An empirical study of technological leadership and persistence in product innovation

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Abstract

We study how technological leadership affects persistence in product innovation. Relying upon a database of 1818 products marketed between 1990 and 1999 by 265 firms active in a high-tech industry we first construct a measure of technological leadership in terms of firm positioning with respect to the frontier and then relate this measure to persistence in innovation. We find that leaders are systematically more persistent innovators than laggards. We also find that leaders in one market can also systematically innovate in a related and adjacent market. Finally, we find evidence that the number of lagged patents increase persistence in product innovation.

Keywords: innovation, persistence, technological leadership

JEL codes: O31, O33, L63

1. Introduction

What determines persistence in innovative behaviour? Do technological leaders differ from laggards in terms of persistence? When are technological leaders in one market able to become persistent innovators in a related market? These issues have been on the agenda of researchers on economics, innovation and strategy for quite some time. Early works in the innovation studies tradition have highlighted that prior innovative activity alone is a good predictor for the length of the innovative spell and that it tends to explain spell length better than other firms' characteristics such as size (Geroski *et al.*, 1997). 'Bimodality' exists in the pattern of persistence suggesting that persistence is stronger for firms that are either non innovators or great innovators (Cefis and Orsenigo, 2001). Persistence in innovation is higher in sectors characterised by technological cumulativeness, R&D complementarities and learning-by-doing processes (Cefis, 2003). A common feature of these early studies is that they measure innovation persistence in terms of patenting activity.

Alongside patents, new product introduction is another important indicator of innovation and several studies have analysed instances of product introduction. Khanna (1995) looks at new product introduction in mainframe computing. Greenstein and Wade (1998) and Stavins (1995) look at the probability of product entry and exit for computer mainframes and PCs respectively. De Figuereido and Kyle (2006) analyse the determinants of product turnover in the laser print market industry. Lerner (1997) and Thomas (1999) study new product introduction in the context of a 'technological race' in the Hard Disk Drive industry. Though these studies analyse the determinants of the incidence of new product introduction, they do not look explicitly at the issue of *persistence in product innovation* (i.e. whether innovators at period *t* more likely to innovate at the next time period). In addition, these papers do not look at the relationship between *technological leadership* and persistence in product innovation.

There are several reasons why it is relevant to study the relationship between technological leadership and persistence in product innovation. In markets characterised by rapid technical change and shortening of product life cycle, new products incorporate novel characteristics making existing products only an imperfect substitute for the new good. Within this context, persistence in product innovation may originate from incumbents' strategies aimed at maintaining their transitory market power. These strategies may entail an expansion of the technological frontier, changes in product portfolio through product proliferation, and extension of product portfolios through innovation in related markets. Differences between technological leaders and laggards in terms of available resources, capabilities and complementary assets will translate into differences in persistence in product innovation.

We examine the relationship between technological leadership and persistence in product innovation in the context of the Local Area Networking (LAN) industry. Our source of information is a comprehensive database of 1818 new products marketed between 1990 and 1999 in three LAN markets: hubs (536 products), routers (747 Products), and switches (535 products). For each product in our dataset we have information on: year of market introduction, technical characteristics, market price, and name of the manufacturer. Our dataset includes 265 firms which have been active in the industry. For each firm in the dataset we have collected information about date of entry into the industry, size in terms of employees, and sales when available. In addition to these data we also collected information on the patenting activity of the firms included in our sample. In particular, by looking at the (8 digits) International Patent Classification (IPC) class of the patents we have been able to link patents to innovative activity in a specific market.

Using these data we carry out the following analyses. First, we employ data on product characteristics and price to calculate an indicator of technological leadership in each market. Here we proceed in two steps. For each market, hedonic price regressions are estimated and predicted prices are calculated. Predicted prices are then used to compute a measure of technological frontier and calculate the relative distance of each firm from the frontier. Second, we use this indicator to distinguish between technological leaders and laggards and produce Transition Probability Matrices (TPMs) to study persistence in product innovation for both types of firms. Third, we perform Conditional Risk Set Duration analysis to study the determinants of the probability to innovate in each period conditional on firms' initial innovative status and technological leadership in the prior period. Our covariates include an indicator of technological leadership, as well a series of firm level controls such as firm size, sales, and possession of intangible capital in terms of patent stock. Particular attention is devoted to estimating cross market effects (i.e. to study the impact of technological leadership in one market on persistence in another market) for multi product firms.

Our main result is that technological leaders are relatively more persistent innovators than laggards. The closer a firm is to the technological frontier at *t* the higher the probability to commercialise a new product in the next time period, though the marginal effect of changes in distance from the frontier varies across markets reflecting different levels of technological opportunities. We also find that in the case of multiproduct firms, technological leaders in one market can also systematically innovate in a *related and adjacent* market. Additional results highlight a direct relationship between persistence in product innovation and (lagged) patenting and between the number of (lagged) patents and persistence in product innovation.

Our findings provide the following contributions. First, they provide novel evidence on the determinants of innovation persistence. Prior empirical research on innovation persistence has mainly relied on patents as an indicator of innovative activity. We provide empirical evidence on persistence in *product innovation*. Second, we directly relate persistence to an indicator of technological leadership at the firm level. Prior empirical studies have instead focussed on other firm characteristics such as size, age, and/or R&D intensity. Third, we consider the case of firms active in related markets.

Some of our findings are consistent the existing empirical literature on the role played by technological leaders in stretching the technological frontier in 'technological races'. Other findings are consistent with prior research on persistence based on patents such as those confirming the presence of bimodality in innovation persistence with great innovators more likely to persist than small innovators. Additional findings, that relate persistence in product innovation to the stock of patents, qualify the prior evidence highlighting that is the stock of intangible assets rather than lagged patenting what matters for innovation persistence. Finally, our findings for the case of related markets allow us to draw some indirect inference about persistence and firms' strategies for changes and expansion of their product portfolios. While both technological leaders and laggards could in principle extend their product portfolio to include related products, only technological leaders can effectively do it in the case of complex products. Laggards instead have to innovate at the lower end of the product spectrum.

The paper is structured as follows. In Section 2 we review the literature on persistence in innovation and propose our framework for analysis. Section 3 introduces some necessary background information on the LAN industry. Section 4 presents our data and method. Section 5 introduces our empirical strategy. Results are presented in Section 6. Section 7 concludes.

2. Conceptual framework and hypotheses

One of the earliest discussions in the literature on economics and technological change has revolved around the relationship between innovation and market structure. While there is a general agreement that innovation is a source of monopolistic rents and therefore market power, less consensus exists on the relationship between market power and *persistence* in innovation. Two opposite views exist depending on the assumptions made on the incentives for incumbents to engage in the innovation race.

On the one hand, there is the view that incumbents with high market power have low incentive to continuously engage in innovation (Arrow, 1962) both because of the nature of the knowledge, which is assumed to be equally accessible to all firms, and because they are afraid of cannibalising their current source of revenues (Reinganum, 1983; 1985). Because of this *'displacement effect'* their market power is *temporary* as their dominant position is quickly challenged and eroded by competitors. New innovators, which are typically small, and newly established firms, systematically substitute for incumbents. This view revolves around a conceptualisation of technical change as a random process driven by a population of homogeneous actors who have a probability of realizing technological opportunities.

On the other hand, there is the view that considers persistence in innovation as crucial for maintaining market power. In this case incumbents have an incentive to continuously engage in innovation to maintain their dominant position (*'efficiency effect'*) either because there are increasing returns to R&D or because they spend more in innovation (Scherer, 1965), or because they learn how to innovate efficiently (Gilbert and Newbery, 1982). Alternatively, persistence can be explained by the characteristics of technology. If technology has a strong tacit component and is highly specific to individual firms (Penrose, 1959; Nelson and Winter, 1982) then innovation results from the accumulation of technological competencies by heterogeneous actors. Over time the firm specific, tacit and cumulative nature of the knowledge-base builds high barriers to entry. As a result, a few and large firms eventually continue to dominate the market in a stable oligopoly.

Prior empirical studies on innovation persistence have produced a series of 'stylized facts'. First, production of innovations is subject to dynamic economies of scale (the 'success-breeds-success' paradigm) but the effect becomes apparent only after a 'minimum innovation threshold' is reached (Geroski *et al.*, 1997). The threshold level of patents likely to induce a patenting spell of 3 or more years is around 5 patents. A firm that produces 5 or more patents has roughly twice the probability of enjoying a patenting spell of any length greater than 3 years than a firm that produces only 4 patents.[1] Second, there is bimodality in the pattern of innovation persistence (Cefis and Orsenigo, 2001). In particular, persistence is stronger for firms that are either non innovators or great innovators (i.e. having 6 or more patents in a year). This means that most firms innovate only occasionally or do not innovate at all. Yet innovative activities are to a significant extent generated by few firms that innovate persistently over time. Institutions and history do influence the patterns of innovation, as suggested by the fact that persistence systematically and consistently differ across countries. Third, persistence in innovation is related to the characteristics of the technology (Cefis, 2003) as it is higher in sectors characterised by technological cumulativeness, R&D complementarities and learning-by-doing processes.

A common feature of these studies is that they measure persistence in terms of patenting activity.[2] In contrast with this focus on patents as an indicator of innovation we consider the case of product innovation. In differentiated, fast changing technology markets, such as the LAN industry studied in this paper, product innovation is a paramount source of market power for incumbents who compete by incorporating in products novel features which make existing products only an imperfect substitute for the new good (Bresnahan *et al.*, 1997).[3] This paper moves the focus beyond the perfect/ imperfect substitutability distinction. In our setting, incentives to persist in product innovation depend on the extent of technological leadership measured in terms of proximity to the technological frontier. We expect to observe differences in persistence between technological leaders and laggards for several reasons.

