
Number of Alliances	-0.806*** (0.308)	-0.771** (0.309)	-0.772** (0.308)
Number of Acquisitions	-1.043 (0.942)	-0.999 (0.937)	-1.017 (0.940)
Business Segment Sales in Wireless	-1.71e-08 (3.31e-08)	-2.23e-08 (3.34e-08)	-2.18e-08 (3.32e-08)
Number of Public Competitors	0.00343** (0.00173)	0.00303* (0.00174)	0.00295* (0.00173)
Entry Year	-0.0835** (0.0362)	-0.0834** (0.0362)	-0.0812** (0.0361)
Observations	2958	2958	2958
Number of firms	428	428	428
Chi-square	130.2	133.9	132.4
Number of failures	109	109	109
Log likelihood	-343.0	-341.1	-341.9

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The results obtained must be seen in the light of the limitations of the method. We tested for the violation of the proportionality assumption of the Cox model. The proportionality test passed for all the variables except one control variable (*Time to First Round).* According to the literature, violation of proportionality is usually not a cause for concern, though it does call for further robustness checks (Allison, 1984). We first assessed the robustness by dropping the problematic variable – this did not change the results. We then performed likelihood ratio tests between models to check for spurious effects. Further robustness checks for unobserved heterogeneity were performed by fitting a shared frailty model with a gamma distribution. There were no significant changes to the coefficients or to the p-values that resulted from these additional tests.

Finally, we address two endogeneity-related issues. First, given the risk of disclosure, firms may choose to not patent. We address this issue in the following ways. Firms in our sample seek venture funding and hence have to prove their worth and as the quote from *Wireless Week* in the beginning of our theory section hints, they are likely to file for patents if inventions promise value creation. The decision to not patent may be influenced by two other factors. First, firms may innovate in a domain of the wireless sector where patenting is at best difficult—for example, network services and software applications. Therefore, the industry code that a firm assigns itself and patenting in those activities may provide some clue (see Table 8). Second, some unobserved characteristic of the founders might condition the firm's propensity towards patent protection, most notably their experiences with knowledge spillover and predatory industry conduct. While this propensity remains, we can explore the effect of their demographic characteristics, for example their prior entrepreneurial experience in the wireless sector, prompting us towards the following analysis which also takes care of the first propensity.

Table 8. Top 10 4 digit SIC code in sample and percentage of firms with patents

4 Digit Primary SIC	Total Firms	% with Patents
7372	84	74%
4812	56	50%
3663	38	89%
7371	32	63%
7375	26	46%
4813	25	56%
4899	22	45%
7373	22	59%
3661	16	88%

We create a binary variable that flags whether a firm patents during its lifetime. This we call the *treatment variable*. Those firms which receive patents are in the treatment group and those which do not in the control group. For firm i, $i = 1, \ldots, N$, with all firms assumed exchangeable, let $\{Y_i(0), Y_i(1)\}$ denote two potential outcomes: $Y_i(1)$ is the outcome of venture i when exposed to the treatment, and $Y_i(0)$ is the outcome of venture i when not exposed to the treatment. If a new venture experiences both outcomes, then the treatment's effect on firm i would be directly observable as $Y_i(1) - Y_i(0)$. However, one of the outcomes is the counterfactual that in this case we obtain by matching to one or more similar firms in the control group. The average treatment effect is then calculated for all firms similarly paired.

Assuming that systematic differences in outcomes between treated and control units with the same values for relevant covariates can be attributed to the treatment (Abadie, Drukker, Herr, & Imbens, 2004; Imbens, 2004), we estimate the effect of receiving patents on start-up dissolution by matching them on two variables, that is, their primary SIC code and the previous experience of its founders. The Stata module nnmatch (Abadie *et al.*, 2004) is used to estimate the average treatment effects for the sample, the treated group versus the control group. No significant differences in the average treatment effects were found for the three groups: the full sample (-0.14), the treated (-0.14), and the control group (-0.13). This robustness check should allay selection concerns based on the two identified attributes that might influence the propensity of a firm to patent.

Finally, we address the concern that forward citations may be premeditated because citing firms may have the strategic incentive to mention as prior art the inventions of those firms that are likely to fail. Our response to that concern is twofold. First, we look at the mean value for the variable *Patent Cite Flow by Firms* for both successful (mean = 3.6) and failed firms (mean = 3.7) and perform a t-test to compare those means. The t-test for difference is not significant. Second, we defer to the literature on patents (Hall, Jaffe, & Trajtenberg, 2001; Hall *et al.*, 2005) that highlights the differences in academic citation, which is often strategic and totally at the discretion of the authors. In addition to the firm, the patent examiner typically adds two-thirds of the citations to an average patent (Alcacer & Gittelman, 2006). Moreover, 40% of all patents have all their citations added by the examiner (Alcacer & Gittelman, 2006). In the light of these striking patterns, concerns for strategic or ulterior motivations for prior art citations should definitely be allayed.

DISCUSSION AND CONCLUSIONS

> *'The patent system provides incentives for innovation. Its benefits far outweigh the problems. But there's definitely some bias against small companies.'*[11]

While patents have putative benefits for start-ups, far less is known about their hazards. This study shows the hazards of revealing information to rivals by measuring the impact of patenting on new venture failure. The hazard of failure increases by 3.4% for each additional forward citation received in a year. In doing so, we shed new light on the high costs that new ventures potentially incur when signaling their worth. Drawing on a novel and rich database of patents, patent citations, patent lawsuits, and corporate data of start-ups in the U.S. wireless sector over two decades, we do find initial support for the positive effect of patents as signals in line with current findings (Hsu & Ziedonis, 2008). However, the distinction of stock and flow adds an important nuance to our understanding of signals, both conceptually and empirically. We find that signals, conceptualized as patent flows, are beneficial but subject to diminishing returns. In fact, at very high levels we encounter almost a 90% reduction in the benefits of signaling, suggesting that more may indeed be less for new ventures with regard to patenting. Indeed, high levels of patenting are more harmful than beneficial, consistent with our hypothesis on the hazards of disclosure.

Those hazards are particularly salient in industries with comparative complex products as opposed to discrete or stand-alone product industries such as chemicals and pharmaceuticals (Cohen *et al.*, 2000; Levin et al., 1987). In these industries, when new

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[11] Lee Bromberg, founder, senior partner, head of litigation at the law firm of Bromberg and Sunstein (Healing the Patent Process. (cover story), by Sue Marek, *Wireless Week,* August 15, 2005, Vol. 11 Issue 17, p6-7).

ventures disclose their technology, they very much risk dissolution from designing around or litigations. If we factor in the reputational toughness of firms (compare Agarwal, et al, 2009) that publicly acknowledge the start-ups' inventions, these hazards are even more accentuated. This insight stands in sharp contrast to existing studies where effects of forward citations—often deemed to be reverent if not obsequious—are generally not considered or observed to be negative (Podolny *et al.*, 1996; Stuart, 1998; Stuart *et al.*, 1999). Perhaps the specificity of our sector, with its weak appropriability regime, might partially account for the harmful effects of disclosures. This was strongly alluded to in Hsu and Ziedonis (2008), which also called for additional studies in other contexts to better understand these effects. Akin to our study, other researchers have also recently begun to question the supposed benefits of deference (compare Jensen, Kim and Kim, 2010). In any event, the level of disclosure by nascent firms in a 'market for lemons' remains a challenging problem.

We also shed light on how start-ups manage to accommodate the competing but simultaneous pressures of conformity and differentiation (compare Deephouse, 1999) by defining the technology space as a network based on two conceptions of technological ties. Start-ups need to fit in, as shown by their technological similarity, yet at the same time they must also differentiate their technology from their peers. To capture this dilemma we constructed two different networks: (1) *start-up technology activity network* and (2) *start-up citation network.* Similarity, inferred from the activity network, conveys conformity to the dominant standards of the wireless sector. Differences in the citation network reveal their relative proximity to other start-ups.

Our results highlight the importance of conformity in a setting where incumbents have the edge. While much attention has been paid to radical innovations and the attacker's advantage in fast-changing environments (Anderson & Tushman, 2001; Christensen & Bower, 1996; Christensen & Rosenbloom, 1995; Tushman & Anderson, 1986), incumbents might not always be at a disadvantage in such environments, especially when complementary assets are under incumbent control and the appropriability conditions are typically not favorable (Teece, 1986; Tripsas, 1997).

Limitations and Future Research

Our study provides important directions for future research on technological entrepreneurship. First, like several prior studies, our study focuses on a single industry and is therefore subject to generalizability concerns. However, although the setting is unique, the wireless sector does share many characteristics with other industries, especially around the creation, accumulation, and appropriability of intellectual property (for example, semiconductors, information technology, and imaging). Second, while we argue that the hazards of disclosures arise because of the dangers of designing around and litigation, we do not directly observe the phenomenon of designing around. Future research could explicitly investigate designing around by examining the content of patents in greater detail.

Third, we rely on the start-up network properties to test the conformity and crowding hypotheses. We assume that incumbents shape these network structures but we have remained agnostic about the actual boundaries and the vertical and horizontal configuration of the wireless sector. An interesting, albeit challenging future project could test these assumptions using the full network of industry players across all areas of the wireless sector (as alluded to in Figure 2). Challenges relate to bounding the sector and its network as well as collecting data on them. Fourth, our distinction of stock and flow is only an approximation for distinguishing the signaling and endowment effects. While we include other signals of quality, an interesting avenue of research could explore any negative consequences of other complementary signals, such as founders' experience or third-party endorsements. Finally, we have investigated only failure. Investigating the effect of signaling on other performance measures—especially 'non-success' outcomes, that is, neither achieving liquidity events for investors nor failing outright—present exciting lines of future enquiry as well.

Conclusion

While not without limitations, this study contributes to our understanding of the entrepreneurship as well as to the broader strategy and organizations literature. We pay attention to a neglected aspect of performance— failure. We provide an example of a high-tech environment where perceived radical innovations do not necessarily pan out and new ventures are rewarded when they conform to the broad areas of technological activities. We provide new evidence on the limits of patents as signals and the dangers of disclosure in a setting hitherto not analyzed, extending our understanding of new ventures' need to signal their quality to obtain resources and increase their life chances (Gans, Hsu, & Stern, 2002a; Hsu & Ziedonis, 2008). Finally, we show that the litigation reputation of firms that build on a start-up's inventions increases the hazards of failure under weak appropriability conditions, pointing indirectly to the threats of designing around and lawsuits, and providing us with interesting research avenues to explore in the future.

Chapter 3: A Glimpse at Persistence without Liquidity Events: Asymmetric Effects on Success and Failure

Performance is a central concept in entrepreneurship, strategy and organization theory. Extant large sample empirical research has extensively studied new venture performance by examining mortality rates of start-ups (Audretsch, 1991; Brüderl et al., 1992; Brüderl & Schüssler, 1990; Carroll et al., 1996; Delacroix & Carroll, 1983; Delmar & Shane, 2003; Dowell & Swaminathan, 2006; Nerkar & Shane, 2003). These studies, grounded primarily in the population ecology tradition, invariably define start-up failure as exit from the industry either due to dissolution or acquisition. Survival, the negation of failure, is assumed to proxy success in these studies as the liabilities of newness are severe (Stinchcombe, 1965).

In contrast to these studies implying success as the opposite of exit, other studies in the entrepreneurship literature have gone a step further and defined various other success criteria, including IPO (Beckman et al., 2007; Giot & Schwienbacher, 2007; Megginson & Weiss, 1991; Stuart et al., 1999), and high-valuation trade-sale (Aggarwal, 2009; Giot & Schwienbacher, 2007; Gompers & Lerner, 2004).[12] Just as the population ecology studies imputed success as the opposite of observable exits, these studies imputed failure as the opposite of successful events.[13] Consequently, new firm performance that occupies the continuum between these two extreme events has received scant attention. To our knowledge, only one study has explicitly analyzed marginally

[12] Studies that use continuous measures such as sales growth are few and limited to non-US setting such as Canada and Scandinavian countries. Majority of the papers treat success as harvest events because of easy availability of such data.
[13] This observation does not apply to the few studies that use continuous measures of start-up performance.

performing new ventures by incorporating survival with different growth levels as key dependent variables (Gimeno et al., 1997).

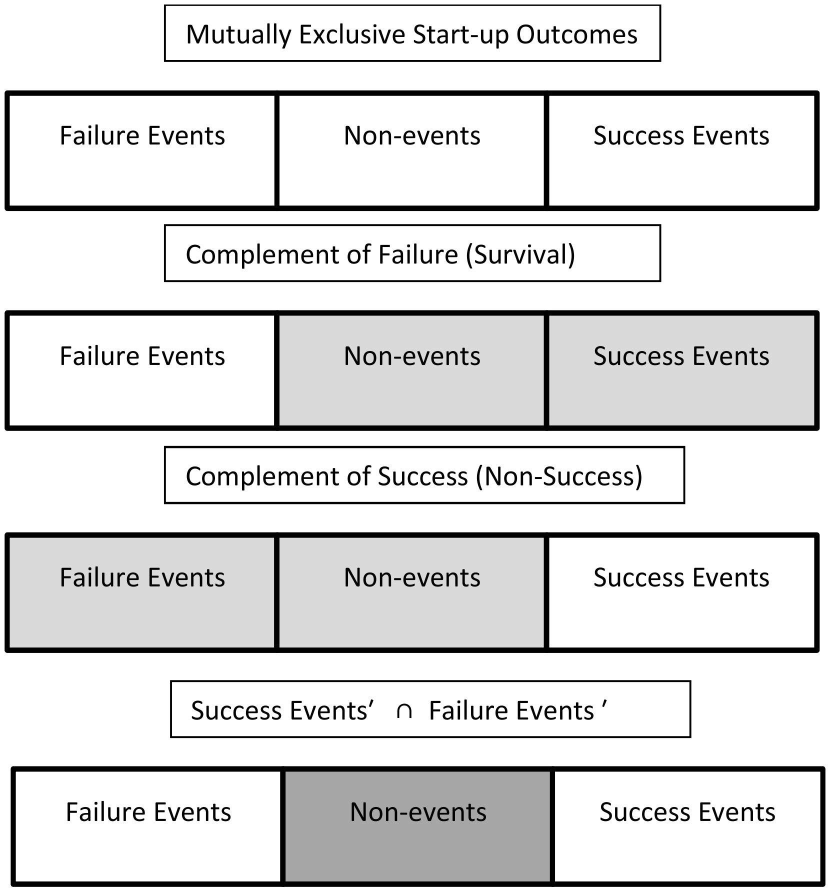
As reviewed above, the vast majority of studies on new venture performance either analyze success or failure as the key outcome—ignoring firms that persist without events such as experiencing an Initial Public Offering (IPO) or termination due to dissolution or merger and acquisition, primarily because it is conceptually easier to measure events such as exit than non-events such as staying in business. In addition, a binary framing of outcomes assumes symmetric effects, implying factors predicting success to prevent failure and vice-versa. This underlying assumption precludes the possibility of exposing persistence through simultaneous analysis of successful and failing ventures. By investigating both success and failure in the same population of entrepreneurial firms, we show that many start-ups neither achieve a successful outcome (defined as achieving an IPO or a trade sale, providing harvest opportunity to investors) nor fail (defined as dissolution due to bankruptcy, voluntary closure or a distressed sale). Further, such an analysis reveals asymmetry in factors predicting success and failure.

Asymmetric effects are not uncommon in the social sciences and have been a source of tantalizing interest in a variety of disciplines. For example, path-breaking contributions in behavioral economics suggest that risk dispositions towards positive payoffs do not mirror those involving negative pay-offs, as illustrated by the well-known prospect theory of expected utility (e.g. Kahneman & Tversky, 1979; Thaler, 1985). Political scientists (e.g. Lieberson, 1987) investigating social class and voting behavior have shown that causes of class-induced voting are not the converse of non-class voting.

In the management sciences, recent contribution by Fiss (2010), using set-theoretic methodology pioneered by Ragin (2008), has likewise suggested that factors affecting an outcome and its negation do not mirror each other. Specifically, analyzing a sample of high-technology firms using the Miles and Snow typology (Miles & Snow, 1978, 2003; Miles, Snow, Meyer, & Coleman, 1978), he shows that such typologies consist of essential core elements that have causal relevance and other peripheral elements that are causally irrelevant. The configuration of these elements within a particular type determines whether the effects are asymmetric or not. Similarly, Lavie & Rosenkopf (2006), reconcile the conflicting effects of the antecedents of exploration and exploitation by separating these activities across domains and by conceptualizing them to be interdependent—arising within a single continuum instead of separate distinct outcomes. This paper follows the example of these studies to construct a more nuanced categorization of entrepreneurial performance consequences—comprising success, failure and the continuum of non-events in between (see Figure 1)—instead of a simple dichotomous framing. This permits us to deduce persistence through asymmetric effects, i.e., factors that diminish both success and failure at the same time, contrary to the usual expectation that those factors preventing failure increase success chances and vice-versa.

We believe that explaining asymmetric effects of the same factor on success and failure simultaneously is an important contribution of this paper and serves as a useful empirical tool to unearth systematic forces that cause persistence. By asymmetry we imply that a predicting factor has the same effect on both success and failure. Conventional thinking would presume success as the opposite of failure and expect opposite effects of the same factor on these two outcomes. We construe as evidence of persistence the fact that a given antecedent inhibits the occurrence of these two concrete events within our conceptualization of new venture performance (Figure 1). We did not find any study investigating success and failure separately with the same factor inhibiting these binary outcomes. Therefore, the inference on persistence by simultaneously modeling the two events in the same analysis is a novel contribution. Our inference is based on the following logic (see Figure 5). First, a factor that prevents failure will not necessarily predict success but just its complementary event, that is, survival (i.e., both success and persistence without events are explained together). Second, an antecedent that inhibits success will explain both non-events and failure. Thus effects that are intersecting, in the language of set-theory, and inhibit these events would explain non-events and consequently lead us to deduce persistence. A causal factor that diminishes failure as well as success will thus expose forces of persistence, the third possibility.

Figure 5. Exposing Persistence



We cast our attention on a *signal of quality*—the breadth of a start-ups’ underlying technology as revealed by third-party use of the new firm’s patents—because by nature signals are equivocal and hence present the opportunity of possible negative effects on failure and success. If the signal in question decreases both success and failure likelihood then we can deduce the presence of systematic factors that predict non-events, a sign of persistence. Evaluating quality of start-ups using signals by resource providers under uncertainty and information-asymmetry is a much discussed topic (Hsu & Ziedonis, 2008; Stuart et al., 1999). Quality information is delivered through signals such as founders’ background (e.g. Burton et al., 2002), endorsements (Stuart *et al.*, 1999) and granting of patents (Hsu & Ziedonis, 2008). We add to this repertoire of available signals that help bridge the information gap between the start-up and others.

The signal of the breadth of a start-up's technology (referred to as technology breadth hereafter) conveys information on the generality or specificity of its applications as discovered over time through application in different domains by others. Specifically, we measure the dispersion across application domains of the future citations that a focal venture's patents receive every year. The number of forward citations that an invention receives from others has been often used as a measure of its quality[14]—the more the inventions are used by others, the higher the impact and derivatively the better the quality (Hall et al., 2001; Hall & Trajtenberg, 2004). Our signal of interest pertains to another aspect of quality, impact—whether the invention has broad applicability or is narrow in scope. Accordingly, this quality signal provides information, both to the venture and outsiders, on the potential opportunity set of applications.

