What is the Right Stuff? The Effect of Preentry Knowledge on the Relationship Between Innovation & the Survival of High Technology Startups

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Abstract

Technological innovation generates strategic, organizational, and market-related uncertainties. Why do some nascent firms successfully overcome these uncertainties and survive, while others fail? Evolutionary economics provides a lens for examining this issue, suggesting that preentry knowledge facilitates learning and that learning is required to combat the uncertainty associated with innovation; as a result, preentry knowledge will improve an innovative firm’s survival chances. This study provides empirical support for the idea that preentry knowledge facilitates learning in a context?high technology entrepreneurship?that is central to innovation and economic growth. This study also extends evolutionary theorizing by showing that unlocking value from technological knowledge requires complementary knowledge. Specifically, we investigate the interactive effect of each of three distinct sources of preentry knowledge and technological innovation on firm survival. We find that prior employment experience in the same industry and prior entrepreneurial experience in a different industry significantly reduce the survival risks generated by innovation; prior entrepreneurial experience in the same industry reduces the survival risk generated by innovation for moderately and highly innovative startups only. Our findings are based on data from the Kauffman Firm Survey that track a representative cross-section of 1,427 U.S.-based high-technology startups from founding to age six. These data provide unprecedented visibility into startups’ early years, avoid issues of survivor bias by tracking a sample of startups founded in the same year over time, and include data on startups operating across a wide spectrum of industries.

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Introduction

Innovative high technology startups introduce novel technologies into the commercial sphere. These startups are heralded as important engines of technological progress and economic growth (Franco et al., 2009; Schoonhoven et al., 1990; Schumpeter, 1942; Teece, 1986). Pursuing novel technological directions, however, generates considerable challenges for a nascent startup: when commercializing an innovation, the strategic, organizational, and market-related pathways necessary for success are unclear (Knight, 1921; Nelson et al., 1977; Schoonhoven et al., 1990). Many startups are not able to overcome strategic, organizational, and market challenges and the success rate of high technology startups is low (Gage, 2012; Luo et al., 2011). The importance of innovative high technology startups, coupled with the challenges they face, suggests a need to better understand why some innovative high technology startups are able to navigate uncharted waters—and survive—and why some others fail.

Evolutionary economics provides two useful insights for examining this issue. First, scholars have suggested that overcoming the uncertainty inherent in commercializing innovations requires learning (Helfat et al., 2000; McGrath et al., 1995). Second, scholars have also pointed out that firms differ in their capacity to learn: firms possessing relevant knowledge should be better able to learn, and, therefore, outperform other firms (e.g., Helfat et al., 2002). Combining these two insights, we suggest that innovative high technology startups possessing relevant strategic and organizational knowledge will be better able to learn—and therefore overcome the uncertainties generated by technological innovation—than startups lacking such knowledge. A key source of relevant knowledge for nascent startups is preentry knowledge—the knowledge that a firm inherits at birth through the prior experiences of its founder (Helfat et al., 2002; Huber, 1991). In this paper, we ask: does preentry knowledge help buffer startups from the uncertainties created by technological innovation and therefore improve a startup’s survival chances?

We both build on and extend existing research. Existing studies examine the direct effect of preentry knowledge, most commonly in the form of prior employment experience in the same industry, on firm survival and find evidence of a positive and significant effect (see Helfat et al., 2002 for a review of this literature). Helfat and Lieberman (2002) point out that although it is inviting to conclude that existing knowledge provides a basis for learning from these results, there is an alternative explanation for the beneficial effect of knowledge on firm survival: it is possible that firms do not adapt to their environments, rather, firms that enter with knowledge better suited to their environments are more likely to succeed. The results of our study provide empirical support for the idea that preentry knowledge provides a basis for learning. We are able to do so because we examine the indirect effect of preentry
knowledge on firm survival; specifically, we examine whether or not preentry knowledge allows a firm to combat the uncertainties associated with commercializing technological innovation. Our study both provides empirical support for evolutionary explanations of firm learning and illuminates the factors that drive the survival of innovative high technology startups.

We examine the effects of three distinct sources of preentry knowledge on the relationship between innovation and firm survival: a founder’s prior employment experience in the same industry, prior entrepreneurial experience in a different industry, and prior entrepreneurial experience in the same industry. The moderating effects of these sources of preentry knowledge on the relationship between innovation and firm survival have not been examined. We choose to examine prior employment experience in the same industry, because the evolutionary economics and entrepreneurship literatures find ample evidence that prior employment experience in the same industry enhances survival chances (Helfat et al., 2002; Klepper, 2001). In contrast, evidence on the effects of prior entrepreneurial experience on survival is mixed, making it an interesting variable to study: several studies find that prior entrepreneurial experience improves a young firm’s survival chances (Delmar et al., 2006; Dencker et al., 2009), whereas others do not find significant effects (Brüderl et al., 1992; Gimeno et al., 1997). To our knowledge, no prior study distinguishes between the effects of same- versus different-industry entrepreneurial experience on firm survival.

We examine the relationship between technological innovation, preentry knowledge, and survival using data on 1,427 high-technology startups drawn from the annual Kauffman Firm Survey (KFS). The KFS data provide visibility into startups’ early years along a number of dimensions that have, historically, been difficult to study in the context of new, private firms, including founder career history, startup patenting activity, and other startup characteristics. The KFS avoids issues of survivor bias by tracking a sample of startups founded in the same year over time. The KFS also collects data on startups operating across a wide spectrum of industries, allowing for the creation of generalizable results.

We analyze the interactive effect of technological innovation and preentry knowledge on startup survival using a Cox proportional hazard model and develop a simulation-based approach to interpret our results. We find that prior employment experience in the same industry reduces the survival risks generated by technological innovation across all levels of technological innovation. We find that both types of entrepreneurial experience reduce the negative effect of technological innovation on survival: different-industry entrepreneurial experience provides benefit at virtually all-levels of technological innovation, whereas same-industry entrepreneurial experience reduces a startup’s survival chances at low levels of technological innovation, and then, as a startup’s level of technological innovativeness increases, provides benefit. In addition, same-industry entrepreneurial experience provides greater survival benefits than different-industry entrepreneurial experience at all but low-levels of technological innovation.
Our study contributes to the fields of strategic management, innovation, and entrepreneurship. This study provides support for evolutionary perspective in an important context. This study also extends evolutionary economics by showing that unlocking value from technological knowledge requires complementary knowledge. Our findings contribute to the entrepreneurship literature by refining our understanding of the effects of prior experience on firm survival and documenting the distinct effects of same-industry and different industry entrepreneurial experience. Methodologically, we extend the use of simulation-based methods to interpret interactive terms in proportional hazard models.