First, technological leaders operate very close to the technological frontier. Though for them the marginal benefits from commercialising 'yet another product' may be decreasing, leaders are better placed to grasp new technological opportunities by extending the frontier, provided they have the resources and the convenience to do that.[4] Greenstein and Wade (1998) look at the product life cycle in the commercial mainframe market. They find that 'stretching' the technological frontier leads to shorter product cycles and more frequent (i.e. persistence in) product introduction. In a study of new production introduction in high-end mainframe computing Khanna (1995) provides evidence that designers engage in 'racing behaviours' when they compete at the frontier. On the contrary technological laggards are not able to extend the frontier and they have fewer incentives to participate in the technological race. Product innovation in this case would largely consist in imitation of existing products (Lee *et al.*, 2011) or be restricted to innovation in low-end niches of a market (Lerner, 1997).[5] Thus:

Hypothesis 1: The closer a firm is to the technological frontier, the more likely is to persist in product innovation, ceteris paribus.

Besides emerging from a 'technological race', persistence in product innovation may also be the consequence of *changes or expansion of product portfolio* linked to strategies of product differentiation. On the one hand there are product proliferation strategies when incumbents enter into unexplored areas of the same market mainly to cater for existing needs and/or to pre-empt competitive entry from potential competitors (Schmalensee, 1978). On the other hand, new products are rarely introduced alone in the market as firms choose instead to compete on the basis of product families (Draganska and Jain, 2005). Introducing product families allows incumbents to offer different variants of the same product in order to cater for different customer preferences. In her study of PC industry, Stavins (1995) relates pre-emption to incumbent's experience as she shows that incumbents disperse more their products in the quality spectrum by exploiting advantages in terms of both reputation and economies of scope. Looking at product turnover in the desktop laser printer industry de Figuereido and Kyle (2006) find a positive correlation between the frequency of new product introduction and the level of firms' innovative capability (as measured by the number of patents). Incidence of entry is even higher for firms that are both innovative and have a strong brand. Sanderson and Usumeri (1995) show how leaders can rely upon their superior design capabilities and division of labour to change product characteristics and tailor them to specific needs. Thus:

> *Hypothesis 2: For multiproduct firms, the closer a firm is to the technological frontier in a specific market, the more likely is to persist in product innovation in the same market, ceteris paribus.*

Persistence can also be the consequence of an *expansion of product portfolios* to include related products (Raubitschek, 1987; Bayus and Putsis, 1999).[6] In this case, persistence may be beneficial for technological leaders that possess the resources to spread the risk of innovating over several markets (Bonanno, 1987; Bhatt, 1987). However, important limitations to portfolio expansion exist. Dowell (2006) finds that wide product portfolios can be detrimental to firms' performance when they include products with very different designs. Similarly, Wezel and van Witteloostuijn (2006) show that benefits from product portfolio expansion is inversely related to the technological distance between the existing and the new products inside the portfolio. These findings highlight that firms' benefits from portfolio expansion may depend on whether changes in new products entails incremental or improvements or radical departures from their existing designs. Within this context, radical departures from an existing design will be less likely pursued because of lack of organizational capabilities (Henderson, 1993), excessive myopia (Tripsas and Gavetti, 2000), strong commitment to an existing customer base (Christensen, 1997) and/or high level of product complexity (Levinthal, 1997).[7] While technological leaders possess the required capabilities to persist in product innovation in their own focal market, they can be expected to enjoy a relative advantage over competitors as long as innovating in the related market does not entail a radical departure from the product design in their focal market.

We thus formulate the following hypothesis:

> *Hypothesis 3: For multiproduct firms, the closer a firm is to the technological frontier in a specific market, the more likely is to persist in product innovation in an adjacent market, ceteris paribus.*

3. Background on the industry

In this paper we study persistence in product innovation for a sample of manufacturers active in the LAN industry between 1990 and 1999. LANs are the infrastructure that enables data communication to occur within localised areas (i.e. a company and/or a university campus). LANs are systems made of technologically related components which play different functions within the network and embody technologies of different level of complexity.[8] Hubs were relatively unsophisticated products whose function was mainly to link computers together. Routers were the most complex from the technological viewpoint as they were able to determine the best path for sending the data. Switches were more complex than hubs but (at least initially) less than routers. During the 1990s additional features (i.e. Layer 3 functionality, and Virtual LAN support), as well as a combination of hardware and software based changes (i.e. the adoption of ASICs based architecture and the implementation of new algorithms for forwarding data packets), enabled switches to directly compete with routers. Thus if we had to 'rank' LAN equipment available during the 1990s in terms of technological complexity we would have hubs at the bottom, switches somewhat in the middle, and routers at the top.

Early LANs were adopted in organizations such as firms and universities during the 1970s. At that time they were closed systems based on proprietary communication standards (i.e. DECnet, SNA) and using computer mainframe and/or minicomputers. Their diffusion took off during the 1980s thanks to the definition of common transmission standards (i.e. Ethernet and Token Ring), the advent of Personal Computers, and innovation in hubs and routers (von Burg, 2001). They diffused widely during the 1990s thanks to new high speed standards (i.e. Fast Ethernet, FDDI, Gigabit Ethernet), the wide adoption of the internet protocol (i.e. TCP/IP) and the introduction of LAN switches (Fontana, 2008).

While the overall structure of the LAN industry would eventually consolidate and evolve toward a tight oligopoly in the 2000s, between 1990 and 1999 it was much more heterogeneous. The router market was already highly concentrated with few firms dominating. Entry was virtually blockaded at the high-end (i.e. the so called multi-protocol router segment) and occurred mainly at the low-end (i.e. the access router segment). The structure of the hub market instead was less concentrated but similarly polarised with few leader firms dominating the high-end of the market and responsible for innovations along the established trajectory and several firms at the 'fringe' producing only relatively unsophisticated products (i.e. 'scaled down' versions) for low-end customers. During the 1990s, the LAN switch market was in its infancy and characterised instead by lower entry barriers and an intense entrepreneurial activity with new solutions marketed by young start-ups as well as by established firms already active in the other two markets.

There are at least two reasons why this industry between 1990 and 1999 represents an interesting case to study persistence in product innovation. First, there is the very fast rate of technical change and the shortening of the product life cycle. New equipment embodied new characteristics, both in the form of new communication standards, new hardware, and/or software. Persistence ultimately depended on the capability of incumbents to extend the technological frontier and/or change their product portfolio.

Second, manufacturers had a strong incentive to entry into related markets. Being part of a technical system, hubs, switches and routers might or not be produced by the same manufacturer. From the customer viewpoint, combining products from the same producer increased utility as benefits from interoperability and standardisation could be reaped. From the viewpoint of the manufacturers, expansion into related markets could enlarge the installed base and strengthen their market position (Chen and Forman, 2006). In this case, persistence was a consequence of the capabilities of incumbents to extend their product portfolio to related markets.

4. Data and method

Our source of information is a comprehensive database of new products marketed between 1990 and 1999 in the LAN industry. The dataset contains 1818 products commercialised in three markets: hubs (536 products), routers (747 Products), and switches (535 products). For each product in our dataset we have information on: year of market introduction, technical characteristics, market price, and name of the manufacturer. This dataset was constructed using information from specialized trade journals (Network World and Data Communications), which periodically published Buyers' Guides and details on new product introductions. Our dataset includes 265 firms which have been active in the industry. These firms represent the population of the firms that introduced at least one new product in the LAN industry between 1990 and 1999. Most of the firms in the dataset were located in US and, though they operated globally, most of their sales were generated in the US in the period considered in this paper. For each firm in the dataset we have collected information about their entry date in the industry, size in terms of employees, and sales when available. This information was gathered from a variety of sources, such as COMPUSTAT, the D&B Million Dollar Database and firms' annual reports. 174(65% of the total) firms in our sample were active in just one market. 67(25%) in two markets. 25(9%) in three markets. 15 firms were active in both hubs and routers. 24 were active in both routers and switches. 28 were active in both hubs and switches. 121 have introduced at least one hub, 136 at least one router, 126 at least one switch. In addition to these data we also collected information on the patenting activity of the firms included in our sample. This information was retrieved from the latest version of the NBER patent database (Hall *et al.*, 2001). Table 1 reports overall summary statistics and broken down by market.

[Insert Table 1 about here]

5. Empirical strategy

5.1. Empirical model

Econometric studies of innovation persistence falls within two groups. One group of studies relies upon the estimation of hazard models for innovation spells (Geroski *et al.*, 1997). Another group of studies (Peters, 2009; Clausen *et al.*, 2010) has instead employed random effect probit models (Wooldridge, 2005) to estimate the effect of previous innovative efforts on the probability to further innovate at a specific point in time. In this paper we follow the former approach.

