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# Evidence From LAN Switch Industry

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# Entry, Innovation, and Exit
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**Abstract**

We investigate whether the form of exit is triggered by the form of entry and technical expertise, an exercise which has been persistently missing in the literature, for a sample of 121 firms in the LAN switch industry. We find that pre-entry experience, technical expertise, and intangible assets are important determinants of firm survival. Extending the analysis to the case of heterogeneous exit, we find that firms with high pre-entry experience and higher technical expertise are more likely to exit by acquisition than by failure. Conversely, possessing a larger intangible capital and previous experience in related markets does not lead to a higher probability of being acquired.

## 1 Introduction

This paper analyses the relationship between entry, innovativeness and exit. In most works, firm exit is captured by the firm's disappearance from census data. It is then considered as the consequence of poor economic performance, the latter being the firm's lack of financial resources and/or innovative capabilities. However, to equate firm exit with poor performance may simply be wrong. We argue that the *form* of exit must be accounted for, because exit by acquisition cannot be treated as exit by bankruptcy. Whereas the latter must definitely be viewed as a failure, the former conceals a positive valuation by the acquiring company. Should this be the case, factors explaining firm exit may vary depending on whether one looks at exit by acquisition or exit by mere failure.

This research is carried out on a sample of 121 firms in the LAN switch industry, a sub-sector of the data communication industry in the 1990s. During this

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period,the LAN switch industry has experienced a rapid and sustained growth characterized by a high rate of firm entry and exit. Innovations have constantly moved forward the technological frontier and have generated opportunities for new firms to enter and challenge the existing leadership. Incumbents often reacted to the challenges by acquiring those firms who possessed the capabilities and the knowledge which threaten them. As a consequence a considerable number of exits witnessed during the 1990s were due to acquisitions.

We use information on the 'fate' of firms as firm failure, firm buy-out or mere survival. Having data on the founders' background to identify the forms of entry as spin-out, start-ups and diversifiers, we investigate whether the form of exit is triggered by the form of entry, an exercise which has been persistently missing in the literature. Moreover, all firms in our sample are 'innovative' in the sense that they have introduced at least one switch equipment during the 1990s. Information on product characteristics is used to describe the firm location on a quality scale. This provides information on the firms' technical expertise and is used as an explanatory variable to predict exit. For all firms we have information on their date of entry and exit from the switch industry. This provides us with the opportunity to develop duration models of two types. First, we estimate a discrete time duration model to understand when exit is considered to be a homogeneous event. Then we consider alternative types of exit such as failure and acquisitions, by means of a multinomial logit competing risk model.

The paper is organized as follows. Next Section provides a review of the literature as well as the necessary background information on the LAN switch industry. In Sections 3 and 4 we develop the econometric model, describe the data sources and the variables that will be used on the empirical analysis. Section 5 presents and discusses the results. Conclusions of the analysis are presented in Section 6.

# 2 Literature Review and Industry Background

The existing literature on entry and exit is extensive. Empirical studies point to firm size, age and market selection, among others, as important determinants of industrial dynamics [5, 2]. Mata and Portugal [21] and Mata et al. [22], provide evidence on the complex nature of the relationship between firm age and survival. While the probability of survival seems to increase for old firms, the relationship is not definite for young firms. Honjo [13] investigates the post-entry performance of a sample of Japanese firms. He finds a negative effect of firm size on exit due to business failure and a positive one for firm age. In this paper we take a broader stance at the issue of the determinants of entry and exit by looking at the relationships between form of entry, innovativeness and form of exit.

The idea that the 'fate' of firms should be linked to innovative activity is not new and several contributions both theoretical and empirical have made this point. At the theoretical level, Ericson and Pakes [6] extend Jovanovic [16] to allow for 'active learning' and R&D heterogeneity among firms. They predict that high rate of innovation and uncertainty should be associated with high rate of exit. Klepper [19] provides another interpretation. His model predicts that time of entry interact with prior experience and with age to condition the hazard of exit. At the empirical level, in his review of determinants of entry, Geroski [10] has pointed out how innovation and firm survival should be strongly and directly linked. Audretsch [1] has found that firms in more innovative industries show lower probability of survival soon after entry and a higher probability after they survive a certain amount of years. Cefis and Marsili [3] find that after controlling for age and size, innovative firms are more likely to survive than non innovative firms. Beside these contributions there is an enormous amount of management oriented literature that links firm survival with both the timing [4] and the strategy of innovation [23, 34]. All in all, these studies point to the presence of a premium associated with survival for innovative firms. However, few analyses exist on firms that are innovative but fail to survive and few contributions have investigated the links between innovation and form of exit.

The empirical literature on the form of exit is rare and scanty. In her seminal work, Schary [29] finds that profitability is a weak determinant of the form of exit and that firms' characteristics (i.e. mainly related to capital structure) should be taken into account. Moreover, the predictive power of firms' characteristic varies depending on the form of exit. Another work has taken up these findings and explicitly considered both industry and firm level determinants of firm exit. Perez et al. [26] for instance perform a competing risk analysis on a sample of manufacturing firms in Spain. They find differences in the determinants of exit depending upon the form of exit (i.e. exit due to business failure as opposed to acquisition). In particular, the risk of failure declines with age and size, while the risk of being acquired seems to increase.

