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**Boundary-Crossing Job Mobility, New Product Area Entry and the Performance of
Entrepreneurial Ventures**

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Abstract

How does career boundary-crossing affect an entrepreneur's new venture? When entrepreneurs cross industry or functional boundaries to lead startups, they may lack specific experience needed for performance. Conversely, the diverse experiences they carry can enhance exploration and lead to the emergence of innovation in startups. We highlight important consequences of career boundary-crossing, using a multi-industry longitudinal sample of high-technology firms. We find that entrepreneurs who cross functional boundaries are more likely to lead their startups into new product areas. We also find that entrepreneurs' industry boundary-crossing is associated with startup failure, but it also increases the probability of an IPO.

Research paper

Key words: Technology entrepreneurship, Job mobility, Innovation formation

INTRODUCTION

Understanding how the characteristics of entrepreneurial leaders influence the outcomes of startups is a central concern of entrepreneurship research. When entrepreneurial leaders found or join startups, the knowledge and experience they bring can play a critical role in a startup's success and even its survival (Colombo & Grilli, 2005; Davidsson & Honig, 2003; Dencker, Gruber, & Shah, 2009). Most directly, prior entrepreneurship experience confers skill in starting new ventures that predicts success in subsequent ventures (D. H. Hsu, 2007; Shane & Khurana, 2003). However, serial entrepreneurs are relatively rare, and even first-time entrepreneurs typically come to new ventures with organizational experience (Audia & Rider, 2006; Sorensen & Fassiott, 2011). Experience in organizations can have lasting effects on new entrepreneurs, and the imprints they carry from prior experience can condition the way they approach entrepreneurship and the outcomes of their ventures (Higgins, 2006; Marquis & Tilcsik, 2013). In particular, the prior experience of entrepreneurial leaders can determine the emergence and direction of innovation for a startup.

The primary underlying mechanism that links individuals' prior jobs with outcomes in a new organization is knowledge or know-how that is carried across organizational boundaries. As entrepreneurs join startup organizations, either as founder or early leader, they carry knowledge from their prior jobs. Research on entrepreneurs' backgrounds using a human capital perspective emphasizes the importance of similar knowledge, such as industry-specific knowledge that is carried in by mobile founders or leaders (Bruderl, Preisendorfer, & Ziegler, 1992; Castanias & Helfat, 2001; Cooper, Gimeno-Gascon, & Woo, 1994). Startups tend to be resource-constrained, and knowledge held by early leaders constitutes a significant part of the resource endowments of

a startup (Shane & Stuart, 2002). Consequently, a lack of useful specific knowledge brought in by mobile leaders can shortchange the needs of a startup.

Despite advances in theory about the knowledge that entrepreneurial leaders carry into startups, questions remain about its effects. First, though there is substantial evidence that an entrepreneur's experience in prior firms affects a startup's innovation and performance outcomes, little is known about how influential different dimensions of experience are (Unger, Rauch, Frese, & Rosenbusch, 2011). In particular, industry-specific experience and function-specific experience may operate differently on firm-level outcomes of interest. Individuals who change industry when entering new jobs might be better equipped to enable strategic change (Boeker, 1997), while individuals changing functional areas might provide better general management, especially for startups (Lazear, 2004). Second, though industry- or function-specific knowledge may be useful for startups, diverse knowledge can also be of benefit to organizations. Organizational learning research emphasizes the value of non-redundant knowledge, and views job mobility as a key way in which small or young firms acquire diverse knowledge from the external environment (Almeida, Dokko, & Rosenkopf, 2003; Rao & Drazin, 2002). Startups with diverse knowledge play an important role in the emergence of innovation, as the recombination of diverse knowledge creates novel products that can define and otherwise shape understanding of the startup's identity as well as the markets it competes in.

In this study, we examine entrepreneurial boundary-crossing as a predictor of startups' entry into new product areas and their ultimate performance. We focus on entrepreneurial leaders because leaders set the strategic direction of firms (Boeker, 1997; Kraatz & Moore, 2002), and because young firms may be particularly susceptible to the influences of founders and early managers (Burton, Sorensen, & Beckman, 2002; Phillips, 2002). We draw on theories of

organizational learning and of human capital to develop predictions about the effects of entrepreneurs' industry and functional boundary-crossing on startup innovation and performance outcomes. Our primary objective in this study is to draw attention to tensions and potential tradeoffs that boundary-crossing entrepreneurs face, and how these affect the course of innovations that emerge. We develop a model of entrepreneurs' boundary-crossing that focuses on differences between entrepreneurial leaders' last jobs and their new jobs, and shows effects for the important outcomes of entry into new product areas and firm performance. By treating the move into entrepreneurial leadership as a job mobility event and focusing on differences between the human capital endowment of an entrepreneurial leader and the nature of the entrepreneurial leadership position, we enrich understanding of how entrepreneurs' human capital affects the startups they lead. We test hypotheses about boundary-crossing entrepreneurial leaders and startup outcomes using a longitudinal, multi-industry sample of high-technology startups.

THEORY AND HYPOTHESES

Boundary-crossing and the emergence of innovation in startups

Emergence involves the generation of something novel, its growth into something viable, and its formation into something with a recognizable identity. The emergence of innovation is a critical process for startups, and can determine whether they thrive or fail. Innovation results from the recombination of knowledge, and more distant and diverse knowledge, like that brought by boundary-crossing entrepreneurs, can be recombined into more novel innovation (Fleming, 2001; von Hippel, 1988). But in addition to generating innovation, startups must decide what to do with it. As fledgling entities, startups are in the process of realizing their identities (King,

Clemens, & Fry, 2011), in part by selecting the markets they will participate in and developing the products they will bring to those markets. In this way, entry into new product areas by entrepreneurial firms is an act of emergence and formation, as startups develop new types of products from the recombination of an entrepreneurial leader's prior experience with a new context. As startups enter product areas with new types of products, they give themselves and their innovations definition and a concrete identity, establishing a distinct form.

In addition, entry into a product area is a claim to membership in that area, which can change how it is defined and understood (Navis & Glynn, 2010; Perretti, Negro, & Lomi, 2008). The introduction of truly novel products can stretch the boundaries of a product area or take it in new directions, accomplishing re-formation of the product area. Innovations brought by new startup entrants can change the identity and meaning of a product category by prompting reinterpretation of the category to encompass them (G. Hsu, Hannan, & Polos, 2011; Negro, Hannan, & Rao, 2011). Moreover, high-technology product areas can generally be considered lenient categories (Pontikes & Barnett, 2015), given that change and innovation are fundamental characteristics of high-tech. Lenient categories are flexible to change by organizational members (Pontikes & Barnett, 2015), making a startup's choice to enter a new product area formative for the product category as well as the innovation.