In particular, we model product innovation by the firms in our sample as a repeated event and assume that after the first product introduction event is observed, the second and the following introductions are different from the first event. The implicit hypothesis that we are making is that, all the rest equal, the more innovative events we observe for a firm the more likely is for that firm to experiment again the event in the future. Within this context, not taking event dependency into account would lead to incorrect estimates of the likelihood to innovate over time. Since we are considering a sample of firms that introduced at least one new product between 1990 and 1999, our sample is both right and left censored. It is right censored because we observe new products' introduction only up to the end of 1999. It is left censored because firms enter the study at different points in time corresponding to the year in which we observe their *second* product innovation event.[9]

Our analysis of time to product introduction event employs variance-corrected semi-parametric Cox's Proportional Hazard (CPH) model. A variance corrected CPH model allows to control for the effects of repeated and interdependent events on the variance-covariance matrix in order to produce robust coefficients and standard errors. The approach we follow here is the conditional risk-set model proposed by Prentice *et al.* (1981).[10] According to this model, at each time t we can define a risk set for observing a product innovation event k by considering all the firms that, at time t, have experienced a product innovation event $k - 1$ but not yet k. In other words a firm cannot be at risk of innovating for the fourth time without having already innovated three times before. This approach takes into account the order of the events and estimates are stratified by the rank of the event (i.e. the second product, the third product etc.).

Let's define with T_{ik} the 'true' total time taken for firm i^{th} to experience the k^{th} product introduction event. C_{ik} is the censoring time for the k^{th} product introduction event and X_{ik} is the observed duration (with $X_{ik} = \min(T_{ik}, C_{ik})$). Finally, we define $\delta_{ik} = I(T_{ik} \leq C_{ik})$, where $I(.)$ indicates whether censoring occurs or not and we define inter-event times as: $G_{ik} = X_{ik} - X_{i,k-1}$. $X_{i0} = 0$ is the time when the firm enters the study (i.e. the time of first product introduction).

The hazard function for the k^{th} product introduction for firm i^{th} at time t is given by:

$$h_{ik}(t;Z_{ik}) = h_{0k}(t - t_{k-1})\exp(\beta' Z_{ik}(t)) \qquad (1),$$

where Z_{ik} is the vector of explanatory variables for firm i^{th} with respect to the k^{th} product introduction. $h_{0k}(t)$ is the event specific baseline hazard for the k^{th} product introduction. β' is the vector of parameters to be estimated.

Let t_j be the j^{th} ordered event time and $R(t_i)$ the set of firms at risk at time t_i , the partial likelihood L can be defined as:

$$L(\beta)=\prod_{j=1}^{d}\frac{h(t_j)}{\sum_{k\in R(t_j)}h(t_k)} \quad (2),$$

and the partial likelihood function in inter-event time as:

$$L(\beta)=\prod_{i=1}^{n}\prod_{k=1}^{K}\left(\frac{\exp(\beta' Z_{ik}(X_{ik}))}{\sum_{j=1}^{n}Y_{jk}(X_{ik})\exp(\beta' Z_{jk}(X_{ik}))}\right)^{\delta_{ik}} \quad (3),$$

where $Y_{jk}(t) = I(G_{ik} > t)$.

5.2. The model specification

The equation introduced above is specified with several covariates. The first, and most important covariate, is a measure of technological leadership. Three types of indicators of leadership can be found in the literature. Indicators based on labour (Amable *et al.*, 2007) or multifactor productivity (Nicoletti and Scarpetta, 2003; Bos *et al.*, 2013); indicators based on financial assets such as Tobin's *q* (Coad, 2011); indicators based on product characteristics and quality (Stavins, 1995). According to this approach product quality may be used to 'rank' firms in terms of distance to the technological frontier. Technological leaders can be distinguished from laggards and their behaviour in terms of persistence analysed.

To construct our measure we follow Fontana and Nesta (2009) and proceed in two steps. First, for each market, hedonic price regressions are estimated and predicted prices are calculated. Second, predicted prices are used to compute a measure of technological frontier and calculate the relative distance of each firm from the frontier. In the first step, we estimate the following hedonic equation (one separate regression for each market):

$$p_{mit} = \alpha + \sum_{t}\sum_{j}\beta_{tj} z_{tjm} + \alpha_t + \mu_t + \varepsilon_{mit} \qquad (4),$$

where p_{mit} is the price of model m introduced by firm i at time t, z_{tjm} is a vector of product technological characteristics j contained in model m, β is a vector of coefficients to be estimated, α_t is a time fixed effect, and μ_i is a firm fixed effect capturing the impact on the price of firms' pricing practices unrelated to product characteristics such as reputation, market power and/or other unobserved characteristics.[11]

In the second step we take the quality adjusted predicted price as an indicator of overall product quality and use it to rank products on 'vertical' product space:

$$q^{'}_{mit} = \hat{p}^{'}_{mit} \qquad (5),$$

we then compute for each product a distance from the technological frontier:

$$d^{f}_{mit} = \max(q_t) - q^{'}_{mit} \qquad (6).$$

The higher is this distance the farther is the product from the frontier. Since firms may introduce in several products in each market in a given year, we calculate for each firm the minimum distance to technological frontier as follows:

$$d_{it}^{f} = \min\left[d_{mit}^{f}\right]_{it} \qquad (7).$$

This indicator is our main measure of technological leadership (DISTANCE TO FRONTIER). Technological leaders (laggards) in a specific market would display relatively lower (higher) values for this indicator. As the indicator is normalised by dividing it by its standard deviation, the distance varies between zero and one. This standardization allows us to perform meaningful cross-market comparisons.

Beside distance to frontier, we consider other control variables that are likely to affect persistence in product innovation. All these variables capture firms' characteristics and are, all but two, time-varying. The variable SIZE is constructed on the basis of the number of full time employees. The existing literature has generally highlighted the presence of a positive relationship between firms' size and persistence in innovation (Cohen and Levin, 1989; Kamien and Schwartz, 1982).[12] However, in some case a non linear trend has been found. To take this into account we include also the square of size (SIZE SQ). We then include total sales (SALES) as a measure of the size of the market for each firm (Henderson, 1993). Sales are measured in million of US dollars. The size of the market can be considered a proxy for the status of the innovator (i.e. *market* leader or laggard).[13] It may be thought to affect persistence in innovation differently depending on the status of the innovator. Market leaders may value more new products since they want to maintain their market position (Gilbert and Newbery, 1982). In this case a positive correlation is expected between sales and persistence. On the other hand, they may prefer to exploit existing products rather than introducing new ones (Reinganum, 1985). In this case, a negative coefficient for this variable is expected.

We then control for the impact of knowledge and intangible assets on persistence in innovation by relying upon some indicators of firms' patenting activity. PATENT STOCK/EMPLOYEES is the sum of the past patents granted to the firm in each year. It is an indicator of the stock of technological experience available to firms.[14] Generally, past technological experience should impact positively on innovative activity through economies of scale in R&D (Cohen and Levin, 1989), learning by doing and/or by using (Rosenberg, 1982; Cohen and Klepper, 1996). However, we may expect this impact to vary also depending on the level of technological opportunity available to the firms. Firms maybe expected to make the most(least) out of technological experience when technological opportunities are the highest(lowest). As the accumulated measure of patents tends to be correlated to the size of the firm, we divide patent stock by the number of employees to make sure that our measure can be interpreted as an indicator of the pool of technology assets available to the firm.

Alongside this variable we introduce two variables aimed at accounting for recent patenting activity. PATENTS (T-1) is a dummy which is equal to one is the firm has filed for a patent in the previous year. This variable is supposed to capture the relationship between patenting activity and the commercialisation of a specific innovation. We further control for this relationship by accounting for the number of patents filed by the firm in the previous year (NUMBER OF PATENTS (T-1)). Though a one to one relationship between a single patent and a product is impossible to establish, we expect persistence in product innovation to be positively associated to patenting.[15] Finally, we control for the 'initial condition' by including a variable measuring the number of new product at entry (NUMBER OF PRODUCT AT ENTRY).

A correlation table for our covariates is reported in the Appendix (Table A4).

[Insert Table A4 about here]

It should be noted the presence of a positive correlation among all our patent based indicators The level of the coefficient is sometimes high but within an acceptable range.[16]

6. Results

6.1. Univariate analysis

We provide preliminary evidence on technological leadership and persistence in product innovation by estimating two states TPMs for several sub-samples of our sample of innovative firms. Cefis (2003) defines persistence in terms of the probability for a firm to remain in the same state it was in period *t* at the subsequent period *t+1*. We are particularly interested in 'persistent innovators' (i.e. firms that persistently remain in the innovator state).

Table 2 reports our preliminary results for each of the three markets.

[Insert Table 2 about here]

In the case of hubs, the probability of being a persistent product innovator is around 44%, it gradually increases for switches (47%) and reaches 57% in the case of routers thus suggesting that 'systematic' innovators are more likely to be found in the case of more complex products. New entry in innovative behaviour is the highest in switches (around 37%) followed by routers (24%) and it is the lowest in hubs (22%). I the light of what we said in Section 3, this latter pattern clearly reflects changes in market opportunities in the LAN industry during the 1990s with the opening up of the switch market and the decline of hubs. In Table 3 we distinguish between technological leaders and laggards.[17]

[Insert Table 3 about here]

A first look at the results suggests that leaders are always more likely to be 'systematic' innovators than laggards. Again probabilities seem to reflect the level of product complexity with leaders displaying the highest persistence in innovation in the case of routers (63%), followed by switches (52%), and hubs (49%). It is interesting to note that laggards in complex products seem to be more persistent than laggards in less complex products. However, the difference between persistent leaders and laggards is slightly higher for complex products (10% in the case of routers vs. 9% in the case of switches and hubs). Laggards are also less likely than leaders to go from a non innovative to an innovative status. The difference is particularly large in the case of switches (44% vs. 33%) suggesting that there might have been new opportunities to innovate in this growing market, however only technological leaders seemed able to capture them.

