Technological leadership and innovation persistence: empirical evidence.

Roberto Fontana[♦], Diana Moriniello[♣]

Paper to be presented at: EMAEE 2011 Conference
14-16 February 2011, Sant'Anna School of Advanced Studies, Pisa, Italy

This Version: January 2011

STILL PRELIMINARY, PLEASE DO NOT QUOTE OR CITE WITHOUT AUTHORS' PERMISSION

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 market. Laggards in one market can instead innovate systematically in another one only if it is less technologically advanced. We also find evidence that patenting increase persistence in product innovation.

[♦] University of Pavia & KITeS – Bocconi University, Via Ferrata 1, 27100, Pavia, Italy. roberto.fontana@unibocconi.it
[♣] KITeS – Bocconi University, Via Sarfatti 25, 20139, Milano, Italy. diana.moriniello@gmail.com

1. Introduction

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 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, 1982; 1983). 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 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 certain 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, 1956; 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.

Starting from the seminal paper by Geroski *et al.* (1997) empirical contributions have highlighted that prior innovative activity 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. This evidence has been confirmed by other studies. Cefis and Orsenigo (2001) find bimodality in the pattern of persistence according to which persistence is stronger for firms that are either non innovators or great innovators (having 6 or more patents in a year). Cefis (2003) highlights how persistence in innovation seems higher in sectors characterised by technological cumulativeness, R&D complementarities and learning-by-doing processes. Other studies further highlight the presence of a minimum threshold of innovative activity necessary for a firm to become an innovator or to remain persistent innovator (Geroski *et al.,* 1997). This threshold has been found to constrain the innovative activity especially of small and medium firms (Malerba *et al.*, 1997). All in all existing contributions that have measured persistence using patent data have highlighted that persistence depends on the incentives to stay in the technological race. These incentives differ according to the status of the innovator (i.e. great vs. small innovator), and the technological regime.

In this paper we focus on persistence in *product innovation*. In particular we look at whether persistence depends on technological leadership. Our empirical analysis is based on a sample of 265 firms active in the Local Area Network (LAN) industry, a high-tech industry, between 1990 and 1999. Using information on products, prices and technical characteristics we construct indicators of technological leadership and link them to persistence in product innovation in three submarkets, hub, router and switches, characterised by different market structures and technological opportunities. We then calculate Transition Probability Matrices and perform conditional risk set duration analysis. We find that technological leadership is always positively associated to persistence in innovation. Moreover, leadership in one market can also be used to systematically innovate in another market.

The paper is structured as follows. In Section 2 we present a review of the literature on persistence in innovation as well as some necessary background information on the LAN industry. Section 3 presents our data, method as well as the variables that will be used in the analysis. Section 4 presents the results. Section 5 concludes.

2. Background literature on persistence in innovation

One of the early empirical attempt to provide evidence on persistence in innovation is the work by Geroski *et al.* (1997) which analyses the hypothesis that the production of innovations is subject to dynamic economies of scale (the 'success-breeds-success' paradigm), namely that the volume of innovations produced by a firm up to date *t* has an effect on the probability that yet another innovation will be produced at *t+1*. Relying upon patents as indicators of innovation, it looks at 'patent spells' (i.e. the number of successive years in which a firm produces at least one patent per year). The paper identifies three regimes of patenting behaviour: single patentees, firms producing a few patents in one short spell; sporadic patentees, firms producing a handful of patents and doing so in a small number of short spells; heavy patentees, firms producing a large number of patents and patenting heavily in every year. Moreover, evidence of a *threshold effect* is found. 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. This evidence is consistent with the view that some form of dynamic economies of scale may govern the production of patents, but the effect becomes apparent only after a certain threshold is reached.

Another paper that found that prior innovative activity explains spell length better than other firms' characteristics such as size is the work by Cefis and Orsenigo (2001) who perform a comparative cross-countries/cross-sectors analysis. Their main result is the existence of 'bimodality' in the pattern of persistence according to which persistence is stronger for firms that are either non innovators or great innovators (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. Moreover, it seems that institutions and history do influence the patterns of innovation, as suggested by the fact that persistence systematically and consistently differ across countries.