Boundary-crossing job mobility as a source of industry and functional knowledge and skill

Despite a large body of research on the human capital of entrepreneurs and venture outcomes, a number of questions remain about the size and even direction of the effect (see Unger et al., 2011 for a meta-analysis of extant research). Many of these studies use general measures of human capital, such as education or years of work experience, and the breadth and

diversity of these measures may be one reason that consistent results are difficult to find. Unger et al. (2011) find that task-related knowledge and skills of entrepreneurs are most strongly predictive of venture success, yet at the same time, diverse backgrounds are predictive of becoming an entrepreneur (Astebro & Thompson, 2011; Lazear, 2005). The scale and scope of the entrepreneurial task and its diverse requirements merit closer examination of aspects of human capital and how they relate to the outcomes of ventures.

In particular, industry-specific experience has been consistently associated with startup survival (e.g., Bruderl et al., 1992; Cooper et al., 1994), yet much less is known about how other dimensions of human capital might operate in entrepreneurship. Entrepreneurial leaders must know and be able to perform a wide range of functional tasks that go beyond the scope of industry-related skills and knowledge (Lazear, 2005). To capture these effects, studies have included variables such as prior general management experience (e.g., Colombo & Grilli, 2010; Cooper et al., 1994; Dencker et al., 2009), or experience in broad functional areas like technology or business (e.g., Colombo & Grilli, 2010; Davidsson & Honig, 2003; Gimmon & Levie, 2010); however, both measurement and findings have been inconsistent.

Outside of the entrepreneurship literature, theory on organizational learning informs how boundary-crossing through job mobility can affect firm outcomes. Individuals entering firms bring with them knowledge and skills that supplement the firm's existing knowledge base such that knowledge transfer from the old firm to the new firm is more likely to occur (Almeida et al., 2003; Song, Almeida, & Wu, 2003). Moreover, the movement of individuals across organizational boundaries can serve to open conduits for ongoing learning through the establishment of interfirm ties with the underpinning of interpersonal relationships (Corredoira & Rosenkopf, 2010). For entrepreneurial leaders, connections to the external environment might

be particularly valuable resources, given the diverse needs and limited resources of most startups.

In addition, the job mobility of entrepreneurial leaders into a startup is of particular importance to startup outcomes. Because entrepreneurial leaders are central to the decision-making and activities of startups, the mental models that they carry from prior experience directly influence the outcomes of startup firms. Mental models are simplified subjective representations of complex phenomena (Porac & Thomas, 1990) that in part result from experiential learning, and contain beliefs about causal relationships. They serve as attention-focusing mechanisms that shape problem definition and responses (Ocasio, 2011). Since startups do not have established attention-focusing routines, the mental models carried by entrepreneurial leaders influence the startup's learning from the external environment and the strategic action that startups take.

Entrepreneur boundary-crossing and entry into new product areas

When entrepreneurial leaders cross industry or functional boundaries to found or join startups, they can affect the likelihood of entry into new product areas. Executive migration is a source of change in strategic choices like product area entry, as leaders' prior experiences shape their expertise and insights about new product market opportunities (Boeker, 1997). Most studies that consider entry into new product areas are concerned with established firms, and consider entry as evidence of innovation or strategic change (e.g. Boeker, 1997; Helfat & Lieberman, 2002; Mitchell, 1989; Nerkar & Roberts, 2004). These issues may be especially significant for startups, since innovation is crucial in the fledgling stages of a firm's life, and multiple strategic changes may be necessary as the startup strategically adjusts to find a viable

business model. There may be fewer barriers to strategic change for startups relative to incumbents, but entering new product areas is a particularly important indicator of the emergence of innovation in startups, as it establishes the form that the innovation will take and how it will be understood by customers and funders. Moreover, strategic change through entry into new product areas signals a fundamental shift in a startup's identity that can position it for success or failure.

For entrepreneurial leaders, their prior endowment of industry knowledge and perspectives can encourage new product entry through two mechanisms. First, the mobility of leaders is a mechanism of diffusion for practices or products (Kraatz & Moore, 2002; Teodoro, 2009). For example, mobile leaders may bring knowledge of strategic opportunities in a particular industry, or knowledge of specific products that can encourage entry into those product areas (Shane, 2000). Therefore, we expect that entrepreneurial leaders crossing industry boundaries will be likely to bring the knowledge and social connections they have from their prior industries, and that these resources will increase the likelihood that the startup will enter product areas already familiar to the entrepreneurial leader.

Second, crossing industry boundaries might create opportunities for product innovation that leads to entry into new product areas. The link between assimilating diverse knowledge and the innovativeness of firms is well-established (Cohen & Levinthal, 1989), and a host of research supports the relationship between job mobility and learning and innovation (e.g. Almeida et al., 2003; Madsen, Mosakowski, & Zaheer, 2002; Rao & Drazin, 2002; Rosenkopf & Almeida, 2003). Some research also finds that hiring from technologically distant areas or other industries is particularly useful for innovation (Song et al., 2003; Tzabbar, 2009). By definition, entrepreneurship is about creating something new, i.e. innovating in some way (Venkataraman,

1997), and innovation may be particularly essential to early stage firms, as they need to start building a portfolio of products or creating strategic distinctiveness in order to grow.

We expect both of these mechanisms to encourage entry into new product areas for entrepreneurial leaders crossing industry boundaries.

Hypothesis 1: Entrepreneur industry boundary-crossing has a positive relationship with entry into new product areas.

In addition to industry-specific experience, entrepreneurial leaders' work backgrounds include experience in specific functional roles. Entrepreneurial leaders' functional responsibilities can diverge considerably from earlier roles. Most positions in organizations are limited in the number of functions that position-holders perform, though higher-level managers can be responsible for multiple functional areas. A transition into general management entails not only the accrued responsibility of multiple functional areas, but also the coordination of those functions. This experience may be typical for entrepreneurial leaders. If they are not serial entrepreneurs, they may normally find themselves in a position that requires new functional skills. Entrepreneurs need to be "jacks of all trades" so that they can manage or even perform the variety of functions that a startup with limited human resources needs (Lazear, 2005).

Functional boundary-crossing should be associated with entering new product areas, because it should enable entrepreneurial leaders to see different perspectives on products they might have worked with in the past, or to have more control to implement strategic change. For example, an entrepreneurial leader with a technical background who takes on marketing and sales responsibilities may see new market opportunities for a particular technology held by a startup that leads them to develop new products based on that technology. In addition, changes in functional responsibilities could increase a leader's ability to implement new product ideas or

market opportunities if the changes involve broader functional responsibilities and increased span of control. Even crossing into distinctly new functional areas may increase implementation ability, as the leader would be better able to communicate ideas and arguments across functional boundaries. Therefore, we expect that functional boundary-crossing will also have a positive effect on introducing new types of products.

Hypothesis 2: Entrepreneur functional boundary-crossing has a positive relationship with entry into new product areas.

