How far from the tree does the (good) apple fall? Spinout creation and the survival of high-tech firms

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Abstract

We develop a model of spinout creation and survival to explain how the initial product market strategies of spinouts may differ with respect to their parent's and how this difference affects their success. We test the model using detailed information on all the entrants in three markets in the Local Area Networking (LAN) industry during the 1990s. Our findings are consistent with the implications of the theoretical model. Concerning spinout generation, the parent firm's technological know-how plays an important role for differentiation. In particular, we find that spinouts tend to imitate 'average' parents and 'keep away from the extremes' (i.e. parents whose know-how is 'too good' or 'too bad' with respect to the technological frontier). Concerning spinout survival, we find that better spinouts survive longer and that there is no direct effect of a parent's know-how on spinout's survival. Finally, too much differentiation with respect to the parent firm can be detrimental for spinout success.

Key words: spinouts, entry, product differentiation, firm survival

JEL codes: O31, M21, L12

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1. Introduction

One of the most important determinants of economic growth and competitiveness is the speed at which firms react to innovative opportunities. In this respect, prior research has highlighted the role of new start-ups as important engines of growth and development at both the industry (Gans and Stern, 2002; Agarwal et al., 2007; Babina and Howell, 2020) and at the country level (Eriksson and Kuhn, 2006; Decker et al, 2014; Haltiwanger et al., 2014). Among the factors that explain their performance, the 'pre-entry experience' of new entrants has been receiving much attention lately (Bayus and Agarwal, 2007; Dencker et al. 2009; Agarwal et al. 2020). In several industries, entrepreneurs with previous experience in the same or in related sectors have successfully seized new opportunities and entered new markets by creating spinouts. Underlying this evidence lays the idea that spinouts are relatively more successful than other entrants in reacting to economic incentives because they take advantage of market (Chatterji, 2009; Buenstorf, 2007), technology (Agarwal et al. 2004), organizational (Hoolbrook et al., 2000) and, more in general, industry-specific know-how (Cheyre et al., 2015) which is embodied in their founder(s) and which has been transferred from the parent firm (Klepper, 2002; Helfat and Lieberman, 2002).

Theories of spinout formation can be grouped in three categories (Klepper and Thompson, 2007). 'Agency theories' highlight the presence of disagreements and/or information asymmetries within the parent firms leading frustrated but 'brilliant' employees to leave the firm to independently pursue their own project in a new company (Anton and Yao, 1994, 1995; Cassiman and Ueda, 2006; Klepper, 2007; Klepper and Thompson, 2010; Thompson and Chen, 2011; Chatterjee and Rossi-Hansberg, 2012; Habib et al., 2013; Nikolowa, 2014; Krasteva et al. 2015; Shekhar, 2018; Zábojník, 2020). 'Organizational inertia theories' focus on the slow response of incumbents firms to radical innovative challenges (Christensen, 1993; Christensen and Rosenbloom, 1995; Henderson, 1993) or to innovation that would cannibalize existing rents (Pakes and Nitzan, 1983) paving the way to the creation of spinouts. 'Employee learning and mobility theories' start from the assumption that employees can learn and exploit the knowledge of the firm they work for (Franco and Mitchell, 2008; Sakakibara and Balasubramanian, 2020; Babina and Howell, 2020) in order to either replicate what the parent firm is doing or to diversify (Klepper and Sleeper, 2005; Franco and Filson, 2006). Empirical investigations inspired by this last approach have provided some interesting findings on the process of spinout formation in specific industries such as lasers (Klepper and Sleeper, 2005) and hard disk drives (Franco and Filson, 2006). However, some predictions remain to a certain extent unexplored.

For instance, the 'employee learning and mobility theory' predicts that at birth spinouts produce a product that is 'similar but differentiated' from the one of their parents. How differentiated? No attempt has so far been made to analyze empirically the similarity or difference in terms of products introduced by spinouts with respect to those of the parent firm.[3] In addition to this, the theory predicts that spinouts performance (in terms of survival) is increasing in their technological know-how. However, to what extent the performance (in terms of survival) is also dependent on the extent of product differentiation with respect to the parent firm? These are the two main questions we tackle in this paper. In order to do this, we develop and test a model of spinout entry and survival which explicitly accounts for product differentiation.

Our game-theoretic model of spinout formation has two distinctive features. First, the effect of market competition on spinout entry is explicitly considered, as in Anton and Yao (1995), Klepper and Sleeper (2005), Franco and Filson (2006) and Franco and Mitchell (2008). This is done in the context of a Hotelling-like model with a focus on competition between the parent, which is initially the monopolist in the market, and the spinout. Second, the advantage from 'superior know-how' is reflected in the entry (or development) cost for the spinout, which is lower the higher is the technological know-how of the parent, and in the uncertainty on future performance which characterizes the spinout at entry (Chatterjee and Rossi-Hansberg, 2012), which is higher the higher is the product differentiation (as captured by the market distance) of the spinout from the parent.

The model generates two predictions. The first prediction points to a positive but non-linear (U-shaped) relationship between the technological know-how of the parent and the product differentiation (i.e. distance in the market) between the spinout and the parent, which results from the combination of two effects. First, a higher market distance from the parent has an unambiguous positive effect on spinout profitability, which is stronger the higher is the technological know-how of the parent. Therefore, when the technological know-how of the parent is high, the product of the spinout must be sufficiently dissimilar from the parent for entry to be profitable. Second, a parent's low level of technological know-how entails higher development costs for the spinout. So, in this case entry will be profitable only when the distance in the market between the parent and the spinout is high.

[3] Muendler and Rauch (2018) is a notable exception within the literature of international trade though.

The second prediction argues that for sufficiently low levels of price competition intensity between the spinouts and the parent, spinouts' survival probability is decreasing in their market distance from their parent. In our model spinouts survival depends on market distance in two ways. On one hand, product differentiation should compensate for a lack of technological know-how of the spinout (what we label as the *'competition effect'*). On the other hand, product differentiation increases the uncertainty concerning the profitability of the spinout (what we label as the *'uncertainty effect'*). When price competition intensity is low (high), the uncertainty effect prevails over the competition effect, and thus spinout survival probability is decreasing (increasing) in the market distance from the parent.

These predictions are empirically tested by using detailed data on the evolution of the Local Area Networking (LAN) industry. We first identify every LAN manufacturer that have commercialized at least one product in one of the three major LAN markets (i.e., Hubs, Routers and Switches) between 1990 and 1999 the period of growth and consolidation of the industry. Then we trace the background of each firm by looking at their founders in order to identify parent firms and spinouts. Using detailed information on the price, and technical characteristics of the products commercialized in each of the three markets we build indicators to reconstruct the product entry strategy of spinouts with respect to their parent. We then employ a two-step Maximum Likelihood Heckman model to estimate the probability for an incumbent to spawn a spinout and the location of the spinout in the market space with respect to the parent. Finally, we estimate a Cox hazard model to see whether entry has been beneficial for the spinout in terms of survival.

Our findings support the idea that the know-how of the parent firm plays an important role for product differentiation. In particular, in line with our theoretical prediction, we find that spinouts locate in the market close to 'average' parents and away from the extremes (i.e., parents whose know-how is either 'too good' or 'too bad'). Concerning the performance of spinouts, we find that better spinouts survive longer and that, once we control for market location of the spinouts, there is no direct effect of parent's know-how on spinout's survival. Finally, too much differentiation with respect to the parent firm can harm spinouts. Therefore, in light our theoretical prediction, the *uncertainty effect* seems to prevail over the *competition effect*.

The structure of the paper is as follows. Section 2 reviews some of the existing theories of spinout formation. In Section 3 we present our theoretical model, highlight its major implications, and derive some testable hypotheses. Section 4 presents the empirical context of our analysis, the LAN industry, describes the data and the estimation method employed in the paper. Section 5 presents the main results. Implications and conclusions are summarized in Section 6.

2. Background literature

In the last two decades, several studies have investigated, both empirically and theoretically, the process of (intra-industry) spinout formation and performance vis-à-vis other types of entrants. From the empirical viewpoint, analyses of sectors as different as automobiles (Klepper, 2007), lasers (Klepper and Sleeper, 2005; Buenstorf, 2007), hard disk drives (Agarwal et al., 2004; Franco and Filson, 2005), tires (Buenstorf and Klepper, 2010), semiconductors (Klepper, 2009; Cheyre et al. 2015), medical devices (Chatterji, 2009), TV-sets (Klepper and Simons, 2000) has produced a set of 'empirical regularities'. In particular, better-performing firms tend to have higher spinout rates, and, in turn, the performance of spinouts is superior to the one of other de-novo entrants. From the theoretical viewpoint, several models of spinouts formation have been proposed depending on the assumptions made about the reasons why employees leave the parent firm to set up an independent firm (Klepper, 2009).