Evidence in support of the idea that persistence should depend on the characteristics of the technology and persistence is instead provided by Cefis (2003). In this paper, she carries out a comparative analysis of persistence across different sectors. Her findings highlight how persistence in innovation seems higher in sectors characterised by technological cumulativeness, R&D complementarities and learning-by-doing processes. Furthermore, the paper acknowledges for little persistence in general, but strong persistence among great innovators, accounting for a large proportion of patents. Again the presence of a '*threshold effect*' is highlighted given that the probability to go from 0 to 1 patent is much lower than from n to $n+1$ patents with $n \geq 1$.

Concerning the interpretation of the threshold effect, Geroski *et al.* (1997) explained 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 retard the production of innovation. Other studies such as Geroski (1999) further highlight the presence of a minimum threshold of innovative activity necessary for a firm to become an innovator or to remain persistent innovator. In Malerba *et al.* (1997) this threshold has been found to constrain the innovative activity especially of small and medium firms.

A common feature of these studies is that they measure persistence mainly in terms of patenting activity. More recently, investigations have started relying upon innovation surveys and/or case studies as the main source of information on firm innovative behaviour. Roper and Hewitt-Dundas (2008) focus on a sample of innovators in Ireland. They find strong persistence both in product and process innovation, though they do not find support for persistence among great innovators. Relying on a large sample of Dutch firms taken from several runs of the European Community Innovation Survey (CIS), Cefis and Ghita (2009) analyse the impact of merger and acquisitions (M&As) on persistence for different classes of firm size. Their findings highlight the positive relationship between M&As and persistence. This is particularly true in the case of medium size firms while in the case of small firms M&As help to overcome the innovative threshold but do not help them to become persistent innovators. Further evidence on persistence of innovation both in manufacturing and services for a sample of German firms is found by Peters (2009), though in this case persistence is measured in terms of total innovation expenditure an indicator of input in the innovation process.

2.1. Persistence in product innovation and technological leadership

With respect to analyses of persistence that rely on patents as indicators of innovative output, these recent papers provide a more direct evidence of firm involvement in innovation as well as on the type of innovation carried out (product vs. process; radical vs. incremental). Persistence in terms of new product introduction has been relatively less studied mainly due to lack of systematic databases (the notable exception being Geroski *et al.*, 1997, which combined data on patent application and new product introduction taken from the SPRU dataset).

Existing economic theories understand persistence in product innovation mainly in terms of product proliferation or diversification. Product proliferation entails entry into unexplored segments of the same market mainly to cater for existing needs and/or to prevent entry from potential competitors (Spence, 1976; Schmalensee, 1978). Product diversification instead entails entry into markets in which firms are not yet active in order to spread risky activities (Bonanno, 1987; Bhatt, 1987).

According to this approach, persistence in product innovation is mainly driven by issues of market size or market contestability and product innovators are likely to face the very same problems highlighted above. Incumbents may enjoy a relative advantage over entrants (Gilbert and Newbery, 1982) or a disadvantage (Reinganum, 1983) depending on whether the design of new products represent incremental improvements of existing ones or radical departure respectively.

In addition to market size and contestability, we argue that it is highly likely that persistence in product innovation depends also on technological leadership understood in terms of firm positioning with respect to the technological frontier.

Existing papers have highlighted that technological leaders perform better than laggards. Coad (2008) has looked at the relationship between leadership and innovativeness. He found a strong positive correlation between leadership and R&D expenditures or patents innovative activity for leaders and a weaker one for laggards. Fontana and Nesta (2009) have looked instead at the relationship between technological leadership and firm survival. Their findings suggest that leaders survive relatively longer or that are also more likely to be acquired if they cannot survive as free-standing enterprises. We expect technological leadership to be an important determinant of product innovation for the following reasons.

First, technological leaders operate very close to the technological frontier. Though for them the marginal benefits from further innovations along a trajectory may be decreasing, they are better placed to grasp new technological opportunities by moving the frontier forward, provided they have the resources to do that. Laggards are not able to move forward the frontier. However, also laggards have incentives to participate in the technological race since for them innovating may be imperative to survive in the market (Levinthal, 2007). Product innovation in this case would largely consist in imitation of existing products or in entry into low end segments of the market.

Second, new products are rarely introduced alone in the market. On the contrary, firms introduce product lines and/or product families (Sanderson and Usumeri, 1995). In this case, persistence is the consequence of changes in the breadth and length of product portfolios. Technological leaders possess the capabilities as well as the complementary assets needed to extent their product portfolios (Teece, 1986). Therefore, they are expected to innovate more systematically than laggards.