Entrepreneur boundary-crossing and venture performance

An entrepreneurial leader's industry boundary-crossing should also affect the overall performance of a new venture, but how? Experience in an industry creates a refined ability to recognize opportunities and strategically position a firm for competitive advantage (Roberts, Klepper, & Hayward, 2011). When entrepreneurial leaders move across industry boundaries to lead startups, they lack industry-specific knowledge about products, market and competitive conditions, and regulations needed to run a successful startup. Without industry-specific knowledge, leaders may need to spend more time and resources on trial-and-error learning to strategically position the venture (Castanias & Helfat, 2001), which can be especially harmful for new ventures. At the same time, industry boundary-crossing could increase ability to learn and innovate. Learning and innovation from mobile leaders' experiences may be particularly relevant for startups in early life stages (Almeida et al., 2003), and the absorptive capacity and diverse social ties that facilitate innovation should also facilitate survival of the startup past the precarious early stages of organizational life.

Against this backdrop, crossing industry boundaries can be conceived of as a risky maneuver that can pay off richly or lead to failure. Entrepreneurs who cross industry boundaries can facilitate more distant exploration of ideas and alternatives, because they bring outside knowledge and outside perspectives to an industry context. This distant exploration is inherently risky because there may not be established models to follow, and because there is more market risk that can result in failure (Hargadon & Douglas, 2001). However, resulting recombination and innovation can be especially impactful, both within and outside of the originating product domain (Rosenkopf & Nerkar, 2001). This argument is in line with findings that knowledge diversity or category-spanning hybridization results in more extreme performance outcomes for products (Fleming, 2001; G. Hsu, Negro, & Perretti, 2012; Taylor & Greve, 2006). Therefore, entrepreneurial leaders coming from outside an industry have different knowledge and cognitive schema that can result in unique products that either yield competitive advantage, or are costly failures.

Hypothesis 3: Entrepreneur industry boundary-crossing will result in extreme (either very good or very bad) performance for startups.

Finally, unlike for industry-specific knowledge, having diverse functional skills should be of general benefit to entrepreneurial leaders because of their need to wear many hats in resource-constrained startups. Individuals who cross functional boundaries have a greater variety of functional experiences to draw on in their current jobs. Having a set of prior functional experiences that differ from the new functions performed can create opportunities for drawing linkages between the old functional responsibilities and new functional responsibilities, and increase the ability to prioritize according to strategic demands. In addition, diverse founding teams have been shown to positively affect startup performance (Beckman, Burton, & O'Reilly,

2007). Diversity in the functions an entrepreneurial leader has experienced responsibility for may enable perspective-taking and the ability to work effectively with a diverse founding team. Therefore, an organizational learning and innovation perspective suggests that entrepreneurs who cross functional boundaries to lead startups will have ventures that are more likely to perform well.

Hypothesis 4: Entrepreneur functional boundary-crossing is positively associated with startup performance.

METHODS

Data and Sample

Our primary data source is the *CorpTech Directory of Technology Companies*, an annual directory of technology-based companies with operations in the U.S. *CorpTech* has been used in numerous studies of technology firms (e.g. Lee, 2007; Sine, Mitsuhashi, & Kirsch, 2006; Stuart, Hoang, & Hybels, 1999), because it covers a large number of public and private firms in diverse technology-intensive industries: 64,688 firms in 17 industries are listed during our study period, ranging from tiny, emerging start-ups to established, public firms. *CorpTech* data are gathered by surveying establishments found through a variety of methods, from industry trade organizations to press releases to telephone directories. Initial surveys are conducted by telephone with a firm executive and the information is also verified through other sources. Subsequent annual listings are updated by phone or mail. Listings contain information about the firm, including executives' names, titles, and functional responsibilities, the primary product categories sold by the firm, sales, founding year, ownership, and a qualitative description of the firm's business. Since *CorpTech* is primarily sold and used as a sales contact database, the quality of management team data is important to the *CorpTech* product. Names and titles are

continuously updated using press releases and testing of contact information¹, giving some assurance that executive-level staffing changes will be recorded in the directories.

We rely on these data to identify career boundary-crossing by entrepreneurs. Specifically, we first identified over 30,000 unique executives who were listed in more than one firm in the *CorpTech* database from 1989-2004, indicating that these executives experienced job mobility across *CorpTech* firms during this 16-year time period. We excluded instances where executives moved between a parent firm and one of its divisions and instances where executives moved between different divisions of the same parent firm. Relying on *CorpTech* records as a source for entrepreneurs' career histories presented the challenge of ensuring that each entrepreneurial leader could be uniquely identified across time, such that his or her career designations and job mobility could be tracked. To uniquely identify an executive, we matched records based on identical first, middle, and last names and also took into account any name suffixes (e.g., Jr. vs. Sr.). Next, we examined the database for instances where there were multiple identical name listings in different firms in the same year. We assumed that a single individual is unlikely to be a leader at multiple firms during the same year, and attempted to resolve these conflicts by searching for biographical data online. We excluded those instances for which we were unable to determine whether the executive name represented a unique individual vs. multiple individuals. Many of these involved "common" names, for which there was often some ambiguity about the individual's uniqueness (e.g., whether or not Bill Holt at Eon Labs and Bill Holt at Process Chemicals were the same person). To be conservative in our identification of unique entrepreneurs (and avoid false matches that would inflate our measures

¹ <http://www.corptech.com/business-information/methodology.php>

of career boundary-crossing), highly common names (e.g., “Mr. David Smith”) were also excluded from the analysis.

This process identified 36,944 distinct mobility events, where 32,610 unique executives moved from 19,792 distinct firms (“Origin Firms”) to 22,863 distinct firms (“Destination Firms”) between 1989 and 2004. Out of these 36,944 mobility events, there were 2,516 instances where the executive joined privately-held Destination Firms as an entrepreneurial leader (CEO or President). Because we are investigating entrepreneurial leaders who joined as founders or early leaders, we further restricted the sample to include only entrepreneurial leaders who joined their Destination Firms within 3 years of founding. We were left with a set of 1,015 distinct ventures with entrepreneurial leaders who joined from another *CorpTech*-listed firm. We compiled longitudinal data on these 1,015 ventures from 1990 to 2004, so our data have a panel structure with firm-year observations.

The *CorpTech* database has three characteristics that make it well-suited to the questions studied here. First, once a mobile executive is identified, the quality and accuracy of individual-level information is likely to be good given the importance of these data to the product that *CorpTech* sells. Second, *CorpTech* contains data about functional responsibilities of individuals. Given the proliferation and ambiguity of job titles in U.S. organizations (Baron & Bielby, 1986; Miner, 1987), functional responsibilities of individuals can be difficult to consistently infer from most archival data sources. *CorpTech’s* data gathering practices standardize reporting of functional responsibilities so that functional boundary-crossing can be observed. Third, *CorpTech’s* proprietary product category codes enable a fine-grained examination of entry into product areas that are new to the firm that is useful for our examination of boundary-crossing.

