RESOURCE PARTITIONING AND STRATEGIES IN THE MARKET FOR TECHNOLOGY

ABSTRACT

By bridging literature on resource partitioning and research on markets for technology, this article predicts that companies that pursue a broad (focused) product strategy buy more (less) technology in the market but sign fewer (more) deals as sellers. The proposed framework reveals that a thicker technology market increases the survival chances of both firms with focused product strategies and firms with broad product strategies; a misalignment between the product strategy and the strategies in the market for technology reduces those chances. To test these contentions, the authors consider a population of 736 firms that entered the security software industry between 1989 and 2002.

INTRODUCTION

Both economists and sociologists (Carroll and Swaminathan, 2000; Hannan and Freeman, 1989; Sutton, 1991) document increasing levels of concentration coupled with rising organizational density in various industries. To explain this empirical regularity, researchers turn to dual market structures (Boone and Van Witteloostuijn, 2004) and propose that large, generalist firms occupy a concentrated, competitive center by making products or services with broad appeal, whereas specialist organizations thrive on the industry's periphery by focusing on a small range of specific customer tastes (Swaminathan, 2001). Resource partitioning theory assumes that competition affects both the levels of specialization and the survival chances of each organization in a population (Soule and King, 2008), such that it creates *indirect* interdependences between generalists and specialists. For example, market concentration among generalists increases the founding rate and lowers the mortality of specialists (Carroll and Swaminathan, 2000; Freeman and Lomi, 1994). However, little research explores the direct interorganizational ties between these two kinds of organizations (Freeman and Audia, 2006).[1] This gap might not seem surprising; generalists and specialists tend to develop heterogeneous codes and routines that govern their behaviors in different strategic domains, resulting in different identities that do not combine easily (Giarratana and Fosfuri, 2007; Sorenson, McEvily, Ren, and Roy, 2006).

But this article posits that a company's position in the resource space, which is the outcome of the underlying resource partitioning process, also affects its propensity to trade resources, thereby creating a direct link between horizontal sub-populations. By overlooking such a link, resource partitioning theory could generate incomplete (or biased) assessments of

[1] Ecology scholars address two kinds of ties. Among horizontal sub-populations, ties materialize because competitive processes lead generalists to move to the center of the resource space, which frees resources for specialists at the periphery (Lomi, 1995; Soule and King, 2008); in vertically related populations, more upstream firms tends to boost the survival chances of both specialists and generalists (Audia *et al.*, 2006; de Figuereido and Silverman, 2012). To the best of our knowledge, direct ties have not been analyzed before.

how competition affects industry evolution and firm survival (Audia, Freeman, and Reynolds, 2006) and thereby inaccurately dismiss the importance of resource trade for firm success. Specifically, we consider trade in technological assets.[2] Technological assets drive differentiation or lower cost positions relative to competitors, so they are more likely to affect survival rates than are commodity assets (de Figueiredo and Silverman, 2012). Moreover, they can be productively employed in applications or contexts far removed from the locus of the idea's generation and become non-rivalrous in their use (Arora and Gambardella, 2010; Gans and Stern, 2010). Then the firm might accumulate technological knowledge that has potentially great value for other companies, such as those that control complementary assets needed to compete in other contexts (Teece, 1986). By extending the resource partitioning model, we derive implications for how and in which conditions trade in technology affects survival.

We draw on a population of 736 firms that entered the security software industry (SSI) between its inception in 1989 and 2002. As a relatively recent segment of the software industry, SSI offers an interesting study context for several reasons. First, because of the distribution of security software users (a relevant resource space in this industry), the industry population consists of both specialist and generalist organizations. Generalists compete at the market center and offer one-stop-shopping software packages. Specialists focus on customers that require state-of-the-art technological solutions to specific problems. Second, SSI encompasses an active technology market (i.e., approximately 15 percent of revenues from licensing, according to Hoover data). Our data show that specialists sell more disembodied technology than generalists, yet generalists resort more to technology acquisition than do specialists. We also find that a misfit between a firm's product strategy and the strategies in the market for technology increases its mortality hazard, whereas a *thicker* market for technology increases firm viability.

[2] Technology trade is increasingly widespread; arm's-length contracts, such as licensing, are popular in various sectors, including semiconductors, chemicals, pharmaceuticals, and software (Arora and Gambardella, 2010).

This study makes several contributions to current literature. First, we focus on how competition, selection, and specialization in one resource space affect behaviors in another. Accordingly, we extend the resource partitioning model by conjecturing that firms' positions in the product space help explain the direction of technology trade. While canonical ecology studies investigate how the fates of generalists and specialists are linked through indirect competitive processes (Dobrev, Kim, and Carroll, 2002; Dobrev, Kim, and Hannan, 2001; Lomi, 1995; Soule and King, 2008), little attention has been placed on direct ties between organizational populations (see Freeman and Audia, 2006), except when they span vertically related industries (Audia *et al*., 2006; de Figueiredo and Silverman, 2012).