From a practitioner perspective, this study provides unique insights regarding factors that influence the survival of nascent high technology startups that are useful to policy-makers, investors, and entrepreneurs. We have access to highly detailed data on a representative sample of startups from birth to age 6. In contrast, few existing studies have been able to investigate the early and formative years after founding due to the difficulties involved in sampling and tracking new, private firms (Haltiwanger et al., 2009). As a result, much of what we know about high technology startups is inferred from data on subsets of startups (e.g., firms that have sold products, venture financed firms, and post-IPO technology firms) and small firms (i.e., firms with fewer than 500 employees. See, for example, Scherer et al., 1990; Ziedonis, 2008). Our data allow us to track a representative sample of high technology startups from birth and therefore improve our understanding of the factors that contribute to their survival.

**Theoretical Background & Hypothesis Development**

**Preentry Knowledge as a Scaffold for Learning**

A main tenet of evolutionary economics is that existing knowledge provides a basis for learning, and thus firms possessing more relevant knowledge will be more likely to succeed (Nelson et al., 1982). The mechanism underlying the evolutionary economic perspective is path dependent learning: “What an organization knows… will determine what it searches for, what it experiences, and how it interprets what it encounters (Huber, 1991, p. 91).” Existing knowledge facilitates the accumulation and integration of new knowledge, allows a firm to comprehend and apply new information in ways that firms lacking that knowledge cannot, and shapes a firm’s ability to successfully adapt to new situations (Cohen et al., 1990; Helfat et al., 2000; Weick, 1996). Evolutionary economics therefore leads us to expect that the knowledge that a firm possesses at birth—preentry knowledge—will shape a firm throughout its life (Helfat et al., 2002; Huber, 1991; Thompson, 2005). For startups, founders are the key source of preentry knowledge (Helfat et al., 2002; Klepper, 2001).

The insight that existing knowledge provides a basis for learning is a cornerstone of evolutionary economics. However, little empirical work has been conducted to support this claim, and scholars have called for additional work in this area, deeming it a “fruitful avenue for future research (Helfat et al., 2002, pp. 752-753).” One empirical study investigates this claim and—based on a sample of startups
founded by unemployed individuals with support from a government assistance program—finds support for the idea that knowledge provides a basis for learning (Dencker et al., 2009). We contribute to this stream of research by providing strong evidence that knowledge provides a basis for firm learning in a context—high technology entrepreneurship—that is central to innovation and economic growth.

Technological innovation necessitates learning on the part of the startup, because commercialization requires unique strategic, market, and organizational capabilities tailored to the needs of the innovation (Helfat et al., 2000; Teece, 1986). Learning is necessary even when the startup’s founder possesses preentry knowledge, because preentry knowledge is accumulated in the context of an existing technology; however, the organizational, strategic, and market knowledge required to exploit an innovative technology is distinct from the knowledge acquired when exploiting an existing technology (Eisenhardt et al., 1995; McGrath et al., 1995). Hence, if we observe that preentry knowledge reduces the survival risk generated by technological innovation, we can infer that preentry knowledge enables learning.

**Unlocking the Value of Technological Innovation**

The extent to which preentry knowledge enables learning in the face of technological innovation is a question ripe for empirical investigation. Several studies suggest that innovative technological knowledge is not sufficient to drive success, and that additional knowledge (i.e., “complementary knowledge”) may be required to derive value from innovation (Franco et al., 2009; Schoonhoven et al., 1990). Research examining the time required for new semiconductor startups to ship their first product to market finds that startups who possessed both manufacturing and marketing knowledge at founding shipped their first product significantly faster than other startups (Schoonhoven et al., 1990). An investigation of disk drive firms finds that technological capabilities must be coupled with market pioneering capabilities to promote survival (Franco et al., 2009). A study of venture-backed medical device startups posits that non-technical knowledge from founders’ prior employment experience in the same industry may lead to performance differentials between firms (Chatterji, 2009). Taken together, these studies suggest that additional, complementary knowledge may be required to unlock the potential of innovative technologies.

From a theoretical perspective, examining such complementary effects is critical: theoreticians have pointed out that possessing multiple knowledge sets is crucial for organizational adaptation in uncertain and complex situations (Grant, 1996; Levinthal, 1997; Nickerson et al., 2004). Few studies have examined the complementary effects of different types of knowledge—most extent studies focus on the direct effects of various types of knowledge (see Helfat et al., 2002 for a review of the literature). We examine whether possessing preentry knowledge can shelter startups from the uncertainties inherent in commercializing technological innovations.
Below, we draw on the innovation, strategy, and entrepreneurship literatures to explain how each of three distinct sources of preentry knowledge possessed by a startup’s founder—employment experience in the same industry, entrepreneurial experience in a different industry, and entrepreneurial experience in the same industry—might allow a startup to better respond to the challenges generated by technological innovation, and thereby reduce the negative effect of technological innovation on survival. To our knowledge, these crucial relationships have not been examined.

Prior Employment Experience in the Same Industry

Prior employment experience in the same industry can provide a founder with three types of knowledge that should allow the startup to better meet the challenges generated by technological innovation: knowledge pertaining to complementary assets and capabilities, familiarity with managing the technology commercialization process, and greater knowledge of business opportunities.

Prior employment experience in the same industry provides a founder with knowledge of the complementary assets (e.g., manufacturing, services, and distribution) used by established firms to commercialize existing technologies (Chandler et al., 1992; Feeser et al., 1990). These assets may be required to commercialize the startup’s innovations as well. Understanding the usefulness of various complementary assets, how to replicate and manage these assets in-house, and/or the options available for contracting for access to complementary assets is critical, because successfully commercializing an innovation requires a startup to identify and then build or access necessary complementary assets (Gans et al., 2003; Teece, 1986). Prior employment experience in the same industry should therefore reduce the negative effect of technological innovation on survival.

Prior employment experience in the same industry provides a founder with opportunities to observe and participate in the technology commercialization process (Bresman, 2013; Gompers et al., 2005). Technology commercialization is a complex and multifaceted task (Brown et al., 1997; Schoonhoven et al., 1990; Taylor, 2010). Experience managing the technology commercialization process should increase a startup’s chances of developing a new product, as well as reduce development time and cost (Gompers et al., 2005; Schoonhoven et al., 1990). Prior employment experience in the same industry should therefore reduce the negative effect of technological innovation on survival.

Prior employment experience in the same industry enables a founder to identify better market opportunities to exploit (Christensen, 1997; Helfat et al., 2002; Klepper et al., 2005). Prior employment experience in the same industry can illuminate unmet needs and unoccupied market niches within the industry’s value chain (e.g., unsatisfied consumer needs, supplier shortcomings, and opportunities that established firms have chosen not to pursue) (Chatterji, 2009; Christensen, 1997). These insights shape the business opportunities that founders pursue (Benner et al., 2012; Shane, 2000).

Taken together, these arguments suggest that prior employment experience in the same industry
should reduce the negative effect of technological innovation on survival.

HYPOTHESIS 1: The negative effect of technological innovation on survival will be reduced for startups whose founders possess prior employment experience in the same industry.