We used Thomson Financial Securities Data's *VentureExpert* database to identify VC funding events, and used Thomson's *Mergers and Acquisitions* database to identify takeovers of companies in our sample, in order to differentiate between firm exits due to failure and exits due to acquisition.

Startup Outcomes

Entry into New Product Area

To measure new product introduction, we compare firms' *CorpTech* product listings in a given year to their product listings in the previous year. *CorpTech* assigns proprietary product-industry codes to the portfolio of product offerings of each firm. *CorpTech's* proprietary product coding scheme has more than 3000 product level codes and is considerably finer-grained than other types of industry classification, such as firm-level SIC or NAICS, in that it categorizes individual product offerings into industry segments, instead of assigning broad primary or secondary industry codes at the firm level (Cockburn & MacGarvie, 2011). Therefore, coding at the product level can reflect the multiple industry segments that a firm's products actually compete in. *CorpTech* product codes classify products at three nested levels of specificity: sector, industry, and segment. We use the segment-level specification to determine if the firm has entered into a new product area. If the product listings include new product categories in a given year, *Entry into New Product Area* is set to 1, 0 otherwise. After excluding cases with missing data, the resulting new product area entry data set included 2,380 firm-year observations for 748 firms.

Startup Performance

We operationalized startup performance as firm survival, the ultimate measure of firm performance. We recorded startup failure (*Failure Rate*) as the first year a firm is either listed as

out of business, or the firm listing for the company disappears from the *CorpTech* directories (continued listing indicates survival). *Failure Rate* is coded 1 in the year of de-listing, 0 otherwise. However, firms may also be de-listed from the *CorpTech* directory if they are acquired by other firms. Acquisitions are often considered successful exits for startup firms (Graebner & Eisenhardt, 2004), so we censored the final spells for firms that were acquired, rather than treating them as failures.

Independent Variables

Entrepreneur Boundary-crossing

For the key independent variables, we considered two dimensions of career boundary-crossing on the part of entrepreneurs: industry and functional. These measures capture the differences between the entrepreneurial leadership position and the job immediately prior. First, for industry boundary-crossing, we constructed a variable (*Industry Boundary-crossing*) that measures the proportion of the industry portfolio that is different between the startup and the prior firm. We base the industry portfolio on *CorpTech's* classification of products. We use these codes to derive product-based NAICS classifications for the startups that captures the set of industries that the startups compete in. To the extent that the entrepreneur is dealing with a different set of industries in the entrepreneurial leadership position and prior job, we consider industry boundary-crossing to have occurred. This proportion variable ranged from 0 to 1 in the analysis sample.

For functional boundary-crossing, we classified primary functional responsibility areas for each entrepreneur's positions as reported in *CorpTech* into six functional categories: General Management, Marketing, Technology/Science/R&D, Operations, Strategy, and

Administrative/Financial/Legal. *Functional Boundary-crossing* measures the proportion of functional areas that changed as an entrepreneurial leader entered a startup. This measure ranges from zero to one in the analysis sample, with zero indicating that none of the entrepreneur's current primary functional responsibilities are new (the entrepreneur has had prior experience in all of his or her current functions) and one indicating that all of the entrepreneur's current primary functional responsibilities are new to him or her. These functional areas were based on *CorpTech's* recording of functional areas. As part of their updating process, *CorpTech* records functional responsibilities in 25 detailed categories (*e.g.*, Marketing, Public Relations, Sales, etc.), which we then collapsed into the six broader categories. Each entrepreneur can have multiple primary functional responsibility codes, and we used all of the primary functional responsibility codes to calculate change in responsibilities.

Controls

We included control variables to account for characteristics of the entrepreneurial leader and the venture that might also affect the likelihood of entering new product areas and venture performance. First, we controlled for several entrepreneur characteristics. Our primary predictors of interest are industry and functional boundary-crossing of entrepreneurs who have moved between firms, but characteristics of the entrepreneur's position in the prior firm and the new firm, as well as personal characteristics might also have a direct effect on entry into new product areas and venture performance. *Leader-Founder* indicates if the entrepreneurial leader was also the founder of the startup. We also controlled for advanced education, *i.e.* if the entrepreneurial leader held a Ph.D., M.D. or J.D. (*Leader-Doctor*), and gender (*Leader-Female*).

Prior firm – Leader indicates if the entrepreneurial leader was also the highest ranking leader of his or her prior firm.

Second, we controlled for characteristics of the firms the entrepreneurial leader left and joined. For the startup, *Firm Age* in years and firm size measured as both *Headcount* and *Sales* (\$'000s) could affect the likelihood of entry into new product areas and venture performance because they represent resources available to the firm. Another factor that could affect a startup's resources is the competitiveness of the industry segments that the firm participates in. We measured *Competitive Environment* using *CorpTech's* annual listing of competitors. *CorpTech* uses its proprietary product coding to identify firms with products in each industry segment. We also controlled for the startup's *Current Product Areas*, measured as the firm's number of unique product-industry codes in a given year. Next, venture capital funding also influences resources available, but in addition, having venture capitalists involved with the startup may increase the likelihood of outcomes that enable "cashing out" (i.e., acquisition or IPO) over others (Metrick & Yasuda, 2010). Therefore, we control for *VC funding* using a binary variable set to 1 if the startup had VC funding and 0 otherwise. Additionally, we included a set of dummy variables indicating a startup's primary industry (e.g., *Manufacturing*, *Medical*, *Computer Hardware*, etc. *Other* is the missing category), region (*Northern CA*, *Southern CA/HI*, *NY Metro*, *New England*, *Other* is the missing category) and year effects to capture variance due to economic or market fluctuations.

For the prior firm, we include controls that account for larger and older firms, since entrepreneurial leaders moving from large firms might face issues in making a transition to a startup. *Prior firm – Size* is 1 when the prior firm had more than 5000 employees, 0 otherwise, and *Prior firm – Age* is the age of the prior firm. *Prior firm – Competitive Environment* captures

if the entrepreneurial leader has experience in competitive environments and is measured in the same way as the analogous measure for the current firm. We also designate if the entrepreneurial leader's prior firm was *VC funded* or *Public* as an indicator of experience with VC funded or public firms.²

ESTIMATION AND RESULTS

Entrepreneur career boundary-crossing and entry into new product areas

Table 1 shows results for Hypothesis 1 and 2, which predicted that boundary-crossing in entrepreneurs' industry and functional experience is positively related to entry into new product areas.

 Table 1 about here

To test these hypotheses, we ran cross-sectional time series logit models, with data in a firm-year panel structure. All models were estimated with the Huber-White correction for standard errors that are robust to heteroskedasticity (Huber, 1967; White, 1980).