Second, we contribute to current research on the antecedents of firms' decisions to participate in technology markets (Arora and Gambardella, 2010), such as lack of complementary assets (Teece, 1986), establishment of technology standards (Garud and Kumaraswamy, 1993), competition among licensors (Arora and Fosfuri, 2003), patents, and market fragmentation (Cockburn, Macgarvie, and Muller, 2010; Gambardella and Giarratana, 2013). Resource partitioning can provide useful firm-level insights into how the establishment of different positions in the product market generates routines and behaviors, with strong imprints on the uses that organizations make of technology markets. By drawing attention to the role of product specialization, we move beyond the limited focus on how variations in downstream market shares affect a propensity to license (e.g., Fosfuri, 2006).

Third, because we combine resource partitioning theory with research on markets for technology, we offer a clearer view of why some firms engage in more technology transactions than others and how the joint consideration of both product and technologies strategies better explains firm performance. Current research indicates that the consistency and fitness of a firm's position in the resource space increase its performance; Zuckerman, Kim, Ukanwa, and von Rittmann (2003) note that job-seeking candidates who can associate themselves with a category enjoy greater success in attracting employers' attention, and Giarratana and Fosfuri (2007) argue that firms attempting to both pursue a broad portfolio strategy and a versioning strategy have lower survival probabilities than companies focusing on one approach. Sorenson *et al.* (2006) also report that specialists that introduce new products within their existing niche experience a lower exit rate, and Dobrev *et al.* (2002) find that changing a niche or its width invokes higher mortality rates. We go further, to suggest that consistency and fitness can extend to other resource spaces, which illuminates a novel link between product positioning and technology strategies.

THEORETICAL BACKGROUND

Assumptions

Our theory rests on three industry-specific assumptions. First, we make the standard assumption in resource partitioning literature of a unimodal resource environment with a clear market center, where the bulk of the demand falls, and a periphery characterized by greater segmentation (Boone and Van Witteloostuijn, 2004; Carroll, 1985). We assume vast demand for standard products and fringe demand for specialized, high quality products. Similar configurations exist in various industries (Carroll and Swaminathan, 2000; Freeman and Lomi, 1994; Swaminathan, 2001).

Second, we restrict our study context to sectors in which technology is a key determinant of final product quality. To satisfy customers that demand the highest quality products, firms must rely on state-of-the-art technology. Consider, for example, the industrial painting and coating sector, in which the types and quality of DPP pigments, the basic technology patented under the IPC C09 patent class, largely determine the quality of the final product (*Paint and Coatings Industry*, 2004).

Third, we assume the technology can be disembodied from the products, evaluated independently, and sold separately (Arora, Fosfuri, and Gambardella, 2001), which is likely in industries with a codified underlying knowledge base, few interdependencies across different production stages, and effective patents for protecting innovations (Arora and Ceccagnoli, 2006), such as in biotechnology. Therefore, entry into a downstream product market does not necessarily require the internal development of technological capabilities, which can be accessed through arm's-length arrangements.

Dual market structures: Generalists vs. specialists

Resource partitioning theory (e.g., Carroll and Swaminathan, 2000) asserts that in the presence of a unimodal heterogeneous resource distribution with a clear market center, organizations secure positions in dense, central resource spaces by making products or services with broad appeal. These firms, called generalists, establish their identities and defend their performance on the basis of scale and scope economies and overall efficiency (Boone and Van Witteloostuijn, 2004; Carroll and Swaminathan, 2000). Competition and concentration among generalists increase the viability of other organizations (i.e., specialists) on the periphery (Hannan and Freeman, 1977), because they establish opportunities to create and occupy viable niches that generalists cannot reach (Kim, Dobrev, and Solari, 2003). Specialist organizations rely on a narrow resource space and appeal to a small range of specific customer tastes; the underlying selection process thus separates the organizational population (Boone, Brocheler, and Carroll, 2000; Carroll, 1985), which leads to a dual market structure. The two groups develop completely different identities and experience reduced direct competition. For example, organizational identity features influence consumers' decisions to buy specialty beer rather than large, mass-market beers (Carroll and Swaminathan, 2000).

Scholars formally distinguish generalists from specialists on the basis of the breath of their product offers (Dobrev *et al*., 2001; Freeman and Hannan, 1983). A firm's product strategy thus offers a tangible reflection of its underlying organization type. In addition, specialists and generalists are governed by different codes, routines, and organizational capabilities. Because specialists display a single-niche orientation, they develop routines, identities, and reputations that are idiosyncratic to a particular activity, which create barriers that prevent them from migrating to other, potentially attractive product niches. Generalists use resources to cope with a broader spectrum of customer demand, so they must develop and rely on heterogeneous routines and capabilities. They tend to be governed by routines that make expansion and diversification easier (Boone and Van Witteloostuijn, 2004).