We theorize about the possible pros and cons of possessing technologies with broad or narrow applicability to examine the signals' effects on success and failure. Endowment of general technology, as inferred from the signal, is beneficial to the firm's survival prospects by increasing the odds of finding sustaining cash flow from a broader set of possible applications and thus ensures at the very least some persistence. Yet, possessing a technology with potential multiple applications is not sufficient for achieving success. A start-up that patents its inventions, thereby disclosing its proprietary

[14] We use quality in a broad sense. Quality is multi-dimensional and typically not observed directly and/or ex-ante. Considerable uncertainty surrounds the quality of a new venture and information from a variety of signals permit evaluators to sort start-ups using some criteria. We do not make any definite assertion about the sorting mechanism using quality signal, just the ability to rank them.

knowledge, contends with uncontrolled knowledge diffusion, with the concomitant risk of dissipating its rent. In addition, the start-up has to commercialize its technologies, which poses a separate set of challenges to achieve growth that leads to harvest for investors. This motivates us to hypothesize about the interaction effect of knowledge diffusion and technology breadth, expecting negative effects on success and failure. A start-up that signals specificity in its technologies and experiences wide diffusion of its knowledge is able to survive because of more opportunities; yet it does not have sufficient growth prospects thus impeding success. In contrast, for commercial challenges we hypothesize symmetrical effects, i.e. coefficients that are of opposite signs, on performance for the interaction with the signal of technology breadth.

We test our hypotheses using a sample of U.S. VC–funded wireless new ventures founded in the period 1990-2009 that invested in patenting their technologies. To simultaneously model success and failure events we conduct an event history study within a competing risk framework (Lee & Wang, 2003). We find evidence of mechanisms that simultaneously improve life chances of some new ventures while impeding the harvest prospects of others—giving us a glimpse of factors that might lead to 'living dead' outcome, i.e., persistence at the edge of success and failure. High knowledge diffusion of a start-up's technology when the underlying inventions are specific is one such mechanism. More such mechanisms are identified and the implications discussed.

Our paper contributes to the literature on entrepreneurial performance, and more generally to the organizations literature, by providing a nuanced description of outcomes rather than assuming the simplistic caricature of success or failure alone. The paper represents one of the first studies that treat success and failure simultaneously and exposes mechanisms that inhibit both these outcomes concurrently. Second, the paper also contributes to the literature on signals of quality used by new ventures to overcome the liability of information asymmetry. The technology breadth of a start-up is an important signal for evaluators—it assists resource providers in assessing the nascent company. Lastly, the signal is also beneficial to the focal start-up by helping them realize applications not conceived by them but discovered by others.

A third contribution is to the patent literature. Forward citation flows have been variously conceptualized as measuring knowledge diffusion, endorsement, and competition (Jaffe et al., 1993; Podolny & Stuart, 1995; Podolny et al., 1996). Certainly the treatment of annual forward citations as a paper trail of knowledge diffusing is not controversial. Yet its frequent interpretation as either deference or competition is at best equivocal and requires understanding its differential impact on different outcomes and adequate conditioning factors to tease apart the two effects.

In line with our claim regarding asymmetry of performance antecedents, we show forward citations to have uneven effects for positive and negative performance. We find that for success outcomes, the effect of forward citations as direct ties between firms has a net endorsement effect (i.e., more of it lead to higher success odds), in line with existing finding (Podolny et al., 1996). In contrast, for failure outcomes, the effect on survival is negative, i.e., the more the inventions of the new firms form the basis of other firms' R&D, the higher the failure rate, thus indicating a net competitive effect. Extant research, primarily predicting success, has not highlighted the harmful effects of forward citations.

We also parse the (net) effects of forward citation flows through an interaction effect of technology breadth and forward citation. This interaction reverses the net benefit in case of successful outcome, and the net harmful effect, in case of failure outcome. Thus, the technology breadth along with forward citations increases the understanding of the mechanisms of endorsement and competition in the technology arena.

Our findings have important practical implications. Both entrepreneurs and their resource providers should pay careful attention to the scope of their technology as revealed by its use over distinct domains. The signal of technology breadth not only provides substantive information to resource providers, peer firms and strategic partners but also sheds light on new possibilities to the inventing startup. For investors, this signal of technology specialization provides valuable clues that may limit the downside risk as the start-ups move forward.

THEORY AND HYPOTHESES

Our theoretical framework centers on an important signal of quality of start-ups—technology breadth, as revealed over time through the diversity of the domains in which its inventions constitute building blocks for other inventions. We analyze the possibilities and promise the range of possible applications, as disclosed through the technology breadth signal, holds for both the venture's prospects as well as the challenges they pose on their road to a liquidity event for investors. We theorize about these effects for both success (defined as either achieving an IPO or a trade sale) and failure (defined as either dissolution or a distressed sale—see Fig 1). By theorizing about both success and failure we can uncover mechanisms that work in the same direction to prevent success and failure and thus deduce persistence. Therefore mechanisms that reveal this causal asymmetry, whereby factors that promote success do not predict failure and vice-versa, are of special interest.. In the following sections we first define what we mean by the signal of technology breadth, explain our motivation to focus on that signal and then develop testable hypotheses.

Signal of Technology Breadth – Possibilities & Promises

The underlying quality of nascent ventures is not observable and surrounded by a good deal of uncertainty. A variety of quality signals to evaluate the potential of a start-up have been investigated; they include (1) founders' demographic backgrounds (Burton *et al.*, 2002; Eisenhardt & Schoonhoven, 1990), (2) endorsements by reputable third parties (Baum et al., 2000a; Fitza et al., 2009; Gulati & Higgins, 2003; Hsu, 2004; Megginson & Weiss, 1991; Stuart et al., 1999), and (3) patents (Hsu & Ziedonis, 2008). We propose a fourth and important signal, mostly overlooked by the entrepreneurial literature, the technology breadth as evidenced by its applicability in different domains. Inventions often have more than one (profitable) application and a given application might represent just one way it can be exploited (Teece, 1982 ; pg 45). Applications may be anticipated a priori, but more crucially they might surface through peer inventors that build on the venture's technologies. As Bassalla (1988 ; pg 141) notes, the applications of an invention may not be known to the firm ex ante, and many applications are never revealed:

> *'When an invention is selected for development, we cannot assume that the initial choice is a unique and obvious one dictated by the nature of the artifact. Each invention offers a spectrum of opportunities, only a few of which will ever be developed during its lifetime. The first uses are not always the ones for which the invention will become best known.'*

Therefore the information received through other organizations in disparate domains building on the inventions of the start-up is an important signal of the underlying technology and its possibilities both to outsiders and the new venture itself. Conceptually, we treat the signal as new information on technology breadth revealed over time.

Technologies vary along a continuum of specificity—some are very unique and idiosyncratic, while others display a very wide range of applications. Scholars distinguish between General Purpose Technology (GPT) and Specific Purpose Technology (SPT), with applications in many versus one or a few domains respectively (Bresnahan & Trajtenberg, 1995; Gambardella & Giarratana, 2009; Hall & Trajtenberg, 2004; Rosenberg, 1976). Obviously, these labels are very coarse but convey a sense of the breadth of domains to which a technology might be applicable. The variety of domains to which the inventions of a venture becomes attached through peer acknowledgement provides information on an important aspect of quality—the breadth of possible applications. The more heterogeneous the domains from which these acknowledgements emanate, the greater the opportunity set of applications, and by implication the greater the future potential. We next consider the effect of the signal of technology breadth on failure and success.

Effect on Failure

The generality of a firms' technology derives from the diversity of domains to which it serves as a foundation for other innovations (Hall & Trajtenberg, 2004). A more general technology will likely have more applications compared to a specialized or narrow range of technology (Arora et al., 2004; Bresnahan & Trajtenberg, 1995; Helpman, 1998). An oft cited example of technology thriving outside the intended domain of application is Viagra, originally developed for cardiovascular applications, but actually more applicable to treatment of male sexual dysfunctions (Rosenkopf & Nerkar, 2001). Similarly, startups with more general technology could thrive or survive through applications outside their originally intended application area.

Possessing a general technology may allow new ventures to either choose from a broader menu of possible source of revenue generating applications, or stumble upon unexpected applications that help them generate sufficient cash-flow to keep afloat. For example, Wireless-Fidelity (Wi-Fi) was originally developed as a wireless Ethernet switch to replace wired Local area networks (LAN). However, over time the technology has been applied for many other purposes not originally envisioned, ranging from short distance serial cable replacement to multi-media applications in video game consoles, MP3 players, smartphones, printers, digital cameras, and laptops. Other unexpected applications include cellular coverage extender, location services for navigation, portable Electrocardiograph (ECG) device to monitor a heart patient at home, home security and baby monitors. Therefore, a start-up commercializing Wi-Fi technology could potentially either find a market that could make them self-sustaining or provide them the opportunity to reinvent by shifting to a different application. For example, Strix Systems, a company founded with the vision of developing Wi-Fi Mesh networking technology for indoor use, first reinvented itself as a provider of outdoor networks in the face of competition from established incumbents, such as Cisco, and the hype of municipalities providing free Wi-Fi access across cities. However, the promise of large-scale Wi-Fi networks have yet to be realized leading Strix to transform yet again into a developer of Wi-Fi products geared towards providing outdoor surveillance systems to enterprises.

Consequently, holding everything else constant, a firm's failure odds decline if its technology enjoys wider appeal, while a counterpart with more specialized technology is more prone to failure. The technologically more general venture is surrounded by a diverse set of opportunities, while the specialized venture faces a restricted set of possibilities. It is therefore plausible to expect the former to outdo the latter in survival prospects. We therefore hypothesize:

> *H1. Holding all else constant, the greater the domain concentration of forward citation flow that a new firm receives, the higher its failure hazard rate.*

Effect on Success

Entrepreneurial success, which translates to a "harvest" event for the shareholders does not stem from just being endowed with a more GPT. Rather success will depend on the technology being matched to a high growth area or exploiting numerous applications which might require foresight, resources and capability development, a commensurate commercial strategy, serendipity or luck (Gompers & Lerner, 2004; Hsu, 2006a). Thus, although favoring the venture with respect to survival, no direct effect of this signal on success is expected. Therefore, we next explore the challenges of delivering on the promise that a signal of GPT entails for a start-up.

Challenges of Delivering on the Promise

The endowment of a start-up with a particular breadth of technology presents two significant challenges to realize the potential value implied. The first challenge relates to the diffusion of proprietary knowledge after new ventures patent their inventions. As the knowledge regarding the invention spreads, its rent-generating potential might diminish (Grady & Alexander, 1992). The technology breadth may dictate the extent of rent dissipation by imposing constraints limiting the value that a resource-strapped new venture can appropriate.

The second challenge relates to commercializing the technology (Gans et al., 2002a; Gans & Stern, 2003). The commercial value of an invention not only depends on its possible applications, but also on factors external and internal to the owner. External factors include growth in the application domain, which in turn might depend on a variety of elements such as existence of necessary industry infrastructures, adoption by users, network effects as well as luck and serendipity (Denrell, Fang, & Winter, 2003; Katz & Shapiro, 1994; Teece, 1986; Thoma, 2009). Internal firm-level factors are intriguing given that technology strategy is a strategic choice for the venture. It would be naïve to assume that start-ups can develop many applications when in possession of a GPT. However, with foresight, luck and more importantly, appropriate commercial strategy, new firms might well benefit from growing markets. For technology start-ups, collaboration is among the most viable modes of commercialization in view of the resource constraints they face and the need to move fast in a high-velocity environment (Gans & Stern, 2003). We therefore analyze the moderating effects of knowledge diffusion and start-up collaboration strategy respectively on the effect of signal of technology breadth on start-up success and failure.

Knowledge Diffusion and Signal of Technology Breadth

When firms patent their inventions they reveal proprietary information that other firms may co-opt while building their R&D programs. Organizations that use these inventions cite them as prior art. These forward citations have been conceptualized by researchers in a number of ways. In the spillover literature they have served as a paper trail for tracking the diffusion of knowledge (Jaffe et al., 1993). In sociological framings, they have been construed as direct ties between organizations, interpreted as 'deference' or respect to the cited firm's contributions (Podolny & Stuart, 1995; Podolny *et al.*, 1996; Stuart & Podolny, 1996). While acknowledging that such direct ties could harm the firm's prospects through increased competition, existing literature has mostly shown net benefits of forward cites (Podolny *et al.*, 1996; Stuart, 1998; Stuart *et al.*, 1999). The net effect of a forward citation as a direct tie on average remains an empirical question. However, the argument for decrease in rent potential as knowledge diffuses widely rests on more solid ground.

The more others leverage a startup's inventions, the thinner the rent-generating potential (Grady & Alexander, 1992; Martin, 1992). Rent from an invention is the returns over and above the opportunity costs of producing related products. Government protection will create and maintain some rents while others may arise from either more efficient production of an existing product or from new products that yields benefits in excess of costs. However, the prospects of rich pay-offs stimulate rent-seeking from both the inventing firms and others, which causes rent dissipation for the start-up.

Grady & Alexander (1992) identify three rent-reducing mechanisms. First, rent anticipation provokes patent races that lead to excess resource commitment. Second, these inventions inform about the existence of follow-on improvements on the focal invention with high expected value thus promoting excessive inventive behavior and consequent resource commitments; again such reactions dissipate some of the rent. Third, in sectors where secrecy is an important value appropriating mechanism and threats of designing around and litigation abound, resources may be diverted to efforts to unlock or engineer around the invention, not to mention the threats of possible litigations. We believe that such rent dissipation scenarios in the wireless sector— the sector of this study, endowed with a weak-appropriability regime—are particularly salient. How this rent dissipation due to knowledge diffusion affects performance also depends on the breadth of technology, i.e., the diversity of domains to which the knowledge diffuses. Hence we develop arguments on this interaction for both failure and success next.

Effect on Failure

We hypothesized the main effects of GPT signal—i.e., low concentration of application domains—on failure to be positive. However, that beneficial relationship is conditional on the rate of knowledge diffusion (i.e., the flow of forward citations) that the start-ups' invention experiences. First, startups face considerably more resource constraints when maintaining a wide array of applications, including requisite capabilities and resources for the development and commercialization of the technology, and to monitor their patent portfolio for infringements. Second, although patents are taken to be a scale-free resource similar to brands without capacity constraints to application in many domains (Levinthal & Wu, 2010), imperfections in patent enforcement and appropriability may limit the ability of cash strapped start-ups to effectively use them across many product markets. Firm's with many applications to exploit, considering everything else equal, will consequently face higher costs in appropriating rents from their intellectual properties than firms with few possible technology application in the face of high knowledge diffusion.

Third, ventures with a general technology portfolio may face greater rent dissipation due to their knowledge diffusing compared to their specialized counterparts due to greater costs albeit potentially higher revenue generating potential. On the revenue side, having a broader technology could imply more potential competitors leading to higher dissipation (Fosfuri, 2006). On the cost side, when developing commercial capabilities, generalist new firms have to deal with multi-point competition, diminished economies of scope due to the dissimilar nature of the partners, higher opportunity costs, or perhaps partnering with firms having complementary knowledge that require significant amounts of inter-firm social capital (e.g. Gulati, 1995) to coordinate the pooling of complementary technology and other intangible assets. Start-ups whose inventive output is associated with only one or a limited set of applications have to deal with similar firms and accordingly may be better able to pool or leverage proximate resources to commercialize their technology. They might also enjoy higher bargaining power when dealing with partners who presumably compete in the same market and are dependent on the start-up's technology. The higher rate of forward citations to a SPT firm's inventions reinforces this dependency indicating greater likelihood of survival when endowed with specific technology widely diffused in a narrow domain. Therefore the conjecture:

> *H2a. The interaction between the forward citations flow and its concentration is negatively related to the focal firm's failure hazard rate.*

Effect on Success

Our reasoning for hypothesis 2a suggested that a signal of high technology concentration (SPT) and high rate of knowledge diffusion may impede failure. Firms with SPT might have discovered a niche technology that is useful to proximate suppliers and competitors. Given the specific nature of the technology, the growth of the niche may not fulfill the expectations that might lead to an IPO or a trade sale. However, the dependency created as evidenced by high levels of forward citations from a handful of domains might generate stable cash flow and positive economic profit. These arguments also resonate with the theories of resource partitioning and niche width in population ecology (Carroll, 1985; Hannan & Freeman, 1977). A sector with a core dominated by generalist behemoths but with a periphery abundant in opportunities, much like the industry under investigation, provides the ideal conditions required for market partitioning. Firms with SPT in such a sector therefore might end up in niches that present low growth prospects not attractive to investors and acquirers while firms with GPT may have higher growth prospects conducive to IPO or acquisition.

Therefore our next hypothesis:

H2b. The interaction between the forward citations flow and its concentration is negatively related to the focal firm's success hazard rate.

Start-up Collaboration Strategy – Alliance Diversity and Technology Breadth Signal

All firms, whether big or small, face financial resource constraints (Schoonhoven, Eisenhardt, & Lyman, 1990), preventing them from developing or commercializing a technology simultaneously across multiple applications (Adner & Levinthal, 2008). This constraint is especially high for start-ups. However, collaborative relationships may enable start-ups to obtain resources necessary to commercialize new technologies, develop links with suppliers and customers, and more generally access financial and technological assets (e.g., Gans et al., 2002a). For those new ventures whose technologies are geared towards multiple domains, alliances or joint ventures can provide complementary resources as well as access to larger markets. Collaborations include joint ventures, licensing as well as strategic alliances in marketing, manufacturing and R&D, collectively termed as alliances henceforth. The greater the heterogeneity of strategic partners, the more a venture will benefit, consistent with the learning and knowledge acquisition literature (Baum et al., 2000a; Powell, 1990; Shan, Walker, & Kogut, 1994).

This learning and knowledge perspective is grounded in the network literature and holds that having a large and diverse set of partners confers survival benefits. In high-velocity environments where knowledge and technology evolves at a fast pace, alliances are common (Powell, 1990). Firms need the dynamic capability to increase their advantage or in many cases to preserve it (Eisenhardt & Martin, 2000). Since any one firm is unlikely to have all the resources and capabilities needed, they benefit from partners to access the requisite knowledge (Powell, 1990). Bringing together the capabilities and knowledge enables more ambitious innovations (Baum et al., 2000a; Shan et al., 1994), not to mention increased innovation rates (Powell, Koput, & Smith-Doerr, 1996). They also give access to a variety of network resources such as markets, human resources and social capital (Gulati, 1999; Lavie, 2007).

Among entrepreneurial firms the benefits of having a diverse set of partners has been repeatedly demonstrated. For example, when a start-up’s alliance network comprises many partners with diverse knowledge and capabilities, its initial performance significantly increases (Baum et al., 2000a). A larger set of partners provides more opportunity to learn and grow (Powell, Koput, and Smith-Doerr, 1996). Start-ups with such inferred social capital enjoy access to a wider range of ideas and information improving decision making (Beckman & Haunschild, 2002), not to mention capabilities for alliance management (Baum et al., 2000a). In short, alliance diversity favors a startup especially in the context of its technology endowments and we explore the moderating effect of alliance diversity with the signal of technology breadth.