Model 1 in Table 1 is the baseline model, containing all the control variables described above. The positive and significant industry controls for *Computer Software* and *Telecom & Internet* indicate that startups with those primary industry classifications are more likely to enter into new product areas, as are startups located in *Southern CA/HI*, *NY Metro*, and *New England* regions. In addition to industry and region controls, the size of the startup and its current number of product areas are both strong predictors of the likelihood on entry into new product areas.

² Descriptive statistics and the correlation matrix for the variables used in the *Entry into New Product Area* analysis are available from the first author.

Model 2 considers the effect of entrepreneur industry and functional boundary-crossing, the independent variables of interest, on entry into new product areas by adding *Industry Boundary-crossing* and *Functional Boundary-crossing* to the baseline model. The coefficient on *Industry Boundary-crossing* is negative, contrary to Hypothesis 1's predicted direction, but is not statistically significant. The estimated coefficient on *Functional Boundary-crossing* is positive and statistically significant, thus supporting Hypothesis 2. According to the estimate, having an entrepreneur who crossed functional boundaries when joining or founding a venture increases the odds of entry into new product areas by 1.58. Model 2 is a statistically significant improvement over the base model (Model 1) ($\chi^2 = 6.7$, 1 d.f., $p < .01$).

Entrepreneur career boundary-crossing and startup performance

Table 2 displays initial reference results for Hypotheses 3 and results for Hypothesis 4.

 Table 2 about here

To provide a reference for our models of startup performance, we estimated piecewise exponential hazard rate models of failure, with firms exiting the risk set after failure.

Specifically, to determine the risk of a firm failing in any given year, we estimated $r(t)$, the instantaneous hazard rate of failure,

$$r(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t, t + \Delta t)}{\Delta t}$$

where \Pr is the likelihood that a firm fails in the interval $(t, t + \Delta t)$. We used piecewise exponential models, which do not require assumptions about the effect of time (firm age) on

failure. The models estimate baseline rates (constants) for each age segment, but allowed the rate of firm failure to vary in an unconstrained way across age segments.

The event histories of each firm were broken into one-year spells (resulting in 4,248 spells for 871 firms) in order to incorporate time-varying covariates. We treated each of the yearly spells as right-censored, except for those that terminated in firm failure.

Model 3 is the baseline model, containing all the control variables. The coefficients on the four age periods show that failure rates increase with age. The industry dummies for *Computer Hardware* and *Telecom and Internet* are positive and statistically significant, showing that startups in these industries have higher failure rates, as do startups in the *Southern CA/HI* region. Unsurprisingly, the negative and statistically significant parameter estimates for *Headcount*, *Sales*, and *Firm Age* suggest that failure rates are lower for larger and older startups. In addition, startups that received VC funding have lower failure rates, as do firms that are in a larger number of product areas. Surprisingly, none of the variables representing entrepreneur characteristics are statistically significant. An entrepreneur's gender, education, and prior experience as leader appear to have no effect on firm failure rates.

Model 4 adds *Industry Boundary-crossing* and *Functional Boundary-crossing* to the base model. The parameter estimate on *Industry Boundary-crossing* is positive and statistically significant, thus suggesting that industry boundary-crossing is positively related to failure, i.e. negatively related to startup performance. According to the estimate, having an entrepreneurial leader who crossed industry boundaries when joining or founding a venture increases the likelihood of failure by 49 percent. Model 4 is a statistically significant improvement over the

base model (Model 3) ($\chi^2 = 4.6$, 1 d.f., $p < .05$). The coefficient on *Functional Boundary-crossing* is not statistically significant, providing no support for H4.³

The preceding survival analysis suggests that industry boundary-crossing is generally bad for startups; however, Hypothesis 3 predicts that industry boundary-crossing will be associated with both extremes of performance. Therefore, we conduct additional analysis of competing risks for positive and negative outcomes for startups whose leaders come from different industries. Failure is not the only outcome of interest for startups. For startups in particular, IPOs and acquisition events are alternative outcomes that are indicative of good performance. We consider these critical performance outcomes for entrepreneurial startups: IPO, Acquisition, and Failure. Each of these represents important performance outcomes that mark the end of a startup's life, but they also represent extremes of performance, with IPO and acquisition representing transition to a more stable organizational life, and failure representing organizational death.

To explore these alternative outcomes, we created a cross-sectional version of our dataset by taking values of the independent variables in the year of the entrepreneurial leader's move. We used these data to estimate multinomial logit models that simultaneously estimate models of the discrete outcomes, making pairwise comparisons of IPO, Acquisition, and Failure against the base case of continuation of the startup without ownership change. We categorized startup performance into four categories that represent important performance outcomes for high-tech startups: *Failure*, *IPO*, *Acquisition*, and Continuing as the omitted category. For the first

³ For robustness purposes, we also estimated our product area entry and firm failure models using alternate measures of our key independent variables. Specifically, for industry boundary-crossing, we considered measures using product SIC codes instead of product NAICS codes. For functional boundary-crossing, we used a measure that separated Administrative/Financial/Legal into distinct categories. These alternate measures of industry and functional boundary-crossing did not change the direction and statistical significance of our main findings.

outcome, we set *IPO* equal to 1 if the startup has an IPO while the entrepreneurial leader is leading the startup, 0 otherwise. We derive this information from *CorpTech*, which records whether a firm is publicly- or privately-held. We verify and supplement these data with records from *VentureXpert* about IPO events for firms that received venture capital funding. We also use these data sources for the second outcome, setting *Acquisition* equal to 1 if the startup is acquired during the entrepreneurial leader's tenure, 0 otherwise. We record an acquisition if the owner code of the entity changes in *CorpTech*'s database, or notes in the database indicate an acquisition. Again, we use *VentureXpert* to verify and supplement the data for firms that received venture capital funding. For the third outcome, *Failure*, we mark a firm as failed if it is no longer listed in *CorpTech* without explanation or is listed as out of business in the notes. After excluding cases with missing data, for the 803 firms remaining in the analysis sample, 32 experienced IPOs, 114 were acquired, 213 failed, and the remainder were still in business as of the end of the study period.

Table 3 shows the results for the multinomial logit models of *Failure*, *Acquisition*, *IPO*.⁴

Table 3 about here

In Table 3, Model 5 is the baseline model, containing all the control variables. The industry dummies for *Manufacturing Equipment*, *Advanced Materials*, and *Chemicals* are negative and statistically significant, showing that ventures in these three industries have a lower likelihood of having IPOs. At the same time, startups in *Advanced Materials* and *Chemicals* are less likely to be acquired, while startups in *Photonics* and *Computer Software* are more likely to

⁴ Descriptive statistics and correlations for the variables used in the multinomial logit model are available from the first author.

be acquired. Startups in *Computer Hardware* and *Telecom & Internet* are more likely to fail, while those in *Chemicals* are less likely to fail than those in *Other* industries (omitted category). For regions, *Northern CA* startups are more likely to have IPOs or to be acquired than other regions, while startups in the *NY Metro* area are less likely to have IPOs and more likely to fail. Next, having a female leader reduces the likelihood of having an IPO and increases the likelihood of acquisition for a startup, while having a leader who is also a founder of the startup increases the likelihood of both IPO and Acquisition. Having higher dollar sales increases the likelihood of acquisition, but having higher headcount is associated with decreased likelihood of failure. Finally, having VC funding increases the likelihood of acquisition, and decreases the likelihood of failure, consistent with previous findings. None of the variables characterizing an entrepreneurial leader's prior firm are statistically significant.