Another aspect to consider is the issue of bimodality in persistence. The literature has highlighted that great innovators generally are more persistent than smaller ones. We first check whether this applies also to our case. Table 4 below reports distinct TPMs for 'great innovators' and 'small innovators'.[18]

[Insert Table 4 about here]

The main result in this case is that the probability to innovate systematically is always higher for great innovators than for small innovators. Among great innovators, the probability to innovate systematically is the highest for switch manufacturers (74%) followed by routers (70%) and hubs

(62%). Among small innovators, the probability is the highest for routers (42%), followed by hubs (25%) and switches (23%). Concerning the probability of going from a non innovator to an innovator state, it is always higher for great innovators than for small innovators and it is the highest in the switch case.

All in all these findings point to the following. In the case of switches, product innovation is a consequence of new opportunities linked to the opening up of the new market. Both great innovators and small innovators take these opportunities though great innovators appear to innovate systematically more than small innovators. In more established markets such as hubs or routers technological opportunities are lower. As a consequence, the probabilities of going from a non innovator to an innovator status are relatively lower than in the switch case for both great innovators and small innovators. This suggests that innovation in these markets should mainly come from older firms: both great innovators wishing to consolidate their market position and smaller innovators wishing to 'defend' their space in the market. In this context, great innovators always tend to be more persistent than small innovators. However, small innovators innovate more systematically than in the case of the switch market.

Finally, we analyse how technological leadership and innovator status interact to affect innovation persistence. Results for great innovators are reported in Table 5. Those for small innovators are reported in Table 6.

[Insert Tables 5 and 6 about here]

In the case of great innovators, technologically leadership generally increases persistence in innovation. This is particularly evident in the case of complex products such as routers (62% for laggards vs. 81% for leaders) and switches (70% for laggards vs. 79% for leaders). It is less evident in the case of hubs (60% for laggards vs. 64% for leaders). In the case of small innovators, an opposite pattern is found. Persistence is lower for leaders in the case of established markets such as routers (43% for laggards vs. 41% for leaders) and hubs (28% for laggards vs. 20% for leaders) and it is slightly higher in the case of switches (23% for laggards vs. 24% for leaders).

Finally, technological leadership seems to ease the transition from a non innovator to an innovator state. In the case of great innovators, it increases the probability for hubs (24% for laggards vs. 37% for leaders). In the case of small innovators, it increases the probability for both routers (21% for laggards vs. 23% for leaders) and switches (30% for laggards vs. 40% for leaders). The following section presents our results for the multivariate analysis and tests our hypotheses.

6.2. Multivariate analysis

Table 7 reports the results of the Cox conditional risk set estimates for persistence in innovation in the hub market. Explanatory variables are introduced in sequence.

[Insert Table 7 about here]

Model (1) considers the impact on persistence of distance to frontier only. The coefficient is negative and significant suggesting that firms located closer to the technological frontier at time *t* have a higher likelihood to introduce a new product in the following period. In other words, leaders are relatively more persistent innovators than laggards. The sign is robust to the inclusion of additional explanatory variables. A one unit decrease in the distance to frontier increases the likelihood to innovate of about 18.4%.[19] In model (2) we control for the impact of firm size, sales, and age on persistence. The inclusion of these variables decreases the number of observation to 126 due to missing information. Consistently with previous findings (Geroski *et al.,* 1997) our results suggest that large firms are more likely to innovate though the relationship seems to be non linear as indicated by the negative coefficient of SIZE SQ. Each additional employee increases the likelihood to innovate on average by 17.1%. The coefficient of SALES is not significant though it becomes significant in the following specification. What is interesting is that the coefficient is always negative evidence that the size of the market negatively impacts on innovation persistence. Also the coefficient of AGE is not significant. In the final specification (model 3) we include our indicators of intangible capital based on patents. We first control for the presence of 'state dependence' by looking at whether product innovation at *t* is associated to patenting at *t-1*. We then check whether the relationship depends on the number of patents. Finally, we further control for the intensity of patenting by dividing the stock of patents by the number of employees. Also in this case the coefficient is positive and significant. Altogether, these results indicate the presence of a 'state dependence effect' in which product innovation in one period is positively associated to both patenting and the number patents filed in the previous period. These effects notwithstanding, the relationship between possession of intangible capital and product innovation is not straightforward given that the coefficient for innovation propensity, as captured by the stock of patents per employees, is negative and significant.

Table 8 reports the result for the router market.

[Insert Table 8 about here]

Again the coefficient for distance to frontier is negative and significant indicating that also in this case technological leadership seem to impact positively on persistence in product innovation. In this case the impact of leadership seems slightly smaller than in the case of hubs as a one unit decrease in the distance to frontier increases the likelihood to innovate of 15.4%. The coefficient is quite stable across specification though the significance level changes as additional variables are added. Two important differences with respect to the previous results exist. First, our controls for size are significant, albeit weakly, only in the final specification. Second, the coefficient of AGE is now negative and significant indicating that in this market young firms are relatively more innovative than older ones. Finally, as in the previous case, the higher the lagged number of patents filed the higher the likelihood of introducing a new product.

Results for the switch market are summarised in Table 9.

[Insert Table 9 about here]

The coefficient for distance to frontier is negative and significant suggesting that the farther firms locate from the technological frontier the lower is the likelihood of introducing a new product in the subsequent year. Again technological leadership seems positively associated to persistence in innovation and in this case the magnitude of the impact if much greater than in the two previous cases. In particular a one unit decrease in the distance to frontier increases the likelihood to innovate of 21.2% suggesting that in the switch market being leaders is crucial for continuing to innovate. Concerning our control variables, we do not find a significant impact of firm size, sales, or age. All our patent indicators are instead significant. In particular, we find evidence of state dependence as suggested by the positive and significant coefficient for the lagged patent dummy. Also, the likelihood of introducing a product innovation increases with the number of patents filed at *t-1*.

All in all these results support Hypothesis 1. To test the remaining hypotheses we turn to the analysis of multiproduct firms.

6.3. Leadership and persistence in innovation in related markets

We now look at whether technological leadership impacts on persistence across related markets. As discussed in Section 3, hubs, routers, and switches are component of technological systems and may or may not be produced by the same firm. In this context it is interesting to understand whether technological leadership in a focal market could lead to persistence in a related market for those firms active in more than one market. We explore this possibility in Table 10 which reports a series of conditional risk set Cox models for firms active at least in two markets.[20]

[Insert Table 10 about here]

Model (1) considers the likelihood of introducing a new hub model for those firms manufacturing both hubs and routers. The coefficient for distance to frontier is negative and significant confirming that technological leadership in the hub market increases the likelihood to innovate in hubs. *This finding supports Hypothesis 2.* The coefficient for distance to frontier in the router market, though negative, is not significant an indication that leadership in this related market is not associated to persistence in product innovation in hubs. Given that hubs and routers represent the two 'extremes' of complexity in the LAN product spectrum (i.e. they are not adjacent markets) this result is somewhat expected. Model (2) analyses the impact on the likelihood of persisting in innovation in hubs of leadership in the switch market. In this case leadership in hubs is still associated to persistence in the hub market (*again supporting Hypothesis 2*).

In Model (3) we look at persistence in routers for routers and hubs producers. Leadership in routers is still relevant as indicated by the coefficient for distance to frontier for routers which is again negative and significant (*supporting Hypothesis 2*). However, the coefficient for leadership in hubs is not significant. These results mirror our findings from Model (1) concerning the relatively 'un-relatedness' of the two markets. Model (4) relates persistence in routers to technological leadership in the switch market. The negative and significant coefficient for distance to frontier in the switch market indicates that leadership in switches positively affects persistence in innovation in routers. A one unit decrease in the distance to frontier in the switch market increases the likelihood to innovate in routers of 27.9%. This evidence suggests that switch leaders could persistently innovate in the router market. *It gives support to Hypothesis 3* according to which the closer a firm is to the technological frontier in a specific market (switch in this case), the more likely is to persist in product innovation in an adjacent market (routers).

Finally, we look at how leadership in related markets affects persistence in innovation in switches. Model (5) considers the case of leadership in hubs. The coefficient for distance to frontier in hubs is negative and significant indicating that leadership in the hub market is positively associated to persistence in switches. Since hubs and switches are adjacent markets, *again Hypothesis 3 is supported*. In this case, a one unit decrease in the distance to frontier in the hub market increases the likelihood to innovate in switches of 36.5%. Leadership in routers instead does not seem to affect persistence in switches (Model (6)).

To summarise, our findings for the case of multiproduct firms always support Hypothesis 2. In particular, the closer a firm is to the technological frontier in a specific market, the more likely is to persist in product innovation in that same market. Hypothesis 3 is also supported. The closer a firm is to the technological frontier in a specific market, the more likely is to persist in product innovation in an adjacent market. However, our findings for related markets need to be further qualified.

All in all our analysis confirms that the structure of the LAN industry in the 1990s was vertically differentiated with three markets each one characterised by products with different levels of complexity. Within each market, technological leaders were relatively more likely than laggards to persist as product innovators. For multiproduct firms, innovating in related markets resembled a *single step-upward-one way* climbing of a 'product quality ladder'. The climbing occurred in 'single steps', because leaders in each market could innovate in an adjacent market only (i.e. go to the next step but not jump directly to the top of the ladder). The climbing was 'upward and one way' because leaders engaged in product innovation in more complex but not in less complex markets. Technological laggards instead could not reach higher steps.