A first set of models focus on the agency relationship within the parent firm, by highlighting the role of information asymmetries (Anton and Yao, 1994, 1995; Cassiman and Ueda, 2006; Chatterjee and Rossi-Hansberg, 2012) and disagreement within the parent firm (Klepper, 2007; Klepper and Thompson, 2010; Thompson and Chen, 2011). Since employers can appropriate the value of ideas revealed by their R&D employees, this can lead the latter to start their own business not to see their idea appropriated by the former (Zábojník, 2020). Disagreement theories instead focus on spinout formation resulting from different perception of employees' ideas or values, which cause the rejection of their projects and lead them to leave the firm to independently pursue their own project in a new company.

A second set of models, that analyze both spinouts and start-ups more in general, focus on the slow response of incumbent firms to radical innovative challenges. Incumbents' might be inertial for different reasons ranging from 'misalignment' between the nature of the innovative challenge and their internal organization of R&D activities (Henderson, 1993), disruption of existing value-chain networks (Christensen, 1993), to the 'fear' that the innovation might cannibalize their existing business (Arrow, 1962; Gilbert and Newbery,1980; Reinganum, 1983). Additional reasons that might explain incumbents' inertia include bureaucratization (Schumpeter 1942), information screening (Arrow 1974) and hierarchy (Sah and Stiglitz 1986).

Two approaches characterize instead 'employee learning and mobility models'. These approaches share some common assumptions: R&D employees can learn and exploit the know-how of the firm they work for (Franco and Mitchell, 2008; Sakakibara and Balasubramanian, 2020) and know-how transfer increases their potential for creating a spinout (Igami, 2017; Babina and Howell, 2020). However, they differ in terms of the mechanisms underlying spinout creation as well as on the focus on the post entry activity of the created spinouts. One approach argues that spinouts 'learn to replicate' what the parent firm was doing (Franco and Filson, 2006). Another approach argues instead that spinouts 'learn to diversify' from the parent firm (Klepper and Sleeper, 2005). In the former case the premise is that the better a firms' know-how, the lower the wage an employee will accept to work for it as the greater is the prospect of appropriating the full value of the employer's know-how by starting a new firm. In the latter case the premise is that the more differentiated is the firm's market, the higher is the probability that the R&D employee who leave the firm will develop a variant of the existing product. If pre-emption is too costly, the parent will 'gamble' that they will not lose market shares to spinouts.

These two approaches make several predictions. Some of them have been confirmed by prior analyses. For instance, the prediction that 'better', thus more knowledgeable, parents generate more spinoffs has found confirmation in the case of lasers (Klepper and Sleeper 2005). The prediction that spinouts survival is increasing in their technological know-how has been confirmed in the case of the Hard Disk Drive industry (Agarwal et al. 2004; Igami, 2017). Other predictions are contrasting and remain to a certain extent unexplored.

The 'learning to replicate' approach predicts that at birth spinouts enter the same market of the parent firm and produce an identical product to exploit inherited knowledge. The 'learning to diversify' approach predicts that spinouts enter the same market of the parent firm but produce a product that is differentiated (i.e. similar but not equal) to the one of their parents in order to relax competition. Which prediction holds, seems to be an empirical matter. However, no industry level study has so far looked specifically at the degree of product differentiation of spinouts with respect to the parent firm. In addition to this, both approaches predict that industry conditions favourable to the creation of niche markets are conducive to spinout formation and that the presence of multiple segments makes an industry suitable for entry by spinouts and for their survival as narrow product lines are likely to shelter spinouts from competition. However, no analysis has explicitly looked at the extent to what, within a segmented market, the post-entry performance of spinouts is also dependent on the degree of product differentiation with respect to the parent firm. This paper tackles these issues both theoretically and empirically. In so doing, it aims at enriching the existing literature on spinout creation and performance.

3. Model

Our model follows Klepper and Sleeper (2005) and Campbell and Franco (2014) in modelling spinout creation and survival in a Hotelling-like framework. The game is in three stages. Initially, an incumbent P (the parent) acts as a monopolist in a market being located at the left extreme of a one-unit Hotelling line (the product space). In the empirical analysis, we deal with multi-product firms, so we should think to the incumbent as being simultaneously present in multiple lines. We denote with $x_P = 0$ the incumbent's position, and with c_P its unit cost of production. Position and cost fully characterize the firms in terms of location in the product space and technological know-how. In the model, this representation allows to analyze separately the impact of market distance between the parent and the spinout and the channels through which parent and spinout's know-how can impact on spinout's creation and performance.

In the first stage of the game, an employee of P gets the idea of a project for a new product. The employee is denoted as S (spinout). More formally, a project is described by a pair (x_S ; $\bar{c}_S$). $x_S \in (0; 1]$ is a location on the Hotelling line. Since P is located at 0, x_S measures also the degree of product differentiation, or what we will call the *market distance* between the parent and the spinout. $\bar{c}_S \in [c_{min}; c_{max}]$ is the mean value of a normal distribution with variance $\sigma_S^2(x_S)$ ($\sigma_S^2(x_S)$ increasing in x_S), from which the actual production cost of S upon entry, c_S, is drawn. x_S and $\bar{c}_S$ are drawn from two independent random variables G_x and G_c, whose distribution does not depend on c_P. c_S it is known (exactly) only after production. In words, as in Jovanovic (1982), Hopenhayn (1992) and Chatterjee and Rossi-Hansberg (2012), the potential spinout is characterized by a degree of uncertainty about its actual level of efficiency upon entry; in addition, uncertainty is increasing in distance in market location between the parent and the spinout, because of relative lack of technological-know-how and market-know-how. We shall assume that $c_P \leq c_{min}$: due to incumbency advantages, the spinout is (on average) less efficient than the parent.

Given the project, and knowing the position and unit cost of the parent, S decides whether to develop the project, thus entering the market, or not (in this case obtaining a pay-off which is normalized to 0).[4] In order to develop the product, the spinout must incur a fixed (and sunk) cost $F(c_P)$, which is an increasing and convex function of the *parent*'s unit cost of production, used a proxy of the parent's technological know-how. This assumption captures the idea that the spinout can build upon the parent's knowledge: the higher is the unit cost of the parent (i.e. the lower its technological know-how), the higher will be the entry cost for the spinout.

In the second stage, if S decides to enter, firms compete by setting (simultaneously) the prices. A crucial assumption is that S and P's decision are based on the expected cost for S (i.e., on $\bar{c}_S$), since the spinout actual cost is revealed only after production. We also assume that S is risk neutral. Moreover, we assume that P's location and efficiency do not vary if S enters the market. The consumers' side is represented as in standard Hotelling game with unit demand. Consumers are uniformly located over the line. A consumer (located at x) who buys from P (S) obtains a utility level $u - tx^2 - p_P$ ($u - t(x_S - x)^2 - p_S$), denoting with $u > 0$ the reservation utility, with $t > 0$ the transport cost parameter, and with p_S and p_P the prices. The market is always covered, i.e. u is large enough that consumers always prefer to buy from one of the two firms. As usual in Hotelling models, t is inversely related to the intensity of price competition, and directly related to firms' market power.

In the third stage, before P and S possibly compete in the market as in the second stage, the actual unit cost value c_S is revealed, both to the spinout and to the parent. The spinout can decide whether to stay or exit the market, on the basis of c_S. Staying in the market, P and S compete in prices keeping constant locations on the Hotelling line, and for S continuing production does not entail further fixed cost. Exiting S's pay-off is normalized to 0. For the sake of simplicity, we assume that S can look only one period forward. In other words, when deciding whether to enter the market (stage 1), S bases its decision on profits resulting from stage 2 only. Therefore, we start looking at the sub-game perfect equilibrium of the game resulting from stage 1 and stage 2.

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[4] The separation between an exogenous process that generates ideas, and the decisions whether to invest in them, follows Green and Scotchmer (1995) and O'Donoghue et al. (1998).