Considering our assumptions about the features of the focal industrial setting, generalists likely compete for a 'standard' customer in multiple market segments with a product offering that satisfies the bulk of the demand. However, this competition leaves unserved consumers' demands for high quality products. This resource space instead is occupied by specialists, which provide high quality products to single niche customers, as the generalists continue to offer standard products to the rest of the market.[3]

Interorganizational relations

The traditional focus of resource partitioning has been on indirect interdependencies between generalists and specialists that derive from competitive processes (Freeman and Audia, 2006). Several scholars find positive relationships between the extent of competition among generalists and the entry rates and survival chances of specialists (Lomi, 1995; Soule and King, 2008). Research at the crossroads of ecology and network theory (e.g., Audia *et al*., 2006; Freeman and Audia, 2006) also analyzes symbiotic and commensalistic linkages. Symbiosis happens when there is complementarity in organizational actions, such as in vertical relationships between a focal industry population and its buyers or suppliers. De Figueiredo and Silverman (2012) show that the viability of firms in the laser printing industry increases if the density of their supplier population increases too. Commensalism instead arises when two different sub-populations deal with the same customers or suppliers, so they can voluntarily or

[3] Product quality and technological sophistication are relatively more important for specialists' customers.

involuntarily share important information related to tackling business opportunities (Audia *et al*., 2006).

Little ecology research addresses the more direct cooperative relationships among sub-populations. We focus on the market exchange of technological assets; in industrial settings characterized by the assumptions we have outlined, these assets are necessary to achieve high quality products but also can be disembodied from the products themselves. We first show how positions in the product space drive firms' behaviors in the technology space. We then focus on how the consideration of technology trade affects their respective survival chances.

HYPOTHESES

Supply side of the market for technology

To sell technology on the market, a focal firm must possess valuable technological assets and have the proper incentives to trade them. We explore both conditions, for both specialists and generalists. Specialists tap demand for high quality products that is left unsatisfied by generalists. They thus gain legitimacy, establish an identity, and increase their survival chances (Carroll and Swaminathan, 2000) by building technological expertise and maintaining their technology at the frontier. Technological excellence *per se* is particularly valued by specialists' sophisticated, high-tech customers (von Hippel, 2005). Thus, specialists cannot survive without being technologically sound. The boundaries that confine specialists in the downstream product market do not extend to the technological space. Technologies are created by significant sunk costs, with several breadth and depth search processes (Ahuja and Katila, 2001), and they display economies of scope by supporting applications in multiple, distant domains (Gambardella and Giarratana, 2013). However, the identity of specialist organizations reflects their narrow focus in the product space (Dobrev *et al*., 2001). Even if they can technically extend beyond their established niche, expansion and diversification generate identity conflicts that deprive specialists of their legitimacy (Carroll and Swaminathan, 2000; Dobrev *et al.*, 2002). In addition, diversification and expansion into other product domains demand different routines and capabilities (i.e., integration and architectural competences) that are not easy to develop in the short term, because they require both built-in differences and path dependence.

Technology licensing offers a possible way out: It generates financial returns from R&D sunk costs and avoids investments in downstream markets that could undermine the specialist's legitimacy. By selling disembodied technology in the market, specialists obtain additional revenues from their technological resources, without compromising their identity. Technology licensing also helps strengthen the legitimacy of specialists. The more a technology gets traded in the market, the more it is recognized as a necessary standard (Garud and Kumaraswamy, 1993). The seller of the technology is perceived as a source of reliable, state-of-the-art technological assets, which is perfectly consistent with and strengthens its identity in the market segment as a provider of high-quality products. That is, technology licensing signals that the firm is at the technological frontier and helps it obtain legitimacy.

Selling technology also can augment competition in the product market, by encouraging entry by other firms or improving the efficiency of current rivals (Fosfuri, 2006). This increased competition is not a serious problem for specialists though. To offset their potential profit losses, specialists that occupy focused, narrow resource spaces can sell their technology to distant market segments that are less likely to breed new direct competitors. For example, Security Innovation (2011), a leading provider of digital signature products and technology, licensed its algorithms to specialized firms like Wave System (network security and management) and Veracode (utility software), as well as to diversified generalists such as Hewlett-Packard (HP), Intel, and Dell. Then HP used Security Innovation's technology to create security process for next-generation cloud-based printing services that allow users to print remotely, a product that Security Innovation did not offer.

Generalists instead compete at the market center, rely on a broad resource space by offering products in multiple niches, and benefit from both scale and scope economies (Carroll and Swaminathan, 2000). Their customers, though displaying a preference for product performance, are willing to trade cutting-edge technological solutions for ease of use, convenience, reliability, and post-sale services. Thus, the generalist's identity and legitimacy depend more on its ability to design product architectures that integrate differentiated knowledge to serve customers with broad needs, which makes it more difficult for them to push the technological frontier in market segments in which they compete. Instead, generalists benefit from investing in R&D targeted at architectural structural knowledge (Henderson and Clark, 1990) that allows them to integrate technologies in a complex portfolio of product offerings. This type of knowledge tends to be characterized by higher tacitness, such that it is difficult to separate from the final product or trade in the market (Teece, 1986).

Regardless of their ability to generate technological assets that can be traded, generalists have fewer incentives to sell their technology on the market, all else being equal. Because generalist organizations compete to occupy the lucrative market center (Carroll, 1985), licensing could lead to saturation and higher competition (Dobrev *et al*., 2001), detrimental to their survival. That is, generalists might suffer greater profit dissipation from licensing than the revenues they earn (Arora and Fosfuri, 2003). Insofar as generalists display larger market shares, this prediction is consistent with Fosfuri's (2006) evidence from the chemical industry. In addition, if their technological expertise can extend to distant product domains, generalists can diversify and grow, without needing to resort to licensing to benefit from their technological assets (Teece, 1986). These arguments suggest:

Hypothesis 1: Specialists sell more disembodied technologies in the market for technology than generalists do.