Finally, there is a strategic component associated to technological leadership and persistence in product innovation. Multi-product firms, active in several submarkets within an industry, may innovate more persistently than single product firms (Raubitschek, 1987). In this respect it is interesting to understand whether and to what extent leadership in a specific submarket may be associated to persistence in the same submarket and/or entry in related ones.

In this paper we tackle these aspects. We define technological leadership in terms of distance from the technological frontier and distinguish between leaders (i.e. firms located close to the technological frontier), and laggards (i.e. firms located far from the frontier). We expect technological leadership to be positively associated to persistence in product innovation in a specific market. We expect this relationship to be true also for multi product firms, though the sign of the correlation is likely to depend on the degree of demand substitution among different products.

2.2. 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 sophistication and complexity.[1]

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

While the overall structure of the 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 and high barriers to entry. The structure of the hub market instead was 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

[1] Without entering into technicalities we can just say that hubs were relatively unsophisticated products whose function was mainly to link computers together. Routers were more sophisticated from the technological viewpoint as they were able to determine the best path for sending the data. Switches were more sophisticated than hubs but (at least initially) less than routers. They allowed for and increase in the speed of data transmission.

low-end customers. Entry was blocked at the high-end and occurred only at the low-end. The switch market was characterised by an intense entrepreneurial activity with entry by new start-ups marketing radical solutions as well as by firms already active in the other two submarkets (Doms and Forman, 2005; Fontana, 2008).

There are at least two reasons why this industry between 1990 and 1999 represents an interesting case to study persistence in product innovation. First, during this period the industry was characterised by a very fast rate of technical change. New technological opportunities, in the forms of new standards and/or changes in equipment hardware appeared. These opportunities led to product proliferation. However, technical change took different forms in the different markets that constitute the LAN industry. It was more incremental in the case of hubs and routers. It was more radical in the case of switches. Thus we expect differences in persistence to depend on the level of technological leadership.

Second, hubs, switches and routers were related markets. Being components of a technological system they may or may not be produced by the same firm. During the 1990s, technical change led to a convergence in the functionalities between switches and routers, and between switches and hubs. From the customer viewpoint, combining products from the same producer increases utility as benefits from interoperability and standardisation can be reaped. From the viewpoint of the manufacturers, being active in related markets may enlarge the potential installed base of users. However, it could also in case new product would turn out to be substitutes for the existing ones. Thus we expect that technological leadership in one market could eventually help or deter entry and persistence in a related market.

3. 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 marketed in three submarkets: 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. 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 submarket. 66 (25%) in two submarkets. 25(9%) in three submarkets. 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).

3.1. Measuring 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); indicators based on financial assets such as Tobin's *q* (Coad, 2008); indicators based on product characteristics and quality (Fontana and Nesta, 2009). 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 submarket, hedonic price regressions are estimated and predicted prices are calculated. Second, predicted prices are then 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 submarket):

$$p_{mit} = \alpha + \sum_{t}\sum_{j} \beta_{tj} z_{tjm} + \alpha_t + \mu_t + \varepsilon_{mit} \quad (1),$$

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.

In the second step we take the predicted price[2] as an indicator of product quality and use it to rank products on 'vertical' product space:

$$q'_{mit} = \hat{p}'_{mit} \quad (2),$$

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

$$d^{f}_{mit} = \max(q_t) - q'_{mit} \quad (3).$$

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

$$d^{f}_{it} = \min\left[d^{f}_{mit}\right]_{it} \quad (4).$$

This indicator is our main measure of technological leadership (DISTANCE TO FRONTIER). Technological leaders (laggards) in a specific submarket would display relatively lower (higher) values for this indicator.

We expect technological leadership to be positively associated to persistence in innovation. However, we expect the magnitude of the impact to depend on market structure as well as on the level of technological opportunity.

3.2. Control variables

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).[3] 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

---

[2] Results for the hedonic price regressions for each submarket are not reported here for simplicity. They are available from the authors upon request.