7. Sensitivity analysis

Though interesting, it may be argued that our results suffer from important limitations. The first limitation concerns the presence of reverse causality. Our main argument is based on the idea that technological leadership leads to product innovation. However, in the industrial organization literature it is often argued that incumbents innovate in order to deter market entry or catching up by followers. If this is true, then technology leadership would follow persistence. To account for this is particularly important in our setting given that our period of observation is, for all but one of the markets, two-sided censored. The second limitation is that the analysis may suffer from an omitted variable bias. Due to information availability constraints in our analysis we are not controlling for any R&D input measures. If one assumes that R&D spending and product innovation are positively related and that persistent innovators spend continuously more on R&D, then it may be argued that our results follows from the fact that R&D spending correlates both with persistence in innovation and technological leadership. In this section we will try to address these two limitations by estimating a model with conditional frailty. In addition to this check, we will also test the robustness of our results to the presence of non-linear relationship between technological leadership and persistence.

7.1. Conditional frailty estimation

In this section we generalize the CPHM introduced in Section 5 by adding an individual time-invariant frailty term (ω_i) to the hazard function (1). The purpose of this generalization is to separate the persistence effect driven by true event dependence form the spurious one caused by time-invariant unobserved heterogeneity across individuals. We adopt the specification of the Conditional Frailty Cox (CFC) model proposed by Box-Steffensmeier and De Boef (2007)[21] by generalizing the hazard and partial likelihood functions (1) and (3) as follows:

$$h_{ik}(t;Z_{ik}) = h_{0k}(t - t_{k-1})\exp\left(\beta Z_{ik}(t) + \omega_i\right) \tag{8}$$

$$L(\beta) = \prod_{i=1}^{n}\prod_{k=1}^{K}\left(\frac{\exp\left(\beta Z_{ik}(X_{ik}) + \omega_i\right)}{\sum_{j=1}^{n} Y_{jk}(X_{ik})\exp\left(\beta Z_{jk}(X_{ik}) + \omega_i\right)}\right)^{\delta_{ik}} \tag{9}$$

Maximization of (9) is performed using the Expectation-Maximization (E-M) algorithm and assuming a gamma distribution for ω_i and treating them as missing data. Controlling for unobserved heterogeneity allows us to partially solve the 'initial condition' problem for left censored observed spells (Ham and Lalonde, 1996) mentioned above. As we do not observe the initial state of the firm in each market, with the exception of the market for switches, our results may be biased by the presence of the 'initial condition' problem . As the CFC model assumes a functional form for the duration distribution of each initial state that is different not only from that of the other spells, but also from that of the other individuals, we can draw more robust conclusions in term of causality interpretation by allowing each firm's initial state to be correlated with its time-invariant unobserved characteristics. Concerning the omitted variable bias, the CFC model can alleviate the problem as long as we assume that some important factors omitted from the hazard equation, such as R&D input measures, do not significantly change over time.[22]

Results from the estimation of the CFC model are reported in Table 11 in which the main findings of the CPHM are confirmed.

[Insert Table 11 about here]

In particular, the coefficient of the distance to the technological frontier is negative and significant in each of the three markets. The magnitude of this effect, which is comparable across markets as the distances to the frontier are standardized, is larger in the case of routers, with a coefficient which is almost double (in absolute terms) than the ones for hubs and switches. Finally, in the case of switches, the Frailty χ^2 Test does not reject the null hypothesis of the absence of a significant unobserved heterogeneity factor (ω_i) for this sub-sample. As the switch market is the only one in our sample which we can observe since its inception, this result suggests that the CFC model is actually helpful in taking into account the initial condition problem that potentially affects the left-censored observations in both the hubs and the routers markets.

7.2. Controlling for the non linearity in the relationship between technological leadership and persistence

In this sub-section we check for the presence of a non-linear relationship between technological leadership and persistence in product innovation which has already been detected in previous works (Lerner 1997; Lee *et al.*, 2011). We perform this analysis by defining, for each market, two dummy variables that identify the firms laying in the second and third tertiles of the distribution of our continuous measure of technological leadership.[23] Results are reported in Table 12.

[Insert Table 12 about here]

In all the three case, the most significant decrease in the hazard to innovate occurs when moving from the 2nd to the 3rd tertile suggesting that the negative effect of being distant from the technological frontier is less severe for firms that can be classified technological leaders (1st tertile) or followers (2nd tertile) and more pronounced for the laggards (3rd tertile).

8. Conclusion

This paper has studied the relationship between technological leadership and persistence in product innovation for a sample of firms operating during the 1990s in three markets in the LAN industry a high-tech sector. During the period analysed here, the three markets under consideration (i.e. hubs, routers, and switches) differed in terms of product complexity, opportunity to innovate, barrier to entry and exit, and levels of concentration thus providing an interesting case to study persistence in product innovation. We first carried out a univariate analysis based on TPMs. Our analysis has revealed that persistence in product innovation is relatively higher for complex products (i.e. product with many technical characteristics and high interdependencies among them). In complex product markets technological leaders seem to innovate more systematically than in non complex products. Also, large innovators tend to be more persistent innovators than small innovators. Finally, technological leadership positively impacts on innovation persistence in the case of greater innovators and negatively in the case of small innovators. However, particularly in the case of complex products, leadership may help small innovators to overcome the innovative threshold and enter in the innovator state.

We then carried out a multivariate analysis by estimating conditional risk sets duration analysis. This analysis has revealed that, controlling for market and firm size, technological leadership seems to be always an important prerequisite for persistence in product innovation with technological leaders always more persistent innovators than laggards. Our results have highlighted the presence of a direct relationship between persistence in product innovation and (lagged) patenting. In addition to this, we also found that the number of (lagged) patents increases persistence in product innovation. Finally, we also found that technological leadership plays an important role for innovating in related markets. In particular, technological leaders in one market can also systematically innovate in an adjacent market. Our sensitivity analysis has revealed that our main results are robust to control for unobserved heterogeneity and for the presence of non linearity in the indicator of technological leadership.

These results have implications for our understanding of firms' strategies for product innovation in high-tech industries. In particular, the finding that technological leaders are more persistent innovators than laggards suggests that these firms are responsible for extending the technological frontier which is not inconsistent with findings from other studies of technological races in hi-tech industries (Khanna, 1995; Lerner, 1997).

Our results also allow us to speculate about the determinants of product portfolio changes and extensions. Our finding that technological leaders are more persistent is consistent with a situation in which they mainly change their product portfolio through product proliferation and the introduction of product families. Our finding for related markets suggests instead that we should expect to find differences between incumbents in terms of expansion of their product portfolio with technological leaders more able to 'stretch' their product portfolio farther than laggards as they can innovate in more complex but adjacent markets.

Though interesting, our analysis is not without important limitations. First, we have considered the case of a specific industry characterised by high dynamism and high rate of innovation. Ideally one would like to compare our results with the case of other industries both high-tech but also low-tech in which technological leadership may be expected to play a less important role for innovation persistence. Second, our analysis is restricted to a ten years time span. Future research should try to extend the time series. Finally, our analysis has focussed on the relationship between technological leadership and innovation persistence. It has remained silent about the issue of persistence in technological leadership. Whether persistence in leadership can be considered a pre-condition for persistence in innovation will be a topic for future research.

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Table 1: Summary descriptive statistics

	Obs.	Mean	SD	Min	Max
Hubs					
DIST FRONT HUBS	204	0	1	-1.570	1.985
SIZE (EMPLOYEES/100)	126	3.157	6.660	0.003	31.270
SALES (LOG - MIL$)	147	1.318	2.363	-2.742	6.775
AGE (LOG - YEARS)	204	2.430	0.822	0	4.477
NUMBER OF PRODUCTS AT ENTRY	204	2.015	1.533	1	8
NUMBER OF PATENTS AT T-1/1000	204	0.080	0.302	0	2.405
PATENT AT T-1 (DUMMY)	204	0.456	0.499	0	1
PATENT STOCK/EMPLOYEES	126	0.176	0.352	0	3.571
Routers					
DIST FRONT ROUTERS	246	0	1	-1.99	2.38
SIZE (EMPLOYEES/100)	246	3.756	7.407	0.001	31.700
SALES (LOG - MIL$)	136	1.242	2.657	-4.500	6.775
AGE (LOG - YEARS)	159	2.375	0.890	0	4.477
NUMBER OF PRODUCTS AT ENTRY	246	2.028	1.329	1	7
NUMBER OF PATENTS AT T-1/1000	246	0.062	0.301	0	2.405
PATENT AT T-1 (DUMMY)	246	0.321	0.468	0	1
PATENT STOCK/EMPLOYEES	136	0.113	0.173	0	0.781
Switches					
DIST FRONT SWITCHES	149	0	1	-2.10	1.81
SIZE (EMPLOYEES/100)	98	2.301	5.081	0.001	30.740
SALES (LOG - MIL$)	113	1.425	2.355	-2.738	6.775
AGE (LOG - YEARS)	149	2.299	0.916	0	4.477
NUMBER OF PRODUCTS AT ENTRY	149	1.745	1.420	1	8
NUMBER OF PATENTS AT T-1/1000	149	0.057	0.233	0	2.405
PATENT AT T-1 (DUMMY)	149	0.544	0.500	0	1
PATENT STOCK/EMPLOYEES	98	0.214	0.433	0	3.571
All markets					
SIZE (EMPLOYEES/100)	360	3.150	6.587	0.001	31.700
SALES (LOG - MIL$)	419	1.318	2.472	-4.500	6.775
AGE (LOG - YEARS)	599	2.375	0.874	0	4.477
NUMBER OF PRODUCTS AT ENTRY	599	1.953	1.426	1	8
NUMBER OF PATENTS AT T-1/1000	599	0.067	0.286	0	2.405
PATENT AT T-1 (DUMMY)	599	0.422	0.494	0	1
PATENT STOCK/EMPLOYEES	360	0.163	0.327	0	3.571