Model 6 adds the independent variables of interest. Model 6 is a statistically significant improvement over Model 5 ($\chi^2 = 9.9$, 1 d.f., $p < .01$). As Model 6 shows, the coefficient for *Industry Boundary-crossing* is positive and significant for the outcome of failure, suggesting that startups led by entrepreneurial leaders who cross industry boundaries are more likely to fail, which is consistent with our survival analysis. At the same time, the parameter estimates for *Industry Boundary-crossing* are positive and statistically significant for the outcome of IPO, suggesting that startups led by entrepreneurial leaders who cross industry boundaries are more likely to go public. *Industry Boundary-crossing* was not related to the likelihood of acquisition, and *Functional Boundary-crossing* was not significant in these models. Taken together, these models show some support for Hypothesis 3, which predicted more extreme outcomes for industry boundary-crossing.

DISCUSSION

Our central interest in this paper is to understand how entrepreneurial leaders' boundary-crossing affects outcomes of startups. Because entrepreneurship is essentially about creating something new, entrepreneurs necessarily cross boundaries when they found or lead startups. Their boundary-crossing enables the emergence of novel innovation and its formation into new products that define a startup's identity or shape the boundaries of product categories that the startups enter. Because entrepreneurs are so central to the new ventures they lead, understanding how their backgrounds affect the capabilities they bring to startups enables better understanding of the sources of startup performance. We draw on organizational learning and human capital perspectives to develop arguments about elements of experience that entrepreneurial leaders may carry as they move into startups, and how they affect entry into new product areas and startup performance.

First, we find that functional boundary-crossing and industry boundary-crossing have distinctly different effects on important entrepreneurial outcomes. The more a person's functional responsibilities change as they move into an entrepreneurial leadership position, the more likely the startup is to move into new product areas. By contrast, industry change doesn't seem to be related to entry into new product areas. Entrepreneurial leaders crossing into new industry areas, all else equal, are making a deliberate choice to go into the new industries and may be unwilling to vary the industry portfolio of products, at least in the short term, whereas entrepreneurial leaders who do not change industries, but accrue or change functional responsibilities may be more willing to implement changes in product areas the startup participates in. Together, these findings suggest that entry into new product areas for startups is less a matter of transporting industry-specific knowledge, than it is about innovating to develop

new products or market opportunities and being able to implement these changes. The findings highlight the importance of diverse functional skills to the innovation process. The formation of innovation into viable, marketable products entails overcoming implementation challenges, which functional boundary-crossing appears to facilitate.

It is worth noting that on the surface, our results appear to be inconsistent with an important study of executive migration that finds that firms enter new product areas when they recruit CEOs whose prior firms were in those product areas (Boeker, 1997). Our study differs from Boeker (1997) in some important ways that might drive the differences in results. First, Boeker (1997) is situated in the semiconductor industry and includes only CEOs recruited from other semiconductor firms. In fact, CEOs recruited from other industries are excluded from analysis (p. 222), since they are unlikely to carry the industry-specific human capital of interest to that study. By contrast, our study's focus is on boundary-crossing and understanding the costs and benefits of changing industries. In addition, focusing on the semiconductor industry enables Boeker (1997) to have a tighter focus on strategic change, since for established firms, product market entry necessarily involves strategic change. For startups, product market entry could be part of the implementation of an initial strategy, not necessarily constituting change; and, strategic change issues are substantively different for established firms, with their established systems and practices.

We find that industry boundary-crossing has a generally negative relationship with firm survival, though it also positively associated with IPOs, a big win for startups. There is increasing evidence that that boundary-crossing and boundary-spanning innovations are associated with extreme outcomes (G. Hsu et al., 2012; Taylor & Greve, 2006). We show that the boundary-crossing of entrepreneurial leaders in their careers also shows this pattern of

outcomes. Our analysis offers only a cross-sectional snapshot of eventual outcomes for startups, without analytically accounting for censoring, but it provides some insight into how industry boundary-crossing plays out in a competing risks format. This pattern of findings suggests that industry boundary-crossing increases the probability of developing innovative products that address needs of the startup's initial industry in new ways and can enable an IPO. We cannot test this proposition directly, since CorpTech does not list new products, only entry into new product categories; however, future research can address this issue.

Interestingly, we did not find a positive relationship between functional boundary-crossing and firm performance, as we predicted in Hypothesis 4. Functional boundary-crossing may generate the ideas and wherewithal to enter new product areas, as predicted and found in Hypothesis 2, but these strategic changes or innovations may not produce the performance necessary to survive. Further, entry into new products areas is generally considered a positive move for established firms, but our findings bring this general assumption into question for less established startups. For established firms, product area entry generally signifies exploratory innovation, which opens new market opportunities, or strategic change, which is assumed to bring the firm into alignment with a changed environment. For startups, new product entry could signify either of these things, but it could also indicate an initial strategy that is unstable or unfit for the market, leading to early strategic change. Multiple early changes could then be an indicator of poor strategy development capabilities that do not contribute positively to startup performance.

Despite providing some evidence that both industry and functional boundary-crossing influence important startup outcomes in different ways, our study suffers from important limitations. First, though *CorpTech* has numerous advantages for our purposes, it is less than

ideal as a source of mobility data. In order for a mobility event to be recorded in these data, an entrepreneur must have held a leadership position in another *CorpTech* listed firm in the time period 1989-2003, and we must have been able to reasonably identify the individual by name. Because of these data limitations, our sample of mobile entrepreneurs is considerably reduced. If there is a systematic reason why the entrepreneurs are missing from the sample, then the estimates would be biased. Second, there are a number of other entrepreneur characteristics that could affect the startup outcomes. An entrepreneur's entire career history prior to the entrepreneurial leadership position could also contain industry-specific experience or a broader range of industry and functional experience than is available in the *CorpTech* data. Also, more refined demographic information, such as leader's age or years of education might be valuable controls. Like other employer-employee matched samples, we trade off richness of data for breadth of coverage (Campbell, 2005). Despite data limitations, *CorpTech* contains better function-level data than are commonly available, which allow us to examine functional boundary-crossing. Finally, a considerable strength of our study is the breadth of high-technology industries we cover; however, the results of our findings may not be generalizable to entrepreneurship outside of the high technology sector. High technology industries tend to change quickly, requiring agility in leadership that other entrepreneurial contexts may not need.

Nevertheless, our findings contribute to the rich literature on entrepreneurs' backgrounds and startup performance. Most of this literature has taken a human capital perspective, using general measures of human capital like education or total work experience (e.g. Colombo & Grilli, 2010; Davidsson & Honig, 2003), with a few studies that consider industry-specific experience (e.g. Dencker et al., 2009; Gimmon & Levie, 2010). We introduce functional work as another general aspect of human capital that affects knowledge and perspectives that are

carried into entrepreneurial jobs. Functional experience merits special attention in the entrepreneurship context because the nature of functional work differs substantively for entrepreneurial leaders versus leaders more generally. Entrepreneurs need to not only lead and coordinate, but also to pitch in to perform functional work where needed, especially in the earlier stages of a startup's life. By examining industry and functional boundaries separately, we are able to gain a more precise understanding of how human capital transfers into entrepreneurial contexts.

We also emphasize boundary-crossing, i.e. differences in industry and function, rather than similarity between the entrepreneurial leadership job and the prior job in order to focus on boundary-crossing as a theoretically interesting feature of experience. Taking a boundary-crossing approach enables us to expand theoretical focus to include job mobility and organizational learning and to consider how these relate to the emergence of innovation. The entry of startups into new product areas with innovative new products represents formation, in that the products declare the identity of the firm and its membership in product market categories, which can in turn shape the identity or boundaries of the categories. Considering mechanisms of external learning generates new predictions about how boundary-crossing entrepreneurs could lead to both positive and negative outcomes for the startups they lead. Our findings indicate the usefulness of this approach, and bring us a step closer to understanding the full role entrepreneurial leaders' backgrounds play in influencing startup performance.

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Table 1: Cross-sectional Time Series Logit Models of Entry into New Product Area

	Model 1		Model 2	
	Coeff.	se	Coeff.	se
Year Effects	incl.		incl.	
Industry Controls				
Biotechnology	0.78	(0.45)	0.87	(0.44) *
Photonics	0.80	(0.59)	0.73	(0.58)
Manufacturing Equipment	0.96	(0.71)	0.80	(0.70)
Medical	0.30	(0.54)	0.35	(0.54)
Computer Hardware	-0.41	(0.59)	-0.33	(0.58)
Computer Software	0.91	(0.32) **	0.86	(0.32) ***
Telecom & Internet	0.77	(0.33) *	0.85	(0.33) **
Advanced Materials	0.56	(1.28)	0.54	(1.26)
Chemicals	-0.25	(1.17)	-0.08	(1.17)
Region Controls				
Northern CA	0.29	(0.20)	0.30	(0.20)
Southern CA/HI	0.66	(0.29) *	0.64	(0.28) *
NY Metro	0.69	(0.30) *	0.61	(0.30) *
New England	0.43	(0.22) *	0.43	(0.22) *
Leader Female	-0.39	(0.41)	-0.40	(0.41)
Leader Doctor	-0.55	(0.43)	-0.60	(0.42)
Leader Founder	-0.07	(0.40)	-0.03	(0.39)
Headcount ^a	0.29	(0.07) ***	0.27	(0.07) ***
Sales (\$'000) ^a	0.002	(0.02)	0.003	(0.02)
Firm Age	0.02	(0.03)	0.01	(0.03)
VC Funded	0.22	(0.18)	0.25	(0.18)
Competitive Environment ^a	0.04	(0.11)	0.05	(0.11)
Current Product Areas	0.34	(0.05) ***	0.34	(0.05) ***
Prior firm - Leader	0.18	(0.16)	0.44	(0.20) **
Prior firm - Size	0.27	(0.28)	0.31	(0.28)
Prior firm - Age	0.001	(0.005)	0.002	(0.005)
Prior firm - Competitive Env. ^a	-0.08	(0.08)	-0.10	(0.08)
Prior firm - VC funded	0.005	(0.17)	-0.01	(0.17)
Prior firm - Public	-0.12	(0.18)	-0.17	(0.18)
Boundary Crossing				
Industry Boundary Crossing			-0.32	(0.19)
Functional Boundary Crossing			0.46	(0.23) *
Constant	-1.59	(1.64)	-1.73	(1.63)
Observations		2380		2380
Groups		748		748
Chi-squared		144.07 ***		152.20 ***
Log Likelihood		-784.62		-781.25
* p < .05; ** p < .01; *** p < .001				
^a natural log of value				

Table 2: Piecewise Exponential Hazard Rate Models of Firm Failure Rates

Table 3: Piecewise Exponential Hazard Rate Models of Firm Failure Rates						
	Model 3			Model 4		
	Coeff.	se		Coeff	se	
0-1 Years	-8.07	(1.33)	***	-8.38	(1.35)	***
1-2 Years	-5.74	(1.24)	***	-6.05	(1.26)	***
2-5 Years	-5.08	(1.24)	***	-5.40	(1.26)	***
5+ Years	-4.53	(1.30)	***	-4.87	(1.32)	***
Year Effects	incl.			incl.		
Industry Controls						
Biotechnology	0.01	(0.54)		-0.03	(0.54)	
Photonics	-0.19	(0.76)		-0.19	(0.76)	
Manufacturing Equipment	0.48	(0.76)		0.61	(0.76)	
Medical	-0.33	(0.76)		-0.36	(0.76)	
Computer Hardware	0.84	(0.40)	*	0.80	(0.40)	*
Computer Software	0.33	(0.28)		0.38	(0.28)	
Telecom & Internet	0.73	(0.28)	**	0.67	(0.28)	*
Advanced Materials	1.00	(1.05)		1.11	(1.05)	
Chemicals	1.23	(1.10)		1.08	(1.10)	
Region Controls						
Northern CA	0.09	(0.18)		0.09	(0.18)	
Southern CA/HI	0.52	(0.24)	*	0.53	(0.24)	*
NY Metro	0.37	(0.26)		0.43	(0.26)	
New England	0.06	(0.22)		0.08	(0.22)	
Leader Female	-0.02	(0.29)		-0.03	(0.29)	
Leader Doctor	-1.40	(0.75)		-1.40	(0.75)	
Leader Founder	0.14	(0.27)		0.14	(0.27)	
Headcount ^a	-0.12	(0.06)	*	-0.12	(0.06)	*
Sales (\$'000) ^a	-0.03	(0.02)	*	-0.03	(0.02)	*
Firm Age	-0.19	(0.06)	**	-0.18	(0.06)	**
VC Funded	-0.52	(0.16)	**	-0.52	(0.16)	**
Competitive Environment ^a	0.06	(0.08)		0.04	(0.08)	
Current Product Areas	-0.12	(0.05)	*	-0.11	(0.05)	*
Prior firm - Leader	0.02	(0.15)		0.03	(0.19)	
Prior firm - Size	0.07	(0.28)		0.07	(0.28)	
Prior firm - Age	-0.001	(0.004)		-0.002	(0.004)	
Prior firm - Competitive Env. ^a	-0.003	(0.07)		0.02	(0.07)	
Prior firm - VC funded	0.14	(0.15)		0.16	(0.15)	
Prior firm - Public	-0.15	(0.16)		-0.17	(0.16)	
Boundary Crossing						
Industry Boundary Crossing				0.40	(0.19)	*
Functional Boundary Crossing				0.01	(0.20)	
Spells		4248			4248	
Subjects		871			871	
Chi-squared		1547.25	***		1539.36	***
Log Likelihood		-481.54			-479.22	
* p < .05; ** p < .01; *** p < .001						
^a natural log of value						