Prior Entrepreneurial Experience in a Different Industry

Prior entrepreneurial experience in a different industry can provide a founder with two types of knowledge that should benefit her startup: experiential knowledge of how to manage in an entrepreneurial context (i.e., under conditions of uncertainty) and general knowledge of how to found a business.

Prior entrepreneurial experience in a different industry can help a founder learn to manage uncertainty. A founder with prior entrepreneurial experience should have greater experience engaging in processes for managing uncertainty, such as improvisation, effectuation, and discovery-driven planning, than a founder without prior startup experience. Improvisation occurs when the design and execution of novel action converge (Baker et al., 2003; Brown et al., 1997; Miner et al., 2001). Effectuation occurs when an individual evaluates the resources that she has and subsequently identifies possible goals (Sarasvathy, 2001). The discovery-driven planning process is built on the idea that little is known and much is assumed at the start of a new venture; as information and facts unfold, this information is incorporated into the ever-evolving plan (McGrath et al., 1995). The ability to better manage uncertain situations should improve a founder’s ability to commercialize an innovative technology, a process that is rife with uncertainty (Knight, 1921; Nelson et al., 1977; Schoonhoven et al., 1990). Prior entrepreneurial experience in a different industry should therefore reduce the negative effect of technological innovation on survival.

Prior entrepreneurial experience in a different industry also provides a founder with general knowledge of how to start and build a firm (Baron et al., 2006; Brüderl et al., 1992). For example, a founder with prior entrepreneurial experience has made operational and organizational decisions concerning issues such as formally incorporating a business, selecting a location, hiring employees, and abiding by labor laws (Baron et al., 2006; Brüderl et al., 1992). Knowledge of these basic, yet essential, tasks allows a founder to focus her time and attention on the unique challenges generated by innovation. This focus is critical, because the ability to make decisions is constrained by limitations on time and attention (March, 1994; Ocasio, 1997; Simon, 1947).

Taken together, these arguments suggest that founding a startup in a different industry should improve a founder’s ability to make technology-related decisions indirectly (i.e., by allowing her to focus on innovation-related challenges) and should therefore reduce the negative effect of technological innovation on survival.

HYPOTHESIS 2: The negative effect of technological innovation on survival will be reduced for startups whose founders possess prior entrepreneurial experience in a different industry.
Prior Entrepreneurial Experience in the Same Industry

Prior entrepreneurial experience in the same industry is a distinct third source of knowledge: a founder with prior entrepreneurial experience in the same industry has previously founded a startup in the same industry as the focal startup. Prior entrepreneurial experience in the same industry provides knowledge of the entrepreneurial process and knowledge of the industry, albeit from the perspective of a startup rather than an established firm. We therefore expect that a startup whose founder possesses prior entrepreneurial experience in the same industry should benefit from the knowledge advantages that accrue to both a startup whose founder possesses prior employment experience in the same industry and a startup whose founder possesses prior entrepreneurial experience in a different industry (as described above).

In addition, a startup whose founder possesses prior entrepreneurial experience in the same industry should benefit from the close match between her pre-entry knowledge and the knowledge required for commercialization of the focal innovation, because learning is most effective when fueled with relevant knowledge (Baum et al., 1998; Huber, 1991; Levitt et al., 1988). We therefore expect that prior entrepreneurial experience in the same industry will generate additional survival benefits by providing an industry-specific understanding of three tasks critical to the survival of an innovative high technology startup: competing within the industry, building and accessing complementary assets, and designing an organization.

Prior entrepreneurial experience in the same industry provides a founder with knowledge of industry dynamics. In order to survive, startups must pursue a strategy appropriate for their position within the competitive environment (Gans et al., 2003; Teece, 1986). Doing so requires undertaking systematic analyses of the level of excludability and the degree to which key complementary assets are controlled by established firms who could prove to be competitive threats (Gans et al., 2003). Prior entrepreneurial experience in the same industry provides a founder with the nuanced understanding of the competitive environment necessary to undertake these analyses, exploit the “blind spots” of incumbent players, and craft superior strategies (Gans et al., 2003, p. 348). In contrast, founders lacking prior entrepreneurial experience in the same industry are not able to conduct strategic analyses at such a nuanced level (Baron et al., 2006; Bhidé, 2000). Therefore, prior entrepreneurial experience in the same industry should enable a startup to craft more effective strategies, and should therefore positively reduce the negative effect of technological innovation on survival.

Prior entrepreneurial experience in the same industry also provides a founder with highly relevant knowledge regarding how to access and build complementary assets from the perspective of a startup (i.e., in the face of resource constraints) (Gans et al., 2003; Hsu et al., 2013; Teece, 1986). A founder with prior entrepreneurial experience in the same industry has had to identify relevant complementary assets, make decisions regarding which complementary assets to build and which to access externally, and
build some complementary assets (Gans et al., 2003; Teece, 1986); this past experience improves a startup’s ability to build complementary assets (Hsu et al., 2013). Prior entrepreneurial experience in the same industry should therefore reduce the negative effect of technological innovation on startup survival.

Finally, prior entrepreneurial experience in the same industry provides a founder with relevant knowledge pertaining to how to design an organization to commercialize the technology. Successfully building a high technology startup requires a detailed understanding of both technology and organization (Van de Ven, 1986), because of the coordination required to commercialize an innovative technology. Coordination is required both across business functions and within the product development function (Brown et al., 1997). Coordination across business functions is required to transform an innovative idea into a commercial reality (Van de Ven, 1986). Coordination within the product development function is required to address interdependencies between components of the technology; changes in one part of a product have implications for other parts as well (Henderson et al., 1990; Simon, 1969; Ulrich, 1995). Because they have built an organization in the same industry before, founders with prior entrepreneurial experience in the same industry are more likely to have addressed issues involving the coupling of technology and organization.

Taken together, these arguments suggest that prior entrepreneurial experience in the same industry should enable a startup to build an organization better able to commercialize the technology, and therefore reduce the negative effect of technological innovation on survival.

**HYPOTHESIS 3: The negative effect of technological innovation on survival will be reduced for startups whose founders possess prior entrepreneurial experience in the same industry.**

**Data and Methodology**

**Study Context**

We examine the interactive effect of preentry knowledge and technological innovation on the survival of high-technology startups. The startups we examine are young—we study them from birth to age six—and hence tend to have relatively few employees. This allows for a clean examination of the effects of preentry knowledge as it reduces the potentially confounding effects of capabilities and routines relating to coordination and information flow within the firm (Cyert et al., 1964; Nelson et al., 1982; Simon, 1947) and means that the founder is likely to lead decision-making (Beckman et al., 2008; Boeker, 1988; Delmar et al., 2006).