Table 2: Transition probabilities between innovative states

	HUBS		SWITCHES		ROUTERS	
	Innovative at t+1		Innovative at t+1		Innovative at t+1	
	Non Innovator	Innovator	Non Innovator	Innovator	Non Innovator	Innovator
Non innovator	77.92%	22.08%	63.29%	36.71%	76.12%	23.88%
Innovator	56.20%	43.80%	52.94%	47.06%	42.52%	57.48%

Table 3: Transition probabilities between innovative states: Leaders vs. Laggards

	HUBS		SWITCHES		ROUTERS	
Leaders	Innovative at t+1		Innovative at t+1		Innovative at t+1	
	Non Innovator	Innovator	Non Innovator	Innovator	Non Innovator	Innovator
Non innovator	76.45%	23.55%	56.10%	43.90%	76.29%	23.71%
Innovator	51.30%	48.70%	47.50%	52.50%	36.64%	63.36%
Laggards						
Non innovator	78.90%	21.10%	67.26%	32.74%	76.00%	24.00%
Innovator	60.14%	39.86%	56.45%	43.55%	47.24%	52.76%

Table 4: Transition probabilities between innovative states: Great vs. Small innovators

	HUBS		SWITCHES		ROUTERS	
Great Inn.	Innovative at t+1		Innovative at t+1		Innovative at t+1	
	Non Innovator	Innovator	Non Innovator	Innovator	Non Innovator	Innovator
Non innovator	70.29%	29.71%	51.85%	48.15%	71.19%	28.81%
Innovator	37.50%	62.50%	26.04%	73.96%	29.30%	70.70%
Small Inn.						
Non innovator	80.17%	19.83%	66.79%	33.21%	78.27%	21.73%
Innovator	74.62%	25.38%	76.85%	23.15%	57.66%	42.34%

Table 5: Transition probabilities between innovative states for Great Innovators: Leaders vs. Laggards

	HUBS		SWITCHES		ROUTERS	
Leaders	Innovative at t+1		Innovative at t+1		Innovative at t+1	
	Non Innovator	Innovator	Non Innovator	Innovator	Non Innovator	Innovator
Non innovator	63.49%	36.51%	44.12%	55.88%	74.24%	25.76%
Innovator	36.00%	64.00%	21.43%	78.57%	19.18%	80.82%
Laggards						
Non innovator	76.00%	24.00%	57.45%	42.55%	69.37%	30.63%
Innovator	39.62%	60.38%	29.63%	70.37%	38.10%	61.90%

Table 6: Transition probabilities between innovative states for Small Innovators: Leaders vs. Laggards

	HUBS		SWITCHES		ROUTERS	
Leaders	Innovative at t+1		Innovative at t+1		Innovative at t+1	
	Non Innovator	Innovator	Non Innovator	Innovator	Non Innovator	Innovator
Non innovator	81.01%	18.99%	60.67%	39.33%	77.11%	22.89%
Innovator	80.00%	20.00%	76.32%	23.68%	58.62%	41.38%
Laggards						
Non innovator	79.66%	20.34%	69.89%	30.11%	79.08%	20.92%
Innovator	72.22%	27.78%	77.14%	22.86%	56.96%	43.04%

Table 7: Conditional risk set Cox models for persistence in innovation (Hub Market)

	[1]	[2]	[3]
DIST FRONT HUBS T-1 (STANDARD.)	-0.222***	-0.259***	-0.203***
	[0.0770]	[0.0844]	[0.0713]
SIZE (EMPLOYEES/100)		0.219***	0.213**
		[0.0744]	[0.0896]
SIZE SQ (EMPLOYEES/100 SQUARED)		-0.00716***	-0.00869***
		[0.00228]	[0.00308]
SALES (LOG - MIL$)		-0.0853	-0.177**
		[0.0543]	[0.0692]
AGE (LOG - YEARS)		-0.117	-0.248
		[0.128]	[0.156]
NUMBER OF PRODUCTS AT ENTRY			0.00794
			[0.0602]
NUMBER OF PATENTS AT T-1/1000			1.538***
			[0.342]
PATENT AT T-1 (DUMMY)			0.728***
			[0.207]
PATENT STOCK/EMPLOYEES			-1.920**
			[0.840]
Observations	204	126	126
No of failures	152	102	102
Time at risk	371	215	215
Log pseudo-likelihood	-463.163	-247.309	-240.333
Wald chisq.	8.34***	19.26***	48.34***

Robust standard errors in brackets. Efron method for ties. Standard errors adjusted for clustering on firms.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Conditional risk set Cox models for persistence in innovation (Router Market)

	[1]	[2]	[3]
DIST FRONT ROUTERS T-1 (STANDARD.)	-0.255***	-0.145*	-0.167**
	[0.0711]	[0.0801]	[0.0841]
SIZE (EMPLOYEES/100)		0.0562	0.101*
		[0.0539]	[0.0593]
SIZE SQ (EMPLOYEES/100 SQUARED)		-0.00193	-0.00379**
		[0.00155]	[0.00169]
SALES (LOG - MIL$)		0.00902	-0.0609
		[0.0585]	[0.0651]
AGE (LOG - YEARS)		-0.184**	-0.345***
		[0.0790]	[0.0814]
NUMBER OF PRODUCTS AT ENTRY			0.0479
			[0.0735]
NUMBER OF PATENTS AT T-1/1000			0.702***
			[0.163]
PATENT AT T-1 (DUMMY)			0.432**
			[0.175]
PATENT STOCK/EMPLOYEES			-0.0570
			[0.461]
Observations	246	135	135
No of failures	191	116	116
Time at risk	386	195	195
Log pseudo-likelihood	-601.639	-279.253	-274.622
Wald chisq.	12.84***	19.45***	61.88***

Robust standard errors in brackets. Efron method for ties. Standard errors adjusted for clustering on firms.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Conditional risk set Cox models for persistence in innovation (Switch Market)

	[1]	[2]	[3]
DIST FRONT SWITCHES T-1 (STANDARD.)	-0.222***	-0.215**	-0.239**
	[0.0820]	[0.101]	[0.0932]
SIZE (EMPLOYEES/100)		-0.0113	0.0244
		[0.0907]	[0.0719]
SIZE SQ (EMPLOYEES/100 SQUARED)		-0.000342	-0.00200
		[0.00237]	[0.00194]
SALES (LOG - MIL$)		0.0524	-0.153
		[0.0958]	[0.0934]
AGE (LOG - YEARS)		-0.0725	0.0792
		[0.143]	[0.111]
NUMBER OF PRODUCTS AT ENTRY			0.0360
			[0.0250]
NUMBER OF PATENTS AT T-1/1000			0.795**
			[0.366]
PATENT AT T-1 (DUMMY)			1.067***
			[0.251]
PATENT STOCK/EMPLOYEES			-0.406**
			[0.174]
Observations	149	98	98
No of failures	111	79	79
Time at risk	199	126	126
Log pseudo-likelihood	-326.393	-198.508	-190.663
Wald chisq.	7.35***	9.05*	92.81***

Robust standard errors in brackets. Efron method for ties. Standard errors adjusted for clustering on firms.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: Conditional risk set Cox models for persistence in innovation – Related market analysis

	HUBS		ROUTERS		SWITCHES	
	[1]	[2]	[3]	[4]	[5]	[6]
DIST FRONT HUBS T-1 (STANDARD.)	-0.263*	-0.242*	-0.0932		-0.455**	
	[0.138]	[0.135]	[0.133]		[0.204]	
DIST FRONT ROUTERS T-1 (STANDARD.)	-0.295		-0.440**	0.00787		-0.0896
	[0.216]		[0.175]	[0.122]		[0.155]
DIST FRONT SWITCHES T-1 (STANDARD.)		0.141		-0.328**	-0.133	-0.290
		[0.16]		[0.166]	[0.197]	[0.248]
SIZE (EMPLOYEES/100)	0.258**	0.182*	0.0426	0.146	0.0673	0.0249
	[0.120]	[0.101]	[0.0824]	[0.109]	[0.145]	[0.120]
SIZE SQ (EMPLOYEES/100 SQUARED)	-0.00111***	-0.00286***	-0.000449*	-0.00206**	-0.000324	-0.000167
	[0.000430]	[0.000668]	[0.000267]	[0.000930]	[0.000342]	[0.000347]
SALES (LOG - MIL$)	-0.193	-0.480***	0.00845	-0.107	-0.144	-0.371**
	[0.139]	[0.179]	[0.155]	[0.128]	[0.132]	[0.170]
AGE (LOG - YEARS)	0.748	-0.213	-0.0635	-0.397	0.128	-0.0809
	[0.508]	[0.453]	[0.169]	[0.300]	[0.360]	[0.152]
NUMBER OF PRODUCTS AT ENTRY	0.781**	0.106	-0.0600	-0.117	-0.00237	-0.0272
	[0.392]	[0.120]	[0.114)	[0.106]	[0.0332]	[0.0382]
NUMBER OF PATENTS AT T-1/1000	1.870***	7.803***	1.371***	3.986*	0.870**	0.533
	[0.614]	[1.838]	[0.333]	[2.113]	[0.387]	[0.344]
PATENT AT T-1 (DUMMY)	-0.0529	2.112***	0.825*	0.852	1.180**	1.635***
	[0.662]	[0.769]	[0.459]	[0.519]	[0.596]	[0.600]
PATENT STOCK/EMPLOYEES	-3.743	-1.985	-1.197	-0.0616	-0.0145	2.109
	[2.508]	[1.453]	[2.722]	[2.070]	[0.352]	[1.826]
Observations	38	49	37	34	48	34
No of failures	29	34	30	29	36	29
Time at risk	61	76	58	48	61	41
Log pseudo-likelihood	-31.418	-36.712	-30.690	-22.828	-58.623	-36.760
Wald chisq.	111.75***	146.73***	44.02***	37.35***	100.23***	316.86***