Demand side of the market for technology

Specialists should be less likely to buy disembodied technology, for at least three reasons. First, there is a potential lack of demand for extramural technology. Specialists focus on a single market segment and are exposed to a relatively narrow set of technological needs. Their potential demand for technology on the market therefore is bounded in its breadth. Second, purchasing disembodied technology might detract from the organization's reputation for technological excellence and weaken its identity, compared with its specialist competitors (Carroll and Swaminathan, 2000). It becomes difficult to convince customers of the firm's technological superiority if it leverages external technological capabilities to develop its products. Why should customers buy from this specialist, if another firm has superior technology? Using third-party technologies even might create difficulties with regard to adapting them to the specific needs of the specialist's own highly sophisticated customers. Third, specialists suffer from limited organizational slack (Boone and Van Witteloostuijn, 2004) and thus might find it difficult to amass the financial resources needed to acquire technological assets on the market. Financial constraints can be particularly binding when the firm seeks to acquire risky assets such as technology, and external sources of capital might be available only at very high costs (Ughetto, 2010).

In contrast, generalists adopt a broad product scope and require technological competences in multiple, diverse technological domains (Dobrev *et al*., 2001). Considering their intense competition with other generalists to secure core positions at the market center, they focus on investments that help them serve the bulk of their demand; that is, they look for legitimacy based on scale and scope economies. Thus, beyond marketing capabilities or production efficiency, generalists have incentives to develop technological capabilities that can maximize the integration of different technologies within a complex portfolio of product offerings (Eggers, 2012). They consider it relatively more attractive to buy technologies that they need to meet the demand of more sophisticated, fringe customers, if those technologies are available on the technology market. Because generalists serve a wider and more heterogeneous set of customers with a larger portfolio of products, if they want to nurture stand-alone technologies, they probably must move resources away from integration and architectural knowledge, which is where they achieve their economies of scale and scope. Purchasing off-the-shelf technologies does not detract from their reputation as providers of efficient solutions; instead, it enables them to exploit their integration capabilities and absorptive capacity. Finally, generalists enjoy greater financial slack, which they can use to speed up time to market by acquiring technological assets on the market. Thus we posit:

Hypothesis 2: Generalists buy more disembodied technologies in the market for technology than specialists do.

Organizational viability

Thus far we have addressed the question of which organizational sub-population is more likely to buy or sell disembodied technology and illustrated how the process of resource partitioning defines positions in not only the product space but also the technology space. We now turn to the core of resource partitioning theory, to understand how the possibility of transacting in the technology market affects firms' performance, measured as survival hazard (Dobrev *et al*., 2001), and how positions in the product and technology space interact.

A main tenant of resource partitioning theory is that environmental conditions matter for firm survival; population density is a key independent variable (Hannan and Freeman, 1989). In our framework, the time-variant characteristics of the market for technology (most important, variation in the functioning of the market) at the industry level should take central stage. This argument aligns with Audia *et al*.'s (2006) findings that increasing symbiotic linkages favor the recognition and exploitation of business opportunities, because relevant information diffuses more efficiently. As we mentioned, a specialist can focus on technological excellence, obtain financial resources, and maintain its identity while leveraging the applicability of its technology to other domains. By buying intellectual property, a generalist can direct all its resources to integration and architectural knowledge plus complementary assets, such as marketing, distribution, and services, which are valued by its customers. Thus, a well-functioning market for technology allows firms to free up resources and reinvest them to strengthen their own specific legitimacy in the product market. But what makes a market for technology more or less well-functioning? A key variable is the number of actors. Gans and Stern (2010: 812) refer to the thickness of the market for technologies as the 'degree to which a large number of buyers and sellers participate within a market, and hence the degree to which each buyer and seller has an opportunity to engage in an effective match.' Market thickness is a necessary condition for effective matching, because it implies that for each technology on sale, there are several potential buyers, and for each demanded technology, there are several potential sellers. All else being equal, the market for technology functions better when more buyers and sellers participate in technology trade. Combining these arguments, we propose:

Hypothesis 3: The thicker the market for technology, the higher the chances of survival for both generalists and specialists.

Although a functioning technology market facilitates organization interactions that are mutually beneficial and increases organization viability, we also explore the circumstances in which, in a resource-partitioned environment, the interaction between product strategies and strategies in the market for technology might affect organizations' survival rates. An underlying consequence of our theoretical model is that a firm enhances its legitimacy and then its survival chances by building consistency and coherence across its product and technology market strategies. Specialists that are more active technology sellers should experience lower exit rates; generalists that overwhelmingly buy technology rather than selling it should display reduced mortality rates. In contrast, a specialist that engages extensively in technology acquisitions likely puts its survival at risk, because its product and technology strategies convey an identity conflict. Similar arguments apply to a generalist that misaligns its product and technology strategies. Therefore, we predict that a correct fit enhances organization viability, but a pairing that contradicts the fundamental identity of the specific organizations is detrimental. This reasoning extends current research in the ecology tradition that highlights the importance of coherence and fit and the liability of mixed strategies for organizational survival (Giarratana and Fosfuri, 2007; Zuckerman *et al.*, 2003); it also leads to the following hypotheses:

Hypothesis 4a: The benefit of a narrow product strategy (specialist) for organizational viability increases if the focal firm predominantly sells disembodied technologies in the market for technology.