Though they provide interesting insights into the nature and causes of different form of exit, none of these contributions explicitly address the relationship between innovativeness and form of exit. In this paper, we want explore the possibility that the form of firm exit can be explicitly linked to firm innovativeness. A strong argument in favor of the hypothesis that innovative firms are more likely to exit by acquisition can be made on the basis of the resource based theory of the firm [25]. By innovating, firms signal that they possess certain capabilities. In particular contexts characterized by rapid technical change, such as the LAN switch market, competitors may find in need of those capabilities and choose to get them by acquiring existing firms instead of developing them [28, 17]. In this case, exit by acquisition is a consequence of the firms being innovative and signals success rather than failure.

Finally, it has to be noted that innovation may also be related to the form of entry. Recently the literature has focused on the relationship between the form of entry and the firm performance in terms of survival. As stressed by Helfat and Lieberman [12], spin-outs may take advantage of assets like industry-specific knowledge embodied in firms founders and transferred from the previous employee and should be more performing than other firms. For a rather large sample of firms in Denmark, Eriksson and Kuhn [7] find evidence of lower risk of failure for spin-outs as opposed to other types of firms. Franco and Filson [9] confirm these findings in the case of spin-outs in the Hard Disk Drive industry. In his historical analysis of the shipbuilding industry, Thompson [33] finds a positive relationship between pre-entry experience and the survival of firms. Indeed, once controlled for this source of heterogeneity, the dependence of survival on age and firms size disappears. Although very important for their implications for the study of the determinants of industrial dynamics, none of these contributions have explicitly addressed the relationship between form of entry and form of exit. Those that did, usually treated exit as a 'homogenous' event.

This paper presents an empirical investigation of entry and exit in the Local Area Network (LAN) switch equipment industry. The LAN switch industry began in the 1990 with the invention of the first switch for data communication. Entry in the industry was initially slow but it dramatically increased starting from 1993. Three different types of firms fueled the entry process. First, we had incumbents from established markets (i.e. routers and hubs) within the LAN industry. Second, there were incumbents from outside the industry but with previous experience either in telecom, in semiconductor, or computer industry. Third, there were new firms searching for new opportunities. These firms were generally highly innovative and founded wither by entrepreneurs who were former academics or by entrepreneurs who were former employees in the industry.

Entry was accompanied by an evolution of the technology which culminated in the opening up of two market segments. In the high-end segment there were products characterized by high performance targeted to customers with large networks. In the low-end segment there were less performing 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 constant search for technical excellence and increasing performance.

Polarisation led to consolidation and to an increase of the rate of exit. Among the firms who exited the industry, the majority consisted of new firms which ended up being acquired by existing incumbents. Indeed for many of the new firms the opening up of the switch market had represented at the beginning the opportunity to enter a new niche. However, it was clear from the start that there were little chances of turning the new venture into a large firm. Indeed, in many cases firms had been 'designed to be acquired from the start' generating an entirely new business model called 'the acquisition-as-exit-strategy' business model ([18]: 234)[1].

In this paper we look at this phase of growth and consolidation of the LAN switch industry and at the dynamics of entry and exit. By carrying out such an analysis, we aim at gaining a better understanding of the relationship between forms of entry, innovativeness and forms of exit. In particular, we examine the following propositions. First, we expect entry by firms with pre-entry experience to be positively associated with the probability to survive. For those firms which exit, pre-entry experience should increase the probability to be acquired. Second, we expect firm technical expertise as measured by the distance to technological frontier to be positively associated with the probability to survive or to be acquired, for those firms who exit. Third, there is a positive relationship between the quality of the stock of knowledge and capabilities available to firms and the probability of exiting by acquisition. Fourth, previous innovative experience and first mover advantage are positively associated with firm survival.

# 3 Econometric Models

We develop two sets of econometric models to evaluate the factors that affect firm exit. First we estimate a standard discrete time duration model to explain the probability of exit; second we apply a competing risk model accounting 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 [27]. Suppose there are firms $i = 1, \ldots, N$, who enter the industry at time $t = 0$. The hazard rate function for firm $i$ at time $t > 0$ and $t = 1, , T$ is assumed to take the proportional hazard form: $\lambda_{it} = \lambda_0(t) \cdot X_{it}^{'}\beta$, where $\lambda_0\left(t\right)$ 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:

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

where $\theta(t)$ is the baseline hazard function relating the hazard rate $h_t\left(X_{it}\right)$ at the $t^{th}$ interval with the spell duration [14].

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

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

where $\varepsilon_i$ 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 $\varepsilon_i$ are distributed normal and Gamma. Assuming that $\varepsilon_i$ is Gamma distributed with mean one and variance $v$, the log-likelihood function is written:

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

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 $\beta$ 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 $v$. Besides, we also 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 form of exit, namely mere firm failure, and firm buy-out. The extension of the standard pooled duration model to two exit forms is referred to as the competing risks model (CRM) [15]. 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 opposite, one pointing to a positive event (firm buy-out), the other pointing to the lack of economic viability (firm failure). In practical terms, the independent competing risk framework treats both exits as right censored [20, 15]. That is, we estimate the following complementary log logistic model similar to 1, but where the full set of parameters is allowed to vary according 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 cautionary note about the interpretation of the coefficient estimates. In CRM models, interpretations of the coefficients are 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 to exit, for instance by firm failure if the estimated coefficient for the hazard rate of firm failure is larger than the corresponding coefficient for the hazard rate of firm buy-out [31]. If we assume that we have intrinsically discrete time data, Eq.4 can be estimated using a 'multinomial logit' competing risk model.