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

market. Sales are measured in million of US dollars.[4] The size of the market may be thought to affect persistence in innovation differently depending on the status of the innovator. Incumbents 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, incumbents may prefer to exploit existing products rather then introducing new ones (Reinganum, 1989). In this case, a negative coefficient for this variable 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 is the sum of the past patents filed by the firm. It is an indicator of the stock of technological experience available to firms.[5] 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).

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 innovation to be positively associated to patenting.[6] Finally, we control for the 'initial condition' by including a variable measuring the number of new product at entry (NUMBER OF PRODUCT AT ENTRY).

Summary descriptive statistics for these variables are reported in Table 1 below.

[Insert Table 1 about here]

3.2. The model

Econometrics studies to 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; Cefis and Ghita, 2009) has instead employed random effect discrete choice panel 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 the more likely is for a 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

---

[4] These are total sales for each firm in a given year. Breakdown of sales for each specific market is not available.
[5] PATENT STOCK is depreciated at the 15% rate.
[6] A qualification is in order here. All our patent based indicators simply consider the total number of patents filed by each firm. A better way of proceeding would be to include in each regression only the patents that are related to the specific LAN product (i.e. hubs, routers, switches). This can be done on the basis of the IPC class of the patent. While identifying the technological classes for hubs and switches is relatively straightforward. For routers the process is more lengthy and complicated. We will deal with this issue in future drafts of the paper.

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 product 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.[7]

Our analysis of time to product introduction event employs variance-corrected semi-parametric Cox's proportional hazard model (CPHM). Variance corrected CPHM allow 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).[8] 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:

$$h_{ik}(t; Z_{ik}) = h_{0k}(t - t_{k-1})\exp(\beta' Z_{ik}(t)) \quad (5),$$

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:

$$L(\beta) = \prod_{j=1}^{d} \frac{h(t_j)}{\sum_{k \in R(t_j)} h(t_k)} \quad (6),$$

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

$$L(\beta) = \prod_{i=1}^{n} \prod_{k=1}^{K} \left(\frac{\exp(\beta' Z_{ik}(X_{ik}))}{\sum_{j=1}^{n} Y_{jk}(X_{ik}) \exp(\beta' Z_{jk}(X_{ik}))} \right)^{\delta_{ik}} \quad (7),$$

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

---

[7] 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 before 1990s.

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

4. Results

4.1. Technological leadership and persistence

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 more technologically advanced markets. New entry in innovative behaviour is the highest in switches (around 37%) followed by routers (24%) and it is the lowest in hubs (22%). This 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.[9]

[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 technological advance of the market 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 overall laggards in technological advanced markets seem to be more persistent than laggards in less technological advanced markets. However, the difference between persistent leaders and laggards is slightly higher in the case of more technologically advanced markets (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 an expanding market, however only technological leaders seemed able to capture them.

Another aspect to consider is the issue of the relationship between persistence in innovation and firms' size. The literature reviewed has highlighted how large innovators are generally more persistent than smaller ones. We first check whether this applies also to our case and then we look at the relationship between firms' size, persistence and technological leadership.

Table 4 below reports distinct TPMs for 'great innovators' and 'small innovators'.[10]

[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

[9] 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 firms in our sample introduce their best product within three years after entry. 65% do it within the first year.

[10] 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 submarket.

(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, entry is a consequence of new opportunities linked to the opening up of the new market. Both great innovators and small innovators take these opportunities. Persistence can be interpreted as evidence of product proliferation strategy after entry has occurred. This strategy is particularly followed by great innovators that appear to innovate systematically much more than small innovators.

In the case of 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 should mainly come from incumbents: 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 technologically advanced markets 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).

Concerning going from a non innovator to an innovator state, technological leadership seems to be more 'effective'. 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 of the probability of being an innovator.

4.2. Econometric exercise

Table 7 reports the results of our 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 on 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 13%.[11] In model (2) we control for the impact of firm size on persistence. The inclusion of this variable 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. Again both coefficients are robust to the inclusion of additional variables. Each additional employee increases the likelihood to innovate by 12%. In model (3) we add sales to capture the impact of the size of the market. The variable is not significant though it becomes significant in the following specifications. What is interesting is that the coefficient is always negative evidence that the size of the market negatively impact on innovation persistence. In model (4) 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. The coefficient in this case is positive but never significant. We then check whether the relationship may depend on the number of patent instead. In this case the coefficient is positive and significant. Altogether, these results seem to indicate that it is not patenting per-se that seems to influence the likelihood to introduce a new product. It is rather the number of patents that matters, suggesting the presence of a threshold beyond which patenting lead to persistence in product innovation. In specification (5) and (6) we control for the initial condition in product innovation and for the overall stock of patents respectively. Previous results do not change.