Hypothesis 4b: The benefit of a broad product strategy (generalist) for organizational viability increases if the focal firm predominantly buys disembodied technologies in the market for technology.

DATA AND METHODOLOGY

Security software industry

The inception of SSI coincided with the growing market for personal computers and the development of the Internet in the late 1980s (Giarratana, 2004). Worldwide sales increased from US$2.2 billion in 1997 to US$6.9 billon in 2002 (International Data Corporation, 2003). North America and Europe accounted for 50 percent and 30 percent, respectively, of worldwide market share in 2002 (International Data Corporation, 2003). The industry featured an active market for technology; 15 percent of its revenues in 2002 came from licensing software algorithms. Crypto-algorithms, which specify the mathematical transformations performed on data, are the main technology of SSI. The crypto-algorithm is responsible for the quality of the security software product, in terms of both its security level and the speed of mathematical calculations (Giarratana, 2004).

From 1989 to 2002, SSI firms undertook more than 400 technology transactions (Infotract Promt, 2003, www.gale.cengage.com). Our data do not suggest that specialized technology suppliers—which only sell technology but do not compete in the product market—are relevant for SSI, as they are in industries such as chemicals, biotechnology, and semiconductors (Arora *et al*., 2001). Most technology trades occur horizontally among firms that have a product market presence and thus compete in the same downstream industry.

Customers of SSI fall into two broad categories: (1) medium- to low-tech users who demand comprehensive security packages, prefer one-stop-shop solutions, and ask for a high level of technological service and assistance or (2) sophisticated buyers who seek the best product quality and demand state-of-the-art technology. Similar to other industries (see Carroll and Swaminathan (2000) for the beer industry, Swaminathan (2001) for the wine industry, and Mezias and Mezias (2000) for the U.S. feature film industry), this customer partitioning makes both generalists and specialists viable, despite strong competitive intensity in the industry. Generalists offer a broad product portfolio that covers several SSI niches and satisfies the needs of the vast majority of customers; specialists thrive by offering continuous updates and improved versions in their established niche, which address the requests of high-tech, sophisticated customers.

Check Point is a good example of a specialist that functions in the firewall niche: Its FireWall-1 product won a prestigious industry award for several consecutive years, offering 'best overall performance, management and logging features, which are three key parts to a security solution' (*Network Computing*, 1998). In contrast, Network Associates provides a good example of a generalist organization that competes in several market niches. The firm has built a large, flexible portfolio of software products to offer its customers (*Fortune*, 1998).

Sample construction

Our study population consists of all firms that introduced at least one off-the-shelf security software product prior to December 2002. Thus, all firms in our sample competed in the downstream market. We gathered product introduction data from Infotrac's General Business File ASAP and PROMT database (formerly Predicast), which reports events in several industrial sectors, as publicized in various trade journals, magazines, and specialized press vehicles (e.g., *eWeek*, *PC Magazine*, PR Newswire, Telecomworldwire). We searched for all press articles that reported a 'product announcement,' 'new software release,' or 'software evaluation' in SSI (standard industrial classification [SIC] code 73726) between 1980 and 2002. We carefully cleaned these data, to avoid product double counting. The first product was introduced in 1989, and from 1989 to the end of 2002, we registered 736 different firms that introduced 2,589 products. According to their SIC codes, we could classify these products into six niches: authentication digital signature, antivirus, data and hardware protection, firewalls, utility software, and network security and management. Table 1 provides the annual average number of active firms and the annual average number of launched products for the periods 1989–1995 and 1996–2002. There is heterogeneity among niches, in terms of both launched products and active firms. Arora and Nandkumar (2012), in their study of startups in SSI, report barriers to firms' mobility across niches due to technological specialization. Figure 1 depicts the trend of active firms and launched products, which shows the consistent expansion of the SSI market during our study period.

Insert Table 1 and Figure 1 about here

From the Infotrac database, we downloaded all articles that reported a licensing event in SIC 73726 (encryption software sector). After carefully reading the abstracts, we kept only those articles that referred to technology licensing contracts and removed articles unrelated to a technology transaction (e.g., marketing, franchising agreements). Finally, using the article texts, we assigned buyer (licensee) and seller (licensor) roles to the firms engaged in each transaction. We assume that the date of the article is the date of the event.

Dependent variables

We used two dependent variables to test the first two hypotheses. The variable *Technology sales* is time variant and corresponds to the annual number of contracts signed by a firm as a technology seller in SSI. The variable *Technology acquisitions* is also time variant and equals the number of contracts signed by a company as a buyer of technology in SSI. For example, Entercept Security Inc. licensed its intrusion prevention technology to iPlanet, and iPlanet embedded it into its core product. The deal enabled iPlanet's users to gain protection against intrusions, website defacement, data theft, and misuse (*Telecomworldwire*, 2001). In an example involving NeoPlanet and Compaq, the former supplied its Viassary security technology to the latter, so that Compaq could include the technology in its Advisor product, which enabled companies to communicate effectively with customers through multiple digital touch points (*PR Newswire*, 2001).