In stage 2, demand functions for S and P are determined, as usual, by finding first the indifferent consumer, given S and P's location and for given prices. Denoting with $\hat{x}$ such a consumer, her position is given by the solution of the following equation:

$$u - t\hat{x}^2 - p_P = u - t(x_S - \hat{x})^2 - p_S \tag{1}$$

which yields:

$$\hat{x} = \frac{p_S - p_P}{2tx_S} + \frac{x_S}{2}. \tag{2}$$

From (2), demand and (expected) profit functions are determined as follows:

$$D_P = \frac{p_S - p_P}{2tx_S} + \frac{x_S}{2} \tag{3}$$

$$D_S = \frac{p_S - p_P}{2tx_S} + 1 - \frac{x_S}{2} \tag{4}$$

$$\Pi_P = (p_P - c_P)\left(\frac{p_S - p_P}{2tx_S} + \frac{x_S}{2}\right) \tag{5}$$

$$E(\Pi_S) = (p_S - \bar{c}_S)\left(\frac{p_S - p_P}{2tx_S} + 1 - \frac{x_S}{2}\right). \tag{6}$$

Equilibrium prices are obtained by solving the system of first order conditions to yield:

$$p_S^* = \frac{2\bar{c}_S + c_P + t(4 - x_S)x_S}{3} \tag{7}$$

$$p_P^* = \frac{2c_P + \bar{c}_S + t(2 + x_S)x_S}{3} \tag{8}$$

Equilibrium (expected) profits are defined as:

$$\Pi_P^* = \frac{[\bar{c}_S - c_P + t(2 + x_S)x_S]^2}{18tx_S} \tag{9}$$

$$E(\Pi_S^*) = \frac{[c_P - \bar{c}_S + t(4 - x_S)x_S]^2}{18tx_S} \tag{10}$$

Therefore, in the first stage, S develops the product if:

$$\frac{[c_P - \bar{c}_S + t(4 - x_S)x_S]^2}{18tx_S} - F(c_P) \geq 0. \tag{11}$$

Moving from the second to the third stage, the actual unit cost of the spinout c_S is revealed both to S and P. If S stays in the market, the equilibrium profits are obtained for P and S substituting c_S to $\bar{c}_S$ in (9) and (10) respectively. Since there are no fixed of productions, firms find convenient to remain in the market as long as profits are positive. We assume that the probability that P's profits are negative is negligible (this poses a limit on unit cost variance). As for S, the condition that profits are positive, and therefore the condition for survival, is given by:

$$c_S < c_P + t(4 - x_S)x_S. \tag{12}$$

A brief discussion of two assumptions is in order. Contrary to papers following an 'agency approach', but similarly to Franco and Mitchell (2008), we do not explicitly consider the possibility that it is the parent to develop the project. Franco and Mitchell (2008) assume that the employer and the employee are asymmetrically informed on the extent the latter has learnt from the former, so that she can profitably start a new firm. Klepper and Sleeper (2005) assume that both the parent and the spinout have a positive probability to receive the idea, and the former will develop it if profitable. In our setting it can be shown that, if the market is covered in all configurations, the incentive for the incumbent to introduce the new product (in terms of additional profits) is lower than the new entrant's incentives due to a standard 'replacement effect'.[5] It follows that, if the employee has a sufficiently low probability of getting the idea, it pays for the parent to gamble that the spinout will not enter.

A second assumption that turns out to be not so critical as it could appear is the "myopic" behaviour of the employee, who does not consider the third stage profit when deciding whether to enter the market or not in the first stage. We note the following. At stage 1, S' expected profits in the third stage depends on the survival probability and the level of profits once the actual unit cost of the spinout is known. Market distance and parent's technological know-how have the same (respectively, positive and negative) effect on S' profit in the third and in the second stage. The survival probability is decreasing in parent's technological know-how, and can be increasing or decreasing in market distance (the latter results is derived in Proposition 2 below). It follows that, as long as the 'profit effect' of market distance is stronger than the possibly counteracting 'survival probability effect', our results will not be qualitatively affected. We also observe that, in highly dynamic markets as the one we consider in the empirical analysis, a short-run focus may be rational as the long-run survival prospects can be low for reasons different from the nature of competition between the parent and the spinout.

3.1. Implications

[5] Details are available upon request.

The model yields two predictions. The first concerns the expected market distance between the spinout and the parent. The second prediction concerns the spinout performance as measured by its survival.

As for the first prediction, we first observe that, since S' product location is not chosen but exogenously given (according to a random distribution G_x independent from c_P and $\bar{c}_S$), what we focus on is the expected market distance, conditional upon spinout entry. This will be higher, the lower is the minimal distance for which entry is profitable. A higher market distance from the parent has an unambiguous positive effect on spinout profitability, as it protects spinouts from direct competition with the parent. This effect is stronger the higher is the technological know-how of the parent, i.e. the lower is its unit cost of production, since the parent is a tougher competition in this case. This suggests that when the technological know-how of the parent is high, the product of the spinout must be sufficiently dissimilar from the parent for entry to be profitable. At the same time, a parent's low level of technological know-how entails higher development costs for the spinout. So, in this case entry will be profitable only when the distance in the market between the parent and the spinout is high. This leads to the following proposition (the proof is in Appendix 1):

PROPOSITION 1: *The relationship between the technological know-how of the parent and the expected distance in the market between the spinout and the parent is U-shaped.*

Results for spinout performance, as measured by its survival probability, are less clear-cut and depend on the other parameters of the model. Spinouts survival would depend on both their technological know-how, and on their parents' know-how. In particular, a spinout exits the market when its actual production cost turns out to be 'sufficiently' larger than expected when the entry decision was taken (see equation (12)).

Market distance between the parent and the spinout has two effects on survival probability. On the one hand, a larger distance implies a higher probability of sustaining a large actual cost for S due to an *uncertainty effect* (UE). Here the idea is that developing a product too dissimilar from the parent's entails an exploration of product design opportunities which are potentially rewarding but nevertheless unfamiliar and riskier for the spinout. On the other hand, a larger distance from the parent increases the set of cost values which allow S's to stay profitable, due to a *competition effect* (CE). If the intensity of price competition is not 'too high', i.e. if t is high enough and therefore product differentiation effectively limits the competitive pressure, UE prevails. This argument leads to the following proposition (the proof is in Appendix 1):

PROPOSITION 2: *If the intensity of price competition is sufficiently mild, spinouts' survival probability is decreasing in their market distance from their parent.*

4. Data and methods

4.1. Data

To empirically test our propositions we rely upon two datasets. The first one is a comprehensive dataset of firms that have been active in the LAN industry since its inception.[6] This dataset virtually includes all the companies that contributed to the birth and rapid expansion of the industry, those who tried and fail and those who began as start-ups and rapidly soared to market dominance (i.e. Cisco Systems). For each firm in the dataset we have collected information on their founders, entry date in a specific market, entry date in the industry, age and, for those that did not survived, date of exit and mode of exit (i.e. failure vs. acquisition). This information has been collected over the years from several sources such as: the D&B Million Dollar database, ABI-Inform, Annual Reports, Lexis-Nexis, CORPTECH. The second dataset includes 1,818 products marketed between 1990 and 1999, the period of take-off, expansion and consolidation of the industry, 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. This information has been collected from specialised trade journals such as *Network World,* and *Data Communications*, press releases and data sheets from manufacturers.

Information on company founders is employed to trace the genealogy of each firm and eventually link it to some specific parent(s) active in the industry. Using this information we have identified 97 spinouts, of which only 13 survive.[7] 84 spinouts instead exit the market either by failure (18) or acquisition (66). For testing Proposition 2, we will only focus on exit by failure. Data on product

[6] LANs form the infrastructure for data communication. Over LANs data travel in packets from a possible sender to a data receiver according to rules defined by standards. The infrastructure of modern LANs is made up of different types of equipment (hubs, routers, and switches) which define different markets. The diffusion of office LANs for data communication started in the second half of the 1970s but the industry experienced a period of rapid growth from mid-1980s and especially during the 1990s when the Internet became commercial and new high-speed standards (Fast Ethernet, FDDI, ATM and Gigabit Ethernet) became available.

[7] A firm is considered to be a spinout if one or more of its founders has previously worked for another LAN firm in the year prior to the spinout creation.

characteristics and prices are employed to construct indicators that will be used in the empirical analysis. Each LAN product (i.e., hubs, routers, and switches) identifies a different market and our model considers the possibility that the spinout will initially enter into the same market of the parent firm.[8]

4.1.2. Entry by spinouts

While we have been able to trace the genealogy of 97 spinouts since the industry inception, our detailed information on products is restricted to the interval 1990-1999. Therefore, we will focus our analysis on the spinouts that originated during this time frame. Though this is a limitation, this is a crucial period in the evolution of the LAN industry because it coincides with its rapid growth and consolidation. In addition to this, 55/97 (or 57%) of the spinouts in our sample entered after 1989. Thus, we expect our analysis to provide a detailed and comprehensive picture of the phenomenon.

We start by looking at the relationship between the spinouts and their parents. For all 55 spinouts we counted the number of times they entered the same market of the parent. This occurred in 39/55 (or 71%) of the cases. 9/39 (or 23%) spinouts initially entered the hub market, 17/39 (or 43%) entered the router market and 29/39 (or 74%) the switch market. Concerning the entry strategies of the spinouts, 24 (or 61%) of those that entered the same market of the parent also produced only one type of LAN equipment at entry. 14 (or 36%) of those that entered the same market of the parent also produced two types of LAN equipment at entry, and only one produced three types of LAN equipment.