Robust standard errors in brackets. Efron method for ties. Standard errors adjusted for clustering on firms.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11: Conditional Frailty Cox models for persistence in innovation

	HUBS		ROUTERS		SWITCHES	
	[1]	[2]	[3]	[4]	[5]	[6]
DIST FRONT HUBS T-1 (STANDARD.)	-0.257	-0.242				
	[0.128]**	[0.131]*				
DIST FRONT ROUTERS T-1 (STANDARD.)			-0.416	-0.428		
			[0.136]**	[0.133]**		
DIST FRONT SWITCHES T-1 (STANDARD.)					-0.215	-0.282
					[0.123]*	[0.134]**
SIZE (EMPLOYEES/100)	0.401	0.398	0.068	0.104	0.011	0.011
	[0.131]***	[0.135]***	[0.077]	[0.078]	[0.116]	[0.116]
SIZE SQ (EMPLOYEES/100 SQUARED)	-0.014	-0.014	-0.002	-0.004	-0.002	-0.002
	[0.005]***	[0.005]***	[0.002]	[0.003]	[0.004]	[0.004]
SALES (LOG - MIL$)	-0.145	-0.233	-0.035	-0.091	-0.141	-0.141
	[0.113]	[0.123]*	[0.086]	[0.091]	[0.141]	[0.141]
AGE (LOG - YEARS)	-0.158	-0.157	-0.212	-0.391	0.167	0.167
	[0.229]	[0.231]	[0.160]	[0.169]**	[0.219]	[0.219]
NUMBER OF PRODUCTS AT ENTRY		0.002		-0.028		-0.092
		[0.116]		[0.101]		[0.083]
NUMBER OF PATENTS AT T-1/1000		0.789		0.878		0.754
		[0.628]		[0.496]*		[0.479]
PATENT AT T-1 (DUMMY)		0.849		0.438		1.148
		[0.324]***		[0.268]**		[0.348]***
PATENT STOCK/EMPLOYEES		-1.956		-0.349		-0.385
		[1.199]		[0.854]		[0.355]
Observations	126	126	135	135	98	98
χ^2 Frailty Test (all ω_i=0)	31.68***	22.86**	16.31*	10.93*	0.01	0.01
Log pseudo-likelihood	-201.9	-197.4	-200.3	-196.8	-163.7	-155.7
LR Test	63.6***	64.7***	40.2***	40.4***	4.31	20.4**

Robust standard errors in brackets. Efron method for ties. Standard errors adjusted for clustering on firms.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 12: Conditional risk set Cox models for persistence in innovation: dummy variable models.

	HUBS		ROUTERS		SWITCHES	
	[1]	[2]	[3]	[4]	[5]	[6]
DIST FRONT (2ND TERTILE)	-0.288	-0.291	-0.069	-0.063	-0.210	-0.051
	[0.243]	[0.261]	[0.185]	[0.180]	[0.258]	[0.221]
DIST FRONT (3RD TERTILE)	-0.526	-0.374	-0.469	-0.562	-0.387	-0.471
	[0.211]**	[0.199]*	[0.207]**	[0.194]***	[0.274]	[0.270]*
SIZE (EMPLOYEES/100)	0.215	0.215	0.056	0.105	-0.012	0.009
	[0.078]***	[0.094]**	[0.053]	[0.056]*	[0.091]	[0.074]
SIZE SQ (EMPLOYEES/100 SQUARED)	-0.007	-0.009	-0.002	-0.004	-0.001	-0.001
	[0.002]***	[0.004]***	[0.002]	[0.002]**	[0.002]	[0.002]
SALES (LOG - MIL$)	-0.074	-0.172	0.010	-0.067	0.059	-0.152
	[0.056]	[0.069]**	[0.058]	[0.063]	[0.095]	[0.091]*
AGE (LOG - YEARS)	-0.127	-0.241	-0.194	-0.370	-0.075	0.101
	[0.127]	[0.153]	[0.075] ***	[0.079]***	[0.138]	[0.108]
NUMBER OF PRODUCTS AT ENTRY		0.022		0.047		0.0517
		[0.061]		[0.070]		[0.031]*
NUMBER OF PATENTS AT T-1/1000		1.504		0.683		0.834
		[0.336]***		[0.154]***		[0.347]**
PATENT AT T-1 (DUMMY)		0.742		0.495		1.056
		[0.211] ***		[0.182]***		[0.242]***
PATENT STOCK/EMPLOYEES		-2.039		-0.059		-0.472
		[0.883] **		[0.465]		[0.168]***
Observations	126	126	135	135	98	98
χ^2 Frailty Test (all ω_i=0)	34.80***	22.44**	20.73**	15.22**	0.01	0.01
Log pseudo-likelihood	-202.6	-198.2	-199.7	-195.85	-164.4	-156.4
LR Test	65.5***	62.9***	47***	48.6***	2.94	18.9**

Robust standard errors in brackets. Efron method for ties. Standard errors adjusted for clustering on firms.
* significant at 10%; ** significant at 5%; *** significant at 1%

APPENDIX

Table A1: OLS regressions on observed hub prices

BACKPLANE CAPACITY (LOG)	0.229
	[0.055]***
MAXIMUM NO OF PORTS (LOG)	0.551
	[0.066]***
TOKEN RING (DUMMY)	0.336
	[0.141]**
OTHER STANDARDS (DUMMY)	0.669
	[0.179]***
MANAGEMENT SOFTWARE (DUMMY)	0.185
	[0.118]
CONSTANT	6.052
	[0.307]***
Observations	518
Rsq	0.802

Dependent variable: logarithm of deflated list product price. Robust standard errors in brackets
*Significant at 10%, ** significant at 5%, *** significant at 1%. Year and firm dummy variables omitted for clarity

Table A2: OLS regressions on observed router prices

MAXIMUM NO OF LANS (LOG)	0.503
	[0.069]***
MAXIMUM NO OF WANS (LOG)	0.376
	[0.058]***
FRAME RELAY SUPPORT (DUMMY)	0.166
	[0.081]**
ISDN & ATM SUPPORT (DUMMY)	0.045
	[0.132]
SONET SUPPORT (DUMMY)	0.425
	[0.213]**
OSPF ALGORITHM SUPPORT (DUMMY)	0.071
	[0.107]
RIP1-2 ALGORITHM SUPPORT (DUMMY)	-0.222
	[0.150]
APPLETALK PROTOCOL SUPPORT (DUMMY)	-0.053
	[0.104]
DECNET PROTOCOL SUPPORT (DUMMY)	0.186
	[0.129]
IPX PROTOCOL SUPPORT (DUMMY)	-0.059
	[0.111]
SNA PROTOCOL SUPPORT (DUMMY)	0.141
	[0.073]**
TCP/IP PROTOCOL SUPPORT (DUMMY)	0.244
	[0.167]
XNS PROTOCOL SUPPORT (DUMMY)	0.141
	[0.108]
CONSTANT	7.785
	[0.402]***
Observations	731
Rsq	0.850

Dependent variable: logarithm of deflated list product price. Robust standard errors in brackets
*Significant at 10%, ** significant at 5%, *** significant at 1%. Year and firm dummy variables omitted for clarity

Table A3: OLS regressions on observed switch prices

BACKPLANE CAPACITY (LOG)	0.191
	[0.038]***
NO OF ETHERNET PORTS (LOG)	0.068
	[0.030]**
NO OF FAST ETHERNET PORTS (LOG)	0.014
	[0.040]
NO OF FDDI PORTS (LOG)	0.031
	[0.069]
NO OF TOKEN RING PORTS (LOG)	0.116
	[0.043]***
NO OF 100VG ANY-LAN PORTS (LOG)	0.185
	[0.131]
NO OF ATM PORTS (LOG)	0.043
	[0.061]
NO OF GIGABIT ETHERNET PORTS (LOG)	0.370
	[0.066]***
VLAN CAPABILITY (DUMMY)	0.145
	[0.115]
CHASSIS (DUMMY)	0.815
	[0.160]***
FIXED CONFIGURATION (DUMMY)	-0.064
	[0.090]
CONSTANT	8.341
	[0.334]***
Observations	513
Rsq	0.666

Dependent variable: logarithm of deflated list product price. Robust standard errors in brackets
*Significant at 10%, ** significant at 5%, *** significant at 1%. Year and firm dummy variables omitted for clarity

Table A4: Correlation matrices

Hubs N=126	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. Dist front hubs	1						
2. Number of products at entry	-0.3676	1					
3. Size (Employees/100)	0.067	-0.2558	1				
4. Sales (Log - Mil$)	0.0164	-0.206	0.9428	1			
5. Age (Log - Years)	-0.0076	-0.1034	0.5853	0.3511	1		
6. Number of patents at t-1/1000	0.165	-0.2549	0.3966	0.2022	0.5868	1	
7. Patent at t-1 (dummy)	0.0641	-0.2057	0.6979	0.5833	0.6105	0.5398	1
8. Patent stock/Employees	0.0149	-0.0988	0.3504	0.2408	0.5161	0.2843	0.2702
Routers N=135							
1. Dist front routers	1						
2. Number of products at entry	0.0909	1					
3. Size (Employees/100)	0.0006	-0.1081	1				
4. Sales (Log - Mil$)	-0.0892	-0.0851	0.7682	1			
5. Age (Log - Years)	0.0522	0.1593	0.4015	0.4117	1		
6. Number of patents at t-1/1000	0.0633	0.059	0.6596	0.4823	0.4963	1	
7. Patent at t-1 (dummy)	-0.1386	0.1307	0.1818	0.4257	0.3918	0.2879	1
8. Patent stock/Employees	0.1029	0.1162	0.3265	0.3451	0.349	0.5058	0.4335
Switches N=98							
1. Dist front switches	1						
2. Number of products at entry	-0.1954	1					
3. Size (Employees/100)	-0.0694	-0.0397	1				
4. Sales (Log - Mil$)	-0.1738	0.0626	0.7551	1			
5. Age (Log - Years)	-0.0738	-0.0068	0.6437	0.6511	1		
6. Number of patents at t-1/1000	-0.0159	-0.0028	0.6715	0.5215	0.4757	1	
7. Patent at t-1 (dummy)	-0.1763	0.1361	0.2575	0.5196	0.1871	0.221	1
8. Patent stock/Employees	-0.0043	-0.0339	0.1019	0.118	0.2237	0.1337	0.0644
All markets N=359							
2. Number of products at entry	-	1					
3. Size (Employees/100)	-	-0.1333	1				
4. Sales (Log - Mil$)	-	-0.044	0.6964	1			
5. Age (Log - Years)	-	-0.0376	0.4457	0.5277	1		
6. Number of patents at t-1/1000	-	-0.0528	0.6747	0.5317	0.5065	1	
7. Patent at t-1 (dummy)	-	0.0453	0.2407	0.4759	0.2969	0.2612	1
8. Patent stock/Employees	-	-0.0701	0.146	0.1891	0.2677	0.2289	0.1638

[1] Concerning the interpretation of the threshold effect, Geroski *et al.* (1997) argue that while dynamic economies may lead to longer and more persistent spells of innovation by firms, they do so only when the threshold of initial or pre-spell innovative activity is high enough to temporarily overcome strong 'within spell forces' which may delay the production of innovation. In Malerba *et al.* (1997) the threshold has been found to constrain the innovative activity especially of small and medium firms

[2] Further empirical investigations based on country level innovation surveys are: Roper and Hewitt-Dundas (2008) who study persistence in both product and process innovation for a sample of innovators in Ireland; Clausen *et al.* (2012) who find that differences in persistence between product and process innovations are mediated by firms' innovation strategies for a sample of Norwegian high-tech and low-tech firms; Raymond *et al.* (2010) who find that firms in the high-tech sector are more persistent innovators than firms in the low-tech one. Further evidence on persistence is found by both Peters (2009) and Castillejo *et al.* (2004). The former paper studies persistence both in manufacturing and services for a sample of German firms. The latter provides evidence on the case of Spanish manufacturing firms. Both these papers measure persistence in terms of total innovation expenditure an indicator of input in the innovation process.

[3] Alternatively incumbents may rely upon other traditional means, such as patents, to continue to benefit from their market power. In the LAN industry, particularly during the period under examination here, competition mainly revolved around the definition and commercialization of *open* transmission and communication standards. Therefore, patents played a minor role as appropriation tools.

[4] The marginal benefits also set the conditions for a leader 'to persist being a leader'. These conditions depend on the opportunity costs of switching to a new technology. When opportunity costs are negligible, as in Schivardi and Schneider (2008), technological leaders are always able to maintain their leadership. When the opportunity costs are assumed to be inversely related to the relative advantage of the leader, as in Metcalf (2011), the leader firm becomes less able to keep its leadership the higher its initial advantage with respect to competitors. In our paper we do not examine the issue of *persistence in technological leadership*. Rather we focus on the relationship between technological leadership and innovation persistence.

[5] Lerner (1997) studies the technology race in the Hard Disk Drive industry. He finds that laggards whose technological performance lies between 25% and 74% of that of the leader are most likely to innovate. No effect is found for the firms located in the bottom 25%.

[6] Alternatively, expansion of a firm's product portfolio to adjacent markets may be the consequence of 'brand extension' when consumers are uncertain about product characteristics and brands may play an informational role (Choi, 1998), or follow from a strategy of entry deterrence (Choi and Scarpa, 1992).

[7] McElheran (2010) provides a recent review of these topics.

[8] According to Levinthal (1997) product complexity can be assessed along two dimensions: number of product characteristics and extent of interdependences among the characteristics. The higher the number of technical characteristics the higher the extent of complexity. The stronger the level of interdependences the more difficult is to change a characteristic without repercussions on the others and therefore on the overall design of a product.

[9] Since technological leadership is measured in terms of firm's location with respect to the technological frontier, we need to use information on the first product introduction to calculate this indicator. Another source of left censoring is the fact that routers and hubs already existed prior to 1990.

[10] For the exposition of the model we draw upon Squicciarini (2009).

[11] An alternative would be to measure the technological frontier by relying upon an overall performance measure (such as data processing speed) and/or upon a single 'representative' technical characteristic. With respect to these options, our approach has at least two advantages. First and foremost it is more comprehensive as it allows the inclusion of several technological characteristics which may impact on the quality adjusted price of the new product. Second, it allows us to include both firm and time fixed effect in the regression. Controlling for firm fixed effect is particularly important to capture unobservable effects (i.e. brand effects), firms' specific practices (i.e. company related quantity discounts), and/or firms' specific innovation strategies (i.e. companies using high quality components through licenses) which may impact on prices. Results for the hedonic price regressions for each market are reported in the Appendix.

[12] For private firms this information was not always available with consequent loss of observations in the econometric exercise.

[13] It is important to stress that leadership in terms of market sales does not necessarily entail technological leadership measured in terms of location with respect to the technological frontier. It is possible that in some markets new entrants (incumbents) may turn out to be technological leaders (laggards) even though their total sales are relative lower (higher) with respect to incumbents (new entrants). In the LAN industry, Cisco Systems, one of the leaders in terms of market shares, is arguably considered to be also the technological leader both in term of patent portfolio and overall quality of its products (Hochmuth, 2006).

[14] PATENT STOCK accounts for the number of citations received by the patents. It is depreciated at the 15% rate.

[15] A qualification is in order here. Our patent based indicators do not simply consider the total number of patents granted to each firm. Instead we consider *only* the patents that are related to the specific LAN product (i.e. hubs, routers, switches). Identification of these patents is done on the basis of the main International Patent Classification (IPC) class (at 8 digits) of the patent.

[16] We assessed the degree of multicollinearity in our survival models by estimating the same models with Ordinary Least Squares techniques, using the logarithm of the time spells as dependent variable, and by computing the Variance Inflation Factor (VIF). For every model, a value of VIF higher than the standard tolerance level of 5 was detected only for the estimates associated with SIZE and SIZE SQ. In all the estimated models the average VIF was never higher than the maximum tolerance level of 10.

[17] In the TPM analysis, we define technological leaders (laggards) those firms whose distance to technological frontier *at entry* is lower (higher) than the average in that year. 82% of incumbents in our sample introduce their 'best' product within three years after entry. 65% do it within the first year.

[18] The average firm in our sample has introduced three products. Thus we adapt Cefis' (2003) definition to our case and define 'great innovators' firms that have introduced at least three new products *in at least one year* included in our time period. Between 30-38% of firms in our sample are great innovators depending on the specific market.

[19] In this and in the following regressions, all marginal effects are calculated with reference to the final model specification (Model 3).

[20] This focus implies a non trivial reduction of the sample size available for our analyses and may raise some concerns about the unbiasedness of our estimates. In fact, as pointed out by Firth (1993), the phenomenon of monotone likelihood (which causes the parameter estimates of a Cox model to diverge, with infinite standard errors, while the likelihood converges to a finite value) primarily occurs in small samples, with substantial censoring and several highly predictive covariates. This problem has been analyzed more in deep by Heinze and Schemper (2001), who studied the behaviour of the bias-reducing penalized likelihood estimator proposed by Firth (1993) using Monte-Carlo simulations and showing that monotone likelihood rarely occurs with continuous covariates and few censored observations. On the basis of these findings we are quite confident on the accuracy of our estimates none of ore estimated coefficients or standard errors tend to diverge, almost all of our covariates, except PATENTS (T-1), are continuous and less than 10% of our observations are censored.

[21] In this paper the authors show, by using simulated and real data taken from clinical trials, that most of the commonly used model for repeated events, such as the Conditional-Cox and the Frailty-Cox models, lead to biased estimates when both true event dependence and unobserved heterogeneity are simultaneously present, whereas with the CFC model the bias disappears at cost of a minimal loss of efficiency.

[22] This assumption seems reasonable in the presence of high adjustment and sunk costs (see for instance: Himmelberg and Petersen, 1994).

[23] The excluded category is the first tertile including the closest firms to the technological frontier.