Effect on Failure

Ventures embracing a broad technology platform as shown through diversity of citations might replicate their technology diversity with a broad base of strategic alliances. Such bundling of technology and partnerships might further enhance their survival prospects (Teece, 1996). By contrast, very focused niche players, whose patents come with one or perhaps a few kindred applications are very much at risk in prematurely exiting the sector, and all the more so if their concentrated technology output is combined with a heterogeneous set of strategic partner. Developing collaboration relationship is costly; more so when they involve partners that are not very similar. Therefore if the firm expends too much energy in such activities without necessarily needing them as indicated by the signal of technology breadth then the survival prospects of the new venture will be compromised. On the other hand, an SPT signal with low diversity in alliance would imply a good fit between technological needs and alliance strategy and could improve performance. Conversely, a GPT signal with low alliance diversity would be indicative of firms not being able to develop relationship with a diverse set of partners thus reducing their opportunity to learn and access much needed resources. Therefore we predict:

H3a. The interaction between alliance diversity and the concentration of forward citations received is positively related to the focal firm's failure hazard rate.

Effect on Success

In the case of this interaction we expect a symmetrical effect on success using a similar logic as the effect on failure. Firms with GPT and a diverse alliance portfolio might thrive because they have higher likelihood of tapping into a growth market when compared to a firm with alliances only in specific markets. Further, they might have the opportunity to learn and experiment with their technologies when they interact with partners across a variety of partners market. In contrast, firms with SPT will not have these opportunities and might be stuck in a market with lower growth prospect, the very reason why they survive through creating dependence on a concentrated group of firms in closely related technologies. Therefore our final hypothesis:

H3b. The interaction between alliance diversity and the concentration of forward citations received is negatively related to the focal firm's success hazard rate.

EMPIRICAL SETTING AND METHODOLOGY

Industry Context

Our study is based in the wireless sector during the period 1990-2009. The sector witnessed transitions from successive generations of standards-based technologies, starting with the second-generation (2G) voice-based technologies and followed by the data-oriented third-generation and fourth-generation (3G & 4G) technologies (Ansari & Garud, 2009). The wireless sector exhibits a very complex 'ecosystem' that is dominated by firms that are vendors of equipment and handsets through control of important complementary assets. The influence of powerful generalist incumbents such as Ericsson, Nokia, and Apple, who conduct R&D across the value chain, however, has not been a deterrent to venture capital funding at the edges of the core controlled by them. New firms not only introduced new wireless technologies, but also spawned new software, applications, and content, both general and specific. Some examples include antenna technology with applications across various domains such as radar, space exploration, and medicine, and embedded systems and software specifically designed for handsets to general purpose reprogrammable radio chips.

Data and Sample

We collected data on VC-funded firms in the U.S. wireless sector that were founded between the years 1990 and 2009. We only include those new firms that engage in patenting its inventions because the signal of interest is applicable only to these firms. Therefore our sample consists of 283 firms[15].

Obtaining data on the alliances of private companies is extremely challenging. SDC Platinum does not provide comprehensive coverage for such alliances (Schilling, 2009). We therefore used Factiva to supplement those alliances (Lavie, 2007). These two combined sources also did not provide full coverage. Many of the press releases were not captured by the major news agencies covered in Factiva. We therefore used the company websites with the help of the Wayback machine (http://web.archive.org) to collect such information. Once the alliance information was downloaded we collected information about the industry affiliations of the partners using Hoovers, Zephyr and CorpTech.[16]

Other sources of data include Derwent, a database of global patents maintained by Thomson since 1969 for patents. The historical Web sites of firms in our sample using the Wayback machine were used to source management team information. SDC, Zephyr, Factiva, and Hoovers provided merger and acquisition and IPO information. Finally, COMPUSTAT was accessed for segment data on publicly listed wireless firms.

Dependent Variables and Empirical Strategy

We conduct an event history study of success and failure rate using a competing risk framework. We categorize failed firms as those ventures that were liquidated due to outright bankruptcy or that were acquired in a distressed sale. These modes of dissolution

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[15] Sample selection bias concerns are allayed by comparing firms that patent and firm that do not as detailed in Chapter 2.

[16] Alliances were identified using codes reported in Factiva and when the press release explicitly stated in its body a strategic alliance, joint venture or licensing deal. Since we look at aggregate alliances, the main effort was destined towards cleaning duplicates and triangulating the information. This was carried out by two RA's with overlapping data points to ensure reliability. We used a combination of manual and automated methods to remove these duplicates.

were primarily determined through VentureXpert, which maintains this information in the ‘Company Current Situation’ field. For those firms involved in a distressed sale, the information came from SDC and Zephyr, which captures this status in the deal description. Failure, a dummy variable, is set to 1 in the year that the focal firm failed and 0 in all other years from founding. Successful firms are those that achieve Initial Public Offerings (IPO) or that are acquired. The information came from VentureXpert, SDC and Zephyr. Success, a binary variable, is set to 1 in the year that the focal firm had the IPO or sale event and 0 in all other years from founding. All the remaining firm-observations were censored at the end of the study period. We identified 56 failed outcomes and 91 successful ones and created firm-year spells from founding to failure or to the end of 2009 when the data are censored. We model the hazard rates for these two events experienced by the firm.

We use a competing risk Cox proportional hazard model (Lee & Wang, 2003) of the two start-up outcome events, success and failure. Prior studies investigating start-up performance have primarily used either a Logit specification for a binary outcome or conducted an event history study of a single event such as failure or IPO with the notable exception of Giot & Schwienbacher (2007), who analyze determinants of exit options for US venture capital funds. Since start-ups after birth face the risk of both failing as well as succeeding, conducting an event history study under a competing risk framework is appropriate, especially when the goal is to uncover asymmetric effects that could point towards persistence tendencies. The idea of the competing risks model is to let the hazard rate vary with the end state. In the framework of a competing risks model, the duration corresponding to the state not realized is truncated. From a methodological point of view, this implies that the realized state will contribute to the likelihood function via its density function, while the truncated state contributes to the likelihood function via its survivor function. Competing risks models focus on both the kind of exits (success or failure) and time to exit (duration) unlike event history studies of single events. It is also superior to a Logit model, which besides not handling censoring, would only focus on the type of exit (binary choice); the likelihood function of a Logit model also does not take duration into account (Giot & Schwienbacher, 2007). The regressions are computed using the *stcox* procedure of STATA.

Independent Variables

Forward Citation Flow

This is a count of the annual flow of citations that the firm receives from others and captures the rate of knowledge diffusion of the focal venture's inventions. On average a start-up in our firm receives 5 citations every year with a range of 0 to 158.

Forward Citation Concentration

To operationalize the signal of technology breadth, our main independent variable, we gather all the patents that cite the start-up firm's inventions as prior-art, also referred to as forward citations to the focal patents. We construct a herfindahl measure of the concentration of the different four digit International Patent Classification (IPC) subclass from which a start-up receives forward citation in a given year—the year the citation was received as indicated by the application date. IPC subclasses capture the functions and applications of an invention and hence indicate possible technical domains to which the invention maybe applicable (Hall, 2002; Hall et al., 2001; Hall & Trajtenberg, 2004). By considering the ongoing addition of forward citation diversity, such an index as signal becomes a time variant indicator of its technological heterogeneity. This variable ranges between 0.07 and 1 with a mean of 0.17.

Alliance Concentration

The diversity of the firms alliance partners is captured using a herfindahl concentration measure of the primary SIC code to which the partner belongs (Baum et al., 2000a). Therefore, this variable, ranging from 0.06 to 1 with an average of 0.34, measures the diversity of product markets that the start-up's collaborative relations span. The lower the value of this variable, the higher the product market heterogeneity of the alliance partners.

Control Variables

We include controls in seven broad categories that effect firm performance. First, we use patent related controls. These include annual patents received, the number of IPC classes from which the firm receives forward citations (to control for the number of technology domains a firm I associated with), the stock of patents granted (Hsu & Ziedonis, 2008), and the stock of forward citations received in the previous years to capture the value of the patents (Hall *et al.*, 2005). The second category relates to market conditions, the IPO and mergers and acquisition activity levels per year, that are important drivers for liquidity events (Sorenson & Stuart, 2008; Stuart & Sorenson, 2003). The third group of controls variables pertain to investor characteristics, including investor quality (Hochberg *et al.*, 2007), using the count of VCs featured in the Forbes

Midas list between 2000 and 2009 that invest in a start-up, investor confidence, using the total number of VCs that invest, and investor expectations for the start-up, using the count of investors who commit funds in all rounds of financing (Sorenson & Stuart, 2008).

Fourth, we control for the number of rounds of financing received and time from founding to the first VC financing as new ventures need resources to survive (Lee et al., 2001). In the fifth group, we include the start-up experience of the founding team to account for variations in initial quality among the start-ups (Burton et al., 2002; Eisenhardt & Schoonhoven, 1990). The sixth category includes corporate development actions that account for endorsement effects that have been shown to be significant predictors of a new venture's success (Stuart et al., 1999). Last, we include product market growth at the sector level (Covin & Slevin, 1989), using the total sales per year in all business segments in which publicly quoted wireless operators (SIC 4812) and vendors (SIC 3663) operate. Finally, we include the start-up entry year to account for potential violation of the non-informative censoring assumption. Table 9 below provides definitions of all variables used, and Table 10 provides summary statistics and correlations.

RESULTS

We report the results for both success and failure from a competing risk Cox regression in Table 11. A glance through the table provides interesting insights on asymmetric effects of factors on outcomes. In our case asymmetry implies that the coefficients for a given factor have the same signs for both success and failure instead of being opposite. We first look at our hypotheses and then analyze some of the interesting effects of the control variables. Models (1)-(3) correspond to failure while (4)-(6) corresponds to success, each of the three corresponding to the three hypotheses for the two events, success and failure.

Our hypothesis about the effect of the signal of technology breadth finds support in the analysis. We expected high concentration of forward citations (i.e., a signal of SPT) to increase failure while no effect was anticipated for success. Models (1)-(3) reveal positive and highly significant effects on Forward Citation Concentration on failure hazard. Models (4)-(6) demonstrate no statistical significance of this variable on success. The coefficient from model (3) implies that at the mean value of Forward Citation Concentration the failure hazard rate increases by 28%, while the percentage increase in the failure hazard rate for an increase from the mean value to one standard deviation above it is 44%.

Table 9. Variable Definitions (Chapter 3)

Variable	Description
Dependent Variables	
(1) Failure	A dummy indicating that the firm had experienced a distressed sale or had become defunct in a given year
(2) Success	A dummy indicating that the firm had experienced an IPO or trade sale in a given year
Independent Variables	
(3) Forward Citation Concentration	Herfindahl measure of concentration of IPC classes that forward citations originate from
(4) Alliance Concentration	Herfindahl measure of concentration of SIC of alliance partners
Control Variables	
Patenting Related	
(5) Patent Grant Flow	Number of new patents granted to the firm in a given year
(6) Forward Citation Flow	Number of new cites received by the firm in a year
(7) Self-Citations	Total number of self-cites received by the firm in a year
(8) Number of IPC Classes	Total number of IPC classes from which a firm receives forward citations
(9) Patent Grant Stock at t-1	Stock of the firm's patents at the start of a year
(10) Total Forward Cite Stock at t-1	Stock of forward cites received by the firm at the start of a year
Exit Market Conditions	
(11) IPO Heat	Intensity of IPO activity in the firm's primary SIC code in a given year
(13) Number of Targets in SIC	Number of targets acquired in the SIC in a given year
Investor Characteristics	
(14) Total Number of Investors	Number of distinct investors that invested in the firm over all rounds
(15) Number of Investors Investing in All Rounds	Number of investors that invest in all rounds
(16) Prominent Investor	Indicator of presence of investor that was in the Forbes Midas list
Financing Related	
(17) Number of Rounds Received	Number of rounds of funding received by the firm till the end of study
(18) Time to First Round	Time in days from founding to receiving first round
Initial Firm Quality	
(19) Founding Team Start-up Experience	Sum of wireless start-ups founding team worked in prior to the focal firm
Firm Strategic Action	
(20) Number of Alliances	Number of alliances by the firm in a year
(21) Number of Acquisitions	Number of acquisitions by the firm in a year
Others	
(22) Business Segment Sales in Wireless	Total sales of all public wireless companies in a given SIC code
(23) Entry Year	Year of entry of the firm in the risk set

Table 10. Summary Statistics and Correlations (Chapter 3)

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	0.03	0.16	0.00	1.00	1.000								
(2)	0.04	0.21	0.00	1.00	-0.036	1.000							
(3)	0.17	0.25	0.07	1.00	0.070	0.052	1.000						
(4)	0.34	0.34	0.06	1.00	-0.007	0.003	-0.048	1.000					
(5)	1.37	3.66	0.00	41.00	0.015	0.045	0.109	-0.029	1.000				
(6)	5.06	13.65	0.00	158.00	0.104	0.083	0.127	-0.031	0.508	1.000			
(7)	0.30	1.26	0.00	23.00	0.033	0.016	0.083	-0.041	0.688	0.639	1.000		
(8)	6.78	6.02	1.00	38.00	-0.036	-0.002	0.147	-0.086	0.395	0.420	0.314	1.000	
(9)	3.80	10.34	0.00	112.00	0.077	0.049	0.166	-0.074	0.390	0.569	0.398	0.427	1.000
(10)	17.53	76.83	0.00	1364.00	0.032	0.021	0.092	-0.058	0.198	0.552	0.358	0.300	0.761
(11)	0.04	0.06	0.00	0.28	-0.053	0.036	-0.033	-0.037	-0.082	-0.084	-0.058	-0.065	-0.092
(12)	137.37	195.44	0.00	662.00	-0.041	0.103	0.019	-0.051	-0.066	-0.054	-0.063	-0.123	-0.082
(13)	6.71	4.84	1.00	29.00	-0.029	0.010	0.120	-0.099	0.148	0.270	0.134	0.323	0.212
(14)	0.88	1.01	0.00	8.00	0.035	-0.002	-0.047	0.048	-0.033	-0.048	-0.022	-0.124	-0.078
(15)	0.68	0.47	0.00	1.00	-0.026	0.046	0.033	-0.027	0.097	0.053	0.028	0.069	0.061
(16)	4.58	2.89	1.00	16.00	-0.045	-0.034	0.105	-0.116	0.041	0.123	0.051	0.145	0.111
(17)	645.96	665.62	0.00	3025.00	-0.018	-0.067	-0.070	0.013	-0.044	-0.027	-0.018	0.013	-0.000
(18)	0.59	1.22	0.00	8.00	-0.066	0.018	-0.055	-0.007	-0.009	-0.080	-0.024	-0.086	-0.051
(19)	0.41	1.04	0.00	13.00	-0.052	0.012	0.117	-0.106	0.073	0.102	0.077	0.026	0.107
(20)	0.04	0.23	0.00	5.00	-0.013	0.132	0.059	-0.011	-0.009	0.017	-0.024	-0.020	0.004
(21)	1.92e+06	3.31e+06	0.00	1.06e+07	0.022	0.008	0.023	0.042	0.107	0.183	0.183	0.205	0.110
(22)	1999.44	3.52	1990.00	2008.00	-0.056	-0.037	-0.085	-0.011	-0.053	-0.216	-0.120	-0.245	-0.141

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(10)	1.000												
(11)	-0.069	1.000											
(12)	-0.056	0.748	1.000										
(13)	0.196	0.072	0.040	1.000									
(14)	-0.057	-0.009	0.026	-0.259	1.000								
(15)	-0.010	0.095	0.120	0.388	-0.045	1.000							
(16)	0.079	0.041	0.036	0.649	-0.433	0.219	1.000						
(17)	0.057	0.031	-0.038	-0.240	-0.030	-0.303	-0.179	1.000					
(18)	-0.071	-0.033	0.049	-0.063	0.121	0.155	-0.011	-0.118	1.000				
(19)	0.110	0.047	0.134	0.161	-0.001	0.149	0.084	-0.103	0.045	1.000			
(20)	0.027	0.008	0.060	0.113	-0.059	0.024	0.063	-0.029	-0.011	0.073	1.000		
(21)	0.106	-0.225	-0.240	0.094	-0.019	-0.049	0.072	-0.046	-0.032	0.008	-0.028	1.000	
(22)	-0.195	-0.096	0.074	-0.274	0.276	0.082	-0.205	-0.429	0.359	0.042	-0.028	-0.141	1.000

Absolute correlations above 0.036 are significant at $p < .10$.

Table 11. Competing Risk Cox Proportional Hazard Regressions (Chapter 3)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Failure			Success		
	H1	H2a	H3a		H2b	H3b
Forward Citation Concentration	1.021**	1.693***	1.464**	-0.00961	0.449	0.594
	(0.507)	(0.518)	(0.645)	(0.465)	(0.485)	(0.627)
Fwd Citation Conc X Fwd Citation Flow		-0.335***	-0.339***		-0.165**	-0.163**
		(0.123)	(0.124)		(0.0769)	(0.0768)
Fwd Citation Conc X Alliance Conc			0.987			-0.528
			(1.575)			(1.495)
Alliance Concentration	-0.651	-0.768*	-1.014*	-0.184	-0.206	-0.0967
	(0.436)	(0.452)	(0.610)	(0.338)	(0.342)	(0.456)
Patent Grant Flow	-0.127	-0.0515	-0.0536	0.208***	0.239***	0.240***
	(0.105)	(0.115)	(0.115)	(0.0800)	(0.0829)	(0.0830)
Patent Grant Flow Square	0.00382	0.00186	0.00190	-0.00821**	-0.00962**	-0.00967**
	(0.00275)	(0.00312)	(0.00313)	(0.00419)	(0.00447)	(0.00448)
Forward Citation Flow	0.0481***	0.117***	0.118***	0.0206**	0.0536***	0.0533***
	(0.0133)	(0.0271)	(0.0271)	(0.00968)	(0.0169)	(0.0169)
Patent Grant Stock at t-1	0.0442***	0.0600**	0.0606**	0.00373	0.00165	0.00164
	(0.0160)	(0.0261)	(0.0263)	(0.0149)	(0.0160)	(0.0160)
Total Fw Cite Stock at t-1	-0.00339	-0.00481	-0.00489	-0.00354	-0.00264	-0.00264
	(0.00366)	(0.00425)	(0.00425)	(0.00345)	(0.00315)	(0.00315)
Self Citations	-0.278*	-0.401**	-0.403**	-0.149	-0.143	-0.144
	(0.150)	(0.170)	(0.170)	(0.131)	(0.135)	(0.135)
Number of IPC Classes	-0.177***	-0.220***	-0.221***	-0.0391	-0.0561*	-0.0550*
	(0.0507)	(0.0566)	(0.0564)	(0.0266)	(0.0297)	(0.0298)
IPO Heat	-9.239	-8.713	-8.745	-0.438	-0.575	-0.539
	(6.740)	(6.553)	(6.528)	(3.156)	(3.175)	(3.184)
Number of Targets in SIC	0.000313	0.000213	0.000240	0.00278***	0.00274***	0.00274***
	(0.00134)	(0.00130)	(0.00129)	(0.000748)	(0.000746)	(0.000747)
Total Number of Investors	-0.0406	0.0186	0.0168	-0.0101	0.00671	0.00569
	(0.0461)	(0.0545)	(0.0549)	(0.0371)	(0.0384)	(0.0385)
No. of Investors Investing in all rounds	0.132	0.101	0.112	-0.0903	-0.0983	-0.0997
	(0.152)	(0.150)	(0.150)	(0.133)	(0.132)	(0.132)
Prominent Investor	0.359	0.259	0.283	0.448	0.406	0.394
	(0.355)	(0.371)	(0.372)	(0.296)	(0.298)	(0.300)
Number of Rounds Received	-0.134	-0.177*	-0.176*	-0.285***	-0.294***	-0.292***
	(0.0871)	(0.0913)	(0.0916)	(0.0778)	(0.0780)	(0.0783)
Time to First Round	-0.000702***	-0.000744***	-0.000748***	-0.00131***	-0.00131***	-0.00132***
	(0.000264)	(0.000277)	(0.000277)	(0.000250)	(0.000249)	(0.000249)
Founding Team Startup Exp	-0.817**	-0.904**	-0.899**	0.235***	0.231**	0.231**
	(0.361)	(0.379)	(0.379)	(0.0899)	(0.0905)	(0.0907)
Number of Alliances	-0.937**	-1.047***	-1.048***	-0.203	-0.233*	-0.234*
	(0.404)	(0.386)	(0.387)	(0.126)	(0.129)	(0.129)
Number of Acquisitions	-0.408	-0.449	-0.470	0.868***	0.866***	0.874***
	(0.937)	(0.974)	(0.977)	(0.233)	(0.237)	(0.239)
Biz Seg Sales in Wireless	3.85e-08	3.41e-08	3.64e-08	7.61e-08**	8.05e-08**	8.00e-08**
	(4.38e-08)	(4.48e-08)	(4.51e-08)	(3.75e-08)	(3.77e-08)	(3.77e-08)
Entry Year	-0.131**	-0.131**	-0.134**	-0.184***	-0.176***	-0.176***
	(0.0553)	(0.0568)	(0.0569)	(0.0527)	(0.0529)	(0.0528)
Observations	2070	2070	2070	2070	2070	2070
Log likelihood	-163.3	-157.4	-157.2	-263.5	-260.6	-260.5
Chi-square	94.44	106.2	106.6	104.9	110.8	111.0
Number of firms	283	283	283	283	283	283
Number of events	56	56	56	91	91	91

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

To test H2a & H2b we interacted Forward Citation Concentration with the Forward Citation Flow. Model (2) and (5) show the results for this analysis. As supposed we observe an asymmetrical effect on failure and success. High Forward Citation Concentration (signal of SPT) and Forward Citation Flow (the curve with diamond high knowledge diffusion rate) reduces likelihood of failure but at the same time also diminishes success chances as shown by the negative and significant (although weak in the case of success) effects on the two events. We plot the interaction effects in Figure 6 and Figure 7 below.