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 market leadership in innovation seem to impact positively on persistence. 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 11%. The coefficient is stable across specification though the significance level changes as additional variables are added. An important difference with respect to the previous results is that in this case our controls are almost never significant. An exception is represented by the indicators for intangible capital. As in the previous case, the higher the number of patents filed in the preceding year 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 always 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 22% 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 while the coefficient for sales is again negative and significant. Our patent indicators are instead significant. In particular, and contrary to what we found in both the hub and the router case, we find evidence of state dependence as suggested by the positive and significant coefficient for the patent at t-1 dummy. Having filed a patent in the preceding year increases the likelihood of

[11] In this and in the following regressions, all marginal effects are calculated with reference to the final model specification (Model 6).

introducing a new product by 23.7%. Again the likelihood of introducing a product innovation increases with the number of patents filed at t-1.

To complete our analysis we look at whether technological leadership impacts on persistence across related markets. As discussed in Section 2, 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 one market could lead to innovation persistence in the same and/or 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. Given the low number of observations results from this analysis should be taken with caution and considered to be mainly explorative.

[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 indicating that technological leadership in the hub market increases the likelihood to innovate. 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 innovativeness in the hubs market. Given that hubs and routers represent two extremes in terms of level of technological sophistication this result was somewhat expected. More interesting are the results of Model (2) which analyse the impact on the likelihood of innovating in hubs of leadership in the switch market. In this case leadership in hubs is still associated to persistence in the hub market. However, the coefficient for distance to the frontier in the switch market is positive and significant indicating that being a laggard in the switch market increases persistence of innovation in hubs. In particular, a one unit increase in the distance to frontier in the switch market increases the likelihood to innovate in hubs of 110%. This result clearly confirms that hubs and switches were substitutes and that two types of firms were successfully competing in this market: leaders in the hub market and laggards in the switch market.

In Model (3) we look at persistence in innovation in routers for routers and hubs producers. Leadership in the router market is still important as indicated by the coefficient for distance to frontier for routers which is still negative and significant but the coefficient for distance in the hub market is not. These results confirm our findings from Model (1) concerning the un-relatedness of the two markets. Model (4) relates persistence in routers to the 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 13%. Interestingly, leadership in routers is no longer significant. This evidence clearly indicates how technical change can shape the strategy of product innovation for firms active in several related markets. Switches were originally introduced to substitute for hubs. Technical change made them substitutes for routers up to the point in which technological leadership in switches became crucial to compete successfully in this market.

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. In this case, a one unit decrease in the distance to frontier in the hub market increases the likelihood to innovate in switches of 21%. Leadership in routers instead does not seem to affect persistence in switches (Model (6)). In this second case it is interesting to notice the negative and significant coefficient for firm size suggesting that persistent innovators active in switch and router market are mainly small firms.

5. Conclusion

This paper has studied the relationship between technological leadership and persistence in product innovation for a sample of firms operating in a high-tech industry. We first carried out a study based on TPMs. Our analysis has revealed that persistence in product innovation is higher in markets characterised by relatively higher technological opportunities. Moreover, technological leaders seem to innovate more systematically. This is particularly true when technological opportunities are higher. Also, large innovators tend to be more persistent innovators than small innovators. This happens particularly for incumbent firms regardless of the technological opportunities. 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 presence of technological opportunities, it 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, even controlling form market and firm size, technological leadership seems to be always an important prerequisite for persistence in product innovation. We also found evidence that patenting also leads to persistence since firms that patent more are more persistent innovators. Finally, we also found that technological leadership also plays an important role for innovating in related markets. Technological leaders can always successfully compete in related markets no matter the level of technological sophistication required. Laggards who are out-competed in more technologically advanced markets can instead successfully compete in less technologically sophisticated ones.

REFERENCE LIST

Amable, B., Demmou, L., and Ledezma, I., 2007. Competition, innovation and distance to frontier. *Mimeo.*

Bhatt, S., 1987. Strategic product choice in differentiated markets. *Journal of Industrial Economics*, 36(2), 207–216.