**Sample**

We test our hypotheses using firm-level microdata from the confidential version of the Kauffman Firm Survey (KFS). The KFS is a longitudinal panel dataset that tracks 4,928 startups founded in 2004 over time. Detailed data on each startup are collected at founding and over time, with follow-up surveys
conducted each year.\footnote{The KFS identifies firm founding through state unemployment insurance paid, FICA, Schedule C income reported on personal income tax, EIN, or the presence of formal legal status.} We utilize data from the initial survey and five follow-up surveys. These surveys collect data on business activities occurring between 2004 and 2009 including startup size and industry, sources of financing, measures of innovation related outcomes such as patents, and data related to the characteristics, experience, and human capital of startup founders (Farhart et al., 2014).

We restrict our analysis to those startups operating in high technology industries. In keeping with a Bureau of Labor Statistics definition, the KFS defines high technology startups as those startups operating in chemicals and pharmaceuticals, industrial machinery and equipment, electronic and electrical equipment, and instruments (Farhart et al., 2014). Our final sample consists of 1,427 startups operating in high technology industries.

The KFS provides several advantages. First, the KFS provides unprecedented visibility into startups’ early years. Second, the KFS avoids issues of survivor bias by tracking a sample of startups founded in the same year over time. Third, the KFS collects data on startups operating across a wide spectrum of industries, allowing generalizable results pertaining to the relationship between technological innovation, preentry knowledge, and survival. A disadvantage of these data is that we are unable to collect additional data to augment the existing dataset due to confidentiality agreements between the KFS and individual startups.

In order to ensure the availability of sufficient data for analyses, the KFS employs a stratified sampling scheme that oversamples startups in high technology industries. We use survey weights, provided by the KFS (Farhart & Robb (2014) provide additional details on the stratification process), to report population-level patterns based on survey data. The econometric processes used reflect standard practices for using weights to analyze complex survey data (Wolter, 2007).

**Dependent Variable**

*Survival.* Our dependent variable measures the number of years from founding to exit, where exit is inclusive of closure, acquisitions, and mergers. A well-established literature considers years to exit to be a crucial performance indicator for young firms (Audretsch, 1991; Caves, 1998; Georgellis et al., 2007). Moreover, this measure is commonly used in studies of preentry knowledge (e.g., Klepper, 2001), thereby providing a direct point of comparison for our analysis.

**Independent Variables**

We analyze the interactive effect of each of three distinct sources of preentry knowledge and technological innovation on survival. To do so, we construct three preentry knowledge variables and a technological innovation variable. These variables are described below. All four of these focal variables are time invariant measures. We measure a startup’s level of technological innovation within one year of
founding as we seek to examine the extent to which a founder’s preentry knowledge helps buffer the startup from the uncertainties generated by commercializing a novel technology in its earliest years.

In accordance with the literature, we measure the preentry knowledge possessed by a startup’s primary founder (Chatterji, 2009; Klepper, 2001). The KFS defines a startup’s primary founder as the individual with the largest ownership share at founding (Farhart et al., 2014). If ownership is equal, the primary founder is defined as the individual who spent the most time actively managing the startup.

Prior Employment Experience Measure

*Same-Industry Employment Experience.* This continuous variable is measured as the number of years that a founder was employed at an established firm operating in the same industry as the focal startup.

Prior Entrepreneurial Experience Measures

We distinguish between three categories of prior entrepreneurial experience: no prior entrepreneurial experience, different-industry entrepreneurial experience only, and same-industry entrepreneurial experience. We create a categorical variable for each type of prior entrepreneurial experience; “no entrepreneurial experience” serves as the omitted category in our empirical estimation. Each startup is assigned to only one of these three categories: this is because, due to design of the survey questions, a founder with prior entrepreneurial experience in the same industry may also possess entrepreneurial experience in a different industry. Our theoretical arguments are valid in light of this classification scheme, because we posit that the benefits that accrue to a startup whose founder possesses same-industry entrepreneurial experience are inclusive of the benefits that accrue to a startup whose founder possesses same-industry employment experience and different-industry entrepreneurial experience.2

*Different-Industry Entrepreneurial Experience.* This variable is measured as whether or not a founder has previously founded at least one startup in a different industry from the industry in which the focal startup operates. This variable takes a value of one if the entrepreneur has previously founded one or more startups in a different industry from the focal startup and zero otherwise.

*Same-Industry Entrepreneurial Experience.* This variable is measured as whether or not a founder has previously founded at least one startup in the same industry in which the focal startup operates. The variable takes a value of one if the entrepreneur has previously founded one or more startups in the same industry and zero otherwise. As noted above, this measure may also include different-industry experience.

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2 Of the founders who indicated that they have previously founded startups in the same industry as the focal startup, roughly half (49%) have founded only one other startup—these founders have only same-industry entrepreneurial experience; the other half (51%) have founded two or more startups—the survey structure tells us that at least one previous startup was in the same industry, but leaves open the possibility that the founder may also have founded a startup(s) in a different industry.
entrepreneurial experience due to the design of the KFS.

*Technological Innovation Measure*

*Technological Innovation.* We use the number of patents possessed by a startup within one year of founding as a proxy for the startups’ technological innovativeness (Guzman et al., 2015; Pakes et al., 1984). Patent possession within one year of founding has been shown to distinguish the type of innovative, high growth ventures that we seek to analyze from other startups (Guzman et al., 2015). Patent counts are widely used as indicators of technological innovativeness (Audretsch et al., 2005; Pakes et al., 1984; Sichelman, 2014; Trajtenberg, 1990; Wagner et al., 2010). Survey-based research finds that firms patent a large share of their patentable inventions (Mansfield, 1986). A patent is a “badge…of a successful innovative high-tech company (technology entrepreneur quoted in Sichelman, 2014, p. 5).” Existing research also establishes that a firm’s patenting record is closely related to its stature in the technical arena (Narin et al., 1987): according to Ahuja (2000), “patents represent externally validated measures of innovative success.”

*Controls*

**Founder Controls (Time-Invariant)**

*Human capital.* A founder’s formal education improves a startup’s survival chances (Bates, 1990). We control for the founder’s highest level of education (*Education*), using the KFS coding scheme. This variable ranges from 1 to 10, with a value of 1 indicating less than a high school degree and a value of 10 indicating a professional or doctoral degree. A value of 7 indicates having a bachelor’s degree. We also include a continuous variable to control for the age of the founder (*Age of Founder*), because older founders have more time to accrue general knowledge (Bates, 1990). We also control for the total number of previous businesses founded, as this has been shown to affect survival (*Number Previous Businesses*) (Delmar et al., 2006).

*Gender and ethnicity.* We control for the gender (*Female*) and ethnicity (*White*) of the founder, as these characteristics have been shown to impact survival rates (Fairlie et al., 2007).

**Startup Controls (Time-Invariant)**

*Locational Network Effects.* Networks can have a positive effect on survival by providing resources and knowledge from which a startup can draw (Thornton, 1999). The literature suggests that startups located in regional hotbeds of entrepreneurial activity may benefit from robust networks providing knowledge and resources (Katila et al., 2008; Saxenian, 1996; Sorenson et al., 2001; Stuart et al., 2003). Following the literature, we include dummy variables equal to 1 if the startup is founded in Massachusetts (*Massachusetts*) or California (*California*) (Hellmann, 2008; Hsu, 2004).

*Multiple Owners.* Startups with larger numbers of founders are likely to have more combined human capital and larger networks (Beckman et al., 2007). We control for this by including a dummy
variable equal to one if the startup is has more than one owner and zero otherwise (Multiple Owners).

**Startup Controls (Time-Varying)**

*Financing.* The literature finds that financing choices influence survival (Robb et al., 2014; Winston Smith, 2012). We therefore control for total debt (Total Debt) and total equity (Total Equity). We take the natural log of both measures in order to narrow the range of values taken by these variables and thus reduce sensitivity to extreme observations (Wooldridge, 2009).

*Startup size.* Firm size is known to increase survival chances (Evans, 1987). We include total assets as a measure of startup size (Total Assets). We also include the total number of employees (Number Employees). We take the natural log of both measures in order to narrow the range of values taken by these variables and thus reduce sensitivity to extreme observations (Wooldridge, 2009).

*Innovation quality.* Startups with higher quality innovations might be more likely to survive. R&D effort might be expected to result in higher innovation quality. We include a variable for the number of full-time employees devoted to research and development (Number R&D Employees). We take the natural log of this measure in order to narrow the range of values taken by this variable and thus reduce sensitivity to extreme observations (Wooldridge, 2009).

*Startup quality.* Higher quality startups might be more likely to survive. Venture capitalists specialize in evaluating the overall quality of startups (Gompers et al., 2010); we therefore include a dummy variable for whether the startup receives venture capital funding (Have VC) as an objective measure of higher startup quality.

**Industry-Specific Hazards**

Industry-specific factors may influence survival rates through idiosyncratic shocks (Cassar, 2014) and inherent differences in demand and technological regimes (Audretsch, 1991). We therefore specify whether a startup operates in one of four focal industries to econometrically allow for industry-level differences that might influence survival (Graham et al., 2010; Levin et al., 1987): medical devices and scientific instruments; biotechnology; chemicals and pharmaceuticals; and software, computer hardware, and internet. The startups in these four industries comprise 18.5% of our sample. The remaining startups are categorized as “other high technology industries.”

**Summary Statistics**

Summary statistics are presented in Table 1. Note that minimum and maximum values are not presented, in accordance with the terms of using the KFS data. Virtually all (97.6%) founders possessed prior employment experience in the same industry. The number of years of prior employment experience in the same industry ranges from 0 to 60 years, with a mean of 15.4 years. 26.5% of founders had previously founded at least one startup in a different industry from the focal startup. 19.7% of founders had previously founded at least one startup in the same industry as the focal startup.
As discussed earlier, patents can be used to identify technologically innovative firms (Ahuja, 2000; Audretsch et al., 2005; Mansfield, 1986; Pakes et al., 1984; Sichelman, 2014; Trajtenberg, 1990; Wagner et al., 2010). Consistent with existing research, we find that some startups in high technology industries are technologically innovative and others are not (Sichelman, 2014). In our sample, 7.4% of the startups report having patents within one year of founding, while 8.6% of startups surviving to year 6 have patents. The majority (57.2%) of startups surviving to year 6 who possess patents, possessed one or more patents within one year of founding.3

The six-year survival rate of the startups in our sample is 66.9%. The majority of startups that exit do so by going out of business (88.2%). A small fraction are either sold (6.3%) or merged (5.4%).

Econometric Strategy

We analyze the interactive effect of each of three distinct sources of preentry knowledge and technological innovation on survival. We use a Cox proportional hazard model to estimate these relationships. We then employ a simulation to estimate the magnitude and statistical significance of the interactive terms in our survival models. This approach is necessary because interactive terms in non-linear models cannot be interpreted directly from regression results (Brambor et al., 2006; Holburn et al., 2010).

Survival Analysis Framework and Estimation

We utilize a survival analysis framework based on the Cox proportional hazard model (Audretsch et al., 1995; Wooldridge, 2002). Similar models have been used in existing studies of firm survival (Audretsch et al., 1995; Bayus et al., 2007; Wagner et al., 2010). In general, the conditional hazard rate for a startup with characteristics \(x_i \) at time \(t\) is given by:

\[
\lambda(t, x_i) = \lim_{h \to 0} \frac{P(t \leq T < t + h \mid T \geq t, x_i)}{h}
\]

The Cox proportional hazard model is a semiparametric model. This means that all startups face the same baseline hazard rate, \(\lambda_0(t)\). Proportional differences in startup-specific hazard functions derive from the covariates, which enter multiplicatively in the model (Cox, 1972). The hazard function, \(\lambda(t, x_i)\), gives the instantaneous hazard of exit at time \(t\), conditional on survival through that time as a function of \(x_i\), the vector of the focal and control variables, \(\beta\), the vector of estimated coefficients, and \(\lambda_0(t)\), the

---

3 These patenting rates appear to be roughly in line with the Berkeley Patent Survey (Graham et al., 2010; Sichelman, 2014). We note that the fraction of startups possessing patents in our study is lower than the fraction in the 2008 Berkeley Patent Survey; this difference is likely due to differences in the sample of firms observed. Whereas the KFS tracks a representative sample of startups from birth, the Berkeley Patent Survey tracks startups and early-stage companies.
baseline hazard common to all startups:
\[
\lambda(t, x) = \exp(x \beta) \cdot \lambda_0(t)
\]  

We use industry stratified hazard regressions to permit each industry to have its own baseline hazard, because the industry in which a firm operates effects firm survival outcomes (Audretsch, 1991).

**Simulation-Based Estimation of Interactive Effects**

Interpreting interaction effects in non-linear models—such as the Cox proportional hazard model we use here—is challenging. While it is possible to calculate the magnitude of the interactive effect at specified values of each constituent variable, it is not possible to directly determine whether or not these values are statistically significant because the marginal effect of each variable in the interactive term varies conditionally with the value of the other interactive variable in a non-linear manner (Ai et al., 2003). We therefore employ simulations to determine both the magnitude and significance of interactive effects across the observed range of values.

Conceptually, our approach extends a handful of papers in the literature that implement simulation-based approaches to interpret multiplicative interaction models. King, Tomz, and Wittenberg (2000) provide a framework for using simulation to present statistical results for linear and logit models. Similarly, in the political science literature, Brambor, Clark, and Golder (2006) use simulation to assess interactive terms in the context of linear models. Zelner (2009) and Holburn and Zelner (2010) apply this insight to logit and probit based models, demonstrating in two-dimensions the range over which interactive effects in their model are statistically relevant. Our simulation method mirrors the approaches above and extends the existing literature in two important ways: our approach allows us to evaluate proportional hazard duration models, an important class of non-linear models; and, we devise a method for visualizing data on both the magnitude and significance of interactive effects in three dimensions using Mathematica.