Figure 6 illustrates this interaction effect on failure at three levels of Forward Citation Flow – i.e., at the mean, and at one standard deviation above and below the mean of this variable. At low levels of Forward Citation Flow (the curve with diamond shaped points), the relationship between Forward Citation Concentration and failure hazard is monotonically increasing. At mean and high values of Forward Citation Flow (shown by curves with square and triangle shaped points) the relationship reverses. Thus, at high values of concentration (signal of SPT) the failure hazard decreases. Analogously, in Figure 7 at high Forward Citation Flow the success hazard decreases (the curve with triangle shaped points). Therefore, firms that receive signals conveying SPT have lower failure as well as success hazard as high levels of knowledge diffuse out in a given year pointing towards existence of persistence. As hypothesized we see asymmetric effect of both failure and success chances being diminished when a signal of SPT is accompanied with high rate of knowledge diffusion. Consequently, the interaction of these two factors, high rate of forward citations and high concentration of those citations in few domains, provides evidence of a systematic causal factor that leads to neither success nor failure events. Therefore, such firms stand the risk of persisting without any events that provide investors the opportunity to exit.

Figure 6. Interaction Effect Technology Breadth & Diffusion H2a (Failure)

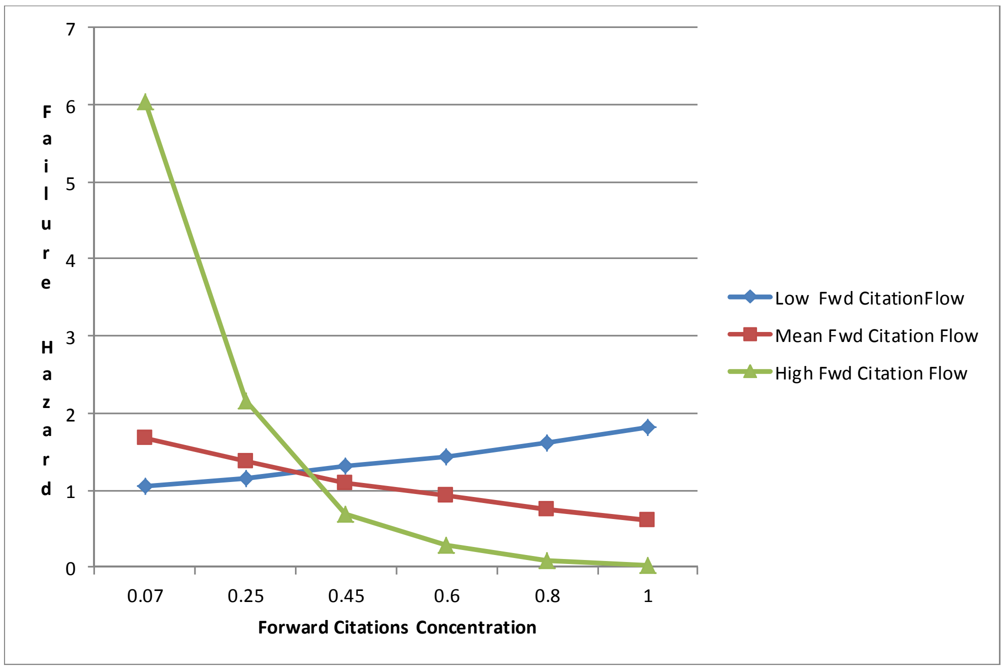
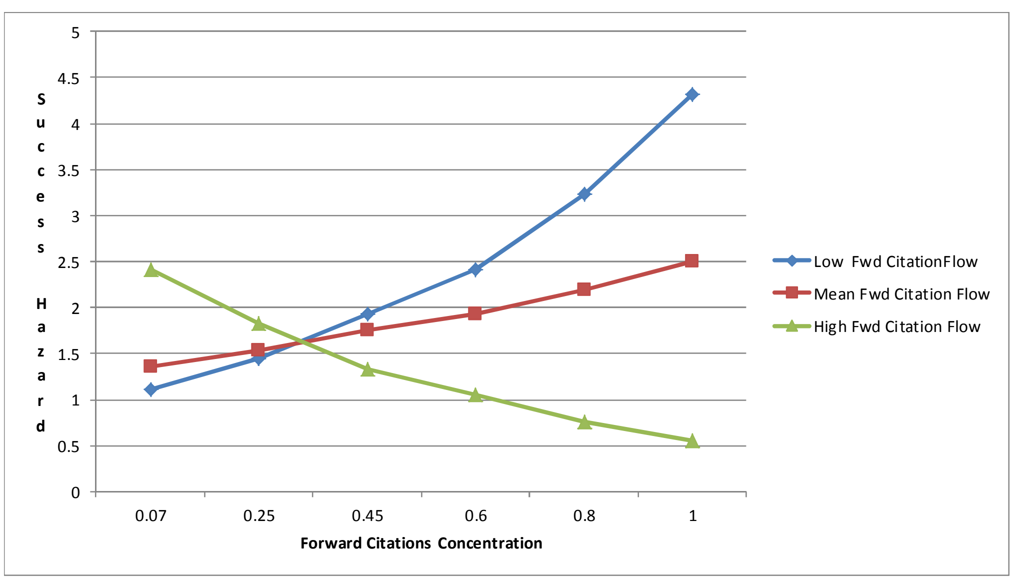


Figure 7. Interaction Effect Technology Breadth & Diffusion H2b (Success)



In contrast, H3a & H3b are not supported in the regression analysis. The interaction of Forward Citation Concentration with Alliance Concentration has no statistical significance. The main effect of Alliance Concentration (included for interpreting the interaction) is also not found to be significant. One explanation could be that many of these alliances do not provide economic benefits; rather start-ups pursue them to gain legitimacy and endorsement. For our analysis we did not look at different types of alliances because Factiva does not categorize strategic alliances in the way SDC does. However, scanning the deals we found very few licensing deals reported. Since licensing deals are generally not publicly reported, our data on alliances may be skewed towards those deals that provide intangible benefits rather than direct monetary compensations.

We highlighted before that evidence of asymmetric effects, as we see in the case of H2a and H2b, could be an important empirical tool to investigate non-events. In that spirit, we finally analyze some of the interesting results in the effect of the control variables on performance. The signaling value of patents is symmetric (i.e. decreases failure and increases success rate) and beneficial for both failure and success as current research predicts. The main effect of Forward Citation Flow (included to interpret the hypothesized interaction effect) is indeed fascinating, demonstrating asymmetry. Higher knowledge diffusion seems to benefit success while increasing failure chances. Thus, forward citation flow has a net endorsement effect for successful firms, but has a net competitive effect for failed firms. In Chapter 2 we theorized and found evidence that forward citations from firms with the reputation to litigate cause start-up failure and explain partially the harmful effects. In additional analysis, not reported here, we find no effect on success events when the citations come from alters with a reputation to litigate. Those results, along with the systematically different effect of forward citation flow between failed and successful outcomes lead us to speculate that a deeper understanding of the actual content of the inventions beyond patent classes and prior-art citations would enlighten us further on the exact mechanisms that lead to either deference or competition.

Further, longer gestation period (measured through Time to First Round) has an asymmetric effect on the two dependent variables. They are good for survival, decreasing failure, but not good for harvest, diminishing success. This could be due to inertial forces setting in as the firm ages, diminishing the potential of VCs to influence or change course. Initial founding team experience has symmetrical and beneficial effects on performance much like the other signal of quality much discussed in the literature, patents. Our study therefore reinforces the importance and reliability of these signals of quality to overcome information asymmetry and prevent the lemon problem (Akerlof, 1970).

Finally, the number of alliances per year has an asymmetrical effect in that higher alliances rate help survival but limit successful harvest opportunities; pointing towards a substitution effect of alliances with successful exit. They might be making the start-up less attractive as an acquisition candidate as well as limiting the growth potential. Overall, these results provide evidence of a number of forces that may be conspiring to create persistence by lowering success probability and increasing survival prospects.

DISCUSSION AND CONCLUSIONS

We want to state upfront that our focus is not on low tech start-ups; rather we focus on ventures that require extensive inputs from outsiders such as VC firms whose expectations about success are high returns in a clear cut time horizon. In other words, we do not consider low tech ventures, or ventures with minimal external inputs such as capital and IPR, and commensurate expectations—including mom and pop restaurants, street-side shoemakers, children's lemonade stands or marginal real estate brokers with little sales revenue.

Our goal in this paper was to look at success and failures of start-ups simultaneously to indirectly catch a glimpse of what has been termed as 'living dead' firms. To achieve that we exploit asymmetric effects on two start-up outcome events, success (achieving IPO or trade sale) or failure (dissolution due to bankruptcy, distressed sale or closing up business). Extant literature has usually centered on either success or failure, thus excluding the possibility to uncover forces that work towards both inhibiting success and failure. We believe that this is an important contribution and can serve well as an empirical tool to study non-events.

We theorized about a signal of quality of the inventions of a new venture that is uncovered over time through their use by others in different domains. With the assumption that a firm might not know *a priori* about all the possible applications of its technology, we make the assertion that a signal of GPT will be good for survival although success will depend on how they cope with challenges of rent dissipation through diffusion of the knowledge and their ability to cope with the commercial challenges.

We found evidence of asymmetry in causal effects of the signal of nature of technology. Having a GPT did help survival, but had no predictive power for success. The most fascinating result is the moderating effect of the forward citation flow that a start-up receives on the signal of the nature of its technology. In both models of success and failure, firms with high concentration of domains citing them combined with high levels of forward citation per year face a lower probability of either succeeding or failing; strong indication of persistence that VC's have labeled 'living dead' (Bourgeois & Eisenhardt, 1987; Ruhnka, Feldman, & Dean, 1992). Future research should explore explicitly this twilight zone that has received scant attention till date.

A broader theoretical explanation of the asymmetric effect of high technology concentration and high knowledge diffusion on performance can be found in the competitive strategy literature. The simultaneous specificity and diffusion of technology attenuates the differentiation possibilities within an industry thus leading to many middle of the road performers. Decreased differentiation leads to broader niches albeit with lower growth prospects that encourage persistence.Perhaps some of the intriguing results appear in the control variables that we did not theorize about. First, we find that more a firm's inventions are used by others, the new venture's survival and success prospects are affected in contrasting manner. They inhibit survival but promote success. Forward citation flows have been used to measure knowledge trail, deference as well as competitive effects (Jaffe et al., 1993; Podolny & Stuart, 1995; Podolny et al., 1996). Failures seem to bear the brunt of the harmful effects of rent dissipation through knowledge diffusion and designing around while successes seem to enjoy the endorsement effects. The technology breadth via the interaction effect gives us clue on the mechanisms in play but also raises further questions on why the amplification of the respective harmful and beneficial effects occurs. An interesting research project would probe further on the content of the inventions and why such a stark difference materializes.

A second interesting finding is that longer gestation period before receiving VC funding has unbalanced effect on performance. Survival chances increases when the time taken to receive first round of funding is longer maybe because the routines and capabilities of the firms get established however the downside is that success chances are lowered pointing towards rigidities developed. This could also reflect some sort of VC selection effect where exciting prospects are picked up early and nurtured to harvest. The VC's may find it harder to influence outcomes when practices, routines and capabilities are more established. Again these issues merit further investigation.

Finally, the amount of annual alliances that a firm undertakes every year increases survival but prevents successful outcome. While easy to explain the beneficial effects, the adverse impact on harvest points towards the downsides of too many alliances; with more alliances it is likely that the new venture partners with prospective buyers. It is probable that with more alliance partners the value appropriation by the start-up is negatively affected. The knowledge spillovers from alliances with powerful players with much higher resources and ambition may decrease the growth prospects of the new firm. These concerns could shed interesting insights and are worth further attention.

Our study is not without limitations. It is set in a single context and applies only to those firms that patent. This is not a big concern in high technology sectors where the norm is to seek patent protection. In addition, the empirical method only allows us to infer persistence indirectly. Identifying ‘living dead’ firms and analyzing them directly would therefore be another interesting research project. Our criteria for success are also specific to the context. Therefore replicating the study in other context and using other success benchmark could help us verify generalizability. Limitations notwithstanding, this study makes important contribution to our understanding of the entrepreneurship as well as the broader performance literature.

Chapter 4: Neither Success nor Failure: Effects of Founding Team Imprinting and their Subsequent Disruption on the 'Living Dead' Outcome

> *'It was not until I got into the VC business that I found out about the terrible, dreadful "living dead" - a term used to describe companies that merely survive, without future prospects. Normally fearless VCs fear the living dead. So do our LPs (the people who invest in VCs) who worry that we might waste our time (and their money) on a bunch of little companies that go nowhere.'*
>
> \- Ho Nam, Altos Ventures, November 7, 2007

Entrepreneurs and their firms face turbulent times during their creation. The overwhelming majority face a premature exit while a smaller subset enjoys enormous rewards.[17] From ecological (Hannan & Freeman, 1984) to conventional entrepreneurial research (Gompers & Lerner, 2004), the twin foci of research have been on success and failure as if the outlook for start-ups is confined to these mutually exclusive outcomes. The prevailing literature notwithstanding, start-ups' success versus failure does not exhaust all possible outcomes; many new ventures neither fail nor succeed, persisting on the edge of failure (or if one prefers a more positively toned framing, sustaining themselves on the brink of success). Such firms are prevalent in many high-tech sectors, yet they have been largely ignored by numerous strands of entrepreneurial research which typically contrast between survival (avoiding willful dissolution, bankruptcy or distressed sale) and success (investor harvest events via Initial Public Offering (IPO) or trade sale) as logically possible outcomes.

[17] Over a ten year period survival rate is 29% in the general population of new single-establishment businesses according to US census data. More than 50% fail before the fourth year (Shane, S. A. 2008. ***The illusions of entrepreneurship: The costly myths that entrepreneurs, investors, and policy makers live by***: Yale Univ Pr.).

This paper investigates founding team characteristics and its effect on marginally performing start-ups that neither succeed nor fail. The founding team of a new venture provides important signals of quality that help venture capitalists identify and rank new firms in terms of human capital endowment (Baum & Silverman, 2004), routines and capabilities (Eisenhardt & Schoonhoven, 1990), reputational capital (Shane & Cable, 2002), and legitimacy (Cohen & Dean, 2005). Proxies of quality such as the team's previous experience in founding other firms, experience in relevant industries and its size provide information on different underlying routines and capabilities that might impact the start-ups performance. In addition, loss of founding team members may signify disruption of these routines or may hint towards problems within the new firm. We analyze the effect of these factors on firms that neither fail nor succeed.

Since extant research revolves around liquidation and liquidity events (closing down the business, IPO and acquisition) as indicators of new venture performance, our knowledge of start-ups that are neither successful nor abject failures, but reside somewhere between these two performance opposites, is limited. Accounting measures of start-up performance usually are not feasible since start-ups are private companies that do not disclose their income statements or balance sheets, explaining why research on such marginally performing firms is sparse. Only two publications mention ventures as residing in the twilight zone between success and failure, through the label of 'living dead' (Bourgeois & Eisenhardt, 1987; Ruhnka et al., 1992). The term 'living dead'—attributed to Franklin "Pitch" Johnson, a noted Silicon Valley venture capitalist (VC)—includes firms who neither provide stellar returns nor allow a quick write-off of the investments to the VC's. The cited authors above also allude to ventures that do not meet their investors' expectations even if self-sustaining and economically viable.

We seek to study this largely ignored phenomenon of 'living dead' in the VC context, contributing to entrepreneurship literature and more generally to the stream of work on "permanently failing organizations" (Meyer & Zucker, 1989). We conceptually define the category of 'living dead', a transitory state. Firms in this state persist for long periods of time beyond the expectations of their investors, representing marginal performance between success and failure. Success and failure are not two sides of the same coin; rather they can be conceptualized as the two extremes of a continuum of new venture performance (see Figure 1). Our research adds additional insights by explicitly treating a part of the largely overlooked middle-ground, i.e., those firms that persist beyond the norm.

The sparse literature on the topic has identified management as a key determinant to enter this state apart from external factors. We theorize about the effect of initial founding team characteristics such as experience and size, an important signal of quality used by investors to select new ventures; these signals presumably reflect underlying skills and routines of the team members as well as factors that shape the routines and capabilities of the firm. VCs in most cases intervene and make changes to the management team when confronted with the 'living dead' situation (Ruhnka *et al.*, 1992). Changes to the founding team, whether voluntary or forced, may prove disruptive given strong imprinting effects that ecological studies have documented (Baron et al., 1999b;

Stinchcombe, 1965). Therefore we also speculate on the effects of these disruptions on 'living dead' outcome in line with prior literature.