These differences in the rate of entry reflect differences in the presence of parents across markets as well as differences in terms of economic opportunities. In the period under examination, hubs and routers were established markets while the switch market was at an initial stage of its life cycle. In this market, innovations in the equipment hardware combined with the definition of new standards for data communications (Fast Ethernet, ATM, FDDI, Gigabit Ethernet) led to the creation of submarkets thus providing further entry opportunities for spinouts. The pattern of entry into the four switch submarkets is depicted in Figure 1.

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[8] All the spinouts considered in our analysis are *independent firms* which means that the parent firm(s) do not retain partial or total control in the new firms through financial support and/or participation to the management board at the time of spinout creation.

[FIGURE 1 ABOUT HERE]

For each submarket, each line in the panel reports the overall pattern of entry (left scale), a 4 periods moving average (thick line), and the cumulative number of spinouts amongst the new entrants (right scale). It can be seen that, despite some difference across submarkets, spinouts make the most out of the total number of new entrants. Consistent with the results of Klepper and Sleeper (2005) for laser, all in all these descriptive statistics indicate a substantial overlap between the product strategy of spinouts at entry and the product portfolio of their parents, a preliminary analysis that is a prelude to a more sophisticated test of our model.

4.1.3. Constructing indicators of product differentiation

In order to test our model we need to construct several indicators of product differentiation between spinout and the parent, and technological know-how for both parent and spinout firms. We will also construct measures of product dispersion for the parent firm, as a proxy for spinout creation opportunities (corresponding, in the model, to multiple Hotelling lines in the which the parent is present). To construct these indicators we follow closely the approach by Stavins (1995) and Fontana and Nesta (2006) based on hedonic price regressions.[9] We start from the assumption that it is possible to reduce the multi-characteristics structure of a LAN product m in market k to a single dimensional measure by projecting its characteristics z onto a linear scale as follows:

$$q_{mk} = \sum_j \beta_j z_{jmk} \qquad (13)$$

where the weights β_j represent the marginal value of characteristic j that both consumers and producers place on the jth characteristic. These weights are approximated by regressing observed prices (deflated to 1996 US dollars using the sector specific deflator for telecommunication equipment provided by the US Department of Commerce, Bureau of Economic Analysis) on characteristics, as follows:

$$p_{mkit} = \alpha + \sum_j \beta_j z_{jmk} + \alpha_t + \varepsilon_{mkit} \qquad (14)$$

[9] Contrary to other high-tech products whose performance can be clearly evaluated along one or two dimensions (i.e. areal density in the case of Hard Disk Drivers, microprocessor power in the case of PCs etc.), in the case of LAN equipment focusing on only one (as done, for instance, by Franco and Filson, 2006) or even on a small subset of characteristics would bias the evaluation because of the presence of complementarities among the characteristics themselves. The hedonic price approach has the advantage of considering a wider number of technical characteristics, thus reducing the bias.

where p_{mkit} is the log of the observed market price for model m introduced in market k by firm i at time t, α is a constant, and α_t is a time fixed effect. Table A1 in Appendix 2 summarizes the results from the hedonic regressions run separately for each market k. The predicted price $\hat{p}_{mkit}$ reflects (by construction) the overall contribution q of each characteristic weighted by its estimated coefficient. We posit:

$$q_{mkit} = \hat{p}_{mkit}. \tag{15}$$

We use q to construct the following indicators.

Market distance. We compute an indicator of the distance between the parent firm and the spinout at entry year t. In this case we use q to compute the distance across products. For each market k we compute the mean Weitzman distance d^c_{kmst} of a given model m produced by the spinout s from all the models introduced by the parent p in the year prior to spinout generation t-1:

$$d^c_{kmst} = \frac{\sum_{n_{kp}}^{N_{kp,t-1}} \sqrt{\left(q_{kmst} - q_{n_{kp,t-1}}\right)^2}}{N_{kp,t-1}} \tag{16}$$

where $N_{kp,\,t-1}$ is the number of products introduced by the parent p in market k at t-1, q_{kmst} is the quality of model m by spinout s at entry into market k and $q_{n_{kp,t-1}}$ refers to model n by parent p in year t-1. Because of the squared differences, this measure does not distinguish between products with high and low level of q. Thus, the market place is characterised as a horizontal scale in which the product locates, consistently with the model. The further from the centre of the scale c, the more peculiar is the product with respect to the representative product of the parent firm. Given that a spinout may introduce several products at entry year t, we take for each spinout and each market the average distance d^c_{kst}.

Market distance will serve as dependent variable for analyzing the location in the specific market of spinout at entry and as explanatory variable for testing Proposition 2 of our model.

Technological know-how. As an indicator of technological know-how we use the location of a firm (both the parent and the spinout) with respect to the technological frontier. To construct the indicator we take q and use it to compute for every model m introduced in market k by firm i at time t its distance from the frontier as follows:

$$d^f_{kmit} = max(q_{kit}) - q_{kmit} \tag{17}$$

where q_{kmit} refers to model m by firm i in market k at t. The higher d^f_{kmit} the farther the model is from the technological frontier. Given that a firm may introduce several products and may be active in more than one market in a given year, we compute for each firm and market the lowest distance from the frontier:

$$d^f_{kit} = min[d^f_{kmit}]_{kit} \tag{18}$$

The lower the measure, the higher is a firm's technological know-how in a specific market. The technological know-how of the parent firm in the year prior to spinout creation will serve as explanatory variable for testing the implications of our model. The technological know-how of the spinout at entry will be employed as control variable in the analysis of spinout performance.

Parent product dispersion. This is an indicator of the width of a parent's product line. To construct it we proceed in two steps. First, for each market k, we construct a measure of product dispersion within the parent's product portfolio:

$$\sigma_{kpt} = \frac{\sum_{m=1}^{M_{pt}}(q_{kmpt}-\bar{q}_{kpt})^2}{M_{kpt}} \quad where \quad \bar{q}_{kpt} = \frac{\sum_{m=1}^{M_{pt}} q_{kmpt}}{M_{kpt}} \tag{19}$$

where M is the number of products introduced by the parent p in market k for a given year. The overall product dispersion in market k is defined as:

$$\sigma_{kt} = \frac{\sum_{n=1}^{N_{kt}}(q_{knt}-\bar{q}_{kt})^2}{N_{kt}} \quad where \quad \bar{q}_{kt} = \frac{\sum_{n=1}^{N_{kt}} q_{knt}}{N_{kt}} \tag{20}$$

where N is the number of products introduced by all the firms for the same year. The relative dispersion index for parent p in market k is defined as:

$$R_{kpt} = \frac{\sigma_{kpt}}{\sigma_{kt}} \tag{21}$$

The (lagged) relative dispersion index will serve as a key explanatory variable in the analysis of spinout creation.

4.2. Estimations

We carry out two types of estimations. We start by employing a Maximum Likelihood Heckman model to estimate the probability of spinout generation and location in the market with respect to the parent firm. In the first stage the dependent variable is the probability for incumbent i to spawn a spinout in market k in period t (P_{ikt}). The main explanatory variable in this estimation is the measure of the parent product dispersion in market *k* in the previous period *(t-1)*. We focus on product dispersion as a key explanatory variable because prior research (Klepper and Sleeper, 2005), has pointed to a positive relationship between parent product dispersion in a specific market and the probability to spawn a spinout. We add other explanatory variables capturing the characteristics of the parent firm. These variables include: the (logarithm of) the total number of years the parent was active in market k and its squared value, the (logarithm of) the total number of years the parent was active in producing LAN equipment, a 1-0 dummy equal to 1 for parent firms that were acquired and 0 for those that were not, and the (logarithm of) the parent age. A full vector of entry-year dummy variables for the parent firm is also included in this first stage.

In the second stage, we estimate the market distance of the spinout from the parent firm at entry. In this case the dependent variable is the mean Weitzman distance between the parent and the spinout as constructed above. The main explanatory variables are indicators of the technological know-how of the parent firm as captured by the parent distance from the technological frontier in market *k* in the previous period *(t-1)* and its squared value. Our Proposition 1 suggests that the market distance is high for high levels of parent technological know-how, decreases for lower levels of technological know-how and then increases again. Therefore, we expect the coefficient of the parent distance from the frontier to be negative, and the coefficient of its squared term to be positive. The (logarithm of) spinouts' age and a full vector of entry-year dummy variables for the spinout are also included.

To estimate the hazard of exit for spinouts we employ a complementary log-logistic discrete time duration model (Bayus an Agarwal, 2007). In this case the main explanatory variable is the distance of the spinout from the parent firm at entry. Proposition 2 suggests that spinout survival probability could be both decreasing or increasing in the market distance from the parent, the former case being observed if the uncertainty effect prevails over the competition effect. Additional explanatory variables include the (logarithm of) spinouts' age, the technological know-how of the parent firm when the spinout was spawned, and the technological know-how of the spinout at birth. Similarly to Agarwal et al. (2004) and Franco and Filson (2006) we expect that spinout survival should increase in the technological know-how of the spinout. A full vector of entry-year dummy variables for the spinout is also included.
Table 1 below summarizes the descriptive statistics for the variables used in the analysis.