Our approach takes the econometric estimates of the Cox proportional hazard regressions as the starting point. We use the known distribution—i.e., the mean and variance—of the coefficients from these estimates to generate a simulated population of sample coefficients. We simulate 10,000 random draws from the normal distribution centered at the mean value of each estimated coefficient. From this simulated population, we identify the upper and lower bounds of each combination of the coefficients within a 90th percentile confidence interval. We calculate a relative hazard of failure for each combination of years of same-industry employment experience and number of patents under conditions of no entrepreneurial experience, different-industry entrepreneurial experience, and same-industry entrepreneurial experience. We then identify whether the outcomes associated with each combination of years of same-industry employment experience and number of patents reflect a hazard of failure that is
statistically different from the baseline hazard.

**Results**

Following standard practice, we present the results of Cox proportional hazard estimations (reported as hazard ratios) in Table 2. However, as noted above, these estimated coefficients and associated standard errors are not sufficient to interpret the interactive effects in a non-linear model. We therefore use these results to feed a simulation model.

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**Multivariate Proportional Hazard Analysis**

Table 2 reports the hazard ratios from our proportional hazard regressions. A hazard ratio greater than one indicates a higher risk of exit; conversely, a hazard ratio lower than one indicates a lower risk of exit. All regressions are run with industry-specific hazards. Column 1 shows the results from estimation including only the direct effects and control variables. Columns 2-4 enter each set of interactions and component variables separately along with all founder and startup controls. Column 5 presents the results from the full model with all interactive and component variables and founder and startup controls. The unit of analysis is the individual startup-year. The sample size for each column reflects the number of startup-years analyzed (any discrepancies in numbers stem from non-responses in the survey data). The results in Table 2 suggest that each of the interactive effects reduces the hazard of failure from technological innovation, providing support for Hypotheses 1, 2 and 3.

**Interpretation of Findings Using a Simulation-Based Approach**

**Hypothesis 1**

Hypothesis 1 posits that the negative effect of technological innovation on survival will be reduced for startups whose founders possess same-industry employment experience. The simulation results support Hypothesis 1. Figure 1 plots the hazard ratio of failure for startups whose founder has no prior entrepreneurial experience. We see that the hazard of failure associated with any level of technological innovation decreases with increasing years of same-industry employment experience.

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At low levels of same-industry employment experience, we see that the hazard of failure is high and significant (p<0.10). At high levels of same-industry employment experience, we see that that overall hazard of failure is negative—that is to say, these startups experience a survival benefit—and significant (p<0.10). The hazard of failure is not statistically significant in regions in between (these regions are unshaded), this is likely because there is a transition from increased to decreased survival hazard with increasing years of same-industry employment experience. The same pattern appears in
Further confirmation of Hypothesis 1 comes from Figures 2a and 3a. The beneficial effect of the interaction between same-industry employment experience and technological innovation on survival are greatest for startups whose founders possess same-industry entrepreneurial experience (Figure 3a), followed by startups whose founders possess different-industry entrepreneurial experience (Figure 2a), and least for startups whose founders possess no entrepreneurial experience (Figure 1).

Hypothesis 2
Hypothesis 2 posits that the negative effect of technological innovation on survival will be reduced for startups whose founders possess prior entrepreneurial experience in a different industry. The simulation results support Hypothesis 2 across virtually all values of technological innovation. In Figure 2b we see that different-industry entrepreneurial experience reduces the hazard of failure associated with technological innovation (the hazard ratio is below 1). This effect is statistically significant for startups possessing 2 or more patents (p<0.10). The magnitude of the beneficial effect increases with increasing numbers of patents (we see that the plane depicting the effect slopes downward).

Hypothesis 3
Hypothesis 3 posits that the negative effect of technological innovation on survival will be reduced for startups whose founders possess prior entrepreneurial experience in the same industry. The simulation results support Hypothesis 3 across most, but not all, values of technological innovation. In Figure 3b we see that same-industry entrepreneurial experience increases the hazard of failure associated with technological innovation at low levels of technological innovation (i.e., less than 2 patents), and decreases the hazard of failure at higher levels of technological innovation (i.e., more than 7 patents). The region in between is statistically insignificant (p<0.10). The magnitude of the beneficial effect increases with increasing numbers of patents (we see that the plane depicting the effect slopes downward).

What might explain the detrimental effect of same-industry prior entrepreneurial experience at low levels of technological innovation? Organizational learning theory suggests that a misplaced belief

---

4 For an innovative high technology startup in our sample, 2 patents represent a relatively low level of innovation: the mean number of patents held by the startups in our sample is 0.22 and the mean number of patents held by startups that innovate (that is, by startups who hold one or more patents) is 4.0.
that the current situation is similar to the past, may lead a startup to make erroneous assumptions rather than engaging in learning (Argote, 1999; Gersick, 1994; Huber, 1991; McGrath et al., 1995; Simon, 1993). Specifically, a founder may misapply assumptions or routines that worked well at their previous startup, leading to a “competency trap” that results in suboptimal or even negative outcomes (Levinthal et al., 1993; Simon, 1993). Because their current situation more closely mirrors their past experience, theory would predict that startups whose founders have prior entrepreneurial experience in the same industry and who are commercializing technologies that are more similar to existing technologies (as reflected in low levels of technological innovation) may be at greater risk of being caught in a competency trap than other founders. This explanation is in line with the patterns observed in the data and in our fieldwork.

Robustness Checks

Robustness to Distributional Assumptions

Our results are robust to distributional assumptions. We check for the correctness of the assumption of proportional hazards using Schoenfeld residuals (Wooldridge, 2002). While the use of proportional hazards is supported, we also carry out robustness checks employing parametric distributions. In untabulated regressions (available from authors), we find that the results of parametric models estimated using the exponential, Gompertz, and Weibull distributions are similar in sign and magnitude to the results of the semi-parametric Cox proportional hazards estimation.

Discussion

We examine the effects of three sources of preentry knowledge on the relationship between innovation and survival, finding that preentry knowledge from each of the three sources reduces the survival hazards generated by innovation; noting that prior entrepreneurial experience in the same industry provides benefit only when the startup engages in moderate or high levels of innovation.

We make three primary contributions to the literature. First, our results suggest that preentry knowledge provides innovative startups in high technology industries with a basis for learning. Second, we extend the evolutionary economics literature by showing that unlocking the benefits of some types of knowledge may require complementary knowledge. Third, we refine our understanding of the effects of prior entrepreneurial experience on survival. In addition, we make a methodological contribution: we devise a method for using simulations to interpret interactive effects in duration models. From a managerial perspective, we illuminate our understanding of the factors that shape the survival of nascent high-technology startups.

Support for Evolutionary Economics: Preentry Knowledge Scaffolds Learning

Evolutionary economics posits that existing knowledge provides a basis for learning, and thus firms possessing more relevant knowledge will be more likely to succeed (Helfat et al., 2000; Nelson et
This insight is a cornerstone of the evolutionary economic perspective, and scholars have called for additional empirical work to validate this claim (Helfat et al., 2002). We provide evidence in support of the evolutionary perspective in a context—high technology entrepreneurship—central to innovation and economic growth. We find that all three types of preentry knowledge examined reduce the negative effect of technological innovation on survival at moderate and high levels of innovativeness. In addition, we find that same-industry entrepreneurial experience increases the negative effect of technological innovation on survival at low levels of innovation; organizational learning theory and our fieldwork suggest that this may be because founders perceive the situation to be similar to that which they experienced before—when the situation has in fact changed—and hence make unwarranted assumptions, rather than engaging in learning (Levinthal et al., 1993; Simon, 1993).

**Complementary Knowledge: Unlocking the Value of Technological Innovation**

Theoreticians have pointed out that possessing multiple knowledge sets is crucial for organizational adaptation in uncertain and complex situations (Grant, 1996; Levinthal, 1997; Nickerson et al., 2004), yet most empirical work examines the direct effects of knowledge on firm-level outcomes. Examining the effects of complementary knowledge on firm-level outcomes therefore appears to be an important next step for the strategic management and organizational learning literatures. We join a handful of studies that move beyond examining the direct effects of knowledge (e.g., Dencker et al., 2009; Franco et al., 2009). Specifically, we examine whether or not preentry knowledge can improve a startup’s ability to meet the challenges generated by technological innovation—envisioning preentry knowledge as a key that “unlocks” a startup’s ability to commercialize an innovative technology, and therefore survive. We find that it does. Our findings contribute to the evolutionary economics literature by showing that unlocking benefits from some types of knowledge requires complementary knowledge.

Engaging in technological innovation casts a strong negative effect on startup survival, an effect that grows as firms engage in higher levels of technological innovation. We find that all three types of preentry knowledge provide greater reductions in survival risk at higher levels of technological innovation, thereby “inoculating” firms from the challenges generated by technological innovation.

**Prior Entrepreneurial Experience: Fueling High Technology Entrepreneurship**

We also contribute to the entrepreneurship literature by refining our understanding of the effects of prior experience on survival. We contribute to the existing literature in two ways. First, much theorizing focuses on the import of prior employment experience in the same industry to startup performance (e.g., Bhidé, 2000; Sorensen et al., 2011). We highlight the fact that other sources of preentry knowledge can be equally or more important. Specifically, we show that by moderating the relationship between innovation and survival, prior entrepreneurial experience has a positive and significant effect on startup performance.
Second, studies examining the direct effects of prior entrepreneurial experience on firm survival find inconsistent results: several studies find that prior entrepreneurial experience improves a young firm’s survival chances (Delmar et al., 2006; Dencker et al., 2009), whereas others do not find evidence of significant effects (Brüderl et al., 1992; Gimeno et al., 1997). These prior studies do not differentiate between same- and different-industry entrepreneurial experience. We provide data and analysis that shows that the effects of prior entrepreneurial experience on firm survival may be more nuanced than previously anticipated. We differentiate same- and different-industry entrepreneurial experience and examine their influence on the relationship between innovation and survival. We find that both types of entrepreneurial experience reduce the negative effect of technological innovation on survival: different-industry entrepreneurial experience provides benefit at virtually all levels of technological innovation, whereas same-industry entrepreneurial experience initially hurts startups and then, as the startup’s level of technological innovativeness increases, provides benefit.

**Interpreting Interactive Effects in Duration Models**

From a methodological perspective, the literature on interpreting interactive terms in non-linear models has focused on discrete choice models such as logit and probit (Brambor et al., 2006; Zelner, 2009). We extend the use of interactive terms to duration models by developing a simulation-based method to interpret the magnitude and significance of interaction terms in Cox proportional hazard and other duration models. We also wrote novel software code to graphically depict the magnitude and significance of these interaction effects using Mathematica (available from authors).

**Insights on Nascent High Technology Startups**

Due to difficulties in identifying and gathering data on nascent startups (Haltiwanger et al., 2009), most existing studies of firm survival examine an elite subset of startups. For example, startups that have introduced a product, obtained venture capital, or conducted an initial public offering (e.g., Agarwal et al., 1996; Chatterji, 2009; Klepper, 2001). Our study avoids these biases: by analyzing data that track a cohort of high technology startups from birth, we contribute unique and valuable knowledge pertaining to nascent startups operating in high technology industries. For example, representative data on patenting rates of nascent firms are particularly difficult to collect (Graham et al., 2010), as are data on new firm survival rates and founder career histories. We illuminate each of these variables, based on data from a cohort of nascent startups operating across a wide-array of high technology industries.

We show that, consistent with extant theory, there exists a strong negative relationship between innovation and the survival of high technology startups (Acemoglu et al., 2014; Knight, 1921; Nelson et al., 1977; Schoonhoven et al., 1990).\(^5\) We find that preentry knowledge from each of three distinct aspects...
sources allows startups to mitigate the negative effects of innovation on survival.

We briefly discuss rates of venture capital financing and IPOs here because these events occupy outsized roles in the literature, although they are not central to our analyses as we examine nascent firms from birth to age 6 and expect that few such firms have experienced these outcomes. Few startups in our sample report having venture financing: 0.006% of startups report having venture capital backing within one year of founding, and 0.003% of report having venture capital backing at the end of year 6. The KFS does not collect data on IPOs. However, few firms in the sample are likely to have gone public, both because of their young age at the end of the time period studied (Ritter, 2014), and because very few startups go public in general (Puri et al., 2012).

**Practical Implications**

Our study provides practical guidance for stakeholders of innovative high technology startups. A core function of investors, such as angels and venture capitalists, is to ensure that startups have the knowledge they need to succeed (Hellmann et al., 2002; Hsu, 2004). Based on our findings, we suggest that investors evaluate a startup’s knowledge assets and provide resources to startups based on specific gaps in their knowledge base. In addition, both startups and investors might consider whether the investor has the knowledge necessary to compensate for gaps in a startup’s knowledge base. Our study also highlights the effects of career history on entrepreneurial success. Based on our findings, potential entrepreneurs might select entrepreneurial opportunities that draw on their existing industry knowledge. Finally, our findings suggest that entrepreneurs carefully consider their assumptions.

**Conclusion**

Innovative high technology startups are critical to societal and economic progress. Scholars have long been aware that these startups face an inherent challenge: the very innovations they develop threaten their survival. Evolutionary economics illuminates a path towards inoculating startups from this threat, suggesting that learning is necessary to overcome the challenges inherent in commercializing technological innovations and that preentry knowledge provides a basis for such learning. Inspired by this logic, we examine the effect of preentry knowledge on the relationship between innovation and survival. We find that preentry knowledge from each of three sources generally allows startups to overcome the survival hazards generated by technological innovation (noting one exception: same-industry entrepreneurial experience is detrimental at low levels of innovation). Our findings provide empirical support for evolutionary economics and bring us an important step closer to identifying “the right stuff” for innovative high technology startups.