For the remaining hypotheses, we estimated a hazard model to predict survival. Our dependent variable is thus a time-variant dummy, equal to 1 if the firm exits the market at time t and 0 if it continues until the next period. We used several sources to identify exits from the market: the U.S. Patent and Trademark Office, Hoover's, Mergent onLine, Bureau Van Djik's Icarus, Jade, and Amadeus. In addition, we searched the Infotrac Company Resource Data Center and Infotrac's PROMT for any press articles that included news related to a firm's exit (e.g., acquisition, bankruptcy, shutdowns).

Independent variables: Generalists and specialists

Organizational niche width provides a commonly used proxy for defining generalist versus specialist organizations. For example, Dobrev *et al*. (2001, 2002) measure the niche width of an automobile producer in terms of the min-max spread of engine capacity across all models manufactured by a firm at a given point in time. Variations across this single dimension (greater or lesser niche width) capture the differences across organizations along the specialist–generalist dimension. In line with prior literature, we computed a *Berry index* of the dispersion of a firm’s product portfolio:

$$\text{Berry}_{it} = \left(1 - \sum_{k=1}^{6} (R_{kt})^2\right) * 100,$$

where R_{kt} is the ratio of the cumulative number of firm *i*’s products in the *k*th niche of SSI to the total number of firm *i*’s products in all niches of SSI in year *t*. Because SSI consists of six major niches, *k* varies between 1 and 6. By construction, the Berry index can vary between 0 (no differentiation) and 100 (maximum differentiation).

The standard interpretation of this measure indicates that organizations with high values on the Berry index are more likely to be generalists than specialists. That is, the single measure captures both population groups. We believe that this standard interpretation of the Berry index (niche width) might be too coarse in our context though, because a low Berry index does not necessarily correspond to a specialist firm. As our theory suggests, and data from SSI confirm, product versioning is a standard practice by organizations that specialize in a particular niche and rely on customization and user-driven innovation practices (Shapiro and Varian, 1999). A low Berry index cannot capture the high degree of product versioning or the constant releases that characterize this industry. We therefore complement it with a second product strategy measure, to increase the chances of depicting our study phenomena accurately.

Specifically, we calculate a *versioning index* that is time variant and equal to the cumulative number of new versions in the product niche that spurred the firm’s entry into SSI. Thus, if firm *i* entered SSI in period *t* with a product in niche *k*, the versioning index counts the cumulative number of products by firm *i* in niche *k*. This entry product niche is crucial, because it enables new ventures to establish their reputation and first-mover advantages, which provide substantial benefits in the fierce market competition that occurs in the periods immediately following entry (Kazanjian and Rao, 1999). A post-entry niche specialization strategy also occurs with more frequency in the same niche that the firm served at its entry (Debruyne, Moenaert, Griffin, Hart, Hultink, and Robben, 2002). Therefore, firms that score high on the versioning index should be more likely to follow a specialist product strategy. Imagine that a firm enters SSI by developing a product in niche *z* in 1997, and by 2000, it updates this product three times, releasing a new version every year. The value of its versioning index would be 2, 3, and 4 in 1998, 1999, and 2000, respectively. If this firm also released products in another niche, it would not affect the *versioning index* but only the *Berry index* .[4]

To ensure the comparability of our findings with those of previous studies, we started with a regression in which we introduced the Berry index, then ran a regression with only the versioning index, and finally included both variables simultaneously in a third regression.[5]

For H3 and H4, the independent variables are *ThicknessMfT* and *NetTechAcquisition*, respectively. Lacking a consolidated empirical tradition for measuring the thickness of technology markets, we developed various proxies that, even if correlated, capture different aspects of the construct. *ThicknessMfT1* is the ratio of the annual number of seller and buyer organizations over the cumulative number of patents in SSI, which captures the realized (licensing parties) versus potential market for technologies (patent availability). [6] *ThicknessMfT2* is the annual number of seller and buyer organizations divided by a concentration measure (Herfindhal index), calculated with the firm's share of products sold by niche, to standardize licensing activity by the actual concentration in downstream markets. *ThicknessMfT3* is a concentration ratio (Herfindhal) of the firm's annual share in technology

[4] As a robustness check, we considered a versioning index, calculated as the average level of versioning in all niches entered by the focal firm. The results, which are available on request, remain qualitatively unchanged.
[5] In another robustness check, we constructed two dummies by combining the indexes: a specialist dummy that equals 1 when a firm attains high values on the versioning index (top quartile) and lower-than-average values on the Berry index, and a symmetric generalist dummy. The results remained qualitatively unchanged.
[6] We also experimented with the simple sum of number of technology sellers and buyers in a given year, which led to similar results.

licensing contracts. Finally, *ThicknessMfT4* is an adaptation of the measure used by Colombo and Grilli (2005) to determine the availability of venture capital markets, equal to the annual firm share of technology sales (over the total technology sales transactions in the sample period), divided by the annual share of firms in SSI with a product. Each measure appears separately in Models 3–6, respectively.