[TABLE 1 ABOUT HERE]

5. Results
Results from the two steps ML Heckman estimation are reported in Table 2.

[TABLE 2 ABOUT HERE]

In each year beginning with its year of entry and extending through 1999, each firm in our sample is considered as a potential parent of a spinout initially entering one of the three markets in the LAN industry (i.e., hubs, routers or switches). Thus, there are many observations per firm and 8,919 in total. Column 1 reports the results of the first step in which the dependent variable is equal to one in the year the parent spawns a spinout in the same market it is active. The coefficient estimate of parent product dispersion (as computed from equation 21) is positive and highly significant (at the 0.01 level). The estimate implies that the higher its product dispersion within a specific market *k* the more likely is a firm to spawn a spinout in that specific market. This relationship is visualized in Figure 2 below.

[FIGURE 2 ABOUT HERE]

For relatively low values, a doubling of parent product dispersion in market *k* (for instance an increase from 0.24 to 0.48) leads to a 15.6% increase in the probability of spawning a spinout in the same market. For relatively higher values, a doubling of product dispersion (from 0.48 to 0.96 for instance) leads to a 33.6% increase in the probability although the confidence interval widens too.

The coefficient estimates of the linear and quadratic terms for prior years of production of product *k* are positive and negative, respectively. They are both very significant at the 0.001 level. These results indicate that the probability of a parent spawning a spinout in the same market it is active in at first increases with the parent's past experience in that market, reaches a peak, and then declines.

The coefficient estimate of the number years of production of LAN equipment is negative and very significant at the 0.001 level. This result suggests that a firm's success in the industry does not increase the probability of spawning a spinout in the same market *k* it is active in. On the contrary, overall success of the parent firm reduces the probability of spinout creation for the firms in our sample.

The coefficient estimate of parent age is positive and very significant at the 0.001 level. This result suggests that older firms have higher probability of spawning a spinout in the same market *k* they are active. To the extent that firm age is also positively correlated to the size of the firm, this result suggests that bigger firms are more likely to spawn spinouts than smaller ones. Finally, the coefficient estimate of the acquisition dummy is not statistically significant. This result indicates that the rate of spinout creation is not influenced by the mode of exit of parent firms and, specifically, does not result from an undergoing situation of distress or crisis which may lead the parent firm to reduce its activity and/or seek an exit strategy.

Column 2 in Table 2 reports the results of the second stage of the Heckman estimation. In this case the dependent variable is the (horizontal) distance in the market k between the parent firm and the spinout at time t as captured by the mean Weitzman distance (equation 16). As we were able to observe this distance only for those parents that have spawned a spinout, the number of observations is a subsample of the initial set of firms. The coefficient estimate of parent age is now insignificant. The coefficient estimates of the linear and quadratic terms for the distance from the technological frontier (our proxy for parent technological know-how) in market k in the year prior to spinouts creation are negative and positive, respectively. They are both significant at the 0.05 level. These results suggest that the relationship between the technological know-how of the parent and the market distance between the parent and the spinout is non-linear. Figure 3 below depicts the relationship for the interval of values in our sample.

[FIGURE 3 ABOUT HERE]

In the figure, the cloud of points visualizes the relationship between the parent know-how in the year prior to spinout creation and the market location of spinout at entry with respect to parent, conditional on spinout creation. The dashed line highlights the non-linear relationship between the two variables. For high levels of parent technological know-how the market distance is high. It decreases for intermediate levels of technological know-how and then increases again. All in all, this result is consistent with Proposition 1 in our model.

We now turn to the analysis of the performance of spinouts. The coefficient estimates and standard errors of the complementary log-logistic estimation are reported in Table 3 where the dependent variable is the hazard of exit and the explanatory variables are measured at spinout birth and added in sequence.[10]

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[10] In this analysis we only focus on exit by failure and treat acquisitions as censored observations. Prior analysis on a larger sample of entrants (Fontana and Nesta, 2009) has found that the higher the technological know-how of the entrant

[TABLE 3 ABOUT HERE]

Column (1) reports the results of our baseline estimation when only the effect of time on the hazard of exit is considered. The coefficient estimate is negative and significant. This suggests that the hazard of exit is relatively higher at young age. In column (2) we add the parent distance from the technological frontier our control for the parent technological know-how. The coefficient estimate of this variable is positive but not significant.

In column (3) we add the control for the technological know-how of the spinout. The coefficient estimate of the spinout distance from the technological frontier this variable is positive and significant at 0.05 level. This result indicates that better spinouts tend to perform better in terms of survival. Interestingly, after the inclusion of this variable, age becomes only weakly significant.

In column (4) we add the market distance variable. The coefficient estimate of this variable is positive and significant at the 0.05 level. This result indicates that the higher the market distance between the spinout and the parent firm at entry the higher the hazard rate for the spinout. In light of Proposition 2, this result suggests that the uncertainty effect turns out to be stronger than the competition effect in this industry, a result that is consistent with the presence of a high degree of product heterogeneity. The magnitude of the effect is quite high as a one standard deviation increase of market distance around the mean leads to a 83% increase in the hazard rate for the spinout.[11] In addition to this, it is interesting to note that after the inclusion of the indicator of market distance in the regression, the variable capturing the technological know-how of the spinout becomes only weakly significant. Also, age ceases to be significant. This evidence suggests that failing to control for the market location of the spinout with respect to its parent may lead to an overestimation of the effects of age and the technological know-how the spinout on the hazard of exit. Figure 3 below shows the predicted hazard rate of spinouts as a function of market distance from their parent. It plots the pattern over the interval of the market distance values included in our sample and for different levels (20th, 40th, 60th and 80th percentile) of the contribution of the other covariates as estimated in Table 3, column (4).[12]

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the higher the survival or the higher the probability of exiting by acquisition for those than do not survive. In addition to this, it has been found that spinouts have a lower hazard rate than other start-ups.

[11] The marginal effect was computed as a discrete change, holding all other independent variables constant at their mean values.

[12] To compute the contribution of the covariates and plot the hazard rate we have followed Mitchell and Chen (2005).

[FIGURE 3 ABOUT HERE]

In Table 4 we perform a sensitivity analysis to understand whether the above results are robust. In particular we carry out two types of analysis. First, we check the robustness of the estimations to changes in the baseline hazard function (columns 2-6). Second, we control for unobserved heterogeneity (columns 7-9).

[TABLE 4 ABOUT HERE]

Column (1) reports our preferred model from Table 3. In column (2) and (3) the link function is the same (a clog-log) as in our preferred model but the baseline hazard is polynomial and piece-wise respectively. In these regressions we do not detect substantial changes in the sign, significance, and magnitude of the coefficients as compared to our preferred specification despite a decline in the number of observations in Model (3).[13] Thus, we conclude that our results are robust to the choice of the baseline hazard. In columns (4) and (5), we change the link function and estimate two parametric models with Weibull and Gompertz baseline hazard respectively and a semiparametric Cox proportional hazard model in column (6).[14] Again, the estimated coefficients for market distance parent-spinout are unchanged. Finally, models (7) to (9) test for unobserved heterogeneity. More specifically, in Column (7) and (8) we assume the heterogeneity term is normally distributed with a logistic and clog-log link function respectively. Results are unchanged. Finally in Column (9) we assumed the 'frailty' follows a Gamma distribution. Again the significance of the estimated coefficients is basically unaffected with respect to our preferred model.[15]

6. Discussion and conclusion

We proposed a model to explain the location of the spinouts in the market with respect to their parents and to analyze how this location influences the post entry performance of spinouts. On the

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[13] In the piece-wise constant specification, we allow the baseline hazard to differ over several intervals, one for each year of spinout creation. In some of the intervals, failure is perfectly predicted and observations are dropped as a consequence.

[14] Parametric Weibull and Gompertz models are consistent with a variety of, exponentially and monotonically increasing or decreasing, shapes of the hazard function. Cox models instead are semi-parametric model that do make a specific assumption on the shape of the hazard function over time.

[15] Results of these estimations are obtained by employing the pgmhaz8 command written by Jenkins (2005) for STATA.

basis of this model we then empirically analysed the drivers of spinouts creation and survival in the LAN industry.

The model builds upon Klepper and Sleeper (2005) but extends its scope in several ways. First, it does not focus only on *whether* spinouts enter or not in the same market of the parent firm but it specifically tackles the issue of *where* they locate in the market with respect to the parent conditional upon entry in the same market. Second, and most importantly, the model establishes a relationship between the market distance and the technological know-how of the parent firm which was not explicitly built into prior models of spinout formation. Third, the model establishes a relationship between market distance and the performance of the spinout, another aspect that was not explicitly modelled before.

The model makes two predictions. First, there is a positive but non-linear (U-shaped) relationship between the technological know-how of the parent and the distance in the market between the spinout and the parent. Second, for sufficiently low levels of price competition between the spinouts and the parent, spinouts' survival probability is decreasing in their market distance from their parent.

We used the model as a guide in our empirical analysis in the LAN industry. Our empirical analysis provided two sets of results that have important implications for the analysis of the determinants of spinout creation and survival. Our finding that entry by spinout in a specific market is positively related to the extent of product dispersion of the parent in that market is consistent with the results of Klepper and Sleeper (2005) for lasers, Brittain and Freeman (1986) and Garvin (1994) for semiconductors, and further qualifies them. Not only each market the parent is active in is a potential context for spinout creation but the more disperse *within the market* are the products, the higher is the probability that a spinout is spawned.

Perhaps the most important implication of our findings concerns the role played by the technological know-how of the parent for both differentiation and survival. As stressed by the prior literature (Klepper and Sleeper, 2005; Klepper, 2001), spinouts inherit know-how from their parents which give them a competitive advantage with respect to other start-ups (Klepper and Simons, 2000). This know-how tends to be *distinctive* and clearly influence the post entry behaviour of the spinout (Garvin, 1983; Holbrook et al., 2000). On the one hand, spinouts clearly benefit from having 'good' parents because this translates into lower development costs for their innovative idea. Low development costs enable them to explore in principle a wider range of market locations for their products. On the other hand, being located in the market as farther away as possible, though always within the boundaries of their inherited skills, is beneficial for the spinout as it avoids direct competition. Our finding about the positive but non-linear effect of parent technological know-how on spinout location provides a clear evidence of these effects.

In terms of survival, our finding that spinout survival is decreasing in the market distance between the parent firm and the spinout indicates that 'too much' differentiation with respect to the parent may be detrimental for the new venture. In our model, this evidence is explained by the prevalence of the uncertainty effect over the competition effect. One reason why the uncertainty effect may prevail over the competition effect is once again provided by the prior literature which has highlighted that the quality of the know-how of the parent firm might be *both* an asset *and* a liability for the inheriting firm. On the one hand, the better the parent know-how, the better the performance of the spinout. On the other hand, however, the better the technological know-how of the parent the stronger competitor it will be after entry.

Alongside these major implications some of our results also confirm and extend previous findings on spinouts in high-tech industries. Our finding concerning the positive but non-linear relationship between parent experience in a market and the probability to spawn a spinout resonates with Klepper and Sleeper (2005). Contrary to them, we also find a negative relationship between the parent prior experience in the industry and the probably of spinout generation. Taken together both results indicate that the probability of spawning is influenced only by the prior experience in producing a specific type of LAN equipment not by the general experience in the industry. An additional implication is that the most successful firms in the LAN industry may tend to retain their best employees (Campbell et al. 2012).

Finally, our findings have also implications for the existing theories of spinout formation. In our review we posed two questions that were relatively underexplored by the theories. The first question was related to the initial market positioning with respect to the parent. The second question was related to the profitability of such positioning. In this respect employee learning theories of spinout formations make two rather contrasting predictions: either spinouts learn to replicate what their parent do or they learn to diversify. Our results reconcile the two predictions by showing that the degree of product differentiation between spinout and the parent is the outcome of the tension between the know-how that spinouts inherit from their parents and the know-how required to successfully outcompete them in the market. While a 'good' parent is certainly a good source of know-how for the spinouts the successful implementation of the new ideas by the spinout will necessarily be constrained by their inherited know-how to a close contour of the parent product portfolio. Venturing beyond this boundary is likely to increase the risk of the project and reduce its profitability.

In conclusion, the idea that spinouts are relatively more successful than other entrants because they take advantage of industry-specific know-how inherited from the parent firm still provides useful insights to understand patterns of entry and industry evolution. From the viewpoint of the business strategy though, the pre-entry experience that represents an advantage for spinouts with respect to other new entrants may become a 'constraint' when they need to compete with their parent. Within this context, the most successful spinouts turn out to be those that neither exactly replicate the same product strategy of the parent nor differentiate too much from it or, in other words, the 'best' apples turn out to be those that fall neither 'too close nor too far' from the tree.

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List of Tables

Table 1: Summary descriptive statistics

Spinout entry variables	**Mean**	**S.D.**
Parent product dispersion in market k at t-1*	0.0618	0.1858
Prior years parent active in market k (Log)	1.0809	1.0553
Prior years parent active in market k squared (Log)	1.9653	2.0476
Number of years parent active in producing LAN equipment (Log)	2.1259	0.7265
Parent acquired (Dummy)	0.5496	0.4981
Parent distance from frontier in market k at t-1§	0.7443	0.3296
Parent distance from frontier in market k at t-1 squared	0.6623	0.1978
Spinout exit variables		
Parent distance from frontier at spinout birth §	1.6593	0.9910
Spinout distance from frontier at birth §	1.9307	1.4491
Market distance parent-spinout +	1.5477	1.0380

Notes: The table reports the descriptive statistics for the variables used in the estimation of spinout entry and exit.
* is computed as in equation (21); § is computed as in equation (18); + is computed as in equation (16).

Table 2: Determinants of spinout generation in market k at time t. Two step Heckman estimation

VARIABLES	(1) Spinout generation	(2) Market distance parent-spinout
Parent product dispersion in market k at t-1	0.824	
	[0.290]**	
Prior years parent active in market k (Log)	2.604	
	[0.438]***	
Prior years parent active in market k squared (Log)	-1.602	
	[0.227]***	
Number of years parent active in producing LAN equipment (Log)	-0.590	
	[0.125]***	
Parent acquired (Dummy)	0.050	
	[0.209]	
Parent age (Log)	1.902	0.268
	[0.191]***	[0.191]
Parent distance from frontier in market k at t-1		-2.578
		[1.267]*
Parent distance from frontier in market k at t-1 squared		2.468
		[1.006]*
Spin Year (Dummy)	No	Yes
Born Year (Dummy)	Yes	No
Constant	-9.061	2.312
	[0.797]***	[0.981]*
Athrho		-0.385
		[0.508]
Lnsigma		-0.120
		[0.175]
Total Observations	8,919	
Censored Observations	8,826	
Uncensored Observations	93	
Wald Chi-square	239.95**	
Log Pseudo-Likelihood	-459.4321	

Notes: Robust standard errors clustered on company id are reported in brackets. + Significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0.1%. The table reports the estimation of a two-step maximum likelihood Heckman model. Model (1) is the selection equation in which the dependent variable is the probability for an existing firm to spawn a spinout in the same market k at time t. Model (2) estimates instead the location of the spinout in market k conditional on spinouts creation. Here, the dependent variable is market distance from the parent at t computed as indicator (16).

Table 3: Analysis of spinout survival. Complementary log-logistic estimation

VARIABLES	(1)	(2)	(3)	(4)
Spinout age (Log)	-0.643	-1.065	-0.691	-0.439
	[0.213]**	[0.273]***	[0.357]+	[0.505]
Parent distance from frontier at spinout birth		0.405	0.523	0.691
		[0.352]	[0.450]	[0.682]
Spinout distance from frontier at birth			0.675	0.833
			[0.336]*	[0.456]+
Market distance parent-spinout				0.605
				[0.277]*
Constant	-3.429	-3.195	-5.406	-7.810
	[0.421]***	[0.765]***	[1.787]**	[2.900]**
Observations (Number of firms x Year)	1,965	606	549	542
Zero outcomes	1,947	596	540	535
Positive outcomes	18	10	9	7
Chi-square	9.093**	15.290**	21.520**	31.960**
Log Likelihood	-98.680	-44.878	-37.637	-28.76

Notes: Robust standard errors clustered on company id are reported in brackets. + Significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0.1%. In all models the dependent variable is the hazard of exit.