Our theoretical framework proposes beneficial effects of team members' prior experience on 'living dead' outcome. We consider two signals related to previous experience—involvement in relevant product market or technology and founding of start-ups. The total experience of founding members, in both the areas, is conjectured to lower the likelihood to enter the perceived limbo of 'living dead.' We also conjecture on the non-linear effect of team size on 'living dead' outcome, speculating high coordination costs when founding teams have two members, possibly representing two foci of power that increase coordination costs and eventually increasing the odds of getting stuck in a transitory state which we call "living dead." In the light of strong imprinting (Stinchcombe, 1965), we speculate that a disruption of founding team endowed with prior entrepreneurial experience, whether voluntary or imposed, is a shock that increases the odds of the new firm ending as marginally performing and persisting entities.

We test our theory using a matched case-control approach on a sample of US wireless ventures that received early stage venture capital financing. We identify 'living dead' firms as cases of interest which we then match to similar firms from three control groups—one that includes any firm that faced some event, liquidity or liquidating, after founding and two others with either successful or failed firms. We find that entrepreneurial experience, a signal of quality that is frequently used by investors, decreases the likelihood of ending up as a 'living dead' firm. Teams with such entrepreneurs also decrease failure hazard but have no effect on success. Hence, our findings suggest that capabilities acquired through founding multiple ventures decreases the chances of persistence and increase the chances of dissolution. Therefore, start-up experience provides some predictive power for not getting stuck with investments for too long a period of time. Teams with two founders are shown to be especially harmful, being much more likely in ‘living dead’ firms when compared to successful firms. Disruptions to the founding team, captured through the loss of members, do not generally affect performance. However, when these changes occur in firms founded by management with previous entrepreneurial experience, they increase the odds of ending up as “living dead.” Loss of founding team members may occur due to VC interventions through forced removal or voluntary departures[18], suggesting changed expectations regarding prospects of the start-up. Although we were unable to disentangle the two effects, it is a useful finding for VC’s for whom ‘living dead’ firms could be an important drag on resources and in their returns on investment.

In the following section, we elaborate on our theoretical framework We define the concept of ‘living dead’, review the literature and state our research questions in the light of the current literature on ‘living dead’ firms, and then derive hypotheses based on the effect of initial team characteristics and losing members of this team on performance.

[18] Other forms of loss such as death or retirement are not observed in our sample, which spans a relatively short period of time.

THEORETICAL FRAMEWORK

'Living Dead' Firms Defined

The literature on VC-backed firms that neither achieve a liquidity event nor fail to survive is very sparse. A sum total of two papers exist in the vast literature on venture backed new enterprises (Bourgeois & Eisenhardt, 1987; Ruhnka et al., 1992). Bourgeois & Eisenhardt (1987) define these firms as 'insufficiently successful to be taken public', not 'clear enough failure to die' and as those for whom success always appears to be 'just around the corner' (Bourgeois & Eisenhardt, 1987 ; pg. 143). Ruhnka et al (1992) in their survey of venture capital managers find 'living dead' firms to be economically self-sustaining albeit unable to produce the level of sales, growth or profitability to produce attractive rates of returns and exit opportunities for their venture capital investors. In effect these are marginally performing firms that tend to persist, yet fail to meet the expectations of the venture capitalists (Ruhnka *et al.*, 1992). While marginally performing new ventures in general have received some attention in the literature (Gimeno et al., 1997), we do not know much about venture backed firms with such performance primarily because of lack of data. Financial measures such as sales and profits are not available for private firms in general and more so for VC-backed new ventures.

'Living dead' can be conceptualized as a transitory state for venture funded firms with marginal performance, a state from which they might eventually exit, even if much longer than expected[19]. These expectations stem from the venture capitalists, who are sought by the entrepreneurs to fuel their dream of founding 'a high-technology company

[19] Rhunka et al. (1992) estimate around 20.6% of a VC's portfolio to belong to this category

which will grow with sufficient speed and prosperity to present a "winning" image and go public' (Bourgeois & Eisenhardt, 1987; pg. 143). This particular propensity and aspiration of entrepreneurs also sets these VC-backed firms apart from other new ventures which may continue to persist due to lifestyle choices (Bhide, 1996) and other benefits, such as psychic income (Gimeno *et al.*, 1997), that the entrepreneur may derive from starting a company. We exclude from our purview small organizations that are formed by lifestyle entrepreneurs, presumably in many cases providing their own resources, to have their own independence (for example, setting up a small real estate agency or a pizzeria) without the ambition or pressure of growing fast and succeeding through an IPO or trade sale.

We contend that in a high-tech VC-backed context, the overriding consideration for all parties is achieving a liquidity event for investors in a reasonable time-frame. Venture capitalists usually invest in companies with expected fast growth rates—as a rule of thumb, reaching sales of at least US$50 million within six years—and which then can then be sold, either to a larger firm or through a public offering (Browning, 2009). Without liquidity, venture capitalists can't return profits to their original fund investors, who typically give the VC's a mandate for ten years (Browning, 2009). In addition, the contractual arrangements between a VC and an entrepreneur also reflect this goal in that entrepreneurs cede both control and liquidation rights to the investors (Kaplan & Strömberg, 2004).

We define persistence as the continued survival of a firm without liquidity events from birth to the end of the window of our study. In the absence of data on financial performance, common for private companies, start-ups are identified as 'living dead' when they persist with fulfilling the VC expectations of generating an exit event within a reasonable time frame. Such expectations are derived from two industry wide norms. First, the investment horizon of a 'typical' venture capital fund and second, the average time that peer start-ups take to generate a liquidity event for investors. Thus only those firms that survive without any exit within the time frame of the study for a duration that exceeds these two norms are classified as 'living dead' firms. Furthermore, 'living dead' firms are a subset of all start-ups in the population that persist without success or failure (see Figure 1).[20] We conceptualize firms to enter this transitory state when the firm persists beyond the norm, treating such a transition as a pseudo-event. Defining this third outcome, which is a state instead of a concrete event, permits us to directly analyze such firms without the empirical tool of indirect asymmetric effects on success and failure in Chapter 3, which provides explanation for all persisting firms without considering time spent in that state.

Literature Review & Research Question

Given the dearth of literature on 'living dead' firms, our primary research goal is to investigate whether there is anything systematic about firms that are in this inherently transitory yet persistent state[21] as defined above. We defer to the sparse literature for

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[20] While, the phenomenon as well as our definition of 'living dead' is specific to venture capital, although other scenarios are conceivable in which firms persist without meeting expectations of key stakeholders. Meyer & Zucker's (1989) 'permanently failing organizations' in which certain dependent actors supplant pure economic interests of the owners and sustain inefficient organizations, could represent one such situation.

[21] Rational expectations lead us to believe that in the long run these firms should experience some exit event, however many persist for extended periods, often beyond expectations. Hence we use the contradictory yet suggestive term of transitory state. In addition since living dead is not an event, we think

clues on factors that may lead a VC-backed firm to this transitory state. The current literature points towards three main risk factors. First, a recent stream of work, building on the behavioral theory of venture capital firms, points to the differential capabilities of VC's to manage unsuccessful investments, that is their ability or inability to write-off bad investments (Guler, 2007). Such interpretation follows the literature on decisional entrapment and the attendant rigidity that befalls agents who have overcommitted themselves (compare Staw & Ross, 1987). Second, environmental factors such as growth of the industry and exit market conditions are deemed salient (Ruhnka *et al.*, 1992). Finally, deficiencies in the management team of these firms are also identified as a major influence (Bourgeois & Eisenhardt, 1987; Ruhnka et al., 1992). We further examine these three factors and discuss their relevance to our paper.

The termination capability of venture capitalists could condition the persistence of a venture, especially if one assumes that such investments are outright failures. However, the very nature of the transitory state that is 'living dead' does not necessarily connote failure. While some ventures maybe 'permanently failing', for others success may be 'just around the corner.' The venture capital model entails the making of a number of bets and thriving on a few highly successful outcomes (Gompers & Lerner, 2004; Ruhnka et al., 1992; Sahlman, 1990). Besides, from a rational perspective, it might not make sense to exit out of an investment that is not yet a complete failure, with exit opportunities however far in the future.[22] The monitoring costs to a VC for a late stage start-up is rather

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it best to conceptualize it as a state. Empirically we create a pseudo-event of entering this state using a time window for persistence.

[22] In the words of a VC interviewed by the author, "the existence of 'a gold nugget' among these 'living dead' firms is usually high."

trivial, thus negating any pressing need to divest (Sorenson & Stuart, 2001).[23] Presumably, the proceeds from the highly successful portfolio firms serve to fulfill the obligations of the VC's to return money to their investors. In addition, entrepreneurs eagerly seeking a VC exit maybe indicative of a lowball deal which the VC's guard against using a non-embarrassment clause (Wright, Thompson, & Robbie, 1996)[24]. A non-embarrassment clause stipulates that if the management sells the company to a third party at a higher price within 18 months of the exit then the VC can reclaim their share from the proceeds. Therefore, given that 'living dead' firms are not outright failures, we conclude that VC termination capability, that is, the ability to pull the plug on investments, is not an important determinant leading to this transitory state.

Environmental factors comprise an important factor in deciding the fate of a venture. Whether the market segment that a start-up develops products and services for fulfills its initial promise of growth will definitely impact the life chances of a venture. Likewise exit market conditions such as the number of IPO's or M&A in the firms sector will determine the odds of a liquidity event materializing (Sorenson & Stuart, 2008). However, sector-wide conditions affect all ventures and certainly will not inform about firm-level differences that impact performance. We therefore chose to focus our theory primarily on the final determinant identified in this sparse literature, the founding management team.

The literature on 'living dead' firms highlights management team characteristics as the single most important factor in marginal performance (Bourgeois & Eisenhardt,

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[23] According to the VC's interviewed, these persistent investments usually end up in a common trust that has no management fees and hence no ongoing costs after the fund is wound up.
[24] This explanation was suggested by the VC's interviewed.

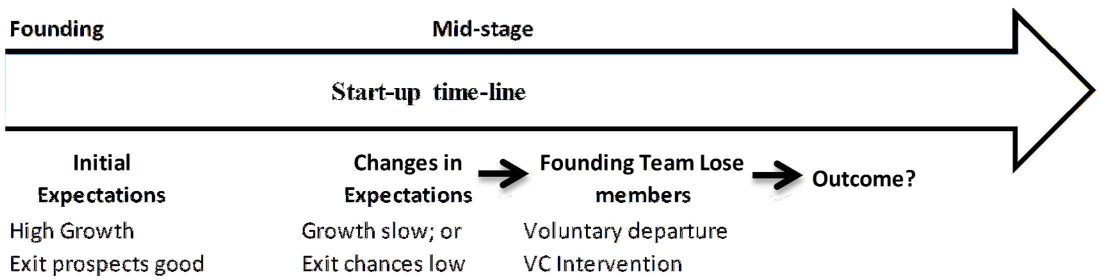
1987; Ruhnka et al., 1992). Bourgeois & Eisenhardt (1987), in their in-depth case-study of a 'living dead' firm, look at the strategic decision processes of the top management team and find them unable to manage 'a series of paradoxes—rational and quick analysis, powerful CEO and powerful team of VPs, bold yet safe decisions' (Bourgeois & Eisenhardt, 1987; pg 157). Their result contrast with successful start-up management teams, despite many other shared characteristics. Ruhnka *et al.* (1992) in their survey of VC's, pin-point management deficiencies as the major causal factor in most 'living dead' investments. The identified deficiencies include 'paying insufficient attention to competitive demands of the marketplace, or improperly positioning the product or market strategy to respond to competitive shifts that had occurred since the venture got underway' (Ruhnka *et al.*, 1992 ; pg 146). Key causes of the 'living dead' state were 'inadequate investee management and adverse market and competitive conditions'(Ruhnka *et al.*, 1992; pg. 147). Ruhnka *et al.* (1992) also survey VC strategies to deal with 'living dead' investments and find replacing management to be a dominant strategy apart from trying to sell or merge the firm with a bigger firm or repositioning the venture. Replacing the management was found to be the usual first step before the options to sell or reposition were contemplated. Building on these findings in the existing literature, we shift our attention on the founding team and subsequent loss of its members.

By focusing on the founding team we are also able to draw from the wider literature about the effect of initial endowments of a start-up on either success or failure, especially the strong imprinting effects that founders have on new ventures

(Stinchcombe, 1965). The literature emerging from the Stanford Project on Emerging Companies (SPEC) that studies top management teams and human resources practices and their effect on high-tech new venture success, demonstrating imprinting and inertia is especially relevant to our research (Baron et al., 1996, 1999a; Baron et al., 1999b, 2001; Beckman, Haunschild, & Phillips, 2004; Burton et al., 2002; Hannan et al., 1996). Interestingly, other research has likewise highlighted the importance of founding team background as a signal of quality and its positive effect on start-up IPO chances (Beckman, 2006; Beckman & Burton, 2008; Burton et al., 2002; Hallen, 2008; Higgins & Gulati, 2006). Similarly, the effect of founding team characteristics on impeding failure has also been documented (Delmar & Shane, 2006; Eisenhardt & Schoonhoven, 1990; Geroski, Mata, & Portugal, 2010). Therefore, we should ask the question whether these signals of quality affect the likelihood of 'living dead' outcomes relative to successful and failed firms. Next, given the paradoxical facts of strong imprinting effects highlighted in the literature and the common practice of VC's intervening and replacing founders begs the question whether changes in management forestalls the transitory state of 'living dead.' Or put differently, does loss of team members, whether forced or voluntary, affect the likelihood of subsequent 'living dead' status.

In the following paragraphs we elaborate on different signals of quality inferred from the founding team that investors use to evaluate new ventures, and hypothesize about their effect on 'living dead' state. As the start-ups progress, expectations on the possibility of an exit event may change. We portray such alterations in expectations as stimuli that lead to disruptions in the founding team (see Figure 8 for an illustration[25]). This could occur either as an intervention by the investors or as the entrepreneur leaving, perhaps by way of response to something gone awry. We hypothesize about the consequences of these disruptions on the likelihood of becoming a marginally performing entity.

Figure 8. Founding Team Disruption Mechanism



Founding Team - Signal of Quality

Prior research has established the importance of founding team composition and the signal it sends to investors about the venture's quality. The strength of the founding team sends an important signal to investors and other potential partners about its viability given the uncertainty of its permanence at birth (Geroski et al., 2010). In addition, prior experiences of founders are conducive to organizational success (Beckman et al., 2007; Hallen, 2008; Higgins & Gulati, 2006; Hsu, 2007). Research has also shown the importance of founding team size to predict start-up outcomes, such as IPO or growth rates (Beckman *et al.*, 2007; Eisenhardt & Schoonhoven, 1990). In the following sections

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[25] This just a caricature of unobserved changes manifesting in loss of founding members that are visible to the researcher. We do not imply that this is the only way or it represents a definite causal mechanism.

we develop arguments on the imprinting effects of previous experience and founding team size on the 'living dead' outcome.

Previous Experience – Startup & Relevant Domain Experience

Following Stinchombe's (1965) seminal piece, scholars have investigated the prehistory of startups, especially the effect of established firms through spin-offs and prior experience (Boeker, 1989; Boeker & Karichalil, 2002; Hannan *et al.*, 1996; Romanelli, 1989). Although mostly focused on the motivations of entrepreneurs to enter an industry and on transfer of "genetic" materials from established firms (Agarwal et al., 2002; Bhide, 1994; Burton et al., 2002; Gompers et al., 2006; Phillips, 2002), a few studies have explored the impact of such inheritance on entry and survival through the distinction between *de-novo* and *de-alio entrants* (Klepper, 2002; Klepper & Simons, 2000). These studies base their argument on the inheritance of routines relevant to the start-up that enable entrepreneurs to better navigate the turbulent journey that they face. We distinguish two different aspects to the routines acquired through prior experience—experience with founding start-ups (corresponding to higher-order routines) and relevant domain experience (corresponding to lower-order routines) (e.g. Knott, 2003).

We begin with the assumption that a start-up's founding team members have endowments whose effect might stretch beyond its adolescence (Brüderl & Schüssler, 1990). These endowments as identified above are mostly general and industry-specific human capital. The former includes involvement in prior start-ups often referred to as serial, renascent or habitual entrepreneurship (Eesley & Roberts, 2009; Gompers *et al.*, 2006; Nanda & Sørensen, 2010; Plehn-Dujowich, 2009). Serial entrepreneurs bring to their firm various assets, some tangible and other intangible. Tangible assets such as cash and commercial paper are often inadequate for bringing the venture beyond the initial years of existence (Nanda & Sørensen, 2010). Intangible endowments entails organizational qualities, learned or acquired during the startup's founding times when the role of the founder is paramount (Baron & Ensley, 2006; Greenberg, 2010; Stinchcombe, 1965). Compared to the de-novo founder, serial entrepreneurs carry into the venture their prior experiences in starting ventures. Such experiences render a venture more successful as indicated by the likelihood of an IPO (Gompers *et al.*, 2006) and by receiving VC funding (Burton *et al.*, 2002; Hsu, 2007). Gompers *et al.* (2006) show that serial entrepreneurs are more likely to succeed than first time entrepreneurs, inferring that a large component in entrepreneurship and venture capital can be attributed to learned higher-order routines. They identify one of these routines as 'market timing', the ability to start a business in the right industry at the right time. We argue that seasoned entrepreneurs also have the ability to time their exit, whether through a successful sale or disengaging from a hopeless venture.

Thus, entrepreneurs with previous experience in founding new firms may have developed necessary higher-order start-up routines through their previous dealings in the venture capital context. First, they presumably have contacts with potential financiers and the social capital to access financial resources. Second, they may also have the edge over novices in assembling requisite human resources either through leveraging the skills of teams from past ventures or through improved understanding of start-up recruitment processes. Third, they may be better prepared to navigate the critical growth phase of the firm through bold but safe decision-making abilities (Bourgeois & Eisenhardt, 1987). Finally, and more crucially, they might have developed an ability of timing both entry into and exit from ventures (Gompers et al., 2006). Previous experience in a start-up environment cultivate the routines and capabilities through learning by doing (Eesley & Roberts, 2009) that underlie the decision-making required in such a context and which in their case study of a 'living dead' firm Bourgeois & Eisenhardt (1987) separates it from successful firms. This experience and learning might also lead teams with serial entrepreneurs to recognize a bad bet early and hence actively seek closure of ventures without successful prospects. Thus, presence of serial entrepreneurs lead to higher success as well as failure likelihood. Hence, we hypothesize:

> *H1. The higher the initial endowment of a firm with founders that have previous start-up founding experience (or serial entrepreneurs), the lower the odds for it to become a 'living dead' when compared to both successful and failed firms.*

The previous hypothesis dealt with prior experience in founding companies. While start-up experience relates to capabilities involving higher-order routines, decision making also involves industry specific tasks and lower-order routines such as product and marketing strategy, forming the right alliances and getting customers. Relevant domain experience of the founding team at birth enhances the transfer of skills and capabilities that boosts the decision making ability as well as communicating legitimacy of the team. Being embedded in a relevant industry context could also provide easier access to strategic partners, customers and employees through prior contacts and networks. While, these lower-order routines and capabilities may translate to better survival chances, they will not guarantee success in the long run (Winter, 2003). Therefore, our second hypothesis contrasts ‘living dead’ firms to failed firms as no effect is expected for comparison to successful firms. Specifically:

> *H2. The higher the initial endowment of a firm with founders that have previous relevant industry experience, higher the odds for it to become a ‘living dead’ when compared to failed firms.*

Team Size & Decision Making

Two oft studied dimensions of founding teams have been team size and its diversity. Findings in extant literature highlight benefits of size and heterogeneity such as fostering innovation and creativity, as well as costs such as conflict and dissension (e.g. Beckman et al., 2007; Pennings & Wezel, 2010). A meta-analysis of the relationship between team design features and team performance finds mixed results for team size effect on performance (Stewart, 2006). Extant research on new venture founding team size show beneficial effects of team size on growth and IPO outcomes (Beckman et al., 2007; Eisenhardt & Schoonhoven, 1990). However, teams have to contend with coordination costs as they get bigger and diverse, which is especially salient for ‘living dead’ outcomes. Bourgeois & Eisenhardt (1987) found that fast but bold decision making with quick consensus among powerful management team members is an important feature that ‘living dead’ firms lacked vis-à-vis successful start-ups. Delmar & Shane (2006) find no effect of founding team size on survival. Therefore, we develop our hypothesis on team size compared to successful firms and not when the comparison group comprises failed firms.

The interplay of the benefits and costs of team size suggests a non-linear relationship, with optimal design achieved at some moderate-level of team size.

However, founding teams typically consist of one or two members with teams larger than three members a rarity (Ruef, Aldrich, & Carter, 2003).[26] Hence, we hypothesize about these smaller groups that drive performance rather than the rarely occurring large groups. Teams that have a single founder may be less susceptible to delays and face lower coordination costs than teams that have multiple founders due to the following two reasons. First, single member teams are presumably guided by a single focused vision, that of the founder. Second, they do not face the problem of multiple leaders and coordination challenges that might present. Both these factors speed up decision making and achieving consensus. In contrast, multiple member teams while adding more resources and capabilities will add coordination costs. Within founding teams with more than one member the problems of lack of consensus leading to gridlocks may be the greatest when there are two founders due to the need of consensus. Since, strategic decisions might require the blessings of both the founders, the prospects of the firm may be harmed through delaying bold decision making. Such problems will not arise with three member teams, where a simple majority might break deadlocks.[27] Thus our third hypothesis:

> *H3. Firms with two founders will have higher odds to become a 'living dead' when compared to successful firms.*

Changing Expectations of Liquidity Event

We developed arguments in the previous section on important dimensions of the founding team that signal its quality and affect the likelihood of entering the transitory

[26] Our sample resembles the general population with 84% of the firms with one or two founders. Including three member teams cover 95% of our sample

[27] We do not take into consideration effects of founding team sizes greater than three because they are rare.

state of 'living dead'. Once the founders have assembled the requisite resources, both financial and human, the firm embarks on its course towards going public with expected pay-offs. VC expectations, whether reasonable or unreasonable have important implications for the trajectory of the start-up (Browning, 2009). In some cases successful liquidity events materialize, while in other cases shareholders realize the futility of their pursuit, resulting in the dissolution of the firm. In the remaining cases, i.e. those that are neither clear failures nor successful enough to achieve an IPO, investors and founders fail to meet their initial expectations. The exact time when such a recalibration of expectation occurs is inaccessible to the outsider, who can only surmise its manifestation through salient changes in the firm. One such event of importance is the departure of members of founding team.

Changes in the founding team may be voluntary or through the intervention of the VC, as members of the core team either leave or are replaced.[28] Founders may leave on their own accord not satisfied with the progress of the company. They might be dissatisfied with the demands of the investors to whom they had ceded control rights when obtaining financing (Kaplan & Strömberg, 2004), especially when future prospects don't meet expectations. This is consistent with 'old guard disenchantment' observed in employee turnovers in high-tech firms (Baron *et al.*, 2001). A more likely scenario, according to Ruhnka et al. (1992), is that investors will change the management team in their effort to turnaround the fledgling company. Beckman et al. (2007) explored the impact of turnover on IPO chances and found that losing founding team members was

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[28] Changes may also occur through retirement or death. Our twenty-year window does not show either. On a larger time-frame these causes which also lead to loss of routines and capabilities might become salient.

detrimental to success. Such disruptions are harmful leading to loss of important resources and capabilities (Chandler, Honig, & Wiklund, 2005). However, these negative effects can be ameliorated by hiring other top management executives although such changes usually require time and effort (Beckman et al., 2007). Thus, the main effect of these losses is an empirical question depending on the specific situation of the start-up affected. However, when such changes occur to teams with members who are serial entrepreneurs, the consequences can be dire.

Disruptions in Founding Teams & Prior Entrepreneurial Endowment

We examine the consequences that loss of founding team members have on the previously hypothesized imprinting effect of entrepreneurial experience endowment in the founding team. Organizational theories, especially from ecological perspectives (Hannan & Freeman, 1984), emphasize the disruptive effects of change. This holds especially for changes in founding members of a nascent firm where such transformations may trigger loss of vital routines and capabilities. Research on the inter-firm mobility of knowledge workers has highlighted the importance of such losses (Corredoira & Rosenkopf, 2010; Groysberg et al., 2004; Marx et al., 2009; Wezel, Cattani, & Pennings, 2006). For example Wezel *et al.* (2006) find that the loss of partners in Dutch accounting firms leads to higher likelihood of failure due to loss of higher-order routines. The effect of these losses would depend on who replaces the outgoing founders. Beckman et al. (2007) find that incoming executives with strong industry experience can help firms overcome these losses and speed up IPO. Their findings do not distinguish between first time entrepreneurs and experienced ones. We argue that given the higher-order routines associated with serial entrepreneurs, especially the ability related to timing and decision making, the loss of team members in 'living dead' cases may be insurmountable. Therefore, we expect 'living dead' firms to show higher likelihood of having teams with high aggregate entrepreneurial experience that also lose core members due to the following two reasons. First, in the case of failed firms, the ability of these entrepreneurs to recognize a bad prospect and take quick action may lead to dissolution before any change occurs in the team. Second, in the case of successful firms, changes in teams with serial entrepreneurs may be infrequent due to the ability to recognize and deliver on good opportunities. Thus we expect:

> *H4. The interaction effect of the initial endowment of serial entrepreneurs with changes in founding team will increase the odds of 'living dead' outcome when compared to both failed and successful firms.*

EMPIRICAL SETTING AND METHODOLOGY

Industry Context and Data

Our study is based in the wireless sector during the period 1990-2009. Rapid high growth potential and a variety of opportunities resulting from deregulation and technological discontinuities spurred entrepreneurial activity and venture capital funding. Unlike sectors such as pharmaceuticals and biotechnology which require risky R&D investments that might take decades to pay off, wireless innovations take much less time to bring to market. The core standards (e.g., GSM, CDMA and UMTS) are managed by powerful industry incumbents with an average of ten years between major generational changes. Major generational cycles have sub-cycles of five years of less (Ansari & Garud, 2009). With our choice we of the sector we try to rule out an important explanation of the 'living dead' phenomenon—long development of technology and growth cycles such as in the biotechnology sector.

We collected data on VC-funded firms in the U.S. wireless sector that were founded between the years 1990 and 2009. We include those new firms that received at least one round of early-stage VC funding because entrepreneurs that seek such funding have to facilitate the exit of the VC within their investment horizon, normally 10 years (Gompers & Lerner, 2004; Kaplan & Strömberg, 2004). Thus achieving IPO or a trade sale is an important success criterion for such a start-up, which may not be so for other types of new ventures that do not seek venture financing (Browning, 2009). The population consists of 428 firms as documented by VentureXpert, the leading source of information about venture capital from Thomson Research, commonly viewed as the most comprehensive and widely used database for research on venture-funded companies (Kaplan & Schoar, 2005).

Obtaining data on the management teams of private companies was extremely challenging. VentureXpert provides some data on the management teams but it is neither longitudinal nor complete. There was no single source with structured data that we could rely on. However, with the advent of the Internet it has become almost mandatory for companies to have a web page about their products, and corporate information such as the management team biography. Therefore websites became the primary source of information of data regarding founding team members. The Internet changes constantly only giving us a snapshot of each website at any given point, however thanks to the Wayback machine (http://web.archive.org), starting from 1996 the Internet archive has been storing all publicly available websites (Notess, 2002). This allowed us to also observe changes in founding team over time. The Wayback machine gave us the bulk of the data on management teams.[29] Remaining data not available from the Internet archive were gathered using two sources: LinkedIn (http://www.linkedin.com), and ZoomInfo (http://www.zoominfo.com). LinkedIn is a business networking service that professionals use to job search and provides data on self-reported resumes of executives. Zoominfo is a free people search engine that scours the Web for information about people. ZoomInfo uses a combination of various technologies to crawl the Web (websites, press releases, electronic news services, SEC filings, etc.) and then organizes all the information about people into a readable, sensible format.

Other sources of data include Derwent, a database of global patents maintained by Thomson since 1969. SDC Platinum, Factiva, and the historical websites of firms in our sample relying on the Wayback machine were used to source data related to alliances. SDC, Zephyr, Factiva, and Hoovers provided merger and acquisition and IPO information. Finally, COMPUSTAT was accessed for segment data on publicly listed wireless firms.

Dependent Variable

Our goal in this study involved identifying 'living dead' firms and comparing them to other firms that don't persist, providing some liquidity event to their investors by either failing or succeeding. Failure is identified as a dummy that is set to one when a firm experiences dissolution, bankruptcy or distressed sale. Success is a dichotomous

[29] The data collection took over a year. The first step involved the use of automated scripts to download the information. Then 3 RA's manually checked the information, supplemented missing data and coded the biographical information. RA's were given jobs that overlapped to ensure reliability.

variable set to one when a start-up goes public or is sold. Living dead is a binary variable that is set to one for all those start-ups that persist during the duration of the study without any form of exit events for more than two measures of expectation, whichever is greater. First, the average time to experience any form of liquidity or liquidating event, which in our case is 5.5 years. Second, the typical duration for which a venture fund is constituted. The vast majority of VC funds have a life of ten years with possibilities of one year extensions up to a maximum of three years (Sahlman, 1990). We therefore define a firm to have entered the transitory state of living dead in the tenth year of persistence for our analysis.[30] Below in Table 12 we summarize the number of cases of 'living dead' obtained by varying the number of years of minimum persistence. We have a total of 184 firms that experienced no events and were censored at the end of the study. The cases are drawn from this pool of firms based on their age. In addition we also report the number of firms that experienced a failure or success events within a duration less than or equal to the years of persistence used to define 'living dead.' For example, using the criterion of at least 10 years of persistence, we have 56 'living dead' firms in our sample, while there are 124 firms that experienced a success event with age less than or equal to 10. For the same age 103 firms had failure events.[31] We can see from the table that the number of firms experiencing some event reduces considerably after 10 years.

[30] Robustness check using values of persistence from seven to eleven years were also performed. We could not do analysis on twelve and thirteen years as the typical fund extension period would suggest as those criteria do not generate enough cases with our twenty year window. With a larger window such analysis would be feasible.

[31] There are 244 firms with either success or failure events in our population. For a time period of 10 years in the sample 227 firms have experienced any event. The remaining 17 firms had events after the age of 10.

Table 12. ‘Living Dead’ Cases – Minimum Years of Persistence

Years of Persistence	Number of Cases (Out of 184)	Number of Failures (Firm Age <= Years of Persistence)	Number of Success (Firm Age <= Years of Persistence)
7	99	77	92
8	83	91	110
9	69	98	117
10	56	103	124
11	34	104	125
12	20	104	128

Independent Variables

Founding Team - Signal of Quality

Prior Entrepreneurial Experience

We use this variable to capture the endowment of the start-up with serial entrepreneurs at founding. We identified the number of companies that each member of the founding team had previously founded and then used the sum as an indicator of signal of previous entrepreneurship experience. This variable ranges from a value of 0 to 4 with an average value of 0.6.

Previous Wireless Experience

To measure the wealth of sector related experience at founding, we counted the number of firms related to wireless that founders had worked for during their career prior to founding the start-up. Firms were identified as wireless using their SIC code and from information from the biographical sketch that often stated the related nature of the previous experience of the founder. A typical firm in our sample had founders with 1.4 related firm experiences prior to founding with a range from 0 to 7.

Two Founders

A dummy set to one when a company was founded by two persons is used to isolate the effect on two member teams on 'living dead' outcome. 31% percent of the firms in the population had two founders.

Founding Team Size

To control for founding team size we use a simple count of the number of members in the team at founding. Teams ranges from a size of 1 to 7 with an average of 1.7 and a standard deviation of 0.9.

Founding Team Changes

Founding Team Member Loss

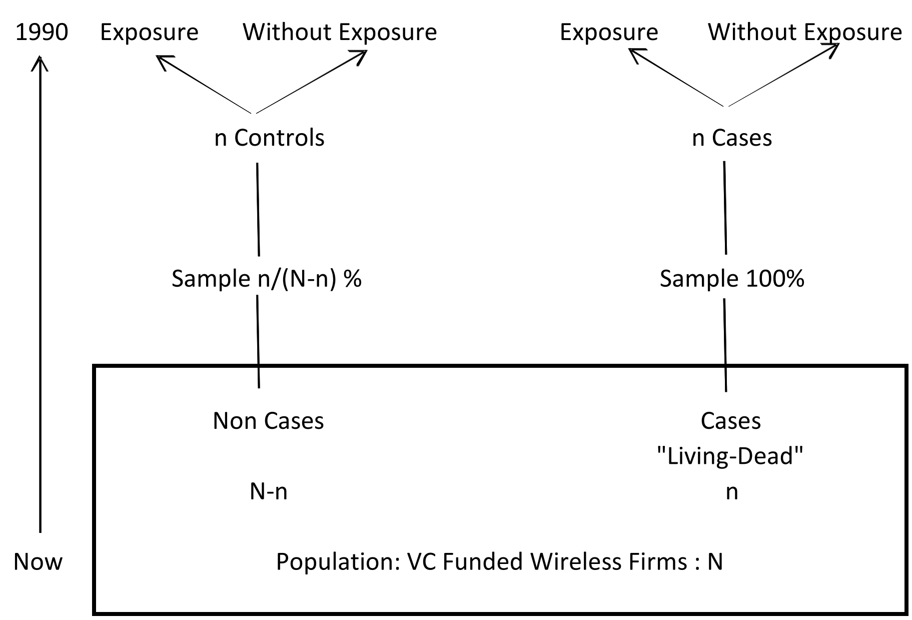
This dichotomous variable was set to one if the founding team lost any of its members at any point from founding to liquidity, liquidating event or reaching 'living dead' stage. The reasons for such changes are unobservable and the exact time of change is very noisy which led us to use such a coarse measure. Only 25% of all start-ups lose a member of the founding team. We interact this variable with Prior Entrepreneurial Experience to test our final hypothesis.

Research Design

Matched Case-Control Study

The 'living dead' outcome is a non-event. Moreover, it is not just persistence but tenacity to exist without exit events for an extended period of time. Since we identify these outcomes and then retrospectively look at factors that may have led to this state, we use a case-control research design. This is a commonly used method in epidemiology with the cases of interest based on their outcome (see Figure 9 for a schema of the study). Specifically, we use a matched case-control design (Schlesselman & Stolley, 1982). The method consists of matching cases to controls (on a 1: 1 or 1: k basis based on the data) on confounding factors other than the risk factors of interests, i.e., the independent variables. We carry out matching with three different control groups—successful companies, failed companies and all companies with a liquidity event (i.e., both successful and failed companies). Once the preprocessing with matching is done, the matched sample is used to calculate the odds ratios of the risk factors to test the hypotheses put forward.

Figure 9. Matched Case-Control Design



Matching Strategies

Start-up performance is influenced by many factors, which implies that there are many confounding factors apart from the hypothesized founding team characteristics that could influence the living dead outcome. Hence, an exact match on few covariates as is normal in many epidemiological case-control studies is not practical. We therefore use optimal matching, a type of propensity score matching (Rosenbaum & Rubin, 1983). Rather than attempting to match on all covariates individually, propensity score matches on the most important scalar summary of the covariates to obtain good balance of all of the covariates. This method is often used for generating control groups in case-control studies (Bergstralh & Kosanke, 1995; Cologne & Shibata, 1995; Hansen, 2007; Ming & Rosenbaum, 2000; Rosenbaum, 1989). We use conditional logistic regression that predicts the living dead outcomes using all covariates that are not a direct consequence of exposure to the risk factors (see Table 13 for a list and definition).

Several techniques are available for propensity score matching (Rosenbaum & Rubin, 1985). Gu & Rosenbaum (1993) provides a comprehensive comparison of the methods. We use the optimal matching algorithm minimizes a global measure of balance (Rosenbaum, 2002). Rosenbaum (2002) argues that the collection of matches found using optimal matching can have substantially better balance when there is intense competition for controls, a situation similar to our study where there are limited amount of controls to choose from. Gu and Rosenbaum (1993) find that optimal matching does better at reducing the distance between pairs although they pick similar controls as other methods (Gu & Rosenbaum, 1993 ; pg. 413):

> *'...optimal matching picks about the same controls [as greedy matching] but does a better job of assigning them to treated units.'*

We use Matchit (Ho, Imai, King, & Stuart, 2004), a package available in the R language (Ihaka & Gentleman, 1996) for statistical computing. The optimal matching is performed using the optmatch package in R (Hansen & Hansen, 2006). We create different datasets of matched samples, evaluate the balance achieved and then carry out the final analysis to obtain the odds ratio.

Odds Risk Estimation Method - Conditional Logit

We use a conditional logit regression (STATA command clogit) to obtain the odds ratio of the risk factors. This is the standard approach in matched studies. When we have pairs matched and wish to estimate association of a within-pair exposure and outcome then each pair has a different intercept (or baseline risk), which is a "nuisance" parameter—we do not care about them, and we cannot estimate them. So, they are "conditioned out" of the analysis in order to address the problem of heterogeneity in the baseline risk. In this approach, each observation (the matched pair) gets a value for each of the different potential options available. So mathematically:

$$\log P_{ij}/P_{ij'} = \left(z_{ij} - z_{ij'}\right)'\alpha \ ,$$

where z_{ij} is a set of outcome-varying covariates and the coefficient α measures the odds of the covariates occurring for the two outcomes.

Table 13. Variable Definitions (Chapter 4)

Variable	Description
Dependent Variables	
Living Dead	A dummy indicating firm has persisted for 10 or more years without liquidity event
Independent Variables	
Prior Entrepreneurial Experience	Number of firms founded by all the founders at founding
Previous Wireless Experience	Number of wireless related firms worked before founding
Two Founders	A dummy that is set to 1 if team size is 2
Founding Team Size	Number of founders as a count
Founding Team Member Loss	A dummy that identifies any change in founding team
Matching Variables	
Patenting Related	
Forward Citation Concentration	Concentration of the forward citations received across IPC classes
Number of Patents	Stock of the firm's patents
Number of Forward Citations	Stock of forward cites received by the firm
Exit Market Conditions	
IPO Heat	Intensity of IPO activity in the firm's primary SIC
Number of Targets in SIC	Average number of targets acquired in the SIC
Investor Characteristics	
Total Number of Investors	Number of distinct investors that invested in the firm over all rounds
Number of Investors Investing in All Rounds	Number of investors that invest in all rounds
Prominent Investor	Indicator of presence of investor that was in the Forbes Midas list
Financing Related	
Number of Rounds Received	Number of rounds of funding received by the firm till the end of study
Time to First Round	Time in days from founding to receiving first round
Firm Strategic Action	
Number of Alliances	Number of alliances by the firm
Number of Acquisitions	Number of acquisitions by the firm
Others	
Business Segment Sales in Wireless	Total average sales of all public wireless companies in a given SIC code
Entry Year	Year of entry of the firm in the risk set

Unmatched Analysis: Competing Risk Cox Proportional Hazard

Matching techniques involve eliminating observations to remove bias. Moreover, case-control studies do not directly account for changes in the covariate values over time. Therefore, we supplement our matched case-control design with an unmatched analysis using a competing risk cox proportional hazard model. Cox regressions have been widely used in matched case-control studies (Breslow, 1982; Gail, Lubin, & Rubinstein, 1981; Goldstein & Langholz, 1992). We assume living dead outcome to be an event. The fact that this is a pseudo-event that deterministically occurs after a fixed time does not create estimation problems because the partial likelihood function takes into account the ordering of events, but not their actual duration. Furthermore, the baseline hazard rate is unspecified and could very well be zero during the gaps between events. We use this analysis as a backup and not the main analysis because of the assumption of treating a transitory state as a concrete event.

RESULTS

Preprocessing - Matching

Living Dead (Cases) vs. Exit Events (Controls)

We have 56 cases of ‘living dead’ firms and a total of 244 firms that experience liquidity or liquidating events (i.e., both success and failure). In the first comparison, all 244 firms that experience some events constitute a pool to create the control group for the 56 identified cases. We match cases to control in 1:1, 1:2 & 1:3 proportions, i.e., each case is matched with 1,2 & 3 ventures from the pool of both successful and failed firms. Table 14 provides the balance comparisons for all the three cases after propensity score matching. The 1:1 matching gives the best balance for our matching as inferred using the mean differences of the variables used for matching between the cases and the controls.

Living Dead (Cases) vs. Success Events (Controls)

Next, we compare our cases to successful firms by matching to a control group drawn from 135 firms that experience success events. We match cases to control in 1:1, & 1:2 pairing. Table 15 provides the balance comparisons for one to one and one to two matching. Again the 1:1 matching gives slightly better balance of the means.

Living Dead (Cases) vs. Failed Events (Controls)

Finally, we use the 109 failed firms as the control group for matching to the cases. We can only do a 1:1 match which is shown in Table 16.

Table 14. Matching Balance – Control Group All Exit Events

	Before Matching				After Matching			
	Mean Cases	Mean Control	SD Control	Mean Diff	Mean Cases	Mean Control	SD Control	Mean Diff
Entry Year	1998.18	1998.45	3.25	-0.27	1998.18	1998.25	3.78	-0.07
IPO Heat	0.03	0.05	0.05	-0.02	0.03	0.03	0.04	0.00
Number of Targets in SIC	109.67	158.31	194.25	-48.64	109.67	110.41	170.56	-0.74
Total Number of Investors	7.46	5.73	4.14	1.73	7.46	6.50	4.60	0.96
Number of Rounds Received	5.29	3.77	2.77	1.51	5.29	4.98	3.71	0.30
Time to First Round	799.11	516.86	664.22	282.24	799.11	817.63	1027.08	-18.52
No. of Investors Investing in all rounds	0.54	1.00	1.16	-0.47	0.54	0.66	0.75	-0.13
Prominent Investor	0.63	0.61	0.49	0.02	0.63	0.64	0.48	-0.02
Forward Citation Concentration	0.21	0.21	0.29	0.00	0.21	0.25	0.31	-0.04
Number Of Patents	16.04	5.69	14.03	10.34	16.04	12.11	24.93	3.93
Number of Forward Cites	81.55	24.71	61.06	56.84	81.55	46.61	101.07	34.95
Number of Alliances	4.89	1.72	3.02	3.17	4.89	3.48	4.91	1.41
Number of Acquisitions	0.43	0.41	1.09	0.02	0.43	0.43	1.11	0.00
Biz Seg Sales in Wireless	1940993.98	2183735.98	3225971.79	-242742.00	1940993.98	1840650.03	2987234.85	100343.95

Sample Sizes	Control	Treated
All	244	56
Matched	56	56
Unmatched	188	0
Discarded	0	0

	Before Matching				After Matching			
	Mean Cases	Mean Control	SD Control	Mean Diff	Mean Cases	Mean Control	SD Control	Mean Diff
Entry Year	1998.18	1998.45	3.25	-0.27	1998.18	1998.51	3.59	-0.33
IPO Heat	0.03	0.05	0.05	-0.02	0.03	0.04	0.04	-0.01
Number of Targets in SIC	109.67	158.31	194.25	-48.64	109.67	126.07	180.34	-16.39
Total Number of Investors	7.46	5.73	4.14	1.73	7.46	6.49	4.62	0.97
Number of Rounds Received	5.29	3.77	2.77	1.51	5.29	4.80	3.36	0.48
Time to First Round	799.11	516.86	664.22	282.24	799.11	681.47	838.53	117.63
No. of Investors Investing in all rounds	0.54	1.00	1.16	-0.47	0.54	0.65	0.74	-0.12
Prominent Investor	0.63	0.61	0.49	0.02	0.63	0.63	0.49	0.00
Forward Citation Concentration	0.21	0.21	0.29	0.00	0.21	0.23	0.31	-0.02
Number Of Patents	16.04	5.69	14.03	10.34	16.04	8.69	18.93	7.35
Number of Forward Cites	81.55	24.71	61.06	56.84	81.55	37.05	78.55	44.50
Number of Alliances	4.89	1.72	3.02	3.17	4.89	2.69	3.93	2.21
Number of Acquisitions	0.43	0.41	1.09	0.02	0.43	0.52	1.32	-0.09
Biz Seg Sales in Wireless	1940993.98	2183735.98	3225971.79	-242742.00	1940993.98	1747242.35	2897914.44	193751.63

Sample Size	Control	Treated
All	244	56
Matched	112	56
Unmatched	132	0
Discarded	0	0

	Before Matching				After Matching			
	Mean Cases	Mean Control	SD Control	Mean Diff	Mean Cases	Mean Control	SD Control	Mean Diff
Entry Year	1998.18	1998.45	3.25	-0.27	1998.18	1998.58	3.43	-0.40
IPO Heat	0.03	0.05	0.05	-0.02	0.03	0.04	0.04	-0.01
Number of Targets in SIC	109.67	158.31	194.25	-48.64	109.67	133.32	180.50	-23.64
Total Number of Investors	7.46	5.73	4.14	1.73	7.46	6.14	4.43	1.33
Number of Rounds Received	5.29	3.77	2.77	1.51	5.29	4.32	3.00	0.96
Time to First Round	799.11	516.86	664.22	282.24	799.11	596.39	738.24	202.72
No. of Investors Investing in all rounds	0.54	1.00	1.16	-0.47	0.54	0.70	0.79	-0.17
Prominent Investor	0.63	0.61	0.49	0.02	0.63	0.63	0.49	0.00
Forward Citation Concentration	0.21	0.21	0.29	0.00	0.21	0.22	0.32	-0.01
Number Of Patents	16.04	5.69	14.03	10.34	16.04	7.21	16.12	8.82
Number of Forward Cites	81.55	24.71	61.06	56.84	81.55	31.10	70.05	50.45
Number of Alliances	4.89	1.72	3.02	3.17	4.89	2.20	3.45	2.70
Number of Acquisitions	0.43	0.41	1.09	0.02	0.43	0.47	1.19	-0.04
Biz Seg Sales in Wireless	1940993.98	2183735.98	3225971.79	-242742.00	1940993.98	2059285.33	3178319.07	-118291.36

Sample sizes	Control	Treated
All	244	56
Matched	168	56
Unmatched	76	0
Discarded	0	0

Table 15. Matching Balance – Control Group Success Events

	Before Matching				After Matching			
	Mean Cases	Mean Control	SD Control	Mean Diff	Mean Cases	Mean Control	SD Control	Mean Diff
Entry Year	1998.18	1998.53	3.24	-0.35	1998.18	1998.21	3.45	-0.04
IPO Heat	0.03	0.06	0.06	-0.03	0.03	0.04	0.04	-0.01
Number of Targets in SIC	109.67	206.18	214.06	-96.51	109.67	144.36	184.88	-34.68
Total Number of Investors	7.46	6.21	4.51	1.26	7.46	6.86	5.39	0.61
Number of Rounds Received	5.29	4.09	2.96	1.20	5.29	5.07	3.63	0.21
Time to First Round	799.11	503.76	706.19	295.35	799.11	662.32	948.45	136.79
No. of Investors Investing in all rounds	0.54	0.90	1.14	-0.36	0.54	0.63	0.73	-0.09
Prominent Investor	0.63	0.68	0.47	-0.06	0.63	0.68	0.47	-0.05
Forward Citation Concentration	0.21	0.22	0.28	0.00	0.21	0.23	0.30	-0.02
Number Of Patents	16.04	5.84	11.22	10.20	16.04	8.91	14.80	7.13
Number of Forward Cites	81.55	24.73	60.18	56.83	81.55	41.39	78.06	40.16
Number of Alliances	4.89	2.27	3.62	2.63	4.89	3.38	4.78	1.52
Number of Acquisitions	0.43	0.65	1.37	-0.22	0.43	0.64	1.49	-0.21
Biz Seg Sales in Wireless	1940993.98	2496008.45	3404568.04	-555014.48	1940993.98	1616070.05	2676853.93	324923.93

Sample Sizes	Control	Treated
All	135	56
Matched	56	56
Unmatched	79	0
Discarded	0	0

	Before Matching				After Matching			
	Mean Cases	Mean Control	SD Control	Mean Diff	Mean Cases	Mean Control	SD Control	Mean Diff
Entry Year	1998.18	1998.53	3.24	-0.35	1998.18	1998.52	3.48	-0.34
IPO Heat	0.03	0.06	0.06	-0.03	0.03	0.05	0.04	-0.02
Number of Targets in SIC	109.67	206.18	214.06	-96.51	109.67	181.79	205.18	-72.12
Total Number of Investors	7.46	6.21	4.51	1.26	7.46	6.33	4.71	1.13
Number of Rounds Received	5.29	4.09	2.96	1.20	5.29	4.43	3.10	0.86
Time to First Round	799.11	503.76	706.19	295.35	799.11	561.96	753.09	237.15
No. of Investors Investing in all rounds	0.54	0.90	1.14	-0.36	0.54	0.71	0.78	-0.18
Prominent Investor	0.63	0.68	0.47	-0.06	0.63	0.67	0.47	-0.04
Forward Citation Concentration	0.21	0.22	0.28	0.00	0.21	0.22	0.28	0.00
Number Of Patents	16.04	5.84	11.22	10.20	16.04	6.44	12.02	9.60
Number of Forward Cites	81.55	24.73	60.18	56.83	81.55	28.80	65.23	52.75
Number of Alliances	4.89	2.27	3.62	2.63	4.89	2.50	3.86	2.39
Number of Acquisitions	0.43	0.65	1.37	-0.22	0.43	0.65	1.43	-0.22
Biz Seg Sales in Wireless	1940993.98	2496008.45	3404568.04	-555014.48	1940993.98	2412099.30	3344920.57	-471105.32

Sample sizes:

Sample size	Control	Treated
All	135	56
Matched	112	56
Unmatched	23	0
Discarded	0	0

Table 16. Matching Balance – Control Group Failure Events

	Before Matching				After Matching			
	Mean Cases	Mean Control	SD Control	Mean Diff	Mean Cases	Mean Control	SD Control	Mean Diff
Entry Year	1998.18	1998.35	3.28	-0.17	1998.18	1998.71	3.24	-0.54
IPO Heat	0.03	0.04	0.05	-0.01	0.03	0.02	0.03	0.01
Number of Targets in SIC	109.67	99.02	147.08	10.66	109.67	79.76	124.37	29.91
Total Number of Investors	7.46	5.14	3.57	2.33	7.46	4.88	3.38	2.59
Number of Rounds Received	5.29	3.39	2.47	1.90	5.29	3.89	2.75	1.39
Time to First Round	799.11	533.10	611.08	266.01	799.11	683.36	723.38	115.75
No. of Investors Investing in all rounds	0.54	1.14	1.17	-0.60	0.54	0.77	0.76	-0.23
Prominent Investor	0.63	0.51	0.50	0.11	0.63	0.46	0.50	0.16
Forward Citation Concentration	0.21	0.20	0.30	0.01	0.21	0.21	0.29	-0.08
Number Of Patents	16.04	5.51	16.93	10.52	16.04	8.50	22.85	7.54
Number of Forward Cites	81.55	24.70	62.42	56.86	81.55	31.63	78.32	49.93
Number of Alliances	4.89	1.05	1.83	3.85	4.89	1.55	2.31	3.34
Number of Acquisitions	0.43	0.11	0.42	0.32	0.43	0.20	0.55	0.23
Biz Seg Sales in Wireless	1940993.98	1796976.49	2959919.14	144017.49	1940993.98	1598206.69	2810317.72	342787.29

Sample sizes	Control	Cases
All	109	56
Matched	56	56
Unmatched	53	0
Discarded	0	0

Odds Ratio – Result from Conditional Logit Regressions

After creating the matched sample we obtained the odds risks associated with our hypothesized independent variables (or risk factors) using a conditional logit specification. The results are summarized in Table 17. Models (1)-(3) report the results for comparison with firms experiencing any events, models (4)-(5) present the results matching 'living dead' firms to successful firms, and model (6) show the results of contrast to failed firms. We report both the coefficients and the odds ratio below.

Table 17. Conditional Logit Regression for Odds Ratio Calculation

	Conditional Logit Regressions											
	(1)		(2)		(3)		(4)		(5)		(6)	
DEP VARIABLE	***livingdead***		***livingdead***		***livingdead***		***livingdead***		***livingdead***		***livingdead***	
Controls matched from	***Success+ Failure***		***Success+ Failure***		***Success+ Failure***		***Success***		***Success***		***Failures***	
Matching Ratio	1:1	OR	1:2	OR	1:3	OR	1:1	OR	1:2	OR	1:1	OR
Prior Entrepreneurial	-0.916*	0.4	-1.119***	0.327	-0.802***	0.45	-0.653	0.521	-0.797*	0.45	-0.822*	0.44
Experience	(0.474)		(0.408)		(0.286)		(0.439)		(0.468)		(0.424)	
Previous Wireless	0.0369	1.038	0.0795	1.083	0.0950	1.100	-0.316	0.729	-0.0117	0.988	0.785	2.192
Experience	(0.267)		(0.233)		(0.251)		(0.299)		(0.220)		(0.534)	
Two Founders	1.112**	3.041	1.016**	2.762	0.743*	2.1	1.118*	3.06	0.939**	2.56	0.972	2.643
	(0.491)		(0.401)		(0.411)		(0.634)		(0.422)		(0.726)	
Founding Team	0.216	1.241	0.560	1.751	0.743	2.103	0.415	1.514	0.861*	2.37	0.510	1.665
Member Loss	(0.534)		(0.442)		(0.453)		(0.589)		(0.515)		(0.630)	
Prior Entrep Exp X	2.143**	8.526	1.441**	4.224	1.353***	3.87	1.261*	3.53	1.371**	3.94	2.746**	15.58
Founding Member Loss	(0.894)		(0.623)		(0.509)		(0.764)		(0.684)		(1.073)	
Founding Team Size	-0.393	0.675	-0.383	0.682	-0.388	0.678	-0.166	0.847	-0.290	0.748	-1.216**	0.296
	(0.359)		(0.342)		(0.303)		(0.364)		(0.350)		(0.483)	
Observations	112		168		224		112		168		112	
Number of firms	112		168		224		112		168		112	
Psuedo R2	0.238		0.247		0.197		0.250		0.208		0.340	
Log likelihood	-29.57		-46.35		-62.38		-29.10		-48.75		-25.63	
Chi-square	14.07		22.75		21.91		19.04		18.75		11.90	

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parenthe

Hypothesis 1 posited that having founders with prior entrepreneurial experience would be beneficial and prevent firms from entering the ‘living dead’ state. We find support for it in all the models that compare ‘living dead’ firms to the three control groups, except in the case of 1:1 matching with successful firms. Models (1) – (3) report the coefficients and odds ratio for the comparison with all firms with any event. Having accumulated entrepreneurial experience at founding reduces the odds of becoming a living dead by 60-67% when compared to all other firms with an exit event. The results are consistent across all three matching criteria, supporting our hypothesis about the benefits of having founders with previous entrepreneurial experience to reduce persistence. The results for comparison with successful firms are reported in models (4) and (5). H1 again finds support in one of the two matching criteria, albeit at a weaker level of significance (p-value < 10%). The reduction in odds risk is similar (around 55% reduction) to that found in the previous comparison. Model (6) summarizes the results for comparison with just failed firms. H1 receives support at 5% significance with a reduction in odds risk of 56% in the presence of entrepreneurial experience endowment. We therefore interpret these results to support our hypothesis on prior entrepreneurial experience and its effect on 'living dead' outcome.

The second hypothesis conjectured positive association of previous industry related experience with 'living dead' outcome when compared to failed firms. We do not find any support for the effect of industry specific experience. In addition, as argued we find no significant effects when compared to successful firms. Presumably, most entrepreneurs have related experience and hence we detect no differences in the odds ration among the three categories of firms.

The hypothesis on two member founders, H3, finds consistent support when compared with successful firms as well as all firms with some exit event. For the matched sample with both success and failed events, the odds risk of 'living dead' is almost 3 times when compared to firms with exit event. The comparison with successful firms yield odds ratio between 2 and 3 with significance at a weak 10% level. As expected there is no difference when contrasted with failed firms. The result of this hypothesis is perhaps the most intriguing and interesting finding of this study, signaling some form of hindrance to swift decision making in teams where consensus as well fast action is vital.

The fourth hypothesis, which tested the interaction effect of loss of founding team members and prior entrepreneurial endowment at founding, finds consistent support across all the comparisons. The odds ratio when compared to failed firms is very high (15.58), indicating that very few failed firms that have founders with previous start-up experience lose their members lending credence to our arguments on the abilities of serial entrepreneurs.

Competing Risk Cox Proportional Hazard Model

Table 18 reports the results from a competing risk Cox model for the three outcomes. Results are in line with those obtained in the matched case-control analysis. Model (3), corresponding to the pseudo-event of 'living dead' shows that there is weak support for H1 at p-value less than 10%. The hazard rate of 'living dead' reduces by 52% in the presence of a unit of entrepreneurial endowment at founding. Our argument on previous founding experience leading to early realization of bad bets also finds weak support in model (2). Failure rate increases with entrepreneurial endowment with a 36% increase in the hazard of failure.

Hypothesis 2 does not find support, although the effect of previous wireless experience in model (2) on failure hazard lends support to our argument of industry specific experience being necessary lower-order routines that helps survival. Previous wireless experience reduces failure rate by 26% and is significant at 5%. Contrary to expectations, H3 is not supported in this analysis with a p-value for the 'living dead' outcome at around 15%.

H4 is supported at the 5% level. Thus losing team members when endowed with previous founding experience signifies loss of higher-order capabilities that have harmful consequences. This line of argument is bolstered by the effects of this interaction on success and failure through asymmetric effects as in Chapter 3. This interaction inhibits success as well as failure in line with the empirical result that the hazard of ‘living dead’ also increases.

Finally, we discuss the effects of control variables on the three outcomes. The results for success and failure follow the same pattern as observed earlier in Chapter 2 & 3. However, the intriguing result is that none of these variables have any effect on the ‘living dead’ event. The Entry Year variable is the only control variable that is significant, increasing the ‘living dead’ hazard by 30%. Thus later a start-up is founded, more likely it is to enter this transitory state, which ties in with the arguments on “market timing” (Gompers et al., 2006). It is also consistent with Ruhnka et al.’s (1992) finding that missing market opportunities is an important cause for the ‘living dead’ state.

Table 18. Competing Risk Cox Proportional Hazard Analysis (Chapter 4)

	(1)		(2)		(3)	
	Success	**HR**	**Failure**	**HR**	**Living Dead**	**HR**
Prior Entrepreneurial Experience	-0.0221	0.978	0.308*	1.36	-0.738*	0.478
	(0.152)		(0.164)		(0.395)	
Previous Wireless Experience	0.208	1.231	-0.302**	0.739	-0.0909	0.913
	(0.153)		(0.136)		(0.235)	
Two Founders	-0.160	0.852	-0.0638	0.938	0.460	1.584
	(0.206)		(0.238)		(0.325)	
Founding Team Member Loss	-0.213	0.808	-0.541*	0.582	0.0618	1.064
	(0.265)		(0.324)		(0.419)	
Prior Entrep Exp X Founding Team	-0.561*	0.571	-0.677*	0.508	1.029**	2.797
Member Loss	(0.337)		(0.391)		(0.497)	
Founding Team Size	-0.0670	0.935	0.190	1.209	0.0621	1.064
	(0.172)		(0.138)		(0.306)	
Forward Citation Concentration	-0.319	0.727	0.271	1.311	-0.289	0.749
	(0.422)		(0.438)		(0.627)	
Patent Grant Flow	0.00694	1.007	-0.0869**	0.917	-0.00510	0.995
	(0.0268)		(0.0430)		(0.0289)	
Forward Citation Flow	0.00545	1.005	0.0244***	1.025	0.0156	1.016
	(0.00737)		(0.00669)		(0.0142)	
IPO Heat	-3.247	0.0389	-14.06***	7.81E-07	-2.434	0.0877
	(2.725)		(4.869)		(6.373)	
Number of Targets in SIC	0.00360***	1.004	0.00174*	1.002	-0.000785	0.999
	(0.000653)		(0.000903)		(0.00131)	
Total Number of Investors	-0.0329	0.968	0.0127	1.013	-0.0397	0.961
	(0.0322)		(0.0387)		(0.0505)	
No. of Investors Investing	-0.0180	0.982	0.120	1.127	-0.229	0.796
in all rounds	(0.101)		(0.103)		(0.247)	
Prominent Investor	0.317	1.372	-0.261	0.770	-0.488	0.614
	(0.212)		(0.230)		(0.395)	
Number of Rounds Received	-0.143***	0.867	-0.195***	0.823	0.0126	1.013
	(0.0544)		(0.0637)		(0.0681)	
Time to First Round	-0.000962***	0.999	-0.00108***	0.999	-5.32e-05	1.000
	(0.000184)		(0.000213)		(0.000242)	
Number of Alliances	-0.202*	0.817	-0.934***	0.393	0.180	1.197
	(0.117)		(0.314)		(0.127)	
Number of Acquisitions	0.790***	2.204	-1.135	0.322	-0.983	0.374
	(0.180)		(0.929)		(0.683)	
Biz Seg Sales in Wireless	1.03e-07***	1	-6.66e-09	1.000	-3.72e-08	1.000
	(2.81e-08)		(3.16e-08)		(6.89e-08)	
Entry Year	-0.0973***	0.907	-0.125***	0.882	0.262***	1.3
	(0.0369)		(0.0351)		(0.0919)	
Observations	2958		2958		2856	
Log likelihood	-653.7		-520.6		-200.5	
Number of events	135		109		56	
Number of firms	428		428		428	
Chi-square	120.4		126.9		47.99	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

DISCUSSION AND CONCLUSIONS

Our investigation of ‘living dead’ firms provides some interesting findings relevant to venture funded companies and their founders. We find that serial entrepreneurs, as members of a founding team, reduce the chances of entering the transitory ‘living dead’ state when compared to other firms, both successful and failed. In addition, they increase the chances of dissolution. A VC-funded firm, financially speaking, is better-off if it does not persist. Entrepreneurs with prior experience starting new firms seem to be better equipped to achieve closure for investors. The higher-order routines that learning by doing entails, endows such entrepreneurs with skills that have a strong imprinting effect, which in turn increases the likelihood of failure and diminishes the chances of becoming a marginally performing firm.

We infer, therefore, that previous experience with founding new ventures at birth presents a signal that investors and other partners should heed when evaluating nascent firms. While not a predictor of success, they may help VC’s to avoid getting stuck with marginally performing firms. Firms with serial entrepreneurs are also prone to fail probably reflecting their ability to recognize and terminate firms that may not lead to the expected liquidity event.

Prior relevant domain experience does not have any predictive power for marginal firms, perhaps because these marginally performing firms might actually need different perspectives and world-view than just industry-specific experience. This opens new avenues of research to explore issues such as bringing in an outsider for possible turnaround.

A founding team of two members is found to increase the odds of 'living dead' outcome compared with successful firms. This supports current literature that posit decision making ability as a key difference between successful and 'living dead' firms. In this respect 'living dead' firms resemble failed firms more than those that succeed. A team size of two may be a indicator for poor decision making ability of a founding team. Future research should probe this aspect by investigating the micro mechanisms underlying this very intriguing finding.

Finally, the effects of loss of founding team members are interesting from a prescriptive point of view. Disrupting the founding team has no effect on the three outcomes. This may be due to the limitations of our data. First, we do not know when the change occurred. Second, we also do not know who replaced these founding members. Both are important factors to consider when analyzing the effect of the loss of founding team members. Despite these limitations, we interpret this as indicating that on average changes to teams are neither harmful nor beneficial. We cannot distinguish between interventions by VC's to change founders and voluntary departures because these are opaque to the outsider. Future research could try to collect data on the exact nature of the loss of founders using surveys. While, the absence of any effect of changes might signal that VC's are justified in forcing changes, our findings also calls for caution. The moderating effect of changes on the imprinting effect of prior entrepreneurial experience is especially illuminating. The likelihood of becoming a 'living dead' grows substantially if changes in founding team with serial entrepreneurs occur. Disrupting founding teams with serial entrepreneurs seem ill advised with dire conditions surrounding the startup getting even worse. So, an important insight for investors is to carefully analyze these changes—voluntary exit may be signs of trouble in the business and active interventions can be counterproductive.

Our pioneering study has a number of limitations. As noted, the results do not hold for small businesses whose creation was due to lifestyle choice without the ambition of growing fast and going public with venture capital as fuel. The findings are restricted to firms whose founders aspire to build a successful high-tech organization that grows rapidly, culminating in a high profile IPO or acquisition—setting a high expectation that induces an entrepreneur to seek venture capital funding. VC funding forms an important boundary condition for the analysis and interpretation of our findings. A major limitation stems from the concept of 'living dead'. 'Living dead' entails a transitory state and its empirical or phenomenological circumscription is challenging. Some firms classified as 'living dead' may be on the path to success while others that did not meet investor expectations and were shut down are excluded. In our data, we cannot observe these cases, yet all things considered our definition of 'living dead' should empirically capture the most problematic cases and is a conservative definition.

Next, since this is a transitory state, firms will eventually be selected out. Robustness to changing the criteria to define this state in our study is a good signal. However, the concept is sensitive to how we conceptually define this state and should be explored in other contexts. Last, understanding this phenomenon with large sample empirical analysis is limiting due to the unobserved nature of the real expectations of the investors, which might explain why only two studies exist. We should try to investigate the ‘living dead’ state further invoking multiple methods. Given the transient nature of the phenomenon, simulation methods represent one possible avenue of future research. This could allow us to tease apart some of the mechanisms and understand the sensitivity of the transitory state to expectations and changes. To conclude, although with many limitations, this novel attempt contributes to our understanding of marginal performance and opens up further avenues for research.

Chapter 5: Conclusions

This dissertation sought to shift the attention from success, i.e., the sale of a VC-funded high-tech firm either to another company or on the stock exchange, to failure and persistence. These performance outcomes were investigated through the lens of three different signals of quality: 1) patents, 2) technology breadth, and 3) founding team characteristics. Quality is multi-dimensional, typically unobserved and unknown ex-ante. In addition, considerable uncertainty surrounds the quality of a new venture. Therefore, the information emanating from a variety of signals, serving as proxy for quality, permits evaluators to sort start-ups based on desired criteria. For example, patents may be used to identify and rank innovative capabilities of firms, while founding team characteristics may provide information on the viability of ventures based on the reputation of the founders. This dissertation enlightens us on the effects of such quality signals on entrepreneurial outcomes such as failure and persistence.

Chapter 2 developed and tested mechanisms that lead to failure as an unintended consequence of patenting. Patents are used by start-ups to bridge the information gap with investors, yet they also disclose proprietary information and technology position, and expose firms to undesired spillovers. I show that firm failure rates increase as their inventions are used at a higher rate by others; increasing even more so when citing firms have a track record of litigiousness. Start-ups also are more likely to fail if their technologies do not conform to the core activities sanctioned by incumbents. Chapter 3 exploits asymmetric effects of factors on success and failure to reveal start-up persistence. Theoretically, it builds on the insights of Chapter 2 by analyzing another signal of quality (technology breadth) generated when firms patent and other organizations subsequently use these inventions in new application domains. Results demonstrate mechanisms that impede success and failure outcomes simultaneously, thereby exposing factors that increase the likelihood of persistence. Firms endowed with a specific technology that experiences widespread diffusion are at a higher risk of persisting without experiencing any liquidating or liquidity events.

Finally, Chapter 4 explicitly analyzes the third outcome, persistence, by examining the ‘living dead.’ Conceptually, the ‘living dead’ outcome is a transitory state to which a start-up is defined to enter when it persists beyond VC expectation norms such as typical investment horizon of investors. Drawing on the imprinting literature, I develop and test hypotheses on the effects of various signals of quality that founding team characteristics emit. Teams endowed with serial entrepreneurs signal underlying start-up related higher-order capabilities acquired through learning by doing in their prior career, and are empirically shown to decreases the odds of becoming one of the ‘living dead.’ Besides, these teams, endowed with previous founding experience, show higher failure rate, although the likelihood of success is not affected. Thus, the presence of serial entrepreneurs may serve as a signal of quality for investors needing quick closure on exit prospects. Intriguingly, two founders are found to increase the odds of marginal performance. Additionally, loss of members of a team that comprises serial entrepreneurs is shown to be a shock that also increases the odds of becoming a ‘living dead’.

Table 19 summarizes the hypotheses and empirical findings from the three chapters. As seen in the column on consequences, this dissertation provides a rich picture on the benefits and hazards of quality signals. Start-ups use a repertoire of signals to overcome information asymmetry; since signals are equivocal and often time-varying their impact on performance is checkered, in contrast to the prevalent portrayal of their benefits. Signals provide information to resource providers and to rivals, and hence are double-edged. This dissertation provides some evidence on the harmful side-effects of signals beyond the benefits espoused in the literature, adding to the body of literature on signaling in entrepreneurship.

Table 19. Summary of hypothesis and empirical results

Ch.	Hypo.	Dependent Variable	Independent Variable	Proposed Relationship	Result	Signaling Consequence
2	1	Failure	Patents granted annually	Curvilinear	Supported	Beneficial with decreasing returns
2	2	Failure	Closeness centrality in technology activity network	Negative	Supported	Benefits of conformity
2	3	Failure	Crowding in technology citation network	Positive	Not supported	
2		Failure	Annual forward citations from other firms	None	NA	Harmful
2	4	Failure	Litigation reputation weighted annual forward citations	Positive	Supported	Harmful
3	1	Failure	Concentration of annual forward citations	Positive	Supported	GPT Beneficial
3	2a	Failure	Interaction of annual forward citation and its concentration	Negative	Supported	SPT & High Citations Beneficial
3	2b	Success	Interaction of annual forward citation and its concentration	Negative	Supported	SPT & High Citations Harmful
3	3a	Failure	Interaction of annual forward citation concentration and alliance concentration	Positive	Not supported	
3	3b	Success	Interaction of annual forward citation concentration and alliance concentration	Negative	Not supported	
4	1	Living Dead	Serial Entrepreneur endowment at birth	Negative	Supported	Beneficial
4	2	Living Dead	Prior relevant domain experience of members of team at birth	Negative	Not supported	
4	3	Living Dead	Two Founders	Negative	Supported	Harmful
4	4	Living Dead	Interaction of Serial entrepreneur endowment and Loss of any founding member	Positive	Supported	Harmful

Overall, this dissertation makes both a theoretical and empirical contribution to the existing literature on performance of new ventures (see Table 20). On the theoretical side, it conceptually defines and treats a third outcome, persistence, beyond the more typical conceptions focusing either on success or failure. It identifies mechanisms related to signals of quality used by start-ups that affect the chances of not succeeding through achieving liquidity for investors. It adds to the menu of signals of quality that are at the disposal of new firms and their evaluators. Specifically, technology breadth, as signaled over time, conveys significant information on the prospects of a start-up, besides the already established signals obtained through patent endowment and founding teams. Finally, it highlights a new competitive mechanism manifested through the litigation reputation of firms that use the start-ups inventions as building blocks of their R&D program. Designing around and litigation threats are important harmful side effects of patenting that increase mortality rates of new firms.

This research is among the few to empirically investigate marginal performance. It is also pioneering in analyzing 'living dead' outcomes using large-sample quantitative methods. Another significant empirical contribution is the exploitation of asymmetric effects to uncover persistence. While research to date has separately analyzed success and failure, their joint analysis is rare. The empirical tool of competing risk event-history, therefore, provides a powerful method to analyze 'non-events' such as persistence. Finally, it contributes to the patent literature by clarifying the role of patent citations as a flow—parsing out the conflated mechanisms of endorsement and competition through interaction with technology breadth and through simultaneous analysis of success and failure.

The results from this dissertation have implications for practice as well, providing insights to entrepreneurs and VCs. Our study reinforces the importance of secrecy and the dilemma entrepreneurs face due to disclosure when using signals that divulge proprietary information. Litigation reputation of other firms and scope of their technologies are important dimensions to pay attention when managing dilemmas, especially in anticipating and positioning the start-up. For VCs, betting on serial entrepreneurs is a good strategy if either liquidity or liquidating events is desired. In addition, investors must be attentive to founding team size and losses of founding team members—voluntary exit may be signs of trouble in the business and active interventions can be counterproductive.

Table 20. Dissertation Highlights

	Chapter 2	**Chapter 3**	**Chapter 4**
Outcome(s)	Failure	Failure & Success simultaneously	Living Dead
Signal	Patents	Technology Breadth	Founding team
Main Contributions			
Conceptual	Separating Stock & Flow	Causal Asymmetry	Living Dead
Theoretical Mechanisms	Litigation Reputation of Firms building on inventions increase failure rate - designing around and threat of litigation	Signal of specificity and high knowledge diffusion decreases chances of failure but at the same time also reduces success probability - pointing the path to ‘living dead’	Strong imprinting effects of serial entrepreneurs. Loss in such teams leads to higher likelihood of 'living dead'.
Empirical	Cox Proportion Hazard + Matching for selection on observables	Competing Risk Cox	Matched Case-Control Study

This dissertation is not without limitations. I have analyzed a single industry in a contrasting setting to existing single-industry studies on new ventures. However, single industry studies pose concerns to the generalizability of the results. Future research should replicate the study in other settings as well as test the hypotheses in a more general sample of VC-funded start-ups. The concept of performance is specific to the VC-context. Many new ventures are founded for reasons other than a lucrative sale. It would be important to define marginal performance with respect to other benchmarks for new ventures as well in other settings where firms persist despite expectation failure of a key stakeholder.

The results on the effect of prior-art citations, in both Chapter 2 and Chapter 3, are intriguing and present opportunities for future research. The basic message echoes the current literature in that who cites your inventions has important implications for performance. Research in organization theory has shown that the status of citing firms increase performance due to implied deference. This dissertation shows that the citing firm's litigation reputation has important consequences and is more strongly associated with failure. An interesting research path would be to investigate both these characteristics of firms together—to what extent are status and litigiousness correlated, and can we isolate their respective effects on performance? In addition, the track record of litigation is assumed to proxy the competitor's tendency to contest fiercely, resorting to designing around and even litigate. Further research should provide concrete evidence to back up that assumption and bolster the findings presented herein.

In Chapter 3 several interesting asymmetric effects were found that could serve as the basis of other research projects. First, longer gestation periods before venture financing seem to increase persistence, leading us to speculate that although nascent firms are deemed to be less susceptible to inertia, such forces do start to make their presence felt quite early as routines and capabilities are established. Therefore, the ability of investors to add value through molding these routines and capabilities may be limited to a certain window after birth. How VC's add value is a rich area of research, and could be further enriched through understanding when VC's add value. Second, alliance rates were found to inhibit success and failure, implying that there are limits to the benefits of alliances. The results indicate that start-ups can increase survival prospects by pursuing many alliances, yet they limit the chances to achieve an IPO or to be acquired. So alliances may be limiting growth prospects as well as acting as substitutes for acquisitions. These are important issues that merit further investigation with implications not only for entrepreneurship, but corporate strategy as well.

Finally, in Chapter 4 I treated 'living dead' as a transitory state where firms persist beyond expectations. Yet success (as indicated by the new venture going public) is also an event leading to another transitory state—the firm becomes a public firm with changed owners, a different set of expectations, and an uncertain future. In other words, the fate of these firms is not final when IPO occurs. An interesting project would study marginal performance after IPO, with the benefit of publicly available financial data. Do the theories developed in this dissertation also apply in such cases? What are the drivers of success and failure there? These are some interesting questions that can enrich our understanding of the phenomenon of marginal performance.

Perhaps the most interesting finding of this dissertation relates to the high odds of finding two founders in 'living dead' firms. I attribute this effect to coordination costs that impede fast but rigorous and consensual decision making—perhaps a too simplistic explanation in the absence of detailed information on personality characteristics and interactions between the two founders. This issue deserves much more attention, especially to understand mechanisms that lead to such coordination costs. Why do two founders have a detrimental effects in 'living dead' state but not in successful or failed firms? This finding throws up more questions than it answers and provides a rich avenue for future investigations.

To conclude, this dissertation contributes to the literature on new venture performance by extending existing theory, conceptualizing a third performance outcome besides success and failure, and providing empirical evidence for persistence and harmful consequences of signaling. In addition, further research areas such as marginal performance after IPO, the timing of VC non-financial value-add, and limits to benefits of alliance, are identified to add to the knowledge on new venture performance. Together they provide me with a rich road map to pursue my research interests as I embark upon my journey as a scholar.

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