We also test whether the two forms of exit, firm failure and firm buy-out, are behaviourally distinct rather than simply incidental. This is equivalent to the null hypothesis of equality of all parameters (except intercepts in the models for the destination-specific hazard). Narendranathan and Stewart [24] show that for continuous time PH models, a test of whether exits to different states are behaviourally 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 maximised log-likelihood from the competing risk model (the sum of those from the component models), $ln(L_{SR})$ is the maximised 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 distributed Chi-squared 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 switch equipment starting from 1990, the year the first switch has been marketed. For each firm in our dataset we have information on: date of entry and exit from the switch industry, number of switches introduced, number of products

introduced in other segments of the LAN industry such as the router and the hub segment, number of patents granted. For each new switch introduced we have information on its price and technical characteristics. Information on firm entry and exit date was gathered from a variety of sources such as the D&B Million Dollar Database and Lexis-Nexis. To gather information on the background of the firms and their founders we searched publicly available databases that aggregate news and press releases such as ABI-Inform as well as 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 instead obtained by looking at announcements in the specialized trade press and at the information contained in the CORPTECH database. Data on product characteristics and prices for switches as well as for hubs and routers were obtained from an original dataset of 1825 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) that periodically publish Buyers' Guides and details on new product introductions. This information has been double checked, with press communications and product announcements released by manufacturers. In our analysis we decided to consider only those manufacturers who marketed four or more products in the period 1990-1999. After consolidation we are left with 121 firms who marketed a total of 503 switch products. Finally, information on patents granted was retrieved from the USPTO Database.

### 4.1 Forms of Entry and Forms of Exit

We use information on pre-entry experience and founders' background to assign to firms a status according to their mode of entry. In particular, we define SPIN-OUT as those firms whose main line of business is the LAN industry but founder(s) were already employed in the LAN industry in the year(s) prior to the founding of the new company. This includes also those cases in which the new firm does not entertain any type of formal relationship with the parent. We define START-UP as those firms whose founder(s) had no prior experience in the LAN industry or no entrepreneurial experience at all at time of founding but whose main line of business is in the LAN industry. Finally, we define DIVERSIFIER as those 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 switch market. All types of firms might have already been operating in the LAN industry when entry in the switch market occurred.

This distinction, which is based on technological experience before entry occurred, can be used to glean some preliminary evidence on the relationship between pre-entry experience and performance in terms of survival. Figure 1 below draws the proportion of surviving firms according to the number of years after entry, distinguishing by mode of entry. We observe the following.

[Figure 1 about here.]

Diversifiers display the highest survival rate after entry with more than 40% of firms surviving at the end of the period. Start-ups and spin-outs trail behind with the former that seem to survive longer than the latter. It is interesting to notice that start-ups experience a higher rate of survival than Diversifier in the first five years after entry thus suggesting that being experienced might be important particularly just after entry has occurred.

This evidence seems inconsistent with previous results which stress the advantages of pre-entry experience in terms of survival [33]. Spin-outs and start-ups benefit from a higher pre-entry experience and should display higher survival rates after entry into the switch market. Klepper [19] argues that at a given age, early entrants and firms with pre-entry experience should display a higher survival rate than late entrants and firms with no experience. However, though spin-outs and start-ups are more experienced, they are generally younger than Diversifiers. In other words, firm age might account for the accumulation of physical, human and organizational capital which, although not necessarily related to the LAN industry, might influence firm performance in terms of survival. To control for this hypothesis we interact the firm status with AGE at time of entry. To account for the time of entry we include in the duration models a vector of entry-year dummy variables.

One of the basic ideas underlying this paper is that pre-entry experience enhances firms' performance in terms of survival. However, for innovative firms, being experienced is a 'double edged sword' in the sense that possession of specific capabilities makes 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 in which 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), Buying-out (i.e. acquisition), and Survival. Table 1 reports the relationship between modes of entry and modes of exit for the firms in our sample. We note two things.

[Table 1 about here.]

First, more than two thirds (69%) of the firms in our sample exit the LAN switch industry after entry. Of those exiting the majority consists of spin-outs followed by start-ups. Second, both spin-outs and start-ups exit mostly by acquisition. Among survivors, Spin-out and Start-up display the largest share of the total although almost half of the Diversifier survives. This preliminary evidence suggests that although firms with higher pre-entry experience make up most of the total survivors, those that exit generally tend to be bought-out thus suggesting that their fate may be linked to their status and that exit should not be rated as a homogenous event. The Chi-square statistics is not significant leading us to retain the null hypothesis of independence between modes of entry and mode of exit. However, this result should be interpreted with care due to low expected frequencies.

## 4.2 Quality Frontier

In this paper, we argue that post entry performance is mainly linked to pre-entry experience but that in the case of innovative firms technical expertise should be considered an important explanatory variable of the fate of firms when exit is not considered to be a homogenous event. We measure technical expertise in terms of firm location with respect to the technological frontier at time of entry. Location in the space of product characteristics has already been linked to firm exit in the literature [30, 32].