Wagner et al., 2010). These results are likely explained by differences in the samples studied: extent studies examine post-IPO high technology firms, while we investigate nascent high technology startups. It is unlikely that nascent startups and post-IPO firms have the same capacity to weather technological innovation.
Figures

Overview of Figures

- Figures 1, 2a, and 3a examine hypothesis 1. These figures plot the hazard ratio for a startup whose founder possesses no entrepreneurial experience (Figure 1), different-industry entrepreneurial experience (Figure 2a), and same-industry entrepreneurial experience (Figure 3a) relative to a startup with no patents and whose founder possesses neither employment nor entrepreneurial experience (the “reference point”).
- Figures 2b and 3b examine hypotheses 2 and 3, respectively. Figures 2b and 3b plot the same data as do figures 2a and 3a, however they present the data with respect to a different reference point to allow for a clear examination of each hypotheses. These figures plot the hazard ratio for a startup whose founder possesses different-industry entrepreneurial experience (Figure 2b) and same-industry entrepreneurial experience (Figure 3b) relative to a startup whose founder possesses no entrepreneurial experience of any kind. Conceptually, these figures illustrate the difference in the hazard of failure for startups whose founder possesses no entrepreneurial experience versus a founder who possesses different- or same-industry entrepreneurial experience.
- Color is used to indicate the sign, relative magnitude, and significance of the hazard ratio. “Cool” colors indicate regions where startups are at a statistically lower risk of failure, with the risk of failure decreasing as the color gets cooler (i.e., from green to blue to purple). Conversely, “warm” colors indicate regions where startups are at a statistically higher risk of failure, with the risk of failure increasing as the color gets warmer (i.e., from yellow to orange to red). Regions shaded in color are statistically significant (p<0.10) based on our simulation results; unshaded regions are not statistically significant at this level.

**Figure 1:** Hazard Ratio for a Startup with No Prior Entrepreneurial Experience Relative to a Startup with No Innovation and No Same-Industry Employment Experience
Figures 2a and 2b: Hazard Ratio for a Startup with Different-Industry Entrepreneurial Experience

(2a) Relative to a Startup with No Innovation and No Same-Industry Employment Experience

(2b) Relative to a Startup with No Prior Entrepreneurial Experience

Figures 3a and 3b: Hazard Ratio for a Startup with Same-Industry Entrepreneurial Experience

(3a) Relative to a Startup with No Innovation and No Same-Industry Employment Experience

(3b) Relative to a Startup with No Prior Entrepreneurial Experience
<table>
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<th>Variable</th>
<th>Mean</th>
<th>Linearized Standard Error</th>
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Notes:
- Taylor linearized standard errors presented in accordance with standard practice when working with stratified survey data (Wolter 2007).
- Minimum and maximum values removed in accordance with KFS confidentiality agreement.
**Table 2. Prior Experience and Technological Innovation, Cox Proportional Hazard Regressions**

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<td>0.952</td>
<td>0.945</td>
<td>0.937</td>
<td>0.967</td>
<td>0.964</td>
</tr>
<tr>
<td>(-0.52)</td>
<td>(-0.60)</td>
<td>(-0.45)</td>
<td>(-0.36)</td>
<td>(-0.38)</td>
<td></td>
</tr>
</tbody>
</table>
(Table 2, Continued)

**Startup Controls (Time-Invariant)**

<table>
<thead>
<tr>
<th>State</th>
<th>0.883</th>
<th>0.858</th>
<th>0.897</th>
<th>0.872</th>
<th>0.787</th>
</tr>
</thead>
<tbody>
<tr>
<td>Massachusetts</td>
<td>(-0.52)</td>
<td>(-0.52)</td>
<td>(-0.45)</td>
<td>(-0.59)</td>
<td>(-0.93)</td>
</tr>
<tr>
<td>California</td>
<td>0.783</td>
<td>0.793</td>
<td>0.776</td>
<td>0.771</td>
<td>0.771</td>
</tr>
<tr>
<td></td>
<td>(-1.24)</td>
<td>(-1.14)</td>
<td>(-1.26)</td>
<td>(-1.34)</td>
<td>(-1.34)</td>
</tr>
<tr>
<td>Multiple Owners</td>
<td>1.381***</td>
<td>1.360**</td>
<td>1.383**</td>
<td>1.357**</td>
<td>1.345**</td>
</tr>
<tr>
<td></td>
<td>(4.12)</td>
<td>(3.79)</td>
<td>(3.85)</td>
<td>(3.93)</td>
<td>(3.65)</td>
</tr>
</tbody>
</table>

**Startup Controls (Time-Varying)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>0.002***</th>
<th>0.002***</th>
<th>0.002***</th>
<th>0.001***</th>
<th>0.001***</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(1+Total Debt)</td>
<td>(-34.67)</td>
<td>(-35.72)</td>
<td>(-34.78)</td>
<td>(-36.52)</td>
<td>(-39.61)</td>
</tr>
<tr>
<td>Ln(1+Total Equity)</td>
<td>0.001***</td>
<td>0.001***</td>
<td>0.001***</td>
<td>0.001***</td>
<td>0.001***</td>
</tr>
<tr>
<td>Ln(1+Total Assets)</td>
<td>(-62.80)</td>
<td>(-64.42)</td>
<td>(-63.98)</td>
<td>(-66.49)</td>
<td>(-42.98)</td>
</tr>
<tr>
<td>Ln(1+Number Employees)</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td>Ln(1+Number R&amp;D Employees)</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td>Have VC</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td></td>
<td>(31.97)</td>
<td>(32.65)</td>
<td>(31.80)</td>
<td>(33.67)</td>
<td>(36.15)</td>
</tr>
</tbody>
</table>

**Industry Stratified**

<table>
<thead>
<tr>
<th>Stratification</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>8412</td>
<td>8412</td>
<td>8412</td>
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<td>8412</td>
</tr>
<tr>
<td>F-test</td>
<td>2699.00</td>
<td>3054.19</td>
<td>2874.56</td>
<td>3178.79</td>
<td>2214.66</td>
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<tr>
<td>Prob &gt; F</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes:
- Hazard ratios are cited. (two-tailed t-statistics in parentheses)
  - p < 0.10.
  - p < 0.05
  - p < 0.01
- Cox proportional hazard regression with survey estimation techniques controlling for stratification and sample weights, robust standard errors clustered on startup.
- Focal variables and founder controls are time-invariant variables. Startup controls are time-invariant or time-varying as indicated in the table.
- The unit of analysis is the startup-year.
References