NetTechAcquisition reflects the difference, for firm *i*, between the number of purchased and sold technologies in each period *t*. It thus captures whether a firm is acting predominantly as a technology seller (negative) or a technology buyer (positive). We next interacted *NetTechAcquisition* with our indicators of specialist and generalist organizations, to capture the notion that being a specialist (generalist) increases survival chances; this effect is stronger if the firm sells more (less) technology than it buys.

Controls

We introduced several time-variant and -invariant control variables. According to ecology research, population density can have a U-shaped relationship with firm exit rates (Carroll, Bigelow, Seidel, and Tsai, 1996; Dobrev *et al*., 2002; Sorenson, 2000). *Density* (i.e., the number of firms operating in each SSI niche) and density squared (*density*^{2}) with a one-year lagged value (Carroll *et al*., 1996) appear in our models, because they are canonical controls in survival analyses (H3 and H4), and we suspect they might equally affect strategies in the market for technology (H1 and H2), such as through increased competition or improved chances to find suitable alternative buyers or suppliers. We introduced experience in the market, measured as the number of years a firm has competed in SSI (*age in market*), or the difference between year t and the year the firm entered the market.

Although our sample contains some large information and communication technology firms, it mostly comprises small- to medium-sized, young firms, which means that traditional, time-varying measures of firm size (e.g., sales, number of employees) are difficult to obtain.

We used a measure of firm size that counts the raw number of products a firm sells in a given year (*total products*). Dobrev and Carroll (2003) suggest a proxy for size as the scale of operations, calculated as the annual number of units produced. We controlled for the firm's technological capital in SSI too. Following Dushnitsky and Lenox (2005), we measured the cumulative number of firm patents granted by the U.S. Patent Office (www.uspto.gov), applying a discount rate of 15 percent (other discount rates lead to similar results). We considered all patents granted in U.S. technological classes 380 ('Cryptology') and 705, subclasses 50–79 ('Business Processing Using Cryptography') (Gambardella and Giarratana, 2013). This variable was labeled *Patents.*

To temper any significant omitted variable problems of firm unobserved heterogeneity, we also introduced *Pat_Forward citations* and *Pat_Generality*. The former is the cumulative number of forward citations divided by the cumulative number of patents, which provides a proxy of patent quality (Fleming, 2001). The latter derives from the generality index introduced by Hall, Jaffe, and Trajtenberg (2001); the measure reflects the annual firm value of the index weighted by the number of firm patents. This generality index offers a proxy of the firm's capability to produce general purpose technology, which correlates with the ability to license (Palomeras, 2007).

Time-invariant control variables capture the effects of several pre-entry conditions. We employed a measure of organizational population density at the time the firm entered the market (*density delay*), a standard control in entry and survival literature (Carroll *et al*., 1996; Sorenson, 2000). The firm's age at market entry proxied for scale and experience effects. Age (*entry age*) is the difference between the entry year and the year of a firm's founding. We also included a dummy variable that takes a value of 1 if the organization is a U.S. firm and 0 otherwise (*U.S. dummy*). This control attempts to smooth out the possible distortion effect for non-U.S. firms, because the United States is the largest and most important market for SSI.

Following Ahuja and Katila (2001), we created control variables that correspond to the pre-sample value of the dependent variable for each firm (i.e., *entryseller* and *entryacquirer*). These measures control for unobserved differences in capabilities and strategic postures in technology markets. Failing to account for such unobserved heterogeneity in the empirical test of H1 and H2 can cause estimation problems, overdispersion, and serial correlation.

Finally, in testing H1 and H2, we inserted year dummies. We provide descriptive statistics in Table 2 and a partial correlation matrix for the variables in Table 3.

Insert Tables 2 and 3 about here

Estimation method

The dependent variables for H1 and H2—that is, the annual number of sold/purchased technologies—are count variables and may take only nonnegative integer values. Applying conventional linear regression models that assume homoskedasticity and normally distributed error terms would lead to biased estimates; a Poisson regression approach is more appropriate (Hausman, Hall, and Griliches, 1984). Thus we estimate the following regression model:

$$Y_{it} = \exp (X_{it}\beta + C_{it}\gamma),$$

where Y_{it} is the number of technology licenses sold or purchased in year t, X_{it} refers to the set of measures of a firm's product market strategy that capture its generalist versus specialist orientation, and C_{it} is a vector of control variables. Results hold unchanged when we lag all independent and control variables by one year. The specification does not account for unobserved heterogeneity, so we followed Ahuja and Katila (2001) and Ahuja and Lampert (2001), who estimate Poisson regression models using the general estimating equation (GEE) approach, which models the longitudinal Poisson data with serial correlation (Liang and Zeger, 1986). A clear advantage of the GEE methodology is that it provides a better treatment for overdispersion and serial correlation, which often are present in panel data sets (Liang and Zeger, 1986). For limited-range dependent variables and longitudinal research designs, GEE produces efficient and unbiased parameter estimates when the dependent variable is highly correlated within subjects (Ballinger, 2004).