Bonanno, G., 1987. Location choice, product proliferation and entry deterrence. *Review of Economic Studies*, 54, 37–45.

Cefis E., 2003. Is there any persistence in innovative activities? *International Journal of Industrial Organization*, 21(4), 489-515.

Cefis E. and Orsenigo L., 2001. The persistence of innovative activities. A cross-countries and cross-sectors comparative analysis. *Research Policy*, 30(7), 1139-1158.

Cefis E. and Ghita M.L., 2009. Post merger innovative patterns in small and medium firms. *Mimeo*, Utrecht University.

Coad A., 2008. Distance to frontier and appropriate business strategy. *DRUID Working Paper Series*, 08-05.

Cohen, W. and Klepper, S., 1996. A Reprise of Size and R&D, *Economic Journal*, 106, 925-951.

Cohen, W. and Levin, R., 1989. Empirical Studies of Innovation and Market Structure, in Schmalensee R., and Willig, R., *Handbook of Industrial Organization*, North Holland, 1060-1107.

Doms, M., and Forman, C., 2005. Prices for Local Area Network Equipment. *Information Economics and Policy*, 17(3), 365-388.

Fontana, R., 2008. Competing technologies and market dominance: standard "battles" in the Local Area Networking industry. *Industrial and Corporate Change*, 17(6), 1205-1238.

Fontana R. and Nesta L., 2009. Product Innovation and Survival in a High-Tech Industry. *Review of Industrial Organization*, 34(4), 287-306.

Geroski P.A., Van Reenen J. and Walters C.F., 1997. How persistently do firms innovate? *Research Policy*, 26(1), 33-48.

Gilbert, R. J. and Newbery, D. M., 1982. Preemptive Patenting and the Persistence of Monopoly. *American Economic Review*, 72(3), 514-26.

Hall, B.H., Jaffe A., Trajtenberg M., 2001. The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools, *NBER Working Paper # 8498*.

Kamien, M. and Schwartz, N., 1982. *Market Structure and Innovation*, Cambridge University Press.

Levinthal, D. A., 2007. Bringing selection back into our evolutionary theories of innovation. In Malerba, F. and Brusoni, S., (eds.), *Perspectives on Innovation*, 293 – 329. Cambridge: Cambridge University Press.

Malerba F., Orsenigo L., Perreto P.,1997.Persistence of innovative activities, sectoral patterns of innovation and international technological specialization. *International Journal of Industrial Organization*,15, 801-826.

Nelson,R., Winter, S., 1982. *An evolutionary theory of economic change*. Harvard University Press, Cambridge

Nicoletti, G. and Scarpetta, S., 2003. Regulation, productivity and growth: OECD evidence. *Economic Policy*, April, 9–72.

Penrose, E., 1959. *The theory of the growth of the firm*. M.E. Sharpe, White Plains, NY

Peters, B., 2009. Persistence of innovation: stylised facts and panel data evidence. *Journal of Technology Transfer*, 34, 226-243.

Prentice, R. L., Williams, B. J., & Peterson, A. V., 1981. On the regression analysis of multivariate failure time data. *Biometrika*, 68, 373–379.

Raubitschek, R., 1987. A model of proliferation with multiproduct firms. *Journal of Industrial Economics*, 25, 269-279.

Reinganum, J. F., 1983. Uncertain innovation and the persistence of monopoly. *American Economic Review*, 73, 741-748.

Reinganum, J. F., 1985. Innovation and industrial evolution, *Quarterly Journal of Economics*, 100, 81–99.

Roper S. and Hewitt-Dundas, N., 2008. Innovation persistence. Survey and case-study evidence. *Research Policy*, 37, 149-162.

Rosenberg, N., 1982. *Inside the black box*. Cambridge University Press.

Sanderson, S. and Uzumeri, M., 1995. Managing product families: The case of the Sony Walkman. *Research Policy*, 24, 761-782.

Scherer, M., 1965. Firm Size, Market Structure, opportunity, and the output of patented innovations, *American Economic Review*, 55, 1097-1125.

Schmalensee, R., 1978. Entry deterrence in the Ready-to-Eat breakfast cereal industry. *Bell Journal of Economics*, 9, 305–327.

Spence, A.M., 1976. Product selection, fixed costs and monopolistic competition. *Review of Economic Studies*, 43, 217–235.

