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Survival of high tech firms: The effects of diversity of product–market portfolios, patents, and trademarks

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ABSTRACT

High tech firms can mitigate potential risks by diversifying their product–market portfolios. A key research question is how such diversification influences firm survival. A firm exits the market in two ways, specifically, dissolution and acquisition. Here, we model how the diversity of a new firm's product–market portfolio influences the times to both types of exits. Specifically, we allow for interaction effects of the competitive intensity of a firm's environment and the diversity of a firm's product–market portfolio with its patents and trademarks. Using a competing risk hazard model, we estimate the effects of various covariates on the time to exit for 1435 US high tech firms.

We observed that a more diverse product–market portfolio, in conjunction with a larger number of patents, hastens the time to a firm's exit by dissolution (9% decrease in survival duration), while in conjunction with a larger number of trademarks, portfolio diversity delays the time to exit by dissolution (12% increase). A more competitive firm environment results in a greater effect on the portfolio's diversity in delaying its exit by dissolution (7% increase). On the other hand, a diverse product–market portfolio, combined with either a larger number of patents or trademarks, hastens the firm's exit by acquisition (19% and 11% decrease respectively).

1. Introduction

New firms, particularly those in the high tech industry, face many challenges resulting in high exit rates. While firms like 3Cube, Neteos, Officeclick.com and Tower Technology failed within a few years of their incorporation, others like Microsoft, Apple, Intuit and Imation have survived and evolved into successful, large enterprises. Still others like Transarc, Intersolv and SoftSolutions were acquired by other firms (i.e., they exited through acquisition). While many factors affect the survival of new firms, their marketing decisions are crucial to their existence. As Lodish (2001) noted, “Marketing decisions are the most important decisions entrepreneurs make—and they make them very badly.” Yet, there are few research-based insights on the effects of a new firm's marketing strategies on its survival.

New firms face uncertainties about the relative attractiveness of their offerings and the markets they serve and they attempt to mitigate the risks associated with those uncertainties by offering a range of products to diverse markets (Stevenson & Gumpert, 1985). However, new firms face resource constraints as they attempt to generate positive cash flows, even as they develop, commercialize and market new products. Hence, a key concern for new firms is their method of using scarce resources as they develop their product–market portfolios. Some researchers (e.g., Meyer & Roberts, 1986) suggest that new firms falter because of their inability to focus on a small set of product-markets, whereas others (e.g., Chaston, 2001) argue the opposite, i.e. that new firms are overly dependent on narrow product-markets. In this paper, we examine the relationship between the diversity of a new firm's product–market portfolio and its survival.

The survival of a new firm is a relevant issue from both managerial and policy perspectives. New firms are an important source of job creation in the United States and in Europe, accounting for over 70% and 40% of net new jobs in the 1990s, respectively (Bednarzik, 2000). In the United States, new firms accounted for more than 67% of all innovations and 95% of radical innovations since World War II (Kauffman Center for Entrepreneurial Leadership, 1999). Yet, estimates of firm exit rates in the United States range from 62% in the first six years to 90% in the first ten years (http://www.sba.gov). Romano Prodi, in a European Union speech, expressed similar concerns, noting that entrepreneurial activity is lower in Europe than in the US, yet Europe has twice the failure rate of the US (http://europa.eu.int).

While significant work relating the effects of marketing mix decisions of well-established firms exists (e.g. Buzzell & Gale, 1987),

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insights into new firm marketing strategies are generally restricted to market entry strategies (e.g., Golder & Tellis, 1993; Srinivasan, Lilien, & Rangaswamy, 2004). New firms face considerable uncertainties about their products' commercial viability and customer acceptance, which they manage, in part, by diversifying their scarce resources across products and markets (Ansoff, 1957). This area has seen little academic research, perhaps because most new firms are privately held with few mandatory reporting requirements, which limits data availability. Further, most new firms have negative cash flows in their early years, making it problematic to study their financial performance. We focus on the link between a firm's product–market portfolio decisions and its survival, as a means of addressing the lack of relevant financial performance information. Thus, we explore how a new firm's marketing strategy, as represented by the diversity of its product–market portfolio, influences its survival.

A firm may exit the market either by being dissolved as a legal business entity or it may be acquired by another firm. While few studies have explored different types of firm exits (e.g. Astebro & Winter, 2002; Mitchell, 1994), we were unable to locate prior work that studied the effects of a firm's marketing strategy on the timing of these two types of exit.

An important theme in the strategy literature is the fit between a firm's strategic use of its resources (Capon, Farley, & Hoenig, 1990; Gatignon & Hanssens, 1987) and its environment (Miller & Friesen, 1983) to optimize its performance. We adapt this concept of strategic fit to develop hypotheses about the interaction effects between the diversity of new firms' product–market portfolio and two key resources, their intangible technological and marketing assets—patents and trademarks, respectively—on the type and length of survival duration. We develop a competing risks survival model (Diamond & Hausman, 1984; Han & Hausman, 1990) to estimate the effects of the covariates on the two types of exit. We use data on 1435 U.S. firms incorporated between 1993 and 2002; 324 firms exited by dissolution and 226 exited by acquisition during that period.

Our results support the competing risks model of firm exit via dissolution or acquisition, compared to a model without competing risks. Although a greater diversity of a firm's product–market portfolio does not, by itself, affect its exit either by dissolution or acquisition, greater diversity combined with more patents shortens the time to dissolution, while greater diversity, in addition to more trademarks, lengthens the time to dissolution. Similarly, greater diversity plus more patents is associated with a shorter time to acquisition, and greater diversity and more trademarks are associated with a shorter time to acquisition. Hence, increasing the diversity of their product–market portfolios may be a good approach for new firms that have a large stock of either patents or trademarks and are positioning themselves for early acquisition. For a firm whose goal is sustained existence through organic growth, it may be better to choose a narrower product–market portfolio. If such firms do pursue a broad product–market portfolio, they can leverage their trademarks, rather than their patents, to prolong their survival.

We organize the paper as follows. In the next section, we develop the conceptual framework. We then describe the data collection, the model and estimation procedures, and the empirical results. We conclude by discussing the paper's contributions, summarizing its limitations, and identifying directions for further research.

2. Hypotheses

Three considerations underlie our hypotheses. First, although every firm is subject to dissolution and acquisition risks, these two types of exits are different, motivating a competing risks model formulation. Nevertheless, there may be some common drivers (e.g., diversity of product–market portfolio and its interactions with other variables) of these two types of risks. Second, our primary focus is on the effects of the firm's strategic choices (i.e., the diversity of product–market portfolio) on its survival. Therefore, we do not hypothesize the main effects of a firm's technological and marketing assets of patents and trademarks, respectively, on its exit. Third, given the limited empirical research on the marketing strategies of new firms, we look to several related literatures to frame our hypotheses. In some instances, the findings in the related literatures are conflicting. In such cases, we present the opposing arguments and resolve the conflict empirically.[3]

2.1. Diversity of product–market portfolio

Exit by dissolution. A more diverse product–market portfolio generates economies of scale in the firm's marketing activities (e.g., distribution, customer relationship management) and increases the efficiency of its research and development (R&D), manufacturing, and marketing investments (Cohen & Levinthal, 1990). In addition, in technology-intensive industries, where most new technologies fail to achieve market acceptance, a diverse product–market portfolio embedding diverse technologies may create strategic “real options” for the new firm (Kogut & Kulatilaka, 2001). For example, titanium dioxide can be formulated to be used in paint, in plastic, in toothpaste and in paper production, suggesting numerous product–market options. In such situations, a firm with a diverse product–market portfolio may leverage its multiple products/technologies, increasing its chances for survival.

However, a diverse product–market portfolio, entailing the creation, commercialization, and marketing of different products in multiple markets, could be viewed, from an organizational learning perspective, as an exploratory routine (March, 1991). The returns to exploratory organizational routines are potentially larger, but are riskier and may be lower for the firm in the short- and medium-term (March, 1991), the time horizon we study. Thus, a new firm that diversifies its product–market portfolio may be trading short- and medium-term performance for superior long-term performance, but jeopardizing its survival by hastening its exit by dissolution.[4]

Exit by acquisition. We expect a different dynamic in the relationship between the firm's diversity of product–market portfolio and its exit by acquisition. First, access to the new product development pipelines of a target firm is a key acquisition motive (Walter & Barney, 1990). A diverse product mix is attractive to potential acquirers in technology-intensive industries because of the uncertainty about which of several technological trajectories will emerge as the dominant design (Anderson & Tushman, 1990; Srinivasan, Lilien, & Rangaswamy, 2006). Thus, a firm with a diverse product–market portfolio may represent a lower risk for the acquirer firm. Second, a diverse product–market portfolio may also signal the new (target) firm's technological and marketing expertise to potential acquirers (Buono & Bowditch, 1989) increasing its desirability as an acquisition target. A diverse product–market portfolio may also increase the new firm's visibility to more potential acquirers, increasing its chances of an early acquisition. Thus, more diversity in a firm's product–market portfolio should hasten its exit by acquisition.

[3] The possibility for an endogeneity bias exists. Thus, rather than the diversification of product portfolio influencing survival duration, a firm that performs well (implying a longer survival duration) may choose to diversify its product–market portfolio. However, superior firm performance is a necessary, but not sufficient condition for product–market diversification (e.g., Hall, 1995). Furthermore, in our analysis, we cannot include all explanatory variables to control for potential endogeneity of the diversity of product–market portfolio.

[4] To rule out the possibility of a non-linear effect of the diversity of the new firm's product–market portfolio on its exit by either dissolution or acquisition, we re-estimated our model including a quadratic term; we found no support for non-linearity.

2.2. Diversity of product–market portfolio and patents

Exit by dissolution. For new firms in the high technology sector, patents are often the key drivers for the firms' formation. Patents offer intellectual property protection (Lerner, 1997) and transferability of ownership, thus providing value for the firm both in use and in transfer (Grindley & Teece, 1997). Indeed, in the traditional conception of property rights, a firm's patents may be viewed as a way to secure rents for its innovation efforts through such mechanisms as licensing and litigation (Lanjouw & Schankerman, 2001).

We explore the effect of the interaction between the diversity of a firm's product–market portfolio and the number of its patents on exit by dissolution. When a firm with a more diverse product–market portfolio also has a large stock of patents, it has a greater potential to appropriate its innovation rents across different products and markets (Dutta, Narasimhan, & Rajiv, 1999), strengthening its performance and delaying its time to exit by dissolution.

An alternative perspective is that a firm with a large stock of patents is following a tight regime for appropriability of innovation rents through the licensing of its patents (Levin, Klevorick, Nelson, & Winter, 1987). Adherence to tight appropriability may potentially isolate the new firm from other profitable technological trajectories, leaving it technologically locked out of the market (Schilling, 1998) and stranded from the emergent dominant design (Srinivasan et al., 2006). Such a technological lockout is especially hazardous for new firms with more diverse product–market portfolios, as they face severe resource constraints. This line of argument suggests that the effect of the interaction between the diversity of a firm's product–market portfolio and the number of its patents should hasten the time to its exit by dissolution.

Exit by acquisition. Access to the target firm's patents is an important reason for acquisition, especially in high technology industries (Yli-Renko, Autio, & Sapienza, 2001). Typically, an acquirer firm has more resources and better access to markets than the target firm. Thus, a target firm with both a diverse product–market portfolio and a large number of patents provides an attractive portfolio of assets, increasing the desirability of acquisition. A firm with a diverse product–market portfolio and numerous patents will also achieve wide exposure to potential acquirers (among its competitors, suppliers, and customers) across different product-markets. Thus, the interaction between diversity of the firm's product–market portfolio and the number of its patents should hasten the time to its exit by acquisition.

2.3. Diversity of product–market portfolio and trademarks

Exit by dissolution. Like patents, trademarks represent transferable intangible assets, providing intellectual property protection for the firm's marketing investments (Hall, 1993). A new firm that registers its trademarks signals that it is pursuing a differentiation strategy with a focus on superior product quality and related investments in brand equity. Such a differentiation strategy has the potential to generate superior profit margins, higher customer loyalty and lower risk. When a new high tech firm has a diverse product–market portfolio, a larger number of trademarks within the firm are likely to strengthen and stabilize cash flows and increase the chances of firm survival. Thus, the interaction of the diversity of a firm's product–market portfolio with the number of its trademarks should delay its exit by dissolution.

Exit by acquisition. More trademarks should increase the attractiveness of a target firm to a potential acquirer (Anand & Singh, 1997; Delios & Beamish, 2001). When a firm with a diverse product–market portfolio also has a large number of trademarks, it signals to potential acquirers its strong brand equity, in addition to its capability to leverage that brand equity in diverse markets, increasing its desirability as an acquisition target. Furthermore, a firm with a diverse product–market portfolio and a large number of trademarks should achieve widespread visibility as an acquisition target across its diverse markets. Thus, interaction between the diversity of a firm's product–market portfolio and the number of its trademarks is likely to hasten its exit by acquisition.

2.4. Diversity of product–market portfolio and competitive intensity

Exit by dissolution. The competitive intensity of the firm's environment significantly affects both its performance and survival (Carroll & Hannan, 1989, 2000). The disadvantages of a diverse product–market portfolio discussed earlier, including the strains on the new firm's resources and capabilities, may be further intensified in competitive environments, lowering its performance and hastening its exit by dissolution. Alternatively, a diverse product–market portfolio may buffer the firm's performance in competitive environments, where several firms compete for scarce resources and customers (Carroll & Hannan, 2000), by enabling the firm to leverage several products in its portfolio and delay its exit by dissolution. We anticipate that the buffering effects of the diversity of product-market portfolio will prevail in competitive environments, delaying the firm's exit by dissolution.

A priori, we do not expect the interaction between product–market portfolio and competitive intensity to influence firm exit by acquisition, but we include this interaction term in the model for completeness. See Table 1 for a summary of these hypotheses.

3. Methods

3.1. Competing risks hazard model

We test our hypotheses using a competing risks hazard model that accommodates the simultaneous evolution of risks of dissolution and acquisition over time. The model has provided a useful framework for the analysis of concurrent risks of failure in different application areas, including labor economics (Diamond & Hausman, 1984; Han & Hausman, 1990), biostatistics (Lawless, 2002) and marketing (Chintagunta, 1998; Dekimpe, Parker, & Sarvary, 2000; Seetharaman & Chintagunta, 2003; Vilcassim & Jain, 1991). We develop an Accelerated Failure Time (AFT) model with time-varying covariates and shared frailty and use STATA 9.0 software to estimate the model parameters via maximum likelihood. The Appendix summarizes the model and the estimation approach.

Table 1
Summary of findings: diversity of firm's product–market portfolio and exit

Effects	Exit by dissolution	Exit by acquisition
	Hypothesized effect (results)	Hypothesized effect (results)
Diversity of product–market portfolio	H1D: The shorter (or longer) the time to exit by dissolution (not supported).	H1A: The shorter the time to exit by acquisition (not supported).
Diversity of product–market portfolio × number of patents	H2D: The shorter (or longer) the time to exit by dissolution (shorter time to exit supported).	H2A: The shorter the time to exit by acquisition (supported).
Diversity of product–market portfolio × number of trademarks	H3D: The longer the time to exit by dissolution (supported).	H3A: The shorter the time to exit by acquisition (supported).
Diversity of product–market portfolio × competitive intensity	H4D: The longer the time to exit by dissolution (supported).	H4A: No effect hypothesized (not significant).

Table 2
Descriptive statistics of measures

Variable	Mean (standard deviation)	1. Diversity of product–market portfolio	2. Number of patents	3. Number of trademarks	4. Competitive Intensity	5. Number of alliances	6. Sales growth	7. Number of employees
1. Diversity of product–market portfolio	0.963 (0.189)	1.00						
2. Number of patents	0.232 (1.557)	0.012	1.000					
3. Number of trademarks	0.935 (1.953)	0.022	0.191	1.000				
4. Competitive intensity	3982.6 (2789.3)	0.035	0.093	0.324	1.000			
5. Number of alliances	0.517 (3.269)	0.013	0.483	0.210	0.135	1.000		
6. Sales growth	0.978 (22.223)	0.016	0.089	0.012	0.022	0.004	1.000	
7. Number of employees	79.8 (327.5)	0.011	0.001	0.103	0.100	0.289	0.169	1.000

Note: correlations above 0.04 are significant at $p<0.01$, correlations above 0.03 are significant at $p<0.05$, and correlations above 0.02 are significant at $p<0.10$.

3.2. Data

We examine the exit of new firms in the technology-intensive industries of semiconductor, electronics, computer hardware and computer software in the United States between 1993 and 2002. We obtained data on these firms from the Corptech Directory of Technology Companies (http://www.corptech.com), used in previous firm exit studies (Barron, Hannan, & Burton, 1999; Puranam, Singh, & Zollo, 2006). Corptech conducts initial phone interviews with company executives, compiles company profiles and sends those profiles to company executives periodically to update and check on accuracy. Corptech collects and provides data on the firm until it exits the market, indicating whether that exit was by dissolution or acquisition.

We selected all firms in the Corptech database in industries that were incorporated between 1993 and 2002. Because we only consider new firms and not existing firms, the data are not left-censored; however, the data are right-censored at 2002. The data set consists of 1435 firms, resulting in 6924 firm-years of data. We observed 550 exits, of which, 324 were dissolutions and 226 were acquisitions, with the remaining data (885 firms) being right-censored. We next discuss the measures of the explanatory variables, all of which vary over time and are lagged by a year.

For the focal construct of diversity of product–market portfolio, we seek a measure that accounts for related and unrelated diversity of a firm's product–market portfolio, is simple, easy to compute, objective and replicable by other scholars. Following these criteria, we use the entropy measure of diversity developed by Jacquemin and Berry (1979) and subsequently refined and empirically tested by others (Chatterjee & Blocher, 1992; Palepu, 1985; Stern & Henderson, 2004). This measure captures three elements: 1) the number of market segments, 2) the distribution of products across these market segments, and 3) the degree of relatedness among the market segments.[5]

The entropy measure is “a weighted average of a firm's diversification within sectors”, and the weights are the logarithms of the inverse of the proportion of total products in each segment (Jacquemin & Berry, 1979; p. 362; Chatterjee & Blocher, 1992). Thus, the formulation of the diversification measure is as follows: $\text{Diversity}_i = \sum_{i=1}^{n} [P_i \times \text{Ln}(1/P_i)]$, where $P_i \neq 0$ is the proportion of products serving market segment *i*, where the market segment is an industry sector measured by the four-digit standard industry classification (SIC) code, so that the proportions of a given firm across all segments is equal to 1. For example, if a firm sells 40% of its products in one segment and 60% of its product in the second segment, the diversity index for the firm is 0.67. If a firm sells 20% of its products in five segments, the diversity index for the firm is 1.61 We compiled data from the Corptech database on the number of markets (denoted by the four-digit SIC code) the firm operated and the number of product groups within each market to compute the proportion P_i. The number of markets varies across firms (mean = 4.12, standard deviation = 2.58).

We obtained the *cumulative number of a firm's patents and trademarks* from the United States Patents and Trademarks Office (http://www.uspto.gov) and we measured the *competitive intensity* for each year as the number of firms in the firm's base industry, which we obtained from the Corptech directory.

Based on insights from the literature, we also included four control variables in the hazard model, which we expect would affect the exit of new high tech firms. First, we included the *number of alliances* for the firm in a year, which strengthens a new firm's performance (Mitchell & Singh, 1996). We collected the alliance data from the SDC Thompson Financial database. Second, we included the firm's *sales growth*, measured as the percentage change relative to the previous year's sales, an indicator of new firm performance. Third, we included the firm's *size* as measured by the number of its employees, a key resource for a new firm (Bruderl & Schussler, 1990). Fourth, because the period includes the late 1990s when developments related to Internet may have influenced new firm activity, we included the *value of the NASDAQ index in the year of firm incorporation* to account for any cohort-specific effects that may affect firm exit (Boeker, 1989).

4. Results

4.1. Descriptive statistics

Table 2 summarizes descriptive statistics for the key variables. Given our focus on new firms in their early years of existence, it is not surprising that the mean number of employees of firms was low at 79.8, with a standard deviation of 327.5, suggesting significant variation across firms. The average duration of a firm's lifetime was 4.0 years for firms that exited by dissolution and 3.5 years for firms that exited by acquisition.

The highest correlation ($\rho = 0.483$) among explanatory variables is between patents and alliances. We assessed potential threats from multicollinearity and found that the VIF (Variance Inflation Factor) and condition numbers were much lower than 10 (average = 1.231; maximum = 3.128) and 15, respectively (average = 1.319; maximum = 2.861), suggesting that multicollinearity and ill-conditioning of variables do not threaten the validity of our findings (Belsley, Kuh, & Welsch, 1980).

4.2. Model estimation and selection

We include all main effects of explanatory variables used to create the interaction terms. We mean-centered all variables to aid in the interpretability of the parameter estimates. We estimated the hazard model with the Weibull, Log-Normal and Log-logistic distributions, all

[5] We also explored an alternative measure of diversification (Wuyts, Dutta, & Stremersch, 2004), which was adapted from the Herfindahl's concentration index. The model specification with this alternative measure did not change the substantive nature of our findings, but had a poorer fit than the one specified here.

of which accommodate non-monotonic base hazard functions. While the pattern of results is generally similar across the three models testifying to the robustness of the results, the Log-logistic hazard model function provided the best log likelihood fit and we discuss the results from that formulation.

Fig. 1, which provides the (smoothed) base hazard function for exit by dissolution and acquisition, indicates a non-monotonic hazard function. The base hazard of a firm's exit by dissolution increases at a faster rate than the base hazard associated with acquisition, reaching a maximum four years after incorporation and then declining dramatically. On the other hand, the hazard for the firm's exit by acquisition increases at a much slower rate, peaking at about eight years after incorporation and declining, but not as rapidly. The hazard rate for exit by acquisition is substantially higher at the end of the ten-year period, relative to the hazard rate for exit by dissolution. While the survivability of firms (against exit by dissolution) strengthens over time, firms remain at substantial risk of exit through acquisition.[6]

Given the data availability constraints for new firms discussed earlier, there may be idiosyncratic characteristics of firms that we are unable to include in our model. Thus, in addition to the error term that accounts for potentially observable, but omitted variables, we also account for unobserved heterogeneity (e.g., the extent of entrepreneurial culture in a firm). We use two commonly applied heterogeneity distributions, namely, Inverse Gaussian and Gamma. Based on the Consistent Akaike's Information Criterion, the Inverse Gaussian distribution outperformed the Gamma distribution for both types of exits, and we report the results for the Inverse Gaussian model (Table 3). In the Inverse Gaussian models (unlike in the Gamma model), the effects of covariates persisted, suggesting that, over time, both intrinsic firm characteristics (unobserved characteristics) and the effect of covariates (in this case, firm strategy) play an important role on influencing the firm's exit, either by acquisition or dissolution (Gutierrez, 2002). Empirical support for the Inverse Gaussian distribution of frailty is consistent with findings in the strategy literature (Bourgeois, 1984), which stress the important role of both choice (e.g., firm strategy) and determinism (intrinsic firm characteristics) on firm performance.

4.3. Results

Model of exit by dissolution. The overall fit of the hazard model for exit by dissolution relative to the baseline model with no explanatory variables (i.e., explanatory variables set to 0) is significant (χ^2 = 119.76; degrees of freedom = 11, p < 0.01) indicates that the model with the explanatory variables fits the data well. The likelihood ratio test for unobserved heterogeneity is significant (χ^2 = 26.502; degrees of freedom = 1, p < 0.01), reiterating the need to account for unobserved firm heterogeneity. The parameter estimate for the Log-logistic distribution is 0.164, suggesting that the base hazard for exit by dissolution first increases and then decreases.

The results of the model for dissolution are seen in Column 1 of Table 3. With respect to the control variables, we find that a firm's number of trademarks ($\hat{\beta}$=0.042, p<0.01) and number of employees ($\hat{\beta}$=0.011, p<0.01) delay the firm's exit by dissolution.[7] In addition, the competitive intensity shortens the time to firm exit by dissolution ($\hat{\beta}$=−0.208, p<0.05), as does the level of the NASDAQ index in the year of firm entry ($\hat{\beta}$=−0.157, p<0.01). On the other hand, patents ($\hat{\beta}$= −0.005, ns), alliances ($\hat{\beta}$=0.027, ns) and sales growth ($\hat{\beta}$=−0.001, ns)

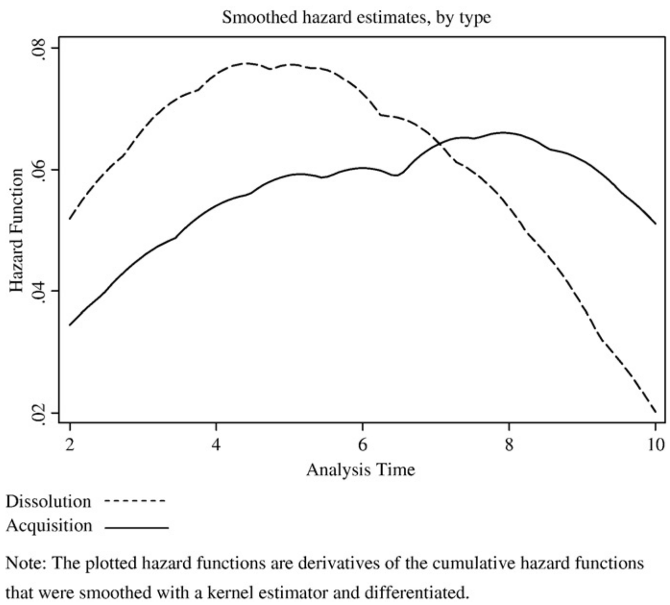

Fig. 1. Smoothed hazard functions for exit by dissolution and acquisition. Note: The plotted hazard functions are derivatives of the cumulative hazard functions that were smoothed with a kernel estimator and differentiated.

have no effect. The null result for the effects of patents is surprising, especially considering the benefits of patents for firms' financial performance (e.g., Dutta et al., 1999), a result we will discuss later. The null result for alliances is consistent with the mixed empirical evidence for the benefits of alliances for new firms (Gulati, 1998).

Next, we discuss the hypothesized effects. The results do not support the main effect of the diversity of the firm's product–market portfolio ($\hat{\beta}$=−0.054, ns) on its exit by dissolution (H1D). The results support the hypothesized negative interaction effects of the diversity of the firm's product–market portfolio and the number of its patents shortening the time to its exit by dissolution ($\hat{\beta}$=−0.089, p<0.05, H2D). Also, the results support the hypothesized positive interaction effect of the diversity of the firm's product–market portfolio and the number of its trademarks in delaying firm exit by dissolution ($\hat{\beta}$=0.121, p<0.05, H3D). As expected, the interaction effect of competitive intensity in the firm's environment with the diversity of its product–market portfolio delays its exit by dissolution ($\hat{\beta}$=0.071, p<0.05, H4D).

Model of exit by acquisition. The results pertaining to firm exit by acquisition are reported in Column 2 of Table 3. The fit of the hazard model for exit by acquisition is significant (χ^2 = 41.99; degrees of freedom = 11, p < 0.01). The likelihood ratio test for unobserved heterogeneity is significant (χ^2 = 20.721; degrees of freedom = 1, p < 0.01) suggesting the need to account for unobserved firm heterogeneity. The parameter for the Log-logistic distribution is 0.232, suggesting that, as with the hazard for exit by dissolution, the hazard for exit by acquisition first increases and then decreases.

When we consider control variables, we find that the number of patents hastens a firm's exit by acquisition ($\hat{\beta}$=−0.052, p<0.01), however a large number of trademarks delays firm exit by acquisition, unexpectedly ($\hat{\beta}$=0.034, p<0.05). We will discuss this later. Firms with more alliances ($\hat{\beta}$=0.028, p<0.01) survive longer. On the other hand, competitive intensity ($\hat{\beta}$=−0.014, ns), sales growth ($\hat{\beta}$=0.010, ns) and employees ($\hat{\beta}$=0.010, ns) do not affect firm exit by acquisition. As expected, firms incorporated during the Internet boom when the NASDAQ index was high had shorter acquisition durations ($\hat{\beta}$=−0.109, p<0.01).

As with the firm's exit by dissolution, the results do not support a main effect for the effect of diversity of product–market portfolio on firm exit by acquisition ($\hat{\beta}$=0.055, ns, H1A). However, the results do support the hypothesized negative interaction between the diversity

[6] Although the inverted U-shapes of both hazard functions seems to suggest a quadratic relationship with age, we found that such a model specification had a poorer fit than the one specified here, and did not change the substantive nature of our findings.

[7] Because the explanatory variables are mean-centered, the coefficients of the main effects have meaningful interpretation and are equivalent to marginal effects when we include interactions in the model.

Table 3
Models of competing risks for duration of new firm exit

Effects	Hazard model (Log-logistic distribution)		Hazard model (Log-logistic distribution)		Single risk; with proposed effects
	(1) Dissolution	(2) Acquisition	(3) Dissolution	(4) Acquisition	(5) Exit
Intercept	1.496 (0.078)***	1.694 (0.074)***	1.641 (0.086)***	1.466 (0.106)***	1.512 (0.078)***
Diversity of product–market portfolio	−0.054 (0.107)	0.055 (0.142)	−0.035 (0.059)	0.045 (0.144)	−0.030 (0.086)
Diversity of product–market portfolio × Number of patents	−0.089 (0.041)**	−0.205 (0.102)**	−0.087 (0.036)**	−0.217 (0.131)*	−0.237 (0.076)***
Diversity of product–market portfolio × Number of trademarks	0.121 (0.059)**	−0.118 (0.055)**	0.119 (0.058)**	−0.113 (0.050)**	0.028 (0.051)
Diversity of product–market portfolio × Competitive intensity × 10^3	0.071 (0.030)**	−0.019 (0.057)	0.070 (0.031)**	−0.019 (0.054)	−0.004 (0.003)
Control variables					
Number of patents	−0.005 (0.016)	−0.052 (0.023)**	−0.005 (0.018)	−0.053 *0.025)**	−0.039 (0.019)**
Number of trademarks	0.042 (0.011)***	0.034 (0.014)**	0.039 (0.011)***	0.038 (0.015)**	0.043 (0.009)***
Competitive intensity × 10^3	−0.208 (0.100)**	−0.014 (0.011)	−0.204 (0.100)**	−0.015 (0.010)	−0.016 (0.007)***
Alliances	0.027 (0.027)	0.028 (0.011)***	0.033 (0.018)	0.028 (0.012)**	0.020 (0.001)***
Sales growth × 10	−0.001 (0.001)	0.009 (0.006)	−0.001 (0.001)	0.009 (0.007)	0.002 (0.002)
Employees	0.011 (0.002)***	0.010 (0.011)	0.014 (0.002)***	0.009 (0.008)	0.010 (0.001)***
NASDAQ index at year of entry × 10^3	−0.157 (0.002)***	−0.109 (0.030)***	−0.165 (0.002)***	−0.098 (0.002)***	−0.131 (0.002)***
Unobserved heterogeneity	Inverse Gaussian	Inverse Gaussian	Gamma	Gamma	Inverse Gaussian
Base duration parameter γ_j) (Log-logistic distribution)	0.164	0.232	0.200	0.178	0.162
Variance of heterogeneity distribution (σ^2)	11.531	4.744	3.324	2.842	10.982
Log-likelihood	−610.286	−541.149	−612.095	−547.223	−1187.079

Note: standard errors in parentheses; ***$p<0.01$, **$p<0.05$ and *$p<0.10$.
Total number of observations in the sample (including censored observations): 6924 firm-years.
Although the variances of the heterogeneity distributions are different for the Inverse Gaussian and the Gamma specifications, both are left-skewed for both dissolution and acquisition. For example, for acquisition, the approximate % of cases that fall below the mean frailty level of 1 is 75% for the Gamma and 77% for the Inverse Gaussian. For dissolution, the corresponding values are 73% and 83%.

of the firm's product–market portfolio and the number of patents, hastening its exit by acquisition ($\hat{\beta}=-0.205$, $p<0.05$, H2A). The interaction effect of diversity of product–market portfolio and the number of trademarks also hastens firm exit by acquisition ($\hat{\beta}=-0.118$, $p<0.05$, H3A). The interaction between the diversity of the firm's product–market portfolio and competitive intensity does not affect its exit by acquisition ($\hat{\beta}=-0.019$, ns, H4A).

4.4. Robustness checks

Next, we report on additional analyses that examine the robustness of the results.

Skewedness in explanatory variables. To assess the robustness of our findings to skewedness in the various explanatory variables, especially the number of patents, we log-transformed all the explanatory variables and re-estimated the models.[8] The results (available on request from the authors) indicate that our findings are robust to the log-transformation of the explanatory variables. However, for ease of interpretation, we retained the untransformed form when reporting our results.

Competing risks versus single risk model. We examined the fit of the competing risks model relative to a model that does not consider the two types of exit (reported in column (5) of Table 3). A Chi-square test between the single exit model (log-likelihood = −1187.079) and the competing risks model (log-likelihood = −1151.435 for the competing risks; log-likelihood = −610.286 for dissolution and log-likelihood = −541.149 for acquisition) rejects the single risk model over the competing risks model ($p<0.01$), thereby supporting the competing risks approach for new high tech firm exits.

Censoring date. An assumption of duration models is that censoring is conditionally independent of both the event of interest and the covariates. To explore the robustness of the results to the use of 2003 as the censoring date, we re-estimated the model with three different censoring dates: 2002, 2001, and 2000. The results (available on request from the authors) indicate that our findings are robust to censoring date.

Independence of competing risks. Dissolution via business entity cessation implies the firm's inability to sustain continued operations. On the other hand, when a firm is acquired, it is being evaluated as a source of potential value to the acquirer, which involves a number of considerations in addition to its ability to sustain its operations. Thus, from a theoretical perspective, we expect the two competing risks to be independent.

From an empirical perspective, independence of the risks is not identifiable from the data for the competing risks model without covariates, (Tsiatis, 1975), i.e. we cannot distinguish between independent competing risks and the infinite number of dependent competing risks that produce similar cause-specific hazards. This problem arises because we only observe the earlier of the two possible types of exits.[9] There is evidence that the risks of dissolution and acquisition may be independent. For example, for financially distressed firms, the probabilities of survival and acquisition are explained differently by the same explanatory variables (Astebro & Winter, 2002). Similarly Table 3 shows a significant negative effect of competitive intensity on the duration of exit by dissolution but no effect on exit by acquisition. We leave a more thorough exploration of the assumption of independence of risks in firm exits by different modes for future research.

5. Discussion

We explored how the diversity of product–market portfolio relates to the timing and type of market exit for new firms. We find that the diversity of the firm's product–market portfolio has no main effect on its exit either by dissolution or acquisition. We conjecture that this null effect could result from the multiple, opposing effects of diversity of product–market portfolio on exit by either dissolution or acquisition. However, the diversity of a firm's product–market portfolio, in

[8] We thank an anonymous review for this suggestion.

[9] Even though models with covariates, such as ours, are identifiable (Heckman & Honore, 1989), this does not necessarily help us develop tests of independence of risks. Crowder (1997) has proposed a test for independence of competing risks for the discrete hazard model and, more recently, Saïd, Ghazzali and Rivest (2007) proposed a test for continuous-time model with covariates. However, neither test is applicable to our continuous-time model with time-varying covariates. Fortunately, the signs of the coefficients seem stable across independent and depending risk specifications and the bias caused by assuming independence of risks appears to be small, especially in models with covariates (see, for example Gordon (2002; Tables 3 and 4, and Saïd et al. (2007; Table 8).

conjunction with the number of its patents and trademarks, affects its exit both by dissolution and acquisition. Thus, the diversity of product–market portfolio, itself, confers no advantage or disadvantage to a new high tech firm. Rather, it is important for the firm to align its product–market strategies with the appropriate assets (e.g., patents and trademarks) to improve its chances of survival or acquisition.

A useful method for assessing the substantive implications of our results is to explore the effect sizes of the parameter estimates from the model. In the AFT model, a unit increase in the covariate value is equivalent to shrinking or expanding the time scale by a certain proportion. For example, when there is a unit increase in the diversity of product portfolio and a unit increase in patents, the expected value of $\ln(t)$ changes by −0.09, or equivalently, the new survival duration is equal to $te^{-0.09}$ (=0.914t) of the old duration. Thus, for a firm predicted to fail at $t=1$, this interaction term would hasten the time of failure to 0.914, or an 8.6% decrease. For a firm predicted to fail at $t=2$, the new time of failure would instead be 1.83, an 8.6% decrease.

The negative interaction effect of the number of patents with diversity of product–market portfolio ($\hat{\beta}=-0.09$) is an interesting finding, which suggests that, at least in the high tech context, firms that gather many patents in diverse fields may be hastening their dissolution time (by about 9%). We conjecture that this may be because a more diverse product–market portfolio and more patents may lower the firm's ability to leverage the value of its patents. With respect to the effects on exit by acquisition, the interaction of product–market portfolio, in conjunction with its patents hastens the time to acquisition by 19%.

In terms of main effects, the firm's number of patents does not affect its exit by dissolution, but hastens its exit by acquisition (a 5% decrease). The null effect of the number of patents on firm survival suggests that the mere possession of patents does not increase new firm survival. This is an intriguing result that differs from those reported in the literature (e.g., Dutta et al., 1999), perhaps for two possible reasons. First, past studies on the performance implications of patents have focused on firms' financial performance, whereas we examine the effects of patents on firm survival. Second, past studies have focused on the effects of patents for publicly listed firms in COMPUSTAT database, which are typically large, well-established (and perhaps older) firms compared to the small, new firms in this study.

The interaction of the diversity of the new firm's product–market portfolio and the number of its trademarks delays firm exit by dissolution (12% increase) while hastening its time to acquisition (11% decrease). In terms of main effects, the number of trademarks increases duration in both types of exit (4% for dissolution and 3% for acquisition, respectively). Interestingly, there are contrasting effects of the number of patents and trademarks on the survival of small high tech firms. Thus, a firm's stock of trademarks increases the survival duration of firms; while its stock of patents does not affect its time to dissolution, but does decrease its time to acquisition.

Our finding that more patents hastens firm exit by acquisition is consistent with empirical research on the value of patents in acquisition (Ahuja & Katila, 2001; Delios & Beamish, 2001). The delaying main effect of the number of trademarks on firm exit by dissolution is generally consistent with theoretical arguments that favor a strong role of marketing assets in improving the level and speed of cash flows (Srivastava, Shervani, & Fahey, 1998). However, the delaying effect of the number of trademarks on firm exit by acquisition is intriguing. It may be that a large number of trademarks signal that the firm is pursuing a strategy of organic, internal growth, holding out against acquisition, or that the firm may be attempting to thwart acquisition attempts in expectation of better offers. Further research on the role of other types of marketing assets (e.g., brands, customer relationships etc.) in acquisitions, including premiums paid and post-merger performance, could assess the relative merits of the alternative explanations.

Our results suggest that more patents increase the market value of the firm (i.e. shortens time to acquisition) both independently, and in conjunction with a diverse product–market portfolio. However, there is a hidden cost to widespread patenting. Firms with diverse product–market portfolios with a large number of patents may be less focused on generating unique propositions for their customer base, thereby jeopardizing their chances of survival, and hastening the time to exit by dissolution.

On the other hand, the positive effects of the number of trademarks on survival (in the model of exit by dissolution) and their negative effects on survival (in the model of exit by acquisition) suggest that trademarks are intangible assets that have value-in-use (i.e. delaying exit by dissolution) both independently and in conjunction with a diverse product–market portfolio as well as value-in-transfer (i.e. hastening exit by acquisition) in conjunction with a diverse product–market portfolio.

Greater diversity in a product–market portfolio in competitive environments delays firm exit by dissolution (7% increase), but does not affect exit by acquisition, suggesting that a more diverse product–market portfolio may buffer the firm against competitive threats.

Exit by dissolution clearly differs from exit by acquisition, as shown by the differential effects of the various explanatory variables on the two types of exits. Methodologically, this finding highlights the need to model different types of exits using the competing risks approach and provides an opportunity for interested scholars to reexamine past research that has treated all firm exits as failures.

5.1. Limitations and research opportunities

Because small, new, private firms are not subject to statutory auditing and reporting requirements, there is limited data on those firms, restricting the explanatory variables available for modeling. For example, private firms are not required to report their research and development and advertising expenditures, important indicators of the firm's investments in intangible technological and marketing assets. Furthermore, our decision to use secondary source firm data precluded incorporating characteristics like organizational culture, initial financing strategy and financial strategy including debt leverage that may affect the time to firm exit by either dissolution or acquisition. Although the incorporation of unobserved heterogeneity through a shared frailty specification accounts for missing variable bias, future research could explore the effects of additional firm-specific explanatory variables and evaluate the construct validity of our technological and marketing assets measures.

We only examined the exit of new firms in the technology-intensive sector in the United States covering the semiconductors, software and computing industries for a period of 10 years between 1993 and 2002, which had idiosyncratic contexts such as the Internet boom (which is accounted for in our model). While the choice of the technology-intensive sector in one country provides focus and reduces error variance, it would be useful to see whether these findings are generalizable to other contexts (e.g., fast moving consumer goods, services) and other periods (before and after the Internet boom).

Some firms may survive their early years, but fail subsequently. Other firms may survive, but not achieve superior performance. Future research relating marketing strategy to other performance metrics (market share, rate of growth, profitability) over longer time horizons would represent useful extensions to this study.

We made some methodological choices that could potentially be relaxed in future research. First, we formulated a continuous time model because the event of interest (firm dissolution or acquisition) occurs in continuous time. However, our data are discrete (measured every year). Though the use of discrete time data with continuous time models is common (e.g., Kalbfleisch & Prentice, 2002, pp. 196–8; Kiefer, 1988), such an approach may create an aggregation bias in the parameter estimates. Given the nature of the data available for strategy research, there is potential value in developing discrete time hazard models with time-varying covariates, competing risks and unobserved heterogeneity (via latent classes or hierarchical Bayes techniques).

We used the AFT formulation to estimate the competing risks model because all of our hypotheses are stated in terms of durations (time to dissolution and time to acquisition). The proportional hazard (PH) model provides greater flexibility with respect to the base function, formulating it as a non-parametric curve. For purposes of comparison with the AFT model, we attempted to estimate a shared frailty proportional hazard model, but we encountered estimation problems. Future research could explore the use of both AFT and PH models within the context of a Hierarchical Bayes specification for modeling hazard, perhaps ameliorating the estimation problems.

Two other areas of future research are worth exploring. The first pertains to the simple cumulative count of patents that we use as a measure of a firm's technological assets. Although patent counts have been used in past research as an indicator of the firm's intangible technological assets, they do not account for the quality of the patents. One such quality-adjusted measure of patents is the citation-weighted count of patents. Because our study was focused on the survival of new firms, only a small proportion of patents (15%) in our data set had citations, which precluded our use of a quality-adjusted, citation-weighted measure. Future research using a citation-weighted count of patents in data sets, where firms survive longer, may provide an opportunity to explore the effect of patent quality.

The second issue pertains to the nature of exit by acquisition. As discussed, in the tech industry, successfully creating a firm and selling it to a larger firm at a premium can be a very successful outcome. However, there is some ambiguity regarding whether an acquisition is always performance enhancing. Following the acquisition, the acquired firm may continue its existence under the new ownership, it may be subsumed under the acquirer's identity, or its assets may be liquidated by the acquirer. A useful extension to this work would focus on refinements of acquisition type to generate insights on what new firm marketing strategies build or destroy value in acquisitions.

5.2. Managerial implications

Positioning the firm for successful acquisition requires different strategies from those needed to maximize survival duration as an independent firm. There are key resource allocation decisions (e.g., focusing on product development versus market development) that follow from this positioning decision; our model provides a mechanism to determine the probabilities (cumulative hazard) of each outcome (exit or acquisition) depending on the diversity of the firm's product–market portfolio. The specific findings in Table 3 quantify the likelihood of a firm's exit by dissolution and determine remedial measures to improve its chances of survival. For example, if a firm is interested in organic growth, a more diverse product–market portfolio combined with increases in trademarks is likely to produce the desired effect.

Our findings should be of interest to policy makers concerned with promoting entrepreneurship activity. The diversity of a new firm's product–market portfolio significantly affects the likelihood of its exit and those effects are contingent on its patents, trademarks and the competitive intensity of its environment.

In summary, this research is a first step in quantifying the relationship between marketing strategy and new firm survival. We hope this paper stimulates further work relating marketing strategies of new firms to their survival, and more broadly, to other aspects of their performance.

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Appendix A. Model and estimation details

A.1. Background

Firm exits occur in continuous time (for all practical purposes). However, typical data are reported only in discrete time intervals (e.g., annually). To account for this aspect of our modeling context, we formulate a continuous time model, but estimate it with discrete time data. In practice, the use of discrete time data with continuous time models is quite common (e.g., Kalbfleisch & Prentice, 2002, pp. 196–8; Kiefer, 1988). Although the use of discrete data could produce an aggregation bias in the estimated coefficients (because all events that occurred during a year are assigned to the end of the year), the bias is likely to be minimal (ter Hofstede & Wedel, 1998, 1999). Specifically, they demonstrate that, in terms of RMSE, the bias is small for both the base hazard parameters and covariates and the use of discrete data do not pose a major risk in terms of incorrect parameter estimates.

Our primary interest is in the factors that influence time to exit by dissolution or acquisition. Therefore, we use various firm characteristics and its markets to explain the observed durations and these characteristics (e.g., number of patents) vary over time. Therefore, we formulate a model with time-varying covariates.

Finally, we use the Accelerated Failure Time (AFT) formulation, rather than a Proportional Hazard (PH) formulation, because our focus is on understanding how various covariates accelerate or delay an event (acquisition or dissolution), rather than on explaining the hazard associated with each type of exit at various points in time.

A.2. A continuous time competing risks AFT model with time-varying covariates

In our context, a firm i will eventually exit because of two different mutually exclusive and collectively exhaustive events (the first being dissolution and the second acquisition). However, the model we use is general and can accommodate more than two types of exits. The specification of our model consists of four components: (1) Description of the probability model for the time of exit due to each cause, (2) Specification of the base-survivor function (i.e., when all covariates are set to 0), (3) Summary of how we incorporate covariates in the model, (4) and Summary of how we incorporate unobserved heterogeneity within the model.

We start by associating with each firm i latent random durations denoted as T_{i1} and T_{i2}, where T_{ij} represents the random time to exit when firm i is exposed just to the exit cause j. We observe only the shortest duration, T_i=Min (T_{i1}, T_{i2}), and the corresponding cause of exit, denoted as C_i. Thus, for each firm, we have a pair of random variables (T_i, C_i) whose joint distribution must be specified. T_i is a continuous random variable in the range 0 to ∞ (although in practice, it is often reckoned in terms of discrete time periods) and C_i takes on values in the set {1,2}.

We specify the joint distribution, (T, C), via the cause-specific hazard functions as follows: (because the same probability model applies to all firms, we simplify notation by suppressing the index i unless we need to incorporate something specific to firm i):

$$h_j(t|X_t) = \lim_{\mathrm{d}t \to 0} \frac{\Pr(t \le T < t + \Delta t, C = j | T \ge t, X_t)}{\mathrm{d}t}; \quad j = 1, 2 \qquad \text{(A1)}$$

where X_t represents the set of covariates. Note that X_t is not a function of time, but is the value of the covariates at a given time t.

The cause-specific hazard functions $h_j(t|X_t)$ often have intuitive interpretation. In human mortality studies, for example, they represent the mortality rates from specific causes at age t, conditional on survival up to age t. The *total hazard* at time t is $h(t|X_t) = \sum_{j=1}^{2} h_j(t|X_t)$ (because of our assumption of independent risks). Analogously, the corresponding cause-specific survivor function is given by $S_j(t|X_t) = \Pr(T_j \geq t|X_t) = e^{-H_j(t|X_t)}$, where $H_j(t|X_t)$ is the cumulative hazard function given by $\int_0^t h_j(u|X_t)du$[10] The survivor function representing the probability of *surviving both types of exits* is given by $S(t|X_t) = \Pr(T \geq t|X_t) = e^{-H(t|X_t)}$ where the corresponding cumulative hazard function, $H(t|X_t)$, is equal to $\sum_{j=1}^{2} H_j(t|X_t)$. Note that, unlike $S_j(t|X_t)$, $S(t|X_t)$ can be interpreted strictly as a survivor function.

For the survivor function, we considered three standard parametric forms, namely, Weibull, Log-Normal, and Log-logistic. The Log-logistic distribution turned out to be the best, and therefore, the rest of our description is based on this distribution. For the Log-logistic, the base survivor function for each cause j is given by:

$$S_{0j}(t) = \left[1 + \{\lambda_j t\}^{1/\gamma_j}\right]^{-1} \quad \text{(A2)}$$

where, λ_j and γ_j are parameters to be estimated.

To incorporate the effects of covariates on the base survivor function, we use the standard approach by specifying $S_j(t|X_t) = S_{0j}(te^{-X_t\beta})$, where β_j (typically a vector) is a set of parameters that capture the effects of covariates. The constant term β_0 in the covariate equation (i.e., when $X_t = 0$) is absorbed into λ_j (i.e., $\lambda_j = e^{-\beta_0}$).[11]

In addition to covariates, unobserved firm heterogeneity due to unmeasured organizational characteristics may also influence firm exit. We incorporate the effects of such unobserved heterogeneity by specifying a multiplicative random-effects term in the hazard function, an approach referred to as the "shared frailty model," which is the survival-data analog of a random-effects model (Han & Hausman, 1990; Hougaard, 1984, 1986). In our context, all the observations belonging to firm i share the same frailty. We incorporate frailty that is both firm and cause-specific through a multiplicative term ($\alpha_{ij} \geq 0$) that scales the hazard function, i.e., $h_{ij}(t|X_{it}, \alpha_{ij}) = \alpha_{ij} h_{0j}(t) e^{-\beta_j X_{it}}$ If $\alpha_{ij} > 1$, that firm faces a higher hazard (i.e., is more frail), other things equal, than the base firm for which $\alpha_{ij} = 1$. Correspondingly, the survivor function (conditioned on α_{ij}) is scaled as $S_{ij}(t|X_{it}, \alpha_{ij}) = [S_j(t|X_{it})]^{\alpha_{ij}}$. The unconditional survivor function can be obtained by integrating out the unobservable α_{ij}, by making a suitable distributional assumption (Hougaard, 1984, 1986; Vaupel, Manton, & Stallard, 1979). In theory, any continuous distribution of α_{ij} with support on $(0,\infty)$ with an expectation of 1[12] and finite variance permits model identification. In practice, studies incorporating heterogeneity in survival models restrict the distributions to finite parameter families, specifically the exponential family with all positive finite moments (Hougaard, 1984; Manton, Stallard, & Vaupel, 1986). Two examples of such distributions used widely in empirical estimation of survival models are the Gamma and Inverse-Gaussian distributions (both of which we explore in the estimation).

[10] Strictly speaking, $S_j(t|X_t)$ does not have a survival function interpretation if we have two or more causes for exit, because a firm may exit before time t due to causes other than j. Also, for purposes of computation, the hazard changes the instant the covariate value changes.

[11] Equivalently, the base hazard function is $h_{0j}(t) = \frac{\lambda_j p_j (\lambda_j t)^{p_j - 1}}{1 + (\lambda_j t)^{p_j}}$ with $p_j = \frac{1}{\gamma_j}$ and the effects of covariates on the hazard function can be represented by $h_j(t|X_t) = h_{0j}(t) e^{X_t \beta_j}$.

[12] Setting expectation equal to 1 facilitates model identification, and does not result in any loss of generality, because the mean frailty across the firms will be absorbed into the base hazard function.

A.3. Model estimation

We use the maximum likelihood approach for estimating model parameters. Assuming non-informative censoring, the likelihood function is composed of two components:

1. For those firms i that survived until the end of the observation period, the probability of "being alive" (i.e., not yet exited) at time t_i is given by $S(t_i|X_{it})$.
2. For those firms i that exit at time t_i from cause j (i.e., conditional on surviving until time t_i), the likelihood is given by $h_j(t_i|X_{it})\, S(t_i|X_{it})$.

We now introduce the indicator variable δ_{ij}, which takes the value 1 if firm i exits the market from cause j during the observation period, and 0 otherwise. For any given sample realization, we can now combine the above two likelihoods succinctly as follows:

$$L(\theta|t_i, \delta_{ij}, X_{it}) = \prod_{i=1}^{n} h_j(t_i|X_{it})^{\delta_{ij}} S(t_i|X_{it}) \quad \text{(A3)}$$

where θ is a summary notation representing all the parameters of the hazard functions in (A3). We can further simplify Eq. (A3) as follows:

$$\begin{aligned} L(\theta|t_i, \delta_{ij}, X_{it}) &= \prod_{i=1}^{n} h_j(t_i|X_{it})^{\delta_{ij}} \prod_{j=1}^{2} e^{-H_j(t_i|X_{it})} \\ &= \prod_{j=1}^{2} \left\{ \prod_{i=1}^{n} h_j(t_i|X_{it})^{\delta_{ij}} e^{-H_j(t_i|X_{it})} \right\}. \end{aligned} \quad \text{(A4)}$$

The last transformation is possible because $\delta_{ij} = 1$ for at most one value of j, but is otherwise equal to 0. Thus, the overall likelihood (L(.)) is a product of two likelihoods, and therefore, we can maximize L(.) by separately maximizing the likelihood for each cause j, for which well-known methods already exist. That is:

$$\begin{aligned} L(\theta|t_i, \delta_{ij}, X_{it}) &= \prod_{j=1}^{K} L(\theta_j|t_i, \delta_{ij}, X_{it}) \text{ where } L(\theta_j|t_i, \delta_{ij}, X_{it}) \\ &= \prod_{i=1}^{n} h_j(t_i|X_{it})^{\delta_{ij}} e^{-H_j(t_i|X_{it})}. \end{aligned} \quad \text{(A5)}$$

We estimate the parameters θ using standard survival analysis software, STATA 9.0. For each cause j, the parameters are estimated by the maximizing Eq. (A5). The resulting estimates are $\hat{\theta}_j = \{\hat{\gamma}_j, \hat{\lambda}_j, \hat{\beta}_j\}$ and $\hat{\sigma}_j^2$ for the heterogeneity distribution, for $j = 1, 2$. Note that $\hat{\lambda}_j = e^{-\hat{\beta}_{0j}}$. For estimation, we treat durations, other than those triggered by exit through dissolution or acquisition, as censored observations. Also, note that once a firm exits, i.e., after we observe $T_i = \text{Min}(T_{i1}, T_{i2})$, the non-minimum T_{ij}'s are no longer observable, and therefore, exits due to those other causes are randomly censored at T_i. Thus, we can treat an exit due to other causes (i.e., either dissolution or acquisition), as a randomly censored observation[13], which enables us to use standard "single risk" estimation methods for estimating the competing risks model.

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[13] This censoring effect is in addition to the censoring effect for those firms that have not exited (due to either cause) at the end of the observation period.

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