Table 4: Analysis of spinout survival. Robustness checks

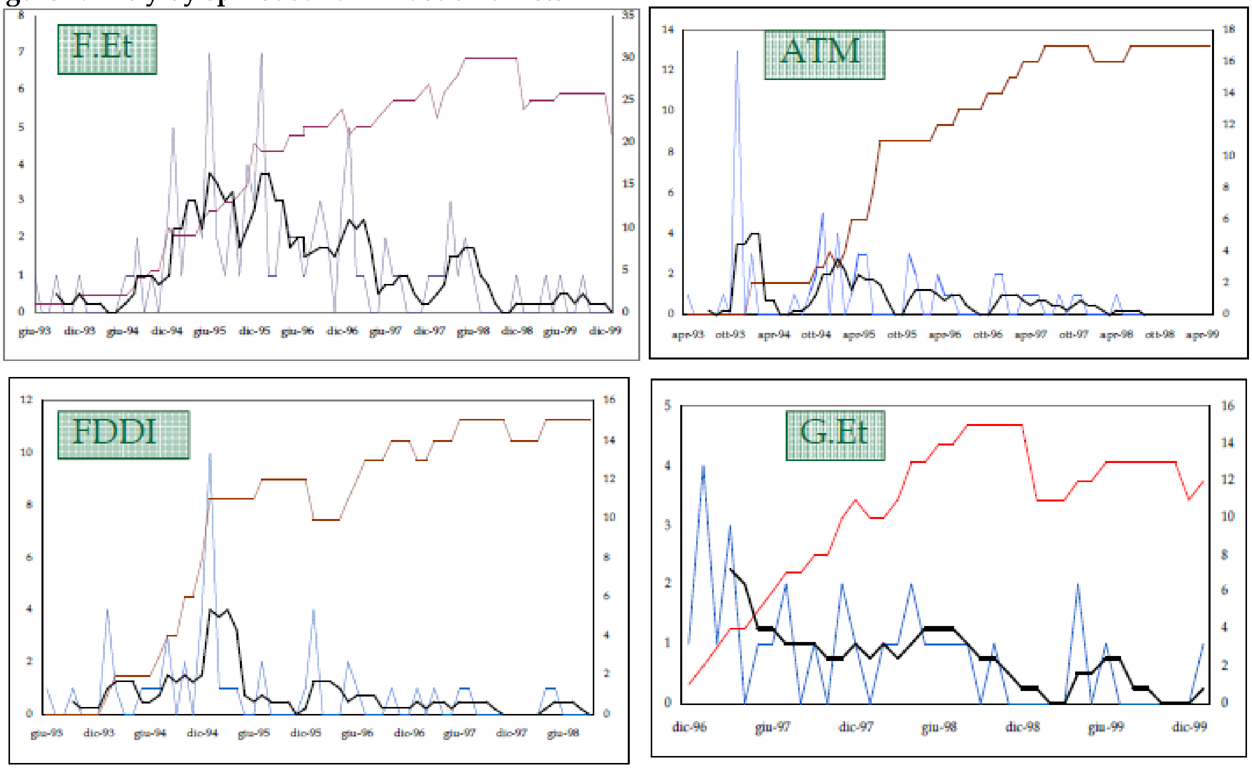
VARIABLES	Baseline hazard						Unobserved heterogeneity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Parent distance from frontier at spinout birth	0.691	0.702	0.690	0.735	0.662	0.642	0.669	0.691	0.690
	[0.682]	[0.657]	[0.660]	[0.709]	[0.559]	[0.531]	[0.465]	[0.466]	[0.324]*
Spinout distance from frontier at birth	0.833	0.913	0.917	0.911	0.765	0.814	0.879	0.833	0.833
	[0.456]+	[0.502]+	[0.492]+	[0.441]*	[0.323]*	[0.369]*	[0.302]**	[0.285]**	[0.156]***
Market distance parent-spinout	0.605	0.683	0.712	0.639	0.564	0.663	0.673	0.605	0.605
	[0.277]*	[0.290]*	[0.341]*	[0.252]*	[0.230]*	[0.288]*	[0.324]*	[0.291]*	[0.245]*
Spinout age (Log)	-0.439						-0.516	-0.439	-0.440
	[0.505]						[0.466]	[0.455]	[0.381]
Constant	-7.81	-9.787	-7.679	-8.813	-7.511		-7.864	-7.810	-7.808
	[2.900]**	[5.102]+	[2.936]**	[3.136]**	[2.080]***		[2.174]***	[2.162]***	[0.000]
Observations	542	542	199	542	542	542	542	542	542
Link function	Clog-log	Clog-log	Clog-log	Parametric	Parametric	Semi-parametric	Logistic	Clog-log	Clog-log
Heterogeneity term							Normal	Normal	Gamma
Baseline hazard function	Weibull	Polynomial§	Piece-wise constant§	Weibull	Gompertz	Cox	Weibull	Weibull	Weibull
Chi-square	31.960**	123.4**	19.37*	12.21**	16.22**	7.31*	15.48**	20.09***	
Log Likelihood	-28.76	-26.89	-23.47	-21.35	-20.518	-18.678	-28.758	-28.876	-28.876

Notes: Robust standard errors clustered on company id are reported in brackets. + Significant at 10%; * significant at 5%; ** significant at 1%; *** significant at 0.1%. In all models the dependent variable is the hazard of exit. All models use the same specification as our preferred one shown in Table 2 column (4). Column (1): preferred model. Models (2) through (6) test for robustness to changes in the baseline function. More specifically: Column (2): estimates a complementary log-logistic model with polynomial baseline hazard. Column (3) estimates a complementary log-logistic model with piece-wise baseline hazard. Columns (4) and (5) estimates parametric models with Weibull and Gompertz baseline hazard respectively. Column (6) estimates a semiparametric Cox proportional hazard model. Models (7) to (9) instead test for unobserved heterogeneity. More specifically: Column (7) a random effect logistic regression. Column (8) estimates a random effect complementary log-logistic model. Column (9) estimate a hazard 'frailty' model with Gamma distributed unobserved heterogeneity.

§ the estimated coefficients for the baseline hazard terms are not reported here for the sake of brevity.