Squicciarini, M., 2009. Science parks: seedbeds of innovation? A duration analysis of firms' patenting activity. *Small Business Economics*, 32, 169–190.

Teece, D., 1986. Profiting from technological innovation: implication for integration, collaboration, licensing and public policy. *Research Policy*,15, 285–305.

von Burg U., 2001. *The Triumph of Ethernet*. Stanford University Press, Stanford

Wooldridge J., 2005. Simple solutions to the initial condition problem in dynamic non linear panel data models with unobserved heterogeneity. *Journal of applied Econometrics*, 20(1), 39-54.

LIST OF TABLES

Table 1: Summary descriptive statistics

	Obs.	Mean	SD	Min	Max
Hubs					
DIST FRONT HUBS	204	2.330	1.482	0	5.272
NUMBER OF PRODUCTS AT ENTRY	204	2.014	1.532	1	8
SIZE	126	325.72	666.02	32	3127
SALES (MIL$)	147	60.59	158.16	0.06	875.48
NUMBER OF PATENTS AT T-1	204	80.33	302.00	0	2405
PATENT AT T-1	204	0.45	0.49	0	1
PATENT STOCK	204	570.75	2049.51	0	14903
Routers					
DIST FRONT ROUTERS	246	2.57	1.29	0	5.660
NUMBER OF PRODUCTS AT ENTRY	246	2.02	1.32	1	7
SIZE	136	375.60	740.71	14	31700
SALES (MIL$)	159	72.27	179.17	0.01	875.48
NUMBER OF PATENTS AT T-1	246	62.11	301.30	0	2405
PATENT AT T-1	246	0.32	0.46	0	1
PATENT STOCK	246	460.37	2069.51	0	14903
Switches					
DIST FRONT SWITCHES	149	2.19	1.04	0	4.09
NUMBER OF PRODUCTS AT ENTRY	149	1.74	1.41	1	8
SIZE	98	230.14	508.12	2	3074
SALES (MIL$)	113	60.70	151.37	0.06	875.48
NUMBER OF PATENTS AT T-1	149	42.73	219.07	0	2365
PATENT AT T-1	149	0.54	0.49	0	1
PATENT STOCK	149	496.24	1812.05	0	14903

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]	[4]	[5]	[6]
DIST FRONT HUBS T-1	-0.15	-0.167	-0.165	-0.143	-0.121	-0.156
	[0.052]***	[0.057]***	[0.057]***	[0.052]***	[0.054]**	[0.057]***
NUMBER OF PRODUCTS AT ENTRY					0.072	0.047
					[0.073]	[0.073]
SIZE		0.124	0.146	0.098	0.114	0.097
		[0.043]***	[0.041]***	[0.053]*	[0.059]*	[0.051]*
SIZE SQ		-0.0004	-0.0005	-0.0004	-0.0004	-0.0003
		[0.000]***	[0.000]***	[0.000]**	[0.000]**	[0.000]**
SALES (MIL$)			-0.001	-0.004	-0.004	-0.003
			[0.000]	[0.001]***	[0.001]***	[0.001]*
NUMBER OF PATENTS AT T-1/1000				1.860	1.993	3.958
				[0.377]***	[0.467]***	[1.041]***
PATENT AT T-1 (DUMMY)				0.325	0.313	0.324
				[0.225]	[0.218]	[0.221]
PATENT STOCK/1000						-0.481
						[0.177]***
Observations	204	126	126	126	126	126
Log pseudo-likelihood	-463.162	-248.25	-248.001	-242.880	-242.559	-241.687
Wald Chisq	8.34***	15.30***	21.35***	63.99***	54.86***	49.36***

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]	[4]	[5]	[6]
DIST FRONT ROUTERS T-1	-0.197	-0.140	-0.129	-0.124	-0.129	-0.116
	[0.055]***	[0.063]**	[0.064]**	[0.067]*	[0.067]*	[0.068]*
NUMBER OF PRODUCTS AT ENTRY					0.043	0.052
					[0.079]	[0.075]
SIZE		0.047	0.024	0.039	0.041	0.023
		[0.033]	[0.047]	[0.048]	[0.048]	[0.051]
SIZE SQ		-0.0002	-0.0001	-0.0002	-0.0002	-0.0001
		[0.000]	[0.000]	[0.000]*	[0.000]	[0.000]
SALES (MIL$)			0.001	-0.0004	-0.0004	0.0004
			[0.001]	[0.001]	[0.001]	[0.001]
NUMBER OF PATENTS AT T-1/1000				0.561	0.552	1.160
				[0.298]*	[0.299]*	[0.438]***
PATENT AT T-1 (DUMMY)				0.209	0.198	0.240
				[0.168]	[0.173]	[0.168]
PATENT STOCK/1000						-0.150
						[0.093]*
Observations	246	136	135	135	135	135
Log pseudo-likelihood	-601.639	-281.107	-280.138	-278.244	-278.113	-277.499
Wald Chisq	12.84***	10.23**	8.17**	48.25***	46.63***	79.61***

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]	[4]	[5]	[6]
DIST FRONT SWITCHES T-1	-0.212	-0.214	-0.206	-0.199	-0.193	-0.200
	[0.078]***	[0.092]**	[0.093]**	[0.087]**	[0.086]**	[0.087]**
NUMBER OF PRODUCTS AT ENTRY					0.019	0.023
					[0.025]	[0.026]
SIZE		0.013	0.054	-0.004	-0.002	0.016
		[0.043]	[0.066]	[0.040]	[0.051]	[0.028]
SIZE SQ		-0.00001	-0.0001	0.00002	0.00001	-0.0002
		[0.000]	[0.000]	[0.000]	[0.043]	[0.000]**
SALES (MIL$)			-0.001	-0.002	-0.002	-0.003
			[0.001]	[0.001]*	[0.001]*	[0.001]***
NUMBER OF PATENTS AT T-1/1000				0.850	0.843	0.371
				[0.311]***	[0.312]***	[0.246]
PATENT AT T-1 (DUMMY)				0.859	0.846	0.813
				[0.249]***	[0.255]***	[0.261]***
PATENT STOCK/1000						0.218
						[0.045]***
Observations	149	98	98	98	98	98
Log pseudo-likelihood	-326.393	-198.694	-198.541	192.111	192.077	-191.450
Wald Chisq	7.35***	7.48**	8.49**	35.96***	39.98***	282.85***

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	-0.145	-0.202	-0.060		-0.226	
	[0.089]*	[0.090]**	[0.068]		[0.109]**	
DIST FRONT ROUTERS T-1	-0.252		-0.376	-0.056		-0.076
	[0.206]		[0.134]**	[0.063]		[0.075]
DIST FRONT SWITCHES T-1		0.350		-0.231	-0.132	-0.057
		[0.169]**		[0.145]*	[0.174]	[0.136]
NUMBER OF PRODUCTS AT ENTRY	0.283	0.068	-0.121	-0.085	0.003	-0.005
	[0.175]*	[0.097]	[0.120]	[0.085]	[0.032]	[0.023]
SIZE	0.164	-0.025	0.011	-0.002	0.050	-0.258
	[0.090]*	[0.153]	[0.027]	[0.064]	[0.078]	[0.109]**
SIZE SQ	-0.0002	-0.0001	-0.0004	-0.002	-0.0004	-0.0005
	[0.000]	[0.001]	[0.000]	[0.000]***	[0.000]***	[0.000]*
SALES (MIL$)	-0.004	-0.004	0.002	-0.001	-0.004	-0.011
	[0.003]	[0.003]*	[0.003]	[0.003]	[0.001]***	[0.003]***
NUMBER OF PATENTS AT T-1/1000	2.562	6.218	1.478	3.648	0.592	-0.151
	[0.676]***	[2.212]***	[0.280]***	[2.331]***	[0.395]	[0.381]
PATENT AT T-1 (DUMMY)	-0.258	1.416	0.824	0.911	0.910	1.173
	[0.565]	[0.536]***	[0.451]*	[0.444]**	[0.471]*	[0.434]***
PATENT STOCK/1000	-0.282	-0.246	-0.116	-0.078	0.318	1.325
	[0.185]	[0.753]	[0.197]	[0.367]	[0.170]*	[0.528]**
Observations	38	49	37	34	48	34
Log pseudo-likelihood	-31.977	-38.516	-30.709	-23.119	-58.351	-36.201
Wald Chisq	43.95***	62.22***	65.43***	51.64***	167.07***	93.82***

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%