Table 3: Multinomial Logit Models for Failure, Acquisition, IPO

	Model 5						Model 6					
	IPO		Acquisition		Firm Failure		IPO		Acquisition		Firm Failure	
	Coeff.	rob. se	Coeff.	rob. se	Coeff.	rob. se	Coeff.	rob. se	Coeff.	rob. se	Coeff.	rob. se
Year Effects												
Industry Controls												
Biotechnology	0.36	(1.84)	1.38	(0.91)	0.08	(0.83)	-0.47	(1.88)	1.19	(0.92)	-0.09	(0.84)
Photonics	1.97	(1.78)	2.33	(0.86)**	0.84	(1.02)	1.51	(2.11)	2.35	(0.85)**	0.87	(1.01)
Manufacturing Equipment	-13.57	(1.25)**	0.61	(1.41)	0.51	(0.91)	-13.12	(1.22)***	0.65	(1.47)	0.56	(0.89)
Medical	1.09	(1.88)	1.38	(1.06)	-0.13	(1.11)	0.42	(1.88)	1.27	(1.03)	-0.19	(1.10)
Computer Hardware	-1.24	(1.48)	1.38	(0.73)	1.54	(0.54)**	-2.13	(1.33)	1.20	(0.73)	1.38	(0.54)*
Computer Software	0.21	(1.00)	1.39	(0.58)**	0.73	(0.38)	0.14	(0.87)	1.45	(0.59)*	0.81	(0.37)*
Telecom & Internet	0.54	(1.05)	1.07	(0.59)	1.01	(0.38)**	0.23	(0.97)	0.99	(0.59)	0.98	(0.38)*
Advanced Materials	-12.93	(1.52)***	-14.08	(0.97)***	0.86	(0.81)	-13.06	(1.58)***	-13.96	(0.95)***	0.90	(0.80)
Chemicals	-17.12	(1.30)***	-16.23	(1.00)***	-16.34	(0.81)***	-17.58	(1.33)***	-16.47	(1.03)***	-16.62	(0.83)***
Region Controls												
Northern CA	2.09	(0.55)***	0.65	(0.29)*	0.35	(0.24)	2.12	(0.52)***	0.65	(0.29)*	0.35	(0.24)
Southern CA/HI	0.49	(1.00)	-0.09	(0.50)	0.63	(0.35)	0.45	(1.17)	-0.07	(0.51)	0.67	(0.34)*
NY Metro	-13.99	(0.75)***	-0.38	(0.63)	0.93	(0.36)*	-13.75	(0.81)***	-0.35	(0.62)	0.97	(0.36)**
New England	-0.61	(0.92)	0.17	(0.36)	0.08	(0.30)	-0.62	(0.89)	0.18	(0.36)	0.10	(0.30)
Leader Female	-14.34	(0.61)***	0.89	(0.45)*	0.12	(0.45)	-14.27	(0.74)***	0.94	(0.46)*	0.19	(0.46)
Leader Doctor	0.42	(1.36)	-0.88	(0.85)	-0.56	(0.84)	0.72	(1.45)	-0.78	(0.83)	-0.49	(0.85)
Leader Founder	2.57	(0.88)**	0.92	(0.46)*	0.41	(0.34)	2.73	(0.95)**	0.93	(0.46)*	0.43	(0.34)
Headcount ^a	0.34	(0.20)	-0.04	(0.12)	-0.31	(0.08)***	0.39	(0.20)*	-0.03	(0.12)	-0.30	(0.09)**
Sales (\$'000) ^a	-0.10	(0.06)	0.06	(0.03)*	0.02	(0.02)	-0.10	(0.06)	0.06	(0.03)	0.01	(0.02)
Firm Age	0.59	(0.35)	0.22	(0.14)	0.02	(0.11)	0.57	(0.35)	0.21	(0.14)	0.01	(0.12)
VC Funded	0.83	(0.63)	0.69	(0.30)*	-0.61	(0.22)**	1.21	(0.67)	0.73	(0.30)*	-0.60	(0.22)*
Competitive Environment ^a	0.16	(0.37)	-0.01	(0.16)	-0.07	(0.12)	0.11	(0.37)	-0.02	(0.16)	-0.10	(0.12)
Current Product Areas	0.03	(0.21)	-0.06	(0.10)	-0.08	(0.08)	0.01	(0.21)	-0.06	(0.10)	-0.08	(0.08)
Prior firm - Leader	0.97	(0.58)	0.27	(0.26)	0.13	(0.20)	1.34	(0.73)	0.22	(0.34)	-0.04	(0.27)
Prior firm - Size	1.16	(0.75)	-0.50	(0.57)	0.17	(0.40)	1.17	(0.81)	-0.52	(0.57)	0.15	(0.40)
Prior firm - Age	0.003	(0.01)	0.01	(0.01)	-0.003	(0.01)	-0.01	(0.01)	0.004	(0.01)	-0.004	(0.01)
Prior firm - Competitive Env. ^a	0.07	(0.22)	0.16	(0.13)	0.06	(0.09)	0.14	(0.22)	0.18	(0.13)	0.10	(0.10)
Prior firm - VC funded	0.84	(0.59)	0.40	(0.28)	0.08	(0.21)	0.96	(0.57)	0.45	(0.28)	0.12	(0.22)
Prior firm - Public	0.36	(0.50)	0.29	(0.29)	-0.21	(0.22)	0.27	(0.52)	0.29	(0.29)	-0.21	(0.22)
Boundary Crossing												
Industry Boundary Crossing							1.35	(0.70)*	0.52	(0.32)	0.54	(0.27)*
Functional Boundary Crossing							0.42	(0.69)	-0.09	(0.36)	-0.24	(0.28)
Constant	-6.71	(3.55)	-4.53	(1.50)**	-0.85	(1.05)	-7.90	(3.79)*	-4.87	(1.55)**	-1.08	(1.08)
Observations		803						803				
Chi-squared		10070.1***						10015.6***				
pseudo-Log Likelihood		-688.45						-683.53				
* p < .05; ** p < .01; *** p < .001. The omitted category for the dependent variable is Other.												
^a natural log of value												