To test H3 and H4, we employed a hazard model to estimate the hazard rate, namely, the probability of exit from the market at time *t*, conditional on being in the market at time *t* – 1. We opted for the piecewise exponential model, as mainstream ecology research suggests. This exponential model can be expressed as $\Lambda_{jt} = exp\ (\alpha_t + X_{jt}\beta_j)$, where X is the covariate vector, β is the vector of coefficients, and α is a constant coefficient associated with the time period *t* (see Blossfeld and Rohwer, 2002). In our regression, the time period is the year, and we control for both left and right truncation.

RESULTS

In Tables 4 and 5, we present the results for all models using the GEE Poisson estimators, with robust standard errors. The baseline models include only firm- and industry-level control variables. Then Model 1 incorporates the Berry index, and Model 2 includes the versioning index. In Model 3, we introduce both indexes simultaneously.

According to the findings in Table 4, we can confirm H1: The estimate of the Berry index is negative and highly significant when it appears separately and when it coexists with the versioning index. Therefore, the larger the niche breadth of a company, the fewer deals it makes as a supplier in the market for technology. The parameter estimate of the versioning index is positive and statistically significant, such that firms that release more versions and updates of their core products sell more disembodied technologies.

Insert Table 4 about here

With regard to the control variables in Model 3 of Table 4, more experience in the market induces firms toward technology sales strategies, given the positive and significant coefficient of *age in market*. Size of firms, as captured by the raw number of products, encourages technology licensing strategies. The variable *Patents* turns out to be positive and significant, suggesting that greater technological capital encourages the sale of disembodied technology. The negative and significant sign of *Pat_Generality* implies that firms with more general patent portfolios reduce technology sales. The proxy for patent stock quality encourages firms to sell technology in technology markets, according to the positive and significant coefficient of *Pat_Forward citations*. The coefficients of the rest of the control variables are not statistically different from zero.

We display in Table 5 the estimation results of the GEE Poisson models with the number of technology acquisitions by a firm in a given year as the dependent variable. These results corroborate H2, in that the estimated coefficient of the Berry index is positive and significant. Organizations with broader niche width tend to buy more technology in the market. The coefficient for the versioning index in Models 2 and 3, though negative, is not statistically different from 0.

Insert Table 5 about here

Regarding our control variables, the positive and significant coefficient of density and the negative and significant coefficient of density squared jointly suggest an inverted U-shaped relationship between technology acquisition strategies and the degree of product market competition. Size, as measured by the raw number of products, enhances the number of technology purchases, perhaps through the provision of greater financial latitude or simply because of greater scale, which implies more demand for disembodied technologies. To the extent organizational capabilities are apt to produce general purpose technologies, firms increase acquisitions of disembodied technologies, shown by the positive and significant coefficient of *Pat_Generality*. Harsher competitive conditions at entry push firms toward technology acquisition strategies, according to the positive and significant coefficient of *density delay*. Age at entry also promotes the purchase of disembodied technologies. De alio entrants (older age at entry) are more likely to license in externally developed technologies. The other controls do not exhibit statistical significance. Finally, the estimated scale parameters do not indicate that overdispersion in the data is a serious concern.

Table 6 provides the results for the hazard estimation. Model 1 is the baseline model that excludes our core covariates, Model 2 encompasses the Berry and versioning indexes, and Models 3 through 6 are the full models that feature the different *ThicknessMfT* variables, together with *NetTechAcquisition*, multiplied by both product strategy indexes. Adding the variables in each model increases the level of fit, as implied by the chi-square test of significance (compared with Model 1: χ^2 = 87.24 for Model 6; χ^2 = 70.68 for Model 5; χ^2 = 103.40 for Model 4; χ^2 = 108.28 for Model 3; χ^2 = 37.76 for Model 2).

ThicknessMfT in Models 3, 4, and 6 exhibits a negative, significant coefficient, meaning that a thicker market for technology augments the survival chances of all competitors in SSI, in support of H3. The variable in Model 5 captures a Herfindhal measure with regard to firms' annual share in technology sale and is positive and significant. Therefore, a less concentrated market for technology (lower value of *ThicknessMfT* in Model 5) implies higher survival chances for the firm population. The interaction between *NetTechAcquisition* and the Berry index is negative, whereas the interaction with the versioning index is positive, in confirmation of H4a and H4b.

Insert Table 6 about here

Taken together, these findings are consistent with our theoretical model, which suggests that by partitioning the resource space, firms increase their survival chances. Both product strategies decrease an organization's likelihood of exiting the market. A firm's position in the product market also interacts with its position in the technology market: The organizational viability of generalists (specialists) increases (decreases) when they engage in relatively more technology purchases than technology sales. Thicker technology markets allow for cooperative interactions among organizations and help boost survival chances.

DISCUSSION

Combining the resource partitioning tradition (Carroll, 1985; Dobrev *et al*., 2001; Swaminathan, 2001) and research on the market for technology (Arora *et al*., 2001; Gans and Stern, 2003)—domains that generally coexist as silos—enables us to understand better why some firms engage, as buyers or sellers, in more technology transactions than others and how markets for technology and the direction of technology trade affect their survival chances.

This hybