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Roberto Fontana, Lionel Nesta

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Roberto Fontana (University of Pavia)

Lionel Nesta (OFCE)

Observatoire Français des Conjonctures Économiques
69, Quai d'Orsay 75340 Paris Cedex 07
Tel : 01 44 18 54 00 Fax : 01 45 56 06 15
E-mail: ofce@ofce.sciences-po.fr Web: http://www.ofce.sciences-po.fr

Product Innovation and Survival in a High-Tech Industry

Roberto Fontana [*]

Lionel Nesta [†]

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Abstract

We investigate the relationship between product innovation and firm survival for a sample of 121 firms in a high-tech industry. We find that location near the technological frontier is an important determinant of firm survival. Firms located near the frontier are also more likely to be acquired than to exit by failure if they cannot survive. This suggests that product location in the technology space acts as a signal of firm quality. Possessing a substantial stock of intangible capital, on the other hand, determines neither exit via failure nor exit via acquisition, although it increases the probability of surviving.

1 Introduction

Why do successful innovators exit the market? And how do they exit, by failing or by being acquired? These are the two questions raised in this paper. Our answer is based on the role of product innovation in shaping the survival rate of firms. Our argument is that successful product innovation has a dual influence on firms' life

[*]Department of Economics, University of Pavia, Via San Felice 5, 27100, Pavia, Italy and CESPRI - Bocconi University, Via Sarfatti 25, 20139, Milan, Italy. Tel: +39 02 58 36 30 37; Fax: +39 02 58 36 33 99. Email: roberto.fontana@unibocconi.it

[†]Observatoire Français des Conjonctures Economiques, Département de Recherche sur l'Innovation et la Concurrence, 250, rue Albert Einstein, 06560 Valbonne - France. Tel: +33 (0)4 93 95 42 39; Fax: +33 (0)4 93 65 37 98. Email: lionel.nesta@ofce.sciences-po.fr

expectancy. On the one hand, product innovation is the result of strategic market positioning whereby firms seek to gain a temporary monopoly by locating in an unexploited segment of the market. Thus, the dominant effect of successful product innovation should be to increase a firm's survival rate. On the other hand, successful product innovation provides an incentive for competitors to acquire the innovator, either because the latter is a threat to the incumbents, or because it represents an opportunity to assimilate rapidly a bundle of technical competencies which otherwise would be time consuming to develop. Therefore, the second order effect of successful product innovation should be ultimately to shorten a firm's life duration.

We test this simple idea on a sample of 121 firms in a rapidly changing high technology industry: the Local Area Networking (LAN) switch equipment industry. We define successful product innovation as improvement that is located at or near the quality frontier of the market. Having information on firms' mode of exit, by failure or by acquisition, we run a discrete time competing risk model to investigate the relationship between the quality of the innovation - measured as the distance from the technological frontier - and the firm outcome - exit by failure, by acquisition, or remaining in business. We control for a series of other important factors such as age, size, R&D intensity and mode of entry. We find that successful innovation has a positive impact on the firm's life expectancy. However provided that a successful innovator exits the market, it does so by being acquired rather than by failing. This general result suggests that mergers and acquisitions are key to moulding the boundaries of firms, determining market competition and shaping the dynamics of industries.

The paper is organized as follows. Section 2 provides a review of the literature and some background information on the LAN switch industry. In Sections 3 and 4 we develop the econometric model and describe the data sources and the variables that will be used in the empirical analysis. Subsection 4.1 presents the method of hedonic prices used to measure distance to the quality frontier as a proxy for successful innovators. Section 5 presents the results, which are discussed in Section

6. Section 7 concludes.

2 Literature Review and Industry Background

Schumpeterian competition as a process of innovation and selection is increasingly viewed as the key to achieving sustained aggregate economic growth, by screening out the least innovative firms and promoting the most *agile* ones (Caves, 1998). When innovation is understood in terms of productivity growth, it has been shown that exiting firms are mostly concentrated in the lowest part of the productivity distribution, suggesting that markets contribute to aggregate productivity growth by rightly selecting against inefficient firms (Baily, Hulten, and Campbell, 1992)[1]. When innovation is understood more directly, for example, in terms of R&D investments or new product innovation, a more complex pattern emerges. In fast changing industries, *soon* after entry firms have a *lower* probability of survival, but once the initial period has been mastered, their life expectancy *increases* significantly (Audretsch, 1995; Audretsch and Mahmood, 1999). Cefis and Marsili (2006) find that after controlling for age and size, innovative firms are more likely to survive than non- innovative firms. Finally, the timing of innovation (Christensen, Suarez, and Utterback, 1998), commercial strategy and relatedness among business lines (Mitchell, 1991; Willard and Cooper, 1985), and the nature of the technological regime (Audretsch, 1991) have a strong influence on the life duration of new firms. On the whole, the idea common to all these contributions is that innovative firms should grow faster, be more profitable and ultimately survive for longer (Geroski, 1995).

Alongside this neat stylized fact, however, there are many examples of innovative firms failing to survive. Indeed exit is far from being a homogeneous event. Although most firms exit by failure, some exit as a result of acquisitions. Exit by acquisition may be the result of innovators being too successful, at least from a technological viewpoint. For competitors, they represent a threat and also an opportunity for them to acquire valuable intangible capital and distinctive skills. However, few analyses have investigated the case of firms that are innovative but fail, and even fewer have looked at the links between innovation and mode of exit (Siegfried and Evans, 1994). In her seminal work, Schary (1991) found that profitability is a weak determinant of exit mode, and that firms' characteristics, mainly related to capital structure, should instead be examined. Interestingly, the predictive power of firms' characteristics varies depending on the mode of exit. Perez, Llopis, and Llopis (2005), for instance, perform a competing risk analysis on a sample of manufacturing firms in Spain. They find differences in the determinants of exit depending on the modes (i.e. exit due to business failure as opposed to acquisition). In particular, while the risk of failure declines with age and size, the risk of being acquired seems to increase. Although they provide interesting insights into the nature and causes of different modes of exit, none of these contributions stresses the role played by innovation.

To our knowledge, the contribution by Cockbrun and Wagner (2007) is the only one to address this issue explicitly. It looks at the survival of a sample of 356 Internet related firms in the aftermath of the dot-com bubble. Employing patent applications as an indicator of innovativeness, they find that possessing a large patent portfolio both increases the probability of survival and decreases the probability of exiting via merger or acquisition. Only those firms with a large share of highly cited patents are more likely to exit by acquisition. Given that citations are a good indication of patent quality (Hall, Jaffe, and Trajtenberg, 2005), this switch in the sign reveals that acquired companies provide intangible capital of economic value. Yet this important result is only weakly significant from a statistical viewpoint, and hard to interpret from an economic one. As the authors acknowledge, the correlation between patenting and firm duration may reflect unobserved firm characteristics such as the quality of the firm's products and intangible assets other than the technology itself.

In this paper, we focus on product innovation. Product innovation is interesting for several reasons. On the one hand, product innovation, understood as strategic market positioning, may confer on firms a competitive advantage, which boosts the life duration of successful innovators. Despite the existence of a substantial theoretical literature (Bonanno, 1987; Brander and Eaton, 1984; Schmalensee, 1978), comparatively less evidence has been provided on the relationship between market positioning and firm survival. Stavins (1995), for instance, analyzes the determinants of entry and exit in a sample of personal computer (PC) models and firms between 1976 and 1988. In modelling survival in terms of probability of exiting the market for both models and firms, she found that models produced by old firms are more likely to survive in the market and that more innovative firms or firms that introduce pioneering models, also experience higher survival rates. Greenstein and Wade (1998) carried out a similar study on a sample of computer mainframes between 1968 and 1982. Employing duration analysis, they found that older models had a lower chance of surviving in the market. Interestingly they also found that the hazard rate of the single model increases in the number of models in the adjacent market segment suggesting, therefore, that location in crowded markets negatively affects the likelihood of product survival.

On the other hand, product innovation is also a signal of firm quality (Bontems and Meunier, 2006). Think, for example, of a market in which products are distinguished on the basis of their technological quality. High quality products are those located near the technology frontier, thus, their market positioning reveals the quality of firms. In this context, high quality firms are very likely to become acquisition targets for a variety of reasons. First, acquiring high quality firms represents an opportunity for competitors to improve and expand their own productive resources quickly. Analyzing acquisitions in the US medical sector, Karim and Mitchell (2000) provide evidence that acquisitions enable buyers both to increase efficiency and to stretch the boundaries of their pre-acquisition markets. In fact, the benefits from acquisition are more likely to occur when there is good synergy between the assets of the targeted and the acquiring firm. For example, Hall (1987) provides evidence of a positive relationship between the R&D intensity of the acquiring and the targeted firms.

Second, acquisition may be used to exclude potential rivals from preferential positions in the market. In this case, the goal of the merger is not to increase productivity or research efficiency, but to increase market power (Salant, Switzer, and Reynolds, 1983), or even to preempt mergers by rival companies (Brito, 2003). Barros, Brito, and de Lucena (2006) show that in the food retailing sector, mergers have had a negative impact on the consumer surplus by raising post-merger consumer prices. In highly dynamic sectors, young firms are more likely to be acquired by incumbents because of the threat they pose to incumbents. In a case study of science based firms in Sweden, Grandstrand and Sjolander (1990) provide preliminary evidence that young firms are more likely to be acquired by incumbents. They also provide evidence on the presence of competition among buyers, which increasingly tends to drive down the age of acquired firms.

This paper provides an empirical investigation of the firm-level attributes determining firm exit from the market. By measuring product innovation on a vertical quality scale, we characterize each firm by its distance from the quality frontier. We investigate product innovation and firm survival in the Local Area Networking (LAN) switch equipment industry. The LAN switch industry began in 1990 with the invention of the first switch for data communication. Entry in the industry was initially slow but it dramatically increased after 1993. Three different types of firms fueled the entry process. First, incumbents from established markets (i.e. routers and hubs) entered the switch industry. Second, there was participation from incumbents outside the industry, but with experience either in telecommunications, in semiconductor, or in the computer industry. Third, there were new firms searching for new opportunities. These firms were generally highly innovative and founded by entrepreneurs, who were either former academics or former employees in the industry.

Entry was accompanied by an evolution in the technology, which culminated in the opening up of two market segments (Fontana and Nesta, 2006). The high-end segment included products characterized by high performance, targeted to customers with large networks. The low-end segment encompassed lower performance switches targeted to customers with small networks. The nature of the competition in the two types of market segments was different. In the low-end segment, manufacturers competed mainly on price. In the high-end segment, competition was mainly based on the constant search for technical excellence and increased performance. Polarization led to consolidation and to an increase in the rate of exit. Among the firms that exited the industry, the vast majority were new firms, which were ultimately acquired by incumbents. Indeed, for many of the new firms the opening up of the switch market had initially represented an opportunity to enter a new niche. However, it was always clear that the chances of turning a new venture into a large firm were very few. Indeed, in many cases, from the start firms had been 'designed to be acquired', generating an entirely new business model which became known as the 'acquisition-as-exit-strategy' business model (Kenney and von Burg, 2000, 234)[2].

In this paper we take the quality of a firm as the distance of its product(s) from the technical frontier. We also include other firm level indicators such as age at entry to the industry, size, R&D intensity, and pre-entry experience. We would expect first that firm quality as measured by distance from the technological frontier to be negatively associated with the probability of surviving. Second, we would expect that for those firms that fail to survive, distance from the technological frontier should decrease the probability of their being acquired. Third, we would expect a positive relationship between possession of innovative capital and the probability of surviving.

3 Econometric Models

We develop two sets of econometric models to evaluate the factors that affect the fate of innovative firms. First, we estimate a standard discrete time duration model to explain the probability of exit. Second, we apply a competing risk model to account for heterogeneity in firm exit.

In the first set of models, we estimate a duration model for grouped data following the approach first introduced by Prentice and Gloeckler (1978). Suppose there are firms $i = 1, \ldots, N$, that enter the industry at time $t = 0$. The hazard rate function for firm i at time t and $t = 1, , T$ is assumed to take the proportional hazard form: $\theta_{it} = \theta_0(t) \cdot X_{it}' \beta$, where $\theta_0(t)$ is the baseline hazard function and X_{it} is a series of time-varying covariates summarizing observed differences between firms. The discrete time formulation of the hazard of exit for firm i in time interval t is given by a complementary log logistic function such as:

$$h_t(X_{it}) = 1 - \exp\left\{ - \exp\left(X_{it}' \beta + \theta(t) \right) \right\} \tag{1}$$

where $\theta(t)$ is the baseline hazard function relating the hazard rate $h_t(X_{it})$ at the t^{th} interval with the spell duration (Jenkins, 1995).

This model can be extended to account for unobserved, but systematic differences between firms. Suppose that unobserved heterogeneity is described by a random variable ε_i independent of X_{it}. The proportional hazard form with unobserved heterogeneity can now be written as :

$$h_t(X_{it}) = 1 - \exp\left\{ - \exp\left(X_{it}' \beta + \theta(t) \right) + \varepsilon_i \right\} \tag{2}$$

where ε_i is an unobserved individual-specific error term with zero mean, uncorrelated with the X's. Model (2) can be estimated using standard random effects panel data methods for a binary dependent variable, under the assumption that some distribution is provided for the unobserved term. In our case, we will assume that the ε_i are distributed Normal and Gamma. Assuming that ε_i is Gamma distributed with mean one and variance v, the log-likelihood function can be written as:

$$\log L = \sum_{i=1}^{N} \log(1 - c_i) \cdot A_i + c_i \cdot B_i \tag{3}$$

where

$$A_i = \left[1 + v \sum_{t_i=1}^{T_i} \exp\left(X'_{it}\beta + \theta(t)\right)\right]^{-(1/v)}$$

and

$$B_i = \left[1 + v \sum_{t_i=1}^{T_i-1} \exp\left(X'_{it}\beta + \theta(t)\right)\right]^{-(1/v)} \quad \text{, if } t_i > 1 \text{ or}$$

$$B_i = 1 - A_i \quad \text{, if } t_i = 1.$$

where c_i is an indicator variable taking unity for firms exiting the market, 0 otherwise, and t_i is the discrete time hazard rate for person i in each duration interval $t_i = 1, \ldots, T_i$. The parameters v and β are to be estimated. Note that the proportional hazards form without heterogeneity is the limiting case as $v \to 0$. The relevance of the estimated unobserved heterogeneity is tested directly by the significance of parameter v. In addition, we perform a likelihood ratio test between the unrestricted model (with unobserved heterogeneity) and the restricted model (without unobserved heterogeneity). The reported estimates are chosen from the LR test.

In the second set of models, we relax the assumption of homogeneous exit by accounting for the mode of exit, namely firm failure, or firm buy-out. The extension of the standard pooled duration model to two exit forms is referred to as the Competing Risks Model (CRM) (Jenkins, 2004). The two destinations are treated as independent, so the probability of exit by failure is assumed not to depend on the probability of exit by acquisition. We consider that these two alternatives can in fact be viewed as contrasting, one points to a 'positive' event (firm buy-out), the other to lack of economic viability (firm failure). In practical terms, the independent competing risk framework treats both exits as right censored Lancaster (1990); Jenkins (2004). That is, we estimate the following complementary log logistic model similar to 1, but allowing the full set of parameters to vary according to the different destinations:

$$h_t\left(X_{ijt}\right) = 1 - \exp\left\{-\exp\left(X_{it}'\beta_j + \theta_j(t)\right)\right\} \tag{4}$$

where, in our case $j = 1$ or 2 respectively, depending on the mode of exit. Finally, a caveat to the interpretation of the coefficient estimates. In CMR, interpretation of the coefficients is not always as straightforward as in the case of the pooled model because the results depend on all the parameters in the model. If the CRM has a proportional hazard form, as is the case in Eq.4, then an increase in X will increase the conditional probability of exit, for instance, by firm failure if the estimated coefficient for the hazard rate of firm failure is bigger than the corresponding coefficient for the hazard rate of firm buy-out (Thomas, 1996). If we assume that we have intrinsically discrete time data, Eq.4 can be estimated using a 'multinomial logit' CRM.

We also test whether the two forms of exit, firm failure and firm buy-out, are behaviorally distinct rather than simply incidental. This is equivalent to the null hypothesis of equality for all parameters (except intercepts in the models for the destination-specific hazard). Narendranathan and Stewart (1991) show that for continuous time PH models, a test of whether exits to different states are behaviorally distinct (rather than simply incidental) corresponds to a particular set of restrictions: equality of all parameters except intercepts in the models for the destination-specific hazards. The test statistic is $2[\ln(L_{CR}) - \ln(L_{SR}) - \sum_j n_j \ln(p_j)]$, where $ln(L_{CR})$ is the maximized log-likelihood from the competing risk model (the sum of those from the component models), $ln(L_{SR})$ is the maximized log-likelihood from the single-risk model, n_j is the number of exits to state j and $p_j = n_j / \sum_j n_j$, where there are $j = 1, \ldots, j$ destination states. This test statistic is Chi-squared distributed with degrees of freedom equal to the number of restrictions.

4 Data

We investigate a sample of 121 firms in the LAN switch industry. All firms in our sample are 'innovative' in the sense that they have introduced at least one piece of switch equipment since 1990, the year that the first switch was marketed. For each firm in our dataset we have information on date of entry and exit from the switch industry and number of switches introduced. For each new switch introduced we have information on price and technical characteristics. Information on firm entry and exit dates was gathered from a variety of sources such as the D&B Million Dollar Database and Lexis-Nexis. Additional information on the firms' backgrounds and founders was gathered by searching publicly available databases that aggregate news and press releases, such as ABI-Inform, and annual reports gathered from the Thomson Research (Global Access) database.

Information on the type of exit (i.e. whether a firm survived or exited either by acquisition or failure at the end of the period) was obtained from a review of announcements in the specialized trade press and information contained in the CORPTECH database. Data on product characteristics and prices for switches, and also for hubs and routers were obtained from an original dataset of 1,825 LAN products (536 switches, 535 hubs, and 754 routers) marketed between 1990 and 1999). The dataset was constructed using information from specialized trade journals (*Network World* and *Data Communications*), which periodically publish Buyers' Guides and details on new product introductions. This information was double checked, with press communications and product announcements released by manufacturers. After consolidation we have a sample of 121 firms that together marketed a total of 503 switch products.

4.1 Measuring Firm Quality Through Product Differentiation

In this paper, we argue that product differentiation should be considered an important explanatory variable of the fate of firms when exit is not considered to be a homogeneous event. We measure product differentiation in terms of firm location with respect to the technological frontier at time of entry, using the generic technological characteristics of the products in the switch market. Indeed for each product our dataset reports information on its technical characteristics, date of market introduction and list price. To measure distances from the quality frontier we follow Stavins (1995) and proceed in two steps. In the first step, we reduce the multi-attribute structure (the technological characteristics) to a single dimensional measure of product quality. Assuming independence across product technological attributes, we project them onto a linear scale as follows:

$$q_m = \sum_j \beta_j \cdot z_{jm} \tag{5}$$

Eq.5 suggests that quality q of model m can be measured as the weighted sum of its characteristics. The weights β_j represent the marginal value of characteristic j that both consumers and producers place on the j^{th} attribute. These weights are approximated by regressing observed prices, deflated to 1996 US dollars using the sector specific deflator for telecommunication equipment provided by the US Department of Commerce, Bureau of Economic Analysis:

$$p_{mit} = \alpha + \sum_j \beta_j \cdot z_{jm} + \alpha_t + \varepsilon_{mit} \tag{6}$$

where p_{mit} is the log is the observed price for model m introduced in the market by firm i at time t, α is a constant and α_t is a time fixed effect. Table 1 provides the results from the hedonic regression. With almost 70% of the variance of prices explained, the overall fit is satisfactory although a substantial part of the observed prices (30%) is due to factors other than those introduced in the regression. This may in turn be due to omitted product attributes and erroneous pricing reflecting changes in demand.

Whereas the observed prices embody error measurements reflecting various factors such as changes in demand, promotional discounts and other non-quality components (Stavins, 1995), the predicted price $\hat{p}$ reflects by construction the quality q

of the product. Thus we posit:

$$q_{mit} = \hat{p}_{mit} \tag{7}$$

Eq.7 states that ranking predicted prices is tantamount to ranking products according to their quality. However, in order to more properly account for product quality, we amend Eq.6 in two ways. First in Eq.6 the estimated weights are constrained to be constant overtime, whereas the technology in the switch market is likely to have evolved over time. This suggests that depending on significant changes in product quality in the 1990s, the pooled regression may produce inexact weights. Therefore, we interact all explanatory variables with year dummy variables, in order to allow the weights β_j to vary with time. Second we include a firm fixed effect μ_i to control for heterogeneity in the firms' pricing practices.

[Table 1 about here.]

For example, positive values of μ_i can be interpreted as persistent over-pricing, i.e. a firm mark-up beyond and above marginal utility (from the consumer's viewpoint) or marginal product (from the producer's viewpoint). The important point here is that values of μ_i provide information on the firms' pricing practices, not on product quality. Therefore, we subtract μ_i from the predicted price $\hat{p}$. Based on the previous paragraph, we amend Eqs.6 and 7 as follows:

$$p'_{mit} = \alpha + \sum_t \sum_j \beta_{tj} \cdot (z_{tjm} \times \alpha_t) + \alpha_t + \mu_i + \varepsilon_{mit} \tag{8}$$

$$q'_{mit} = \hat{p}'_{mit} - \mu_i \tag{9}$$

Including the full vector of explanatory variables as specified in Eq.8 yields an increased r^2 of 0.85, implying that accounting for changes in the marginal values of product characteristics and firm mark-ups explains a significant share of the variance of observed prices in the LAN Switch market.

In the second step, we use estimated product quality $q^{'}$ to compute distances of products from the quality frontier, that is, we rank products on a vertical product space. To do so, for every product we compute its distance from the quality frontier as follows:

$$d_{mit}^{f} = \max\ (q_t) - q_{mit}^{'} \tag{10}$$

where $q_{mit}^{'}$ is the quality of model m by firm i in year t. The higher d_{mit}^{f}, the farther the product is from the quality frontier. Again, because firms can introduce several products in a given year, we computed the DISTANCE TO FRONTIER for each firm as: $d_{it}^{f} = \min \left[d_{mit}^{f} \right]_{it}$. Both this measure and its square are used as explanatory variables.

4.2 Control Variables

Recent studies have stressed that firm survival is also related to mode of entry. As stressed by Helfat and Lieberman (2002), spin-outs may take advantage of assets, such as industry-specific knowledge embodied in firm founders and transferred from the previous employee, and exhibit higher survival rates than other firms. For a rather large sample of firms in Denmark, Eriksson and Khun (2006) find evidence of lower risk of failure for spin-outs compared with other types of firms. Franco and Filson (2006) confirm these findings in the case of spin-outs in the US Hard Disk Drive industry. In his historical analysis of the shipbuilding industry, Thompson (2005) finds a positive relationship between pre-entry experience and the survival of firms. Indeed, having controlled for this source of heterogeneity, the dependence of survival on firm size and age disappears. As shown by Klepper (2002), this result seems to be common to many industries that have evolved to become oligopolies such as cars and tires. All in all, these studies point to the presence of a premium associated with survival for innovative firms or firms with pre-entry experience.

We use information on founders' background and firms' main activity to assign to firms a status defining their mode of entry. In particular, we define SPIN-OUTS as those firms whose main line of business is the LAN industry. This includes cases where the founder(s) were already employed in the LAN industry in the year prior to the founding of the new company, and university spin-offs. We define DIVERSIFIERS as firms whose founder(s) had no prior experience in the LAN industry and whose main line of business was outside the LAN industry (i.e. computer, semiconductor etc.) at the time of entry into the switch market.

These definitions are used to provide some preliminary evidence on the relationship between mode of entry and survival. Figure 1 depicts proportions of surviving firms in relation to years in the market , distinguishing by mode of entry. We can see that Diversifiers have the highest survival rate with more than 40% of firms surviving until the end of the period.

[Figure 1 about here.]

This evidence seems inconsistent with previous results which stress the advantages of pre-entry experience in terms of survival (Thompson, 2005). Spin-outs benefit from greater pre-entry experience and should display higher survival rates after entry into the switch market. Klepper (2002) argues that at a given age, early entrants and firms with pre-entry experience should display a higher survival rates than late entrants and firms with no experience. However, for innovative firms, being experienced might be a 'double edged sword' in the sense of making them liable to being bought-out by competitors. This is particularly true in contexts, such as the LAN switch industry, characterized by rapid technical change, which means that competitors do not have time to develop the capabilities to catch up with innovators. We identify three possible modes of exit: Failure (i.e. bankruptcy), Buy-out (i.e. acquisition), and Survival. Table 2 reports the relationship between modes of entry and modes of exit for the firms in our sample. We note two things.

[Table 2 about here.]

First, more than two thirds (69%) of the firms in our sample exited the LAN switch industry after entry. The majority of these were Spin-outs. Second, Spin-outs exit mostly as a result of acquisition. Among the survivors, Spin-outs are the largest share of the total although almost half of Diversifiers survive. This preliminary evidence suggests that although firms with greater pre-entry experience constitute most of the survivors, those that exit generally tend to be bought-out, thus indicating that their fate may be linked to their status and that exit should not be rated as a homogeneous event. The Chi-square statistics are not significant leading us to retain the null hypothesis of independence between modes of entry and modes of exit. However, this result should be interpreted with care due to low expected frequencies.

In addition to pre-entry experience, the extensive empirical literature on firm survival points to firm size and age as the prime determinants of firm selection (Dunne, Roberts, and Samuelson, 1988; Audretsch, 1997). Mata and Portugal (1994) and Mata, Portugal, and Guimaraes (1995) provide evidence on the complex nature of the relationship between firm age and survival. While the probability of survival seems to increase for older firms, the relationship is not so clear for young firms. Honjo (2000), investigating the post-entry performance of a sample of Japanese firms, found a negative effect of firm size on exit due to business failure, and a positive one for firm age. We therefore introduce additional explanatory variables in order to capture the role of firm level variables, such as size and age, in firm survival. The size variable (SIZE) is constructed as the logarithm of the total number of employees at time of entry. We define AGE AT ENTRY as the number of years at the time of entry in the switch market, since the firm was institutionally born[3]. We also add R&D Intensity (R&D INTENSITY) as a measure of innovative capital. This variable is constructed as the share of R&D expenditures in total revenues, at time of entry, and can be interpreted as knowledge capital at time of entry, similar to **?** patent stock measure (see Griliches and Mairesse (1998)). It is important to note that after accounting for revealed firm quality through product differentiation, mode of entry, intangible capital and firm size, the variable AGE AT ENTRY captures two effects: (i) the combined influence of availability of financial resources and diversification in the firm's product portfolio; (ii) a residual unobserved heterogeneity effect, related essentially to the firm's past experience in *doing business*, implying that older firms are more able to survive in their economic environment. Finally, to capture the effect of industry life cycle on firm survival (Klepper and Simmons, 2005), we add two industry level variables. ENTRY RATE and EXIT RATE are the number of new firms and the number of firms exiting the switch industry respectively. Both variables are based on the year preceding entry.

[Table 3 about here.]

Summary descriptive statistics for these explanatory variables are reported in Table 3. In all these regressions, we consider 121 firms, of which 83 eventually exit the industry. All firm level variables take values at the time when the firm enters the industry. All duration models include a full vector of entry-year dummy variables. Expanding the dataset by time intervals yields a total of 600 observations.

5 The Determinants of Market Selection in The LAN Industry

We use a discrete time duration model with a Weibull hazard function to understand the impact of product differentiation on firm survival. Several models have been estimated. In these models the explanatory variables are introduced in sequence and exit is treated as a homogeneous event. We check the robustness of our analysis by employing different types of hazard functions and controlling for unobserved heterogeneity. Finally, we extend the analysis to account for heterogeneity of exit by estimating a 'multinomial logit' CRM.

5.1 Preliminary Results

Six models were estimated using a discrete time duration model with a Weibull hazard function (see Table 4). In the first model we look at the impact of time duration on the hazard rate of exit. We then sequentially add AGE AT ENTRY and SIZE, firm location in the vertical product space (DISTANCE TO FRONTIER), innovative capital (R&D INTENSITY), mode of entry (SPIN-OUT), ENTRY and EXIT RATE.

[Table 4 about here.]

Columns (1) and (2) report the results for the baseline hazard function together with our controls for age and size. In column (1), we observe negative time duration, in line with existing work on firm survival (Audretsch, 1995). This result is robust to the subsequent addition of control variables. In the full specification in Column (6), one standard deviation around the mean of the log of time implies a reduction in the probability of exit of more than 50%. In Column (2) the negative and significant coefficient of AGE AT ENTRY indicates that older firms have a lower probability of leaving the industry. At first, the marginal effect may look small given that, in the full model, a one-year increment around the mean age at entry is associated with a reduction of only 5% in the probability of exit. However, when we compare two firms - one at the 10^{th} and one at the 90^{th} percentile (aged 1 and 28 respectively), we observe that the former is five times as likely to exit the market at the end of the period than the latter. Thus, as expected, entry age is extremely critical to firm survival. As in most of the literature on firm survival, the coefficient of SIZE is negative, although not significant in models (2) and (3). However in the full model, the negative sign is bigger and highly significant: one standard deviation around the sample mean size entails a 43% reduction in the probability of exit.

The impact of product differentiation as measured by position of the firm with respect to the technological frontier is estimated in Column (3). Based on previous results (Fontana and Nesta, 2006), we assume a non-linear relationship between product quality and survival and we enter both DISTANCE TO FRONTIER and its squared value. DISTANCE TO FRONTIER is positive, indicating that firms capable of being close to the frontier have a relatively higher probability of surviving. However, the negative and significant coefficient of the squared value suggests that the relation is non-linear and that exits mainly occur among firms located in the *middle* of the market. This is a good reflection of the situation in the switch market during the 1990s, which was polarized between high-end and low-end. At the high end of the market firms compete to be at the frontier and those that lag behind do not survive. At the low end competition occurs at the boundaries with the high-end of the market, where firms struggle to survive, while firms serving niches at the bottom of the low end have a higher probability of surviving. Again, the sign of both coefficients is robust to the introduction of additional control variables (specification 6).

It is worth noting the net marginal effects associated with distance to frontier measures. For example, for the firm with mean product quality, the probability of exit is twice as large as for the firm with a frontier product, i.e. its hazard rate of exit is multiplied by a factor of 2.1 (+115%). Interestingly, the non-linear estimates implies that for 23% of the firms in the sample - those located far from the frontier - the net effect is to actually reinforce firm survival compared to firms at the frontier. This result suggests that firms at the low end of the market specialize in niche products in order to escape the huge of competition from product innovation in the high-end segment. Thus, three important conclusions can be drawn: (i) the effect of product quality on firm survival is very large, much larger, in fact, than that of the usual firm characteristics such as size and age; (ii) the effect of product quality on firm survival is highly non-linear, in line with the idea of a two-tier market structure where firms located in the middle of the market are the least likely to survive and make it to the next round; (iii) locating in the low-end of the market appears to pay for a quarter of the firms in the sample.

We next control for the role of intangible capital stock and mode of entry separately. In Column (4), R&D INTENSITY enters with a significant negative sign, suggesting that possessing a higher stock of innovative capital reduces the probability of leaving the industry (by 30% at the margin). It is interesting to note that accounting for intangible capital makes both SIZE and DISTANCE TO FRONTIER significant (at the 10% and 5% levels, respectively). This reveals a complex mix of the effect of size, stock of innovative capital and product differentiation within firms, such that life duration analysis should adequately account for them *all*. We control for mode of entry in Column (5). The variable SPIN-OUT enters negatively and significantly indicating that firms' with higher pre-entry experience have a relatively lower probability of exiting the switch industry. The marginal effect is actually quite large, since spin-outs enjoy a hazard rate of exit 70% lower than diversifiers. Lastly, in model (6) we add the industry level controls. Though the coefficients show the expected sign, they are weakly significant or not at all significant in the case of EXIT RATE.

Altogether the sample is behaving as expected. First, product differentiation, as measured by firm location with respect to the technological frontier, matters for survival. In particular, firms located close to the technological frontier have a better post entry performance in terms of probability of surviving. The relationship is not linear, implying that locating far from the frontier may be a beneficial survival strategy. Second, possessing innovative capital increases the probability of surviving. Third, pre-entry experience mainly reduces the probability of exit when exit is considered a homogeneous event. Lastly, age and size also impact positively on firms' survival, as was expected from previous works.

5.2 Robustness Checks

We check the robustness of these results in Table 5, which provides alternative specifications for Column (6) . We carry out two types of robustness check. First, we explore different specifications of the baseline hazard function. The polynomial specification in Column (7) substantially confirms our previous results that both the sign and magnitude of the parameter estimates are stable. The fully non-parametric specification is reported in Column (8). This type of specification makes no assumptions about the shape of the baseline hazard function and introduces a full vector of year dummy variables rather than constraining the effect of duration to be monotonic (Column 6) or polynomial (Column 7). Again, the signs and significance levels of the coefficients are very stable, confirming the robustness of our results with respect to different assumptions on the duration effect. Only ENTRY RATE loses significance.

[Table 5 about here.]

Second, we control for unobserved heterogeneity by estimating a standard random effect model for binary dependent variable with error terms. Estimates reported in Columns (9) and (10) assume that error terms are normally distributed. Compared to the previous models, this specification yields similar results for the sign of the coefficients. In Column (11) we assume that the firm-specific terms are distributed gamma. In this specification all explanatory variables lose some significance although the direction of the parameter estimates remains consistent. The test for significant frailty (LR frailty test) suggests that unobserved heterogeneity is not important in our sample. Therefore, in what follows, we concentrate on modes of exit and ignore the question of unobserved heterogeneity.

5.3 Product Differentiation and Modes of Exit

In industries characterized by rapid technical change where competitors may not have the time to develop their capabilities, mergers and acquisitions are very frequent and they cannot be treated the same as exit by failure. In these contexts it is likely that product differentiation, pre entry experience, and intangible capital influence both survival and, for those firms that do not survive, mode of exit. Our short review of the existing empirical literature shows that this crucial aspect is missing from many analyses of innovation and firms' survival. To explore the relationships between product differentiation, pre entry experience, intangible capital, and firm survival we now consider exit as being a heterogeneous event by running a multinomial logit CRM (Table 6).

[Table 6 about here.]

Column (12) reports the results of the comparisons between the alternatives of exiting by failure and surviving. DISTANCE TO FRONTIER has a positive and significant coefficient suggesting that firms located relatively farther away from the technological frontier do in fact have a higher probability of exiting by failure than of surviving. Again, the relationship is non-linear as indicated by the negative and significant coefficient of $(\text{DISTANCE TO FRONTIER})^2$. Choosing to locate in the middle of the quality scale is the most dangerous strategy for firms, while a positioning at either end - near the frontier or far from the frontier - may be the right response to escape competition. Coefficients for AGE AT ENTRY, R&D INTENSITY and SIZE are all negative and significant, indicating that bigger firms with a large stock of innovative capital and better availability of financial capital have a relatively higher probability of surviving. The coefficient of SPIN-OUT is also negative and significant indicating that possessing pre-entry experience decreases the probability of exiting by failure rather than surviving. Interestingly, none of the industrial controls significantly affect the probability of failure when contrasted with survival. Results of the comparison between exit by Buy-out, and Survival are reported in Column (13). Again, we find that location in the product space matters, in the sense that firms locating far from the technical frontier have a higher probability of exiting (in this case by being bought-out) than surviving, as suggested by the positive and significant coefficient of DISTANCE TO FRONTIER. In general, there are no major differences with respect to the previous estimates though marginal effects seems to vary.

Finally, column (14) compares the two alternatives of exiting by buy-out and exiting by failure. In this column, the coefficients are estimated as the difference between those in Column (13) and those in Column (12). Thus, an increase in the explanatory variables coefficients will increase the conditional probability of exit, for instance, by firm buy-out if the estimated coefficient for the hazard of firm buy-out is larger than the corresponding coefficient for the hazards of firm failure. Major differences with respect to the previous estimates are found in the coefficients of our measures of firm location, which change sign and are the only variables that remain significant. DISTANT TO FRONTIER is negative, suggesting that only firms located close to the frontier have a higher probability of being acquired than exiting by failure. This is confirmed by the coefficient (DISTANCE TO FRONTIER)^2, which here is positive and indicates that the probability of being acquired, is high for firms located very close to the frontier, decreases as distance increases and then increases again for those firms located farthest away. Overall, both these results confirm that acquisitions are mainly triggered by the need to appropriate the technology of rival firms, enrich firm portfolios and improve research activities.

Finally, the direction of the effect of R&D intensity is as expected (i.e. positive on survival and negative on both acquisition and failure) and supports the general idea that a large stock of intangible capital is important for firm survival. Moreover, although possessing a large innovative stock may also increase the attraction of firms in the market, it also makes potential targets more expensive to purchase (Hall, Jaffe, and Trajtenberg, 2005). In a context where knowledge obsolescence is extremely rapid, this may in turn inhibit acquisitions.

Altogether, these estimates provide new results that enrich our analysis and shed some light on our initial hypotheses. When exit is treated as a homogeneous event product differentiation is an important determinant of firm survival, in the sense that being located close to the frontier increases the probability of surviving. However, among exiting firms, only those located close to the frontier are more likely to be acquired; thus, position relative to the technological frontier seems to act as a signal of firm quality. In other words, firms located near the frontier are more likely to survive, but, if they do not, they are more likely to be acquired than to discontinue productive activities. We also find support for the hypothesis that there is a positive relationship between the stock of intangible capital and the probability of surviving. However, in the case of an exit from the market, intangible capital determines neither exit via plant closure nor exit via acquisition.

6 Discussion

The rapid growth of the LAN switch industry in the 1990s gave rise to a large number of both entries and exits. Of the 121 companies that entered the industry, only 38 still existed in 2005; 15 had exited through closure and 68 had been acquired by a third party. In this section, we explore the determinants of firms' fates by looking at the marginal effects of firm level variables, the role of distance to frontier in shaping the outcomes and the relationship between market positioning, time and entry and exit mode.

Table 7 displays the predicted probability of each mode of exit. We first computed the predicted probability using the *median* values of the continuous variables (time, age, size, distance to frontier, R&D intensity) and the *mean* values of the dichotomous variables (entry-year dummy variables and entry type). All marginal effects were computed as discrete change, holding all other independent variables constant at their mean or median values. We observe that for the median firm with average entry year and entry type, the overall failure rate is 5.5%, the risk of acquisition is 18.1% and the survival probability is 75.5% [4]. At first sight, the overall risk of exit, either by failure or by acquisition, seems low: the median firm has three chances out of four to actually make it to the median-plus-one period. Comparison of this result with the observed overall exit rate for the whole period 1990-2005 suggests the presence of large effects at the margin of each independent variable.

We therefore compute the marginal effects of each firm-level Variable only (not the insignificant variables for industry turbulence). Again, we compute the discrete change in the predicted probability by imputing a variation of two quintiles around the median value of each continuous variables - i.e. from the $30th$ to the 70^{th} percentile - holding all other variables constant. Because of the non-linearity of the effect of distance from the frontier on survival, we compute the change in the predicted probability of being at the frontier to being at the 40^{th} percentile. For the dichotomous variable SPIN-OUT, we computed the discrete change from being a diversifier to being a spin-out. All changes are reported as absolute and relative change in probability. We obtained the following main observations.

[Table 7 about here.]

First, we observe that time impacts differently on the mode of exit from the industry. Although the marginal effect of time on survival confirms the role of post-entry experience, the mode of exit plays a larger (marginal) role in terms of exit by acquisition compared to exit by failure. In other words, firms that exit as a result of failure survive longer in the market than firms that are acquired. This result has at least two explanations. The first is based on the notion of a Jovanovic (1982) learning effect. Although they may perform poorly, entrants gather information on their *relative* performance only slowly so that the decision to exit takes time. Looking at the marginal effect of age at entry on exit by failure actually confirms this intuition: experience in *doing business* accounts for several unobserved characteristics of firms. One is their ability to learn their relative economic performance, so that the decision to exit by failure takes less time. The second interpretation is related to the presence of sunk costs and assumes that, on average, exit by acquisition has lower sunk exit costs than exit by plant closure. Based on this scheme, firms struggling in the market should always prefer to exit by acquisition than by failure. These firms would enter the mergers and acquisitions market, and offer their *quality* at a given price to potential buyers. In other words, they enter a market in which firms compete to be acquired, the choice of exit by failure being a last resort.

These two explanations could be considered to be complementary. However, they differ in one fundamental respect. Whereas exit by failure is the decision solely of the firm, exit by acquisition is the outcome of two decisions, one by the acquired company and the other by the acquiring company. Unfortunately, we do not have information on the underlying rationale for the two firms combining their activities through a merger or acquisition. However, we can trace their relative distance - i.e. the mutual distance between their best quality products - in order to get a better understanding of the logic underlying mergers and acquisitions[5]. On average, the acquiring company is located closer to the frontier than the target firm, although the gap is neither large nor significant. The width of the quality gap is an indication, albeit a preliminary one, of the motivation underlying the acquisition. A relatively large gap suggests that buyer and target firms were 'complements' rather than 'substitutes' and that the main objective of the acquisition was the growth of their productive resources or the enlargement of the product portfolio. Importantly, this gap tends to decrease over time, implying a change in merger and acquisition motivations over the industry life cycle. In particular, a closing gap between buyers and targets indicates that as the market evolved toward consolidation, acquisitions mainly involved firms that were imperfect substitutes in the market [6]. As competition grew, firms increasingly used acquisitions to exclude potential rivals from preferential positions in the market.

Second, the presence of a non-linear relationship between firm location and survival hints at the possibility that there are some regions in the quality space where firms are more at risk. In particular, firms located at the 30^{th} percentile have to cope with the highest probability of exiting by any mode, and of exiting through failure in particular. Firms located close to the frontier face an increasing probability of being acquired, since the risk of being acquired peaks at the 30^{th} percentile. Thus, competition in the LAN industry is a race in which most players commit resources to innovate along the quality ladder. However, only one firm will make it to the frontier, whereas others will innovate with products of substantial but lower quality. Our analysis reveals that these *good*, but *not-good-enough* innovators will be exposed to acquisition. This stylized fact is further illustrated in Table 8. The top panel of the table reports the relationship between location with respect to the frontier and mode of exit, decomposed by mode of entry[7]. For both entry modes, firms in the 20^{th}, 30^{th}, and 40^{th} percentile are those more at risk of exiting the industry *tout-court*. However, the probability of exiting is just 9.6% for diversifiers against 31.7% for spin-outs as a consequence of the much higher probability of the latter being acquired. Thus, diversifiers generally display a significantly higher probability of surviving than spin-outs for each distribution percentile. The gaps becomes dramatic for firms within the second, third, and fourth decile. Thus, while the probability of surviving is always higher for diversifiers in every position with respect to the frontier, pre-entry experience has important effects in determining the mode of exit for firms located close to each other.

[Table 8 about here.]

Finally, the role of pre-entry experience shown in Table 8 suggests that spin-outs are generally more at risk of exit than diversifiers. This seems incompatible with the marginal effects in Table 7, revealing that, *ceteris paribus*, the net effect of being a spin-out is to raise the probability or surviving or exiting by acquisition[8]. To investigate this result further, we analysed the exit mode probability, by mode of entry (diversifier or spin-out). These results are reported in the bottom panel of Table 8. For both types of firm, the risk of being acquired is particularly high immediately after entry and then decreases monotonically. It can be seen that using the median values by group, changes the results significantly in the sense of substantially increasing the hazard for spin-outs. In particular, spin-outs have a higher probability of being acquired than of surviving. Altogether, these results confirm the important role of pre-entry experience on survival, above and beyond the distance from the frontier. They also confirm that possessing pre-entry experience makes spin-outs more likely than diversifiers to be acquired. In short, previous experience in the LAN industry, such as individual skills and social networking, matter for survival, and thus the fate of firms is also rooted in the mode of entry into the industry.

Our analysis has the following important implications. From the viewpoint of the literature on industrial dynamics, our results offer additional insights into the relationship between mode of entry to an industry and mode of exit from an industry. Recent studies have highlighted the importance of pre-entry experience for firm survival (Klepper, 2002; Thompson, 2005). Our results are consistent with these findings, but also stress that firms with higher pre-entry experience are relatively more likely to be acquired, especially immediately after innovation has occurred, which demonstrates the importance of looking at firm exit as a heterogeneous event instead of treating mergers and acquisitions as censored exits. We also extend the empirical literature on the determinants of exit in turbulent industries. Indeed, most of the existing contributions on this topic focus on exit from declining industries, mainly by looking at the financial determinants of exit. Our study, however, provides insights that are relevant to highly innovative sectors.

Our analysis also has implications for the empirical literature on aggregate economic growth at industry level (See Baily, Hulten, and Campbell, 1992; Haltiwanger, 1997; Baily, Bartelsman, and Haltiwanger, 2001, among others). These empirical analyses seek to decompose sectoral - or aggregate - economic growth into an internal firm effect (firms increase their own levels of productivity), an external effect (changes in market shares across incumbents) and a market selection effect (the impact of firm entry and exit on economic growth). In particular when entrants perform better than exiting companies, market selection contributes positively to aggregate economic growth[9]. Because information on modes of exit is not readily available in large datasets, exit is treated as an homogeneous event, such that exit by acquisition equates with exit by failure. Our analysis challenges these results and points to a possible measurement error in the turnover component. Since acquired companies are located closer to the frontier than firms that exit by failure, the benefits of markets selection may have been underestimated. Depending on data availability, future research on the role of market selection on economic growth should take into consideration both types of exit.

Finally, our analysis of innovativeness and mode of exit has also important policy implications. In dynamic industries, acquisitions are mainly finalized at strengthening market positions at the expenses of the closest competitors. Our results highlight that targeted firms are generally young, endowed with experience inherited from skilled founders, and located far away from the acquirers. This suggests that acquisitions are a means of acquiring knowledge and innovative assets that the buyers do not possess. Evaluating these implications in terms of welfare gains/losses from these mergers is not straightforward and beyond the scope of this paper. However, acquired assets are generally costly to replicate and require time to be developed. The occurrence of these mergers allows the existing resources to be kept within the economic system while at the same time avoiding duplication of costs. This is an important aspect that should be taken into consideration by antitrust authorities, which usually are more concerned with the anticompetitive effects of mergers and acquisitions.

7 Conclusion

This paper has investigated the relationship between product innovation and firm survival in a high-tech industry. First, we looked at the hazard rate of firms by considering exit as a homogeneous event. We found that firm quality, as captured by firm location with respect to the technological frontier, innovative capital, pre-entry experience, age and size are important determinants of firm survival. Second we have extended the analysis to the case of heterogeneous exit. We found that, when controlling for firm level attributes, among firms that exited, only those located close to the frontier were more likely to be acquired, suggesting that position with respect to the technological frontier acts as a signal of firm quality. We also found support for the presence of a positive relationship between the stock of intangible capital and the probability of surviving. However, provided that the firm exits, intangible capital determines neither exit via plant closure nor exit via acquisition.

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Notes

[1]A non-exhaustive list of contributions includes, among others, Haltiwanger (1997), Foster, Haltiwanger, Krizan, Hulten, Dean, and Harper (2001) for the United States, Griliches and Regev (1995) for Israel, Aw, Chen, and Roberts (2001) for South Korea and Taiwan.

[2]According to this business model, new companies usually revolved around a single innovative product or technology. Acquisition usually entailed the purchase of the new firms in stock swap, followed by integration of the product as well as the technology. Cisco Systems, the leader in the LAN switch market was one of the proponents of this acquisition strategy (Kenney and von Burg, 2000).

[3]This is different from studies that use census data, in which the age of the firm is generally taken as the number of years of presence in the census (i.e. the dataset).

[4]Note that the sum of the predicted probabilities equals unity.

[5]To explore this issue, we focus on firms that were acquired by incumbents from within the switch industry. This sub-sample of 40 target firms represents 59% of all mergers and acquisitions.

[6]This result echoes the results of Blonigen and Taylor (2000) who considered a sample of acquisitions in the US electronic and electrical equipment industry between 1983 and 1993 and found evidence of an inverse relationship between R&D intensity and acquisition activity for acquiring firms, indicating that the buyer treats the assets of the targeted firm as an imperfect substitute of its own.

[7]Note that the predicted probabilities are computed using the *median* values

of the continuous variables (time, age at entry, size, R&D intensity) and the *mean* values of the dichotomous variables (entry-year dummy variables), where the mean and median were computed for each type of firm. The table highlights important differences, but also some similarities.

[8] In Table 7, we compute the net effect of being a spin-out given the characteristics of the representative firm over the whole sample of firms.

[9] With a few exception (Nishimura, Nakajima, and Kiyota, 2005), the contribution of this market selection is generally positive. According to textbook economics, this is to be expected since it implies that only the most profitable companies stay in the industry.

Table 1: OLS Regression on Observed Prices

Backplane Capacity	0.236
	[0.036]***
Number of Ethernet Ports	0.09
	[0.028]***
Number of Fast Ethernet Ports	0.04
	[0.037]
Number of FDDI Ports	0.024
	[0.060]
Number of Token Ring Ports	0.132
	[0.046]***
Number of 100VG-AnyLAN Ports	0.248
	[0.122]**
Number of ATM Ports	0.112
	[0.042]***
Number of Gigabit Ethernet Ports	0.361
	[0.055]***
VLANs Capability	0.394
	[0.099]***
Chassis	0.899
	[0.130]***
Fixed Configuration	-0.222
	[0.088]**
Constant	8.37
	[0.389]***
Observations	503
R-squared	0.699

Dependent Variable: Deflated Product Price. Robust standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. Year dummy variables omitted for clarity.

Table 2: The relationship between modes of entry and exit in the LAN industry

	Failure	Buying-Out	Survival	Total
Spin-Out	12 *12.5*	60 *56.8*	29 *31.7*	101
Diversifier	3 *2.5*	8 *11.2*	9 *6.3*	20
Total	15	68	38	121

Expected frequencies in *italics*. To be interpreted with care due to low expected frequencies. Chi-square statistics = 2.66 (P = 0.265)

Table 3: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Failure	121	0.12	0.33	0.00	1.00
Bought-Out	121	0.56	0.50	0.00	1.00
Survivor	121	0.31	0.47	0.00	1.00
Spin-Out	121	0.83	0.37	0.00	1.00
Diversifier	121	0.17	0.37	0.00	1.00
Age at Entry	121	9.61	12.54	1.00	84.00
Size (log)	121	6.16	2.16	2.71	13.30
Dist. Frontier	121	2.42	1.09	0.00	4.69
R&D Intensity	121	0.11	0.20	0.00	0.70
Entry Rate $(t-1)$	600	1.23	2.00	0.00	6.80
Exit Rate $(t-1)$	600	0.44	0.58	0.00	2.00

Table 4: Firm Entry and the Hazard Rate of Exit in the LAN Switch Industry

	(1)	(2)	(3)	(4)	(5)	(6)
Time (Log)	-0.830	-0.747	-0.699	-0.670	-0.616	-1.072
	[0.147]***	[0.150]***	[0.150]***	[0.152]***	[0.155]***	[0.270]***
Age at Entry		-0.040	-0.035	-0.041	-0.063	-0.060
		[0.017]**	[0.016]**	[0.017]**	[0.019]***	[0.019]***
Size (Log)		-0.071	-0.091	-0.138	-0.206	-0.250
		[0.073]	[0.072]	[0.076]*	[0.081]**	[0.082]***
Dist. Frontier			0.788	1.161	1.186	1.213
			[0.495]	[0.527]**	[0.506]**	[0.517]**
(Dist. Frontier)^2			-0.256	-0.359	-0.363	-0.364
			[0.120]**	[0.130]***	[0.124]***	[0.126]***
R&D Intensity				-2.021	-1.938	-1.860
				[0.874]**	[0.864]**	[0.858]**
Spin-Out					-1.232	-1.410
					[0.468]***	[0.479]***
Entry Rate ($t-1$)						-0.243
						[0.132]*
Exit Rate ($t-1$)						0.103
						[0.351]
Constant	-1.767	-0.656	-0.736	-0.119	1.671	3.138
	[0.516]***	[0.754]	[0.776]	[0.812]	[1.042]	[1.263]**
Number of firms	121	121	121	121	121	121
Number of firm exit	83	83	83	83	83	83
$P(Y\|X)=1$	.109	.095	.093	.089	.087	.083
Log Likelihood	-216.7	-209.6	-205.3	-202.3	-199.1	-196.8
Chi-square	49.0	63.2	71.7	77.7	84.1	88.8
LR Chi-Square	49.0***	13.2***	8.6**	5.9*	6.4**	4.7*

Number of observations: 600. Discrete Time Duration Model with Weibull Hazard Function. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All duration models include a full vector of entry-year dummy variables, not reported here for clarity.

Table 5: Robustness Checks for Discrete Time Duration Model

	Hazard Rate Function			Unobserved Heterogeneity		
	(6)	(7)	(8)	(9)	(10)	(11)
Age at Entry	-0.060	-0.060	-0.059	-0.077	-0.064	-0.067
	[0.019]***	[0.019]***	[0.019]***	[0.024]***	[0.020]***	[0.029]**
Size (Log)	-0.250	-0.220	-0.230	-0.217	-0.266	-0.279
	[0.082]***	[0.082]***	[0.083]***	[0.121]*	[0.087]***	[0.123]**
Dist. Frontier	1.213	1.216	1.234	1.837	1.266	1.307
	[0.517]**	[0.513]**	[0.517]**	[0.677]***	[0.547]**	[0.660]**
(Dist. Frontier)^2	-0.364	-0.369	-0.370	-0.540	-0.383	-0.399
	[0.126]***	[0.125]***	[0.126]***	[0.168]***	[0.133]***	[0.182]**
R&D Intensity	-1.860	-1.812	-1.796	-3.066	-1.999	-2.119
	[0.858]**	[0.862]**	[0.862]**	[1.147]***	[0.910]**	[1.249]*
Spin-Out	-1.410	-1.314	-1.326	-2.083	-1.500	-1.568
	[0.479]***	[0.478]***	[0.480]***	[0.678]***	[0.513]***	[0.690]**
Entry Rate $(t-1)$	-0.243	-0.109	-0.154	-0.301	-0.259	-0.272
	[0.132]*	[0.137]	[0.142]	[0.164]*	[0.136]*	[0.163]*
Exit Rate $(t-1)$	0.103	-0.079	0.016	0.080	0.124	0.141
	[0.351]	[0.348]	[0.362]	[0.433]	[0.355]	[0.375]
Constant	3.138	2.448	-0.900	4.738	3.365	3.676
	[1.263]**	[1.416]*	[1.555]	[1.682]***	[1.343]**	[2.051]
Link Function	C log-log	C log-log	C log-log	Logistic	C log-log	C log-log
Hazard Function	Weibull	Polynomial	Non Par.	Weibull	Weibull	Weibull
Number of Firms	121	121	121	121	121	121
Number of Firm Exit	83	83	83	83	83	83
Log Likelihood	-196.8	-195.6	-194.0	-192.9	-196.8	-196.7
LR test for frailty	-	-	-	0.480	0.150	0.117

Number of observations: 600. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All duration models include a full vector of entry-year dummy variables, not reported here for clarity. Baseline Hazard Function: (6), (9), (10) and (11) Log of time (Weibull); (7) Polynomial of order 2;(8) Fully non parametric. Distribution of Unobserved Heterogeneity: (9) and (10) Normal; (11) Gamma

Table 6: The Determinant of the Forms of Firm Exit in the LAN Switch Industry

	(12)	(13)	(14)
Time (Log)	-0.793	-1.351	-0.559
	[0.464]*	[0.352]***	[0.549]
Age at Entry	-0.071	-0.073	-0.002
	[0.025]***	[0.023]***	[0.031]
Size (Log)	-0.463	-0.413	0.051
	[0.152]***	[0.110]***	[0.171]
Dist. Frontier	5.008	1.579	-3.429
	[1.342]***	[0.631]**	[1.418]**
(Dist. Frontier)^2	-1.261	-0.457	0.804
	[0.328]***	[0.154]***	[0.346]**
R&D Intensity	-6.152	-2.318	3.834
	[2.564]**	[1.034]**	[2.680]
Spin-Out	-2.424	-2.001	0.423
	[0.814]***	[0.649]***	[0.887]
Entry Rate $(t-1)$	-0.304	-0.229	0.075
	[0.225]	[0.169]	[0.260]
Exit Rate $(t-1)$	0.249	0.024	-0.224
	[0.590]	[0.434]	[0.673]
Constant	4.76	5.216	0.456
	[2.277]	[1.651]	[2.513]
Log Likelihood	-259.1		
Hausman Test (IAA)	-35.5	0.000	
Wald Test (Combined)	38.9***	64.2***	19.8

Number of observations: 600. Competing Risk Duration Model. Standard errors in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%. All duration models include a full vector of entry-year dummy variables, not reported here for clarity.
(12) Failure vs. Survival
(13) Buying-out vs. Survival
(14) Buying-out vs. Failure

Table 7: Marginal Effects of Firm-Level Variables on the Mode of Exit

	Failure	Acquisition	Surviving
Predicted Probability	0.055	0.191	0.755
Time			
Predicted at the 30^{th} percentile	0.062	0.254	0.684
Predicted at the 70^{th} percentile	0.049	0.150	0.802
Absolute Change	-0.013	-0.105	+0.118
Relative Change	-21.6%	-41.2%	+17.3%
Age at Entry			
Predicted at the 30^{th} percentile	0.067	0.236	0.698
Predicted at the 70^{th} percentile	0.039	0.135	0.827
Absolute Change	-0.028	-0.101	+0.129
Relative Change	-41.9%	-42.8%	+18.5%
Size			
Predicted at the 30^{th} percentile	0.070	0.236	0.694
Predicted at the 70^{th} percentile	0.026	0.100	0.874
Absolute Change	-0.044	-0.136	+0.181
Relative Change	-63.1%	-57.7%	+26.0%
Distance to Frontier			
Predicted at the 1^{st} percentile	0.001	0.085	0.914
Predicted at the 40^{th} percentile	0.074	0.220	0.706
Absolute Change	+0.074	+ 0.135	-0.208
Relative Change	$+\infty$	+158.5%	-22.8%
R&D Intensity			
Predicted at the 30^{th} percentile	0.068	0.202	0.730
Predicted at the 70^{th} percentile	0.041	0.176	0.783
Absolute Change	-0.026	-0.027	+0.053
Relative Change	-38.8%	-13.2%	+7.2%
Spin-Out			
Predicted for SPIN-OUT=0	0.184	0.456	0.360
Predicted for SPIN-OUT=1	0.037	0.141	0.822
Absolute Change	-0.146	-0.316	+0.462
Relative Change	-79.8%	-69.1%	+128.3%

The predicted probability has been computed using the *median* values of continuous variables (time, age, size, distance to frontier, R&D intensity) and the *mean* values of the dichotomous variables (entry-year dummy variables and entry type). All marginal effects have been computed as discrete change, while holding all other independent variables constant at their mean or median values.

Table 8: Distance to Frontier, Time and the Mode of Exit, by Mode of Entry

	Distance to frontier (percentiles)[a]										
	1	10	20	30	40	50	60	70	80	90	100
Diversifier											
Failure	0.000	0.004	0.015	0.024	0.021	0.015	0.009	0.005	0.002	0.001	0.000
Acquisition	0.021	0.052	0.072	0.072	0.066	0.054	0.042	0.033	0.023	0.017	0.002
Surviving	0.979	0.945	0.913	0.905	0.913	0.931	0.949	0.962	0.975	0.983	0.999
Spin-Out											
Failure	0.001	0.016	0.059	0.092	0.084	0.062	0.038	0.023	0.010	0.005	0.000
Acquisition	0.082	0.182	0.232	0.225	0.210	0.183	0.149	0.123	0.089	0.065	0.006
Surviving	0.918	0.802	0.708	0.684	0.706	0.756	0.813	0.854	0.901	0.930	0.994

	Time (in years)[b]												
	1	2	3	4	5	6	7	8	9	10	11	12	13
Diversifier													
Failure	0.044	0.032	0.025	0.021	0.018	0.016	0.014	0.013	0.012	0.011	0.010	0.009	0.009
Acquisition	0.325	0.162	0.102	0.072	0.054	0.043	0.035	0.030	0.025	0.022	0.020	0.017	0.016
Surviving	0.632	0.806	0.873	0.907	0.928	0.941	0.951	0.958	0.963	0.967	0.970	0.973	0.976
Spin-Out													
Failure	0.080	0.073	0.063	0.055	0.049	0.044	0.040	0.037	0.034	0.032	0.030	0.028	0.026
Acquisition	0.548	0.340	0.235	0.175	0.137	0.111	0.092	0.079	0.068	0.060	0.053	0.048	0.043
Surviving	0.372	0.587	0.702	0.770	0.814	0.845	0.868	0.885	0.898	0.909	0.917	0.925	0.931

[a] The predicted probability is computed using the *median* values of continuous variables (time, age at entry, size, R&D intensity) and the *mean* values of the dichotomous variables (entry-year dummy variables), where the mean and median are computed for each type of firm.

[b] The predicted probability is computed using the *median* values of continuous variables (age at entry, size, distance to frontier, R&D intensity) and the *mean* values of the dichotomous variables (entry-year dummy variables), where the mean and median are computed for each type of firm.

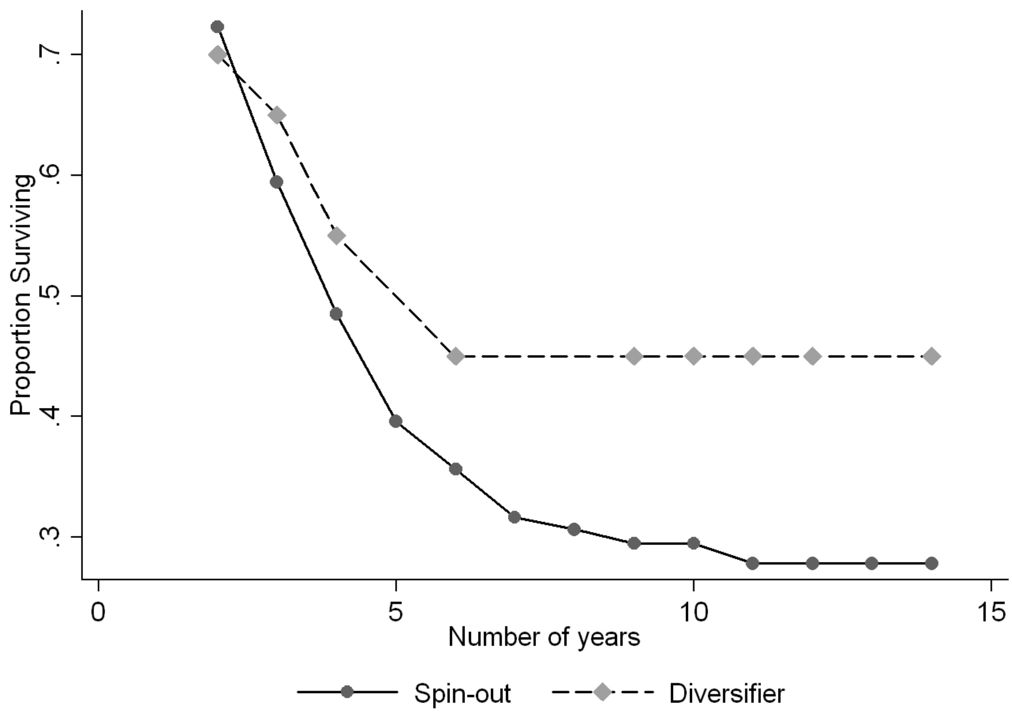

Figure 1: Kaplan Meier Survival Estimates