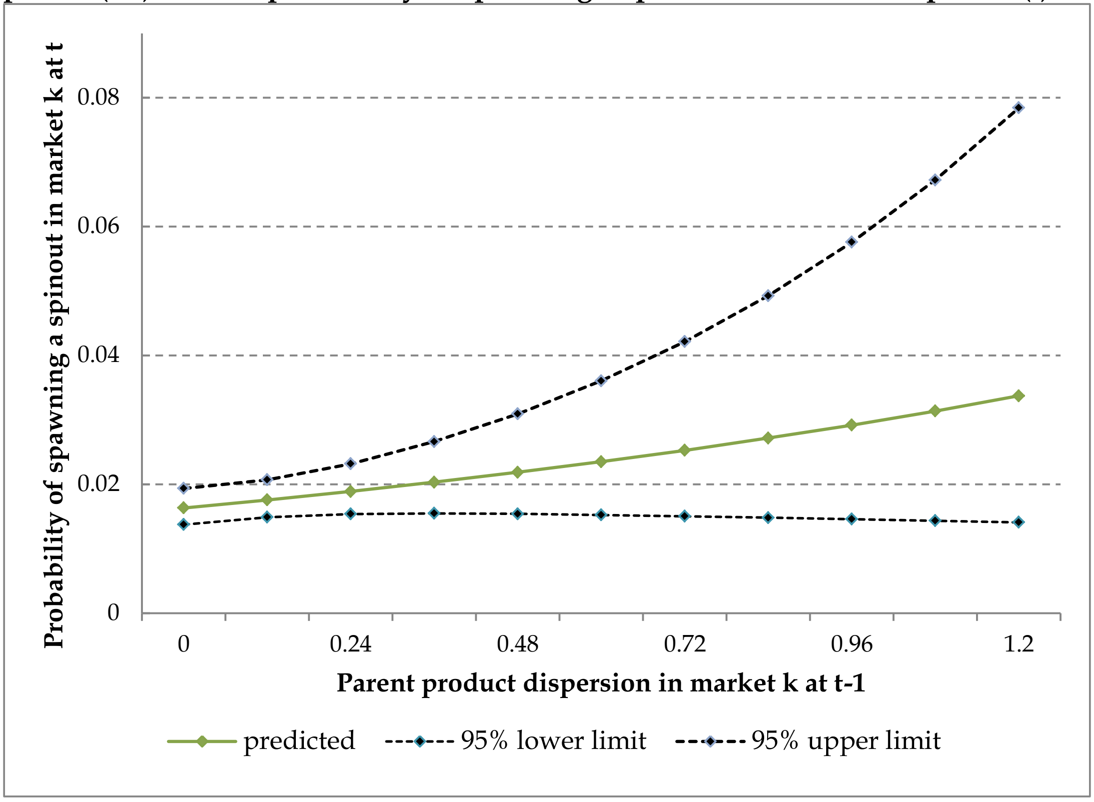
List of Figures

Figure 1: Entry by spinout and LAN submarkets



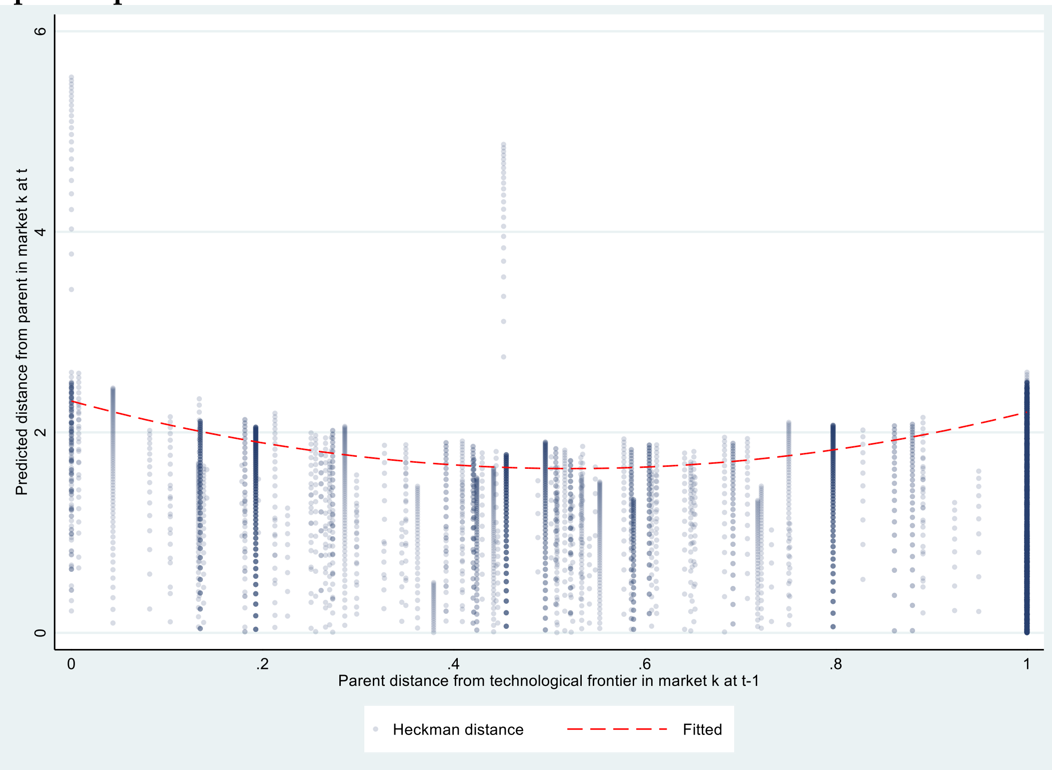
Notes: for each LAN market, Fast Ethernet (F. Et.), ATM, FDDI, and Gigabit Ethernet 9G. Et.), the figures report the monthly number of entry by spinouts (blue line), its (3 periods) moving average (black line), and the evolution of the number of spinouts incumbents (red line on right axis).

Figure 2: The relationship between the product dispersion of the parent firm in market k at period (t-1) and the probability of spawning a spinout in market k at period (t)



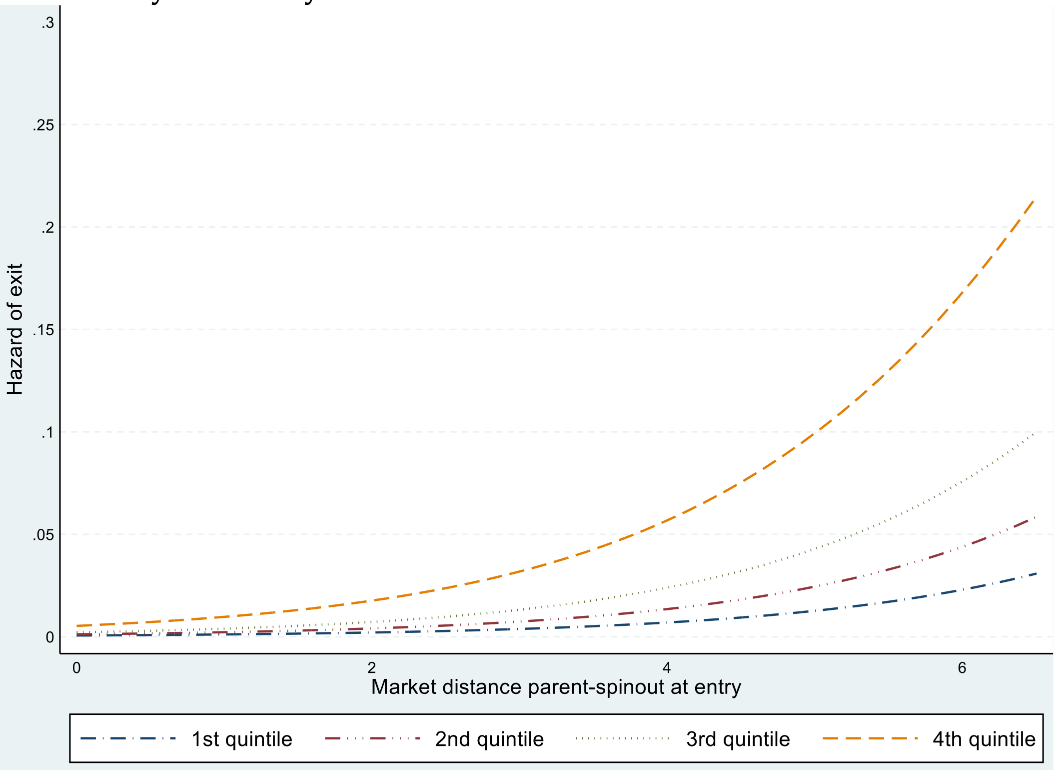
Notes: the solid line corresponds to the estimated effect of parent product market dispersion in the year prior to spinout creation on the probability of spawning a spinout in the following year in the same market. It results from the estimation of a Maximum likelihood Heckman selection model (first step, see Table 2, Column (1)). The 95% confidence interval (computed on the basis of robust standard errors clustered on firm id) is plotted in dashed lines.

Figure 3: The non-linear relationship between the technological know-how of the parent and spinout-parent market distance



Notes: the scatterplot captures the relationship between parent know-how in the year prior to spinout creation and the market location of spinout at entry with respect to parent, conditional on spinout creation. The dashed line highlights the non-linear relationship between the two variables. Both come from the estimation of a Maximum likelihood Heckman selection model (second step, see Table 2, Column (2)).

Figure 4: Spinouts hazard exit as a function of the market location with respect to the parent firm in the year of entry



Notes: the figure plots the (in sample) predicted hazard of exit of spinouts as a function of market distance from their parent. Each line is computed for different levels (20th, 40th, 60th and 80th percentile) of the other covariates as estimated in Table 3, model (4).

APPENDIX 1

Proof of Proposition 1

Since the distribution function G_x is independent both from c_P and $\bar{c}_S$, the Proposition follows if the locus of c_P and x_S for which $\Pi_S^*(x_S, c_P) - F(c_P) = 0$ is U-shaped. This is given by:

$$\frac{[c_P - \bar{c}_S + t(4 - x_S)x_S]^2}{18tx_S} - F(c_P) = 0 \tag{A1}$$

By applying the implicit function theorem, we obtain:

$$\frac{dx_S}{dc_P} = \frac{-\frac{2[c_P - \bar{c}_S + t(4-x_S)x_S]}{18tx_S} + F'(c_P)}{\frac{[c_P - \bar{c}_S + t(4-x_S)x_S][2tx_S(4-2x_S) - (c_P - \bar{c}_S + t(4-x_S)x_S)]}{18tx_S^2}} \tag{A2}$$

The denominator of (A2) is positive (in particular, $2tx_S(4 - 2x_S) - (c_P - \bar{c}_S + t(4 - x_S)x_S)$ is positive if $c_P - \bar{c}_S \leq 0$, as we assumed. The sign of the numerator is ambigous: however, since $F'(c_P)$ is increasing, $\frac{dx_S}{dc_P}$ can only turn from negative to positive, so that (A1) is U-shaped.

Proof of Proposition 2

Given equation (12), the survival probability for S is given by:

$$Pr(c_S \leq c_P + t(4 - x_S)x_S) = \frac{1}{2}\left(1 + erf\,\frac{c_P + t(4 - x_S)x_S - \bar{c}_S}{\sigma(x_S)\sqrt{2}}\right)$$

where erf stands for the error function. By deriving with respect to x_S, and defining $z = \frac{c_P + t(4-x_S)x_S - \bar{c}_S}{\sigma(x_S)\sqrt{2}}$ one obtains:

$$\frac{1}{2}\frac{2}{\sqrt{\pi}}e^{-z^2}\frac{t(4 - 2x_S)\sigma(x_S) - [c_P + t(4 - x_S)x_S - \bar{c}_S]\sigma'(x_S))}{\sigma^2(x_S)\sqrt{2}}$$

which is negative when:

$$\frac{\sigma'(x_S)}{\sigma(x_S)} \geq \frac{t(4 - 2x_S)}{[c_p - \bar{c}_S + t(4 - x_S)x_S]}$$

The right quantity turns out to be decreasing in t (since $c_P - \bar{c}_S \leq 0$), therefore for t sufficiently large the inequality is satisfied, and survival is decreasing in distance.

APPENDIX 2

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.
** p<0.01, * p<0.05, + p<0.1

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.
** p<0.01, * p<0.05, + p<0.1

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.
** p<0.01, * p<0.05, + p<0.1