We represent the location of product in a vertical space 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 [30] 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 $\beta_j$ represent the marginal value of characteristic $j$ that both consumers and producers place on the $j^{th}$ attribute. Such weights are approximated by regressing observed prices, deflated into 1996 US dollars using the sector specific deflator for telecommunication equipment provided by the U.S. Department of Commerce, Bureau of Economic Analysis:

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

where $p_{mit}$ is the log is the observed price for model $m$ introduced in the market by firm $i$ at time $t$, $\alpha$ is a constant and $\alpha_t$ is a time fixed effect. Table 2 provides the results from the hedonic regression. With almost 70% of the variance of prices explained, the overall fit is satisfactory enough 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.

[Table 2 about here.]

Whereas the observed prices embody error measurements reflecting various factors such as changes in demand, promotional discounts and other non-quality components [30], the predicted price $\hat{p}$ reflects by construction the quality $q$ of the product. Thus we posit:

$$q_{mit} = \hat{p}_{mit} \qquad (7)$$

Eq.7 says 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 is the Switch market is likely to have evolved over time. This suggests that depending on significant changes in product quality in the nineties, the pooled regression may produce inexact weights. Therefore, we interact all explanatory variables with year dummy variables, in order to allow the weights $\beta_j$ to vary with time. Second we include a firm fixed effect $\mu_i$ to control for heterogeneity in the firms' pricing practices.

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

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

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

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 the 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, we compute for every product its distance from the quality frontier as follows:

$$d^f_{mit} = \max\left(q'_t\right) - q'_{mit} \tag{10}$$

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

### 4.3 Control Variables

Additional explanatory variables are intended to capture the role of intangible capital and firm size. We measure intangible capital in terms of patents (PATENT STOCK). This variable is constructed as the logarithm of the simple count of the total number of patents held by firms at time of entry, as retrieved from the NBER U.S. Patent Citation Database [11][2]. The size variable (SIZE) is constructed as the logarithm of the sum of the total number of products introduced in the Router and Hub market when entry occurred. To the extent to what the number of products influences firms' revenues, we may consider it also a sensible proxy for size. Lastly, we define AGE as the number of years since the firm was institutionally born. This is different from works using census data where the age of the firm is generally grasped by the number of years in the census (i.e.dataset). AGE has a fixed value equal to the age of the firm at time of entry in the industry. Thus, AGE measures pre-entry experience.

[Table 3 about here.]

Summary descriptive statistics for these explanatory variables are reported in Table 3[3].In all the regressions, we consider 121 firms, of which 83 eventually exit the industry. All variables take values at the time when the firm enters the idnustry, including AGE. 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 Results

To understand the impact of pre-entry experience on firms' performance several models have been estimated considering first exit as a homogeneous event. We use a discrete time duration model with a Weibull hazard function. In this model the explanatory variables are introduced in sequence and exit is treated as homogeneous. Then 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' competing risk model.

## 5.1 Homogeneous Exit

Five models have been estimated using a discrete time duration model with a Weibull hazard function (see Table 4). In the first models we look at the impact of pre-entry experience alone. We then add sequentially AGE, firm location in the product space (DISTANCE FROM FRONTIER and (DISTANCE FROM FRONTIER)$^2$, intangible capital (PATENT STOCK) and economies of scope (SIZE).

[Table 4 about here.]

Column (1) and (2) report the results for our main variables together with the baseline hazard function. In column (1) pre-entry experience does not seem to significantly impact on the probability of exit whereas when interacting the same variable with firms' age, some coefficients become significant. In particular, in column (2) the negative and significant coefficients of AGE $\times$ SPIN-OUT and AGE $\times$ DIVERSIFIER indicate that this type of firms have a lower probability of leaving the industry. It has to be noted that the sign of these coefficients does not change across subsequent specifications. Only the coefficient of AGE $\times$ DIVERSIFIER remains persistently significant, implying that diversifiers benefit more from past-experience than spin-outs and start-ups.

The impact of technical expertise as measured by firms' location with respect to the technological frontier is estimated in column (3). DISTANCE FROM FRONTIER enters positively thus suggesting that only firms capable to locate close to the frontier survive. However, the relationship between location in the product space and survival is non linear. Indeed, the negative and significant coefficient of (DISTANCE FROM FRONTIER)$^2$ suggests that exits mainly occur among firms located in the 'middle of the market'. This well reflects the situation in the switch market during the 1990s which was polarized between a high-end and a low-end [8]. At the high end of the market firms compete to be on 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. Interestingly, when adding the contribution of firm location in the product space, the coefficient of the SPIN-OUT dummy becomes significant, thus suggesting that firms with high pre-entry experience have relatively lower probability of exiting the industry with respect to Diversifiers.

We then control for the contribution of intangible capital stock and size separately. In column (4) we add the variable PATENT STOCK. The coefficient is negative and significant suggesting that possessing a higher stock of intangible capital reduces the probability of leaving the industry. It is interesting to note that with the inclusion of this variable also the START-UP dummy becomes significant thus confirming the importance of pre-entry experience. SIZE is added in column (5). The variable enters positively but not significantly and suggests that firms' size does not pay a significant role as determinant of the probability of exit. This result conflicts with most of the existing literature on firm survival. However, since it accounts for the total number of products introduced at time of entry, this is a measure of economies of scope rather than size, and it accounts for the role of experience in related markets.

Altogether our results confirm that the sample is behaving as expected. In particular, we observe two things. First, pre-entry experience mainly reduces the probability of exit when exit is considered a homogeneous event. Age also impacts positively on firms' survival but significantly only in the case of firms with limited pre-entry experience. Both results are consistent with previous findings [19, 33]. Second, firms with high technical expertise, as measured by their location with respect to the technological frontier, have a better post entry performance in terms of probability of surviving, though the relationship is not linear. Possessing intangible capital increases the probability of surviving while firms' size does not seem to play an important role.

We provide a sensitivity analysis for these results in Table 5 where alternative specifications of column (5) are reported. We carry out two types of robustness check. First, we explore different specifications of the baseline hazard function. The polynomial specification in column (6) substantially confirms our previous results, where both the sign and magnitude of the parameter estimates are stable. The non parametric specification is reported in column (7). This type of specification makes no assumption about the shape of the baseline hazard function by introducing a full vector of year dummy variables, instead of constraining the effect of duration to be monotonic (Column 5) or polynomial (Column 6). Again the signs and significance levels of the coefficients are very stable, confirming the good robustness of our results with respect to different assumptions on the duration effect.

[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 column (9) assume that error terms are normally distributed. When compared to the previous models, this specification yields similar results concerning the sign of coefficients. Both START-UP and SPIN-OUT lose their significance at 5 percent level although the size of these coefficients is substantially higher than in our reference model. In column (10) we assume that the firm-specific terms are distributed gamma. In this specification all the explanatory variables lose significance although the direction of the parameter estimates remain consistent. Only our proxy for technical expertise (DISTANCE FROM FRONTIER2) remains weakly significant. 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 heterogeneous exit without addressing the question of unobserved heterogeneity.

## 5.2 Heterogenous Exit

We now consider exit as being a heterogeneous event. Mere firm exit may conceal important insights on the form of exit. As argued above, in industries characterised by rapid technical change where competitors may not have time to develop their capabilities mergers and acquisitions are very frequent and they cannot be considered as exit by failure. In these contexts it is likely that pre entry experience, technical expertise, and intangible capital influence both survival and, for those firms that do not survive, the type of exit. Our short review of the existing empirical literature shows that this crucial piece of information is missing from many analyses of innovation and firms' survival. To explore the relationships between pre entry experience, innovativeness and firm survival we ran a 'multinomial logit' competing risk model (Table 6). For comparison purposes, column (5) reports the coefficient from our previous Weibull hazard rate estimation.

[Table 6 about here.]

Column (11) reports the results of the comparison between the alternatives of exiting by failure and surviving. Coefficients for SPIN-OUT, START-UP, and DIVERSIFIER interacted with AGE are all negative and significant indicating that firms with pre-entry experience have a lower probability of exiting by failure than surviving. It is interesting to note that for Spin-Outs and Start-ups, the latter has the lowest coefficients, implying that firms with the highest pre-entry experience within the industry have a higher chance of surviving. DISTANCE FROM FRONTIER has a positive and significant coefficient suggesting that indeed firms lagging behind in terms of technical expertise have a higher probability of exiting by failure than surviving. However, the relationship is non linear as indicated by the negative and significant coefficient of (DISTANCE FROM FRONTIER)$^2$. Location in the middle of the quality scale is the most dangerous game for firms, whereas locating either near the frontier or far from the frontier may be the favoured response to escape competition. The coefficient of PATENT STOCK is positive and significant suggesting that firms with a high stock of intangible capital are more likely to fail than survive, a result somewhat unexpected which deserves further analysis. Finally SIZE, measured as the total number of products introduced in related markets, is not significant.

Results of the comparison between exit by Buy-out and Survival are reported in column (12). Again we find that technical expertise 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 FROM FRONTIER. Major differences with respect to the previous estimates are found in the significance and sign of the coefficients of the variables related to pre-entry experience and intangible capital respectively. The coefficient of START-UP is now weakly significant suggesting that firms with 'intermediate' pre-entry experience have a lower probability of being bought-out than surviving. The coefficient of PATENT STOCK is now negative and strongly significant thus suggesting that possessing a large patent portfolio protects firms against acquisition.

Finally, column (13) compares the two alternatives of exiting by buy-out and exiting by failure. In this column, coefficients are the difference between those in column (12) and those in column (11). Thus an increase in the coefficient of the explanatory variables will increase the conditional probability to 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. Interaction terms now exhibit a positive coefficient suggesting that, when controlling for age, pre-entry experience increase the probability of exiting by acquisition rather than failure. Since coefficients can be interpreted as log odd ratios, they rank the impact of pre-entry experience on the forms of exit: Buy-out versus failure), by type of entry. We observe that pre-entry experience for Spin-Outs display the highest probability of exiting by acquisition, less so for Start-ups. For Diversifiers, pre-entry experience protects again exit as a whole, but seems to have no effect on the type of exit.

Both our measures of technical expertise change sign and lose some significance with respect to previous estimates. DISTANT FROM FRONTIER is negative, though weakly significant, 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 FROM FRONTIER)$^2$ which is now positive and indicates that the probability of being acquired is high for firms located very close to the frontier, decreases as distance increase and then increases again for those firms located farther away. All in all, both results confirm that acquisitions are mainly triggered by the need to acquire technical expertise and are consistent with the polarized structure of the switch market mentioned above. Finally, the coefficient of PATENT STOCK is again negative and significant suggesting that the higher the stock of intangible asset the less likely firms are to exit the industry by acquisition than by failure.

Altogether, these estimates provide new results that enrich our analysis and shed some light on our initial hypotheses. Interestingly, when exit is treated as a heterogeneous event pre-entry experience alone loses significance as a determinant of the fate of firms while age becomes a 'mediating' factor of firms' post entry performance particularly important when comparing the hazard of firm buy-out and firm failure. Concerning the impact of technical expertise on post entry performance, we find support for our hypothesis. Being located close to the frontier increases the probability of surviving. Moreover, among the exiting firms, only those located close to the frontier are more likely to be acquired. Finally, our results suggest that the relationship between technical expertise and the fate of firms is non linear. We have found only partial support for the hypothesis that there is a positive relationship between the the stock of knowledge and the probability of exiting by acquisition. On the contrary, possessing a larger intangible capital generally increases the probability of surviving. However, if exiting, firms with larger intangible capital fail, they are not acquired. Our interpretation is that although large knowledge stocks may make firms more appealing on the market, they also make firms more expensive to buy. In a context where knowledge obsolescence is in fact extremely rapid, this may in turn inhibit acquisitions. Finally, our analysis does not provide support for the hypothesis that previous innovative experience in related fields is associated to firm survival.

# 6 Conclusion

This paper has analysed the relationships between form of entry, innovativeness and form of exit in the LAN switch industry a sub-sector of the data communication industry in the 1990s. First, we looked at the hazard rate of firms by considering exit as a homogeneous event. We found that pre-entry experience, technical expertise, and intangible assets are important determinants of firms' survival. Second we have extended the analysis to the case of heterogeneous exit. We found that, among those which exited, and once controlled for age, firms with high pre-entry experience and higher technical expertise are more likely to exit by acquisition than by failure. On the contrary, possessing better intangible assets and previous production experience in related markets does not lead to a higher probability of being acquired.

Our analysis has important implications for the existing literature on entry, innovation and exit. First, we provide further support to the empirical literature on the importance of pre-entry experience as a determinant of post entry performance and extend it to the case of heterogeneous exit. Second, we extend the empirical literature on the determinants of exit in turbulent industries. Indeed, most of the existing contributions on this topic have focused on exit from declining industries, mainly by lookingy at the financial determinants of exit. By focussing on the LAN equipment industry our study provides insights on the case of a highly innovative sector. Third, this paper also contributes to the literature on innovation, acquisition and industrial dynamics. The existing literature on innovation has looked at acquisitions mainly as a way of acquiring knowledge and innovative capabilities that require time to be developed. Our results stress that in a dynamic industry, acquisitions may be mainly finalized at gaining positions in the market rather than at acquiring competences *per se*.

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## Notes

[1]According to this business model, the new companies usually revolved around a single innovative product or technology. Acquisition usually entailed the purchase of new ones in stock swap and then the integration of the product as well as of the technology. Cisco Systems, the leader in the LAN switch market is one of the proponents of this strategy (Kenney and von Burg, [18] ; Mayer and Kenney, 2004

[2]We do not weight patents by citation counts, due to problems of time trunction in the available dataset. Moreover, summing all patents may lead to an overestimation of patents relevant for the LAN industry especially for diversifiers, whose main line of business is outside the LAN industry. We have computed alternative measures of intangible capital, notably by summing patents related to technological field H04L12 only, which is the main technology used in the industry. We find that the results are neither affected nor improved by the use of these alternative measures.

[3]Information on more 'traditional' indicators of firms' size such as R&D expenditure and total number of employee is available only for a subset of companies , mainly survivors and those that were publicly traded at the time they were acquired. Employing these measures in the regression is likely to introduce a bias in the analysis.

Table 1: The relationship between modes of entry and exit in the LAN industry

| | Failure | Buying-out | Survival | Total |
|---|---|---|---|---|
| Start-up | 7 | 19 | 13 | 39 |
| | *4.8* | *21.9* | *12.2* | |
| Spin-out | 5 | 41 | 16 | 62 |
| | *7.7* | *34.8* | *19.5* | |
| Diversifier | 3 | 8 | 9 | 20 |
| | *2.5* | *11.2* | *6.3* | |
| Total | 15 | 68 | 38 | 121 |

Expected frequencies in *italics*
To be interpreted with care due to the low expected frequencies
Chi-square statistics = 6.26 (P = 0.180)

Table 2: OLS Regression on Observed Prices. Dependent Variable: Deflated Product Price

| | |
|---|---|
| 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 |

Standard errors in brackets
Significant at 10%; ** significant at 5%; *** significant at 1%
Robust standard errors in brackets
Year dummy variables omitted for clarity

Table 3: Summary Statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Failure | 121 | 0.13 | 0.33 | 0.00 | 1.00 |
| Bought-out | 121 | 0.56 | 0.49 | 0.00 | 1.00 |
| Survivor | 121 | 0.31 | 0.47 | 0.00 | 1.00 |
| Spin-out | 121 | 0.51 | 0.50 | 0.00 | 1.00 |
| Start-up | 121 | 0.32 | 0.47 | 0.00 | 1.00 |
| Diversifier | 121 | 0.17 | 0.37 | 0.00 | 1.00 |
| Age | 121 | 9.61 | 12.54 | 1.00 | 84.00 |
| Distance from frontier | 121 | 2.30 | 1.05 | 0.00 | 4.69 |
| (Distance from frontier)$^2$ | 121 | 6.37 | 4.60 | 0.00 | 22.01 |
| Patent stock (log) | 121 | 1.39 | 2.20 | 0.00 | 9.99 |
| Size (log) | 121 | 0.72 | 1.02 | 0.00 | 3.47 |

Table 4: Firm Entry and the Hazard Rate of Exit in the LAN Switch Industry (N=600, Discrete Time Duration Model, Weibull Hazard Function)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Time (Log) | -0.810 | -0.711 | -0.678 | -0.63 | -0.627 |
| | [0.147]*** | [0.153]*** | [0.153]*** | [0.154]*** | [0.154]*** |
| Spin-Out | 0.448 | -0.597 | -1.105 | -1.519 | -1.486 |
| | [0.343] | [0.592] | [0.631]* | [0.667]** | [0.673]** |
| Start-Up | 0.120 | -0.926 | -1.086 | -1.571 | -1.568 |
| | [0.363] | [0.676] | [0.695] | [0.728]** | [0.734]** |
| Age × Spin-Out | | -0.086 | -0.058 | -0.044 | -0.053 |
| | | [0.043]** | [0.044] | [0.043] | [0.045] |
| Age × Start-Up | | -0.047 | -0.056 | -0.041 | -0.055 |
| | | [0.037] | [0.038] | [0.038] | [0.043] |
| Age × Diversifier | | -0.062 | -0.075 | -0.067 | -0.070 |
| | | [0.025]** | [0.027]*** | [0.026]** | [0.027]*** |
| Dist. Frontier | | | 0.833 | 0.985 | 0.947 |
| | | | [0.494]* | [0.492]** | [0.494]* |
| (Dist. Frontier) $^2$ | | | -0.265 | -0.308 | -0.297 |
| | | | [0.120]** | [0.120]** | [0.120]** |
| Pat. Stock (Log) | | | | -0.202 | -0.209 |
| | | | | [0.076]*** | [0.078]*** |
| Size (Log) | | | | | 0.117 |
| | | | | | [0.154] |
| Constant | -1.996 | -0.452 | -0.326 | 0.543 | 0.583 |
| | [0.578]*** | [0.774] | [0.808] | [0.864] | [0.869] |
| Number of firms | 121 | 121 | 121 | 121 | 121 |
| Number of firm exit | 83 | 83 | 83 | 83 | 83 |
| Log-Likelihood | -215.3 | -208.1 | -204.0 | -200.0 | -199.7 |
| Chi-Square | 51.7*** | 66.1*** | 74.4*** | 82.4*** | 83.0*** |
| LR Chi-Square | - | 14.4*** | 8.3** | 8.0*** | 0.6 |

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: Firm Entry and Hazard Rates of Exit in the LAN Switch Industry (N=600). Checking Robustness of Discrete Time Duration Model

| | Hazard Rate Function | | | Unobserved Heterogeneity | | |
|---|---|---|---|---|---|---|
| | (5) | (6) | (7) | (8) | (9) | (10) |
| Spin-out | -1.486 | -1.612 | -1.551 | -1.486 | -1.621 | -2.871 |
| | [0.673]** | [0.676]** | [0.676]** | [0.673]** | [0.894]* | [2.321] |
| Start-Up | -1.568 | -1.663 | -1.624 | -1.568 | -1.806 | -2.703 |
| | [0.734]** | [0.738]** | [0.738]** | [0.734]** | [0.948]* | [1.965] |
| Age × Spin-out | -0.053 | -0.045 | -0.047 | -0.053 | -0.07 | -0.002 |
| | [0.045] | [0.046] | [0.046] | [0.045] | [0.058] | [0.092] |
| Age × Start-Up | -0.055 | -0.056 | -0.054 | -0.055 | -0.056 | -0.053 |
| | [0.043] | [0.044] | [0.044] | [0.043] | [0.049] | [0. 066] |
| Age × Diversifier | -0.070 | -0.073 | -0.071 | -0.07 | -0.076 | -0.100 |
| | [0.027]*** | [0.028]*** | [0.027]*** | [0.027]*** | [0.032]** | [0.069] |
| Dist. Frontier | 0.947 | 1.007 | 1.012 | 0.947 | 1.185 | 1.677 |
| | [0.494]* | [0.500]** | [0.500]** | [0.494]* | [0.625]* | [1.051] |
| (Dist. Frontier) $^2$ | -0.297 | -0.315 | -0.314 | -0.297 | -0.366 | -0.570 |
| | [0.120]** | [0.122]*** | [0.122]*** | [0.120]** | [0.153]** | [0.327]* |
| Pat. Stock (Log) | -0.209 | -0.221 | -0.220 | -0.209 | -0.26 | -0.425 |
| | [0.078]*** | [0.078]*** | [0.078]*** | [0.078]*** | [0.098]*** | [0.309] |
| Size (Log) | 0.117 | 0.135 | 0.128 | 0.117 | 0.099 | 0.143 |
| | [0.154] | [0.156] | [0.156] | [0.154] | [0.189] | [0.277] |
| Constant | 0.583 | 0.450 | -10.657 | 0.583 | 0.866 | 2.209 |
| | [0.869] | [0.895] | [1.054] | [0.869] | [1.111] | [3.170] |
| Link Function | C log-log | C log-log | C log-log | Logistic | C log-log | C log-log |
| Number of Firms | 121 | 121 | 121 | 121 | 121 | 121 |
| Number of Firm Exit | 83 | 83 | 83 | 83 | 83 | 83 |
| Log Likelihood | -199.7 | -195.9 | -193.4 | -199.7 | -199.7 | -200.4 |
| LR test for frailty | - | - | - | 0.00 | 0.46 | 2.27* |

Baseline Hazard Function: (5) (8) (9) (10) Log of time (Weibull),(6) Polynomial of order 2, (7) Non parametric
Distribution of Unobserved Heterogeneity: (8) (9) Normal, (10) Gamma
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 6: The Determinant of the forms of firm exit in the LAN Switch Industry (N=600, Competing Risk Duration Model)

| | (5) | (11) | (12) | (13) |
|---|---|---|---|---|
| Spin-Out | -1.486 | 0.242 | -1.368 | -1.610 |
| | [0.673]** | [1.060] | [0.873] | [1.280] |
| Start-Up | -1.568 | 1.052 | -1.558 | -2.611 |
| | [0.734]** | [1.235] | [0.937]* | [1.453]* |
| Age × Spin-Out | -0.053 | -0.357 | -0.018 | 0.338 |
| | [0.045] | [0.152]** | [0.050] | [0.157]** |
| Age × Start-Up | -0.055 | -0.227 | -0.039 | 0.189 |
| | [0.043] | [0.091]** | [0.048] | [0.101]* |
| Age × Diversifier | -0.070 | -0.077 | -0.066 | 0.011 |
| | [0.027]*** | [0.030]*** | [0.035]* | [0.044] |
| Dist. Frontier | 0.947 | 3.653 | 1.008 | -2.645 |
| | [0.494]* | [1.290]*** | [0.519]* | [1.367]* |
| (Dist. Frontier) $^2$ | -0.297 | -0.906 | -0.321 | 0.585 |
| | [0.120]** | [0.302]*** | [0.124]*** | [0.322]* |
| Pat. Stock(Log) | -0.209 | 0.383 | -0.281 | -0.664 |
| | [0.078]*** | [0.119]*** | [0.107]*** | [0.154]*** |
| Size (Log) | 0.117 | 0.450 | 0.082 | -0.368 |
| | [0.154] | [0.286] | [0.186] | [0.329] |
| Constant | 0.583 | -4.682 | 0.708 | 5.390 |
| | [0.869] | [1.834]** | [0.926] | [1.971***] |
| Log Likelihood | -199.7 | -234.80 | | |
| Wald Test | | 30.51*** | 57.16*** | 31.70*** |

(5) Homogeneous Exit
(11) Failure vs. Survival
(12) Buying-out vs. Survival
(13) Buying-out vs.Failure
Robust 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. Unreported baseline hazard function: Log of time

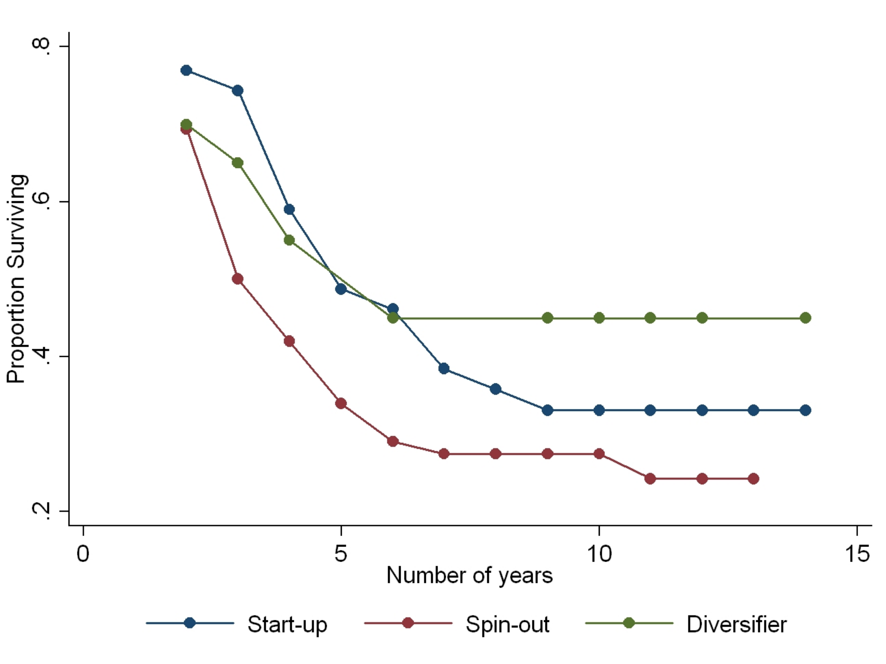


Figure 1: Kalplan Meier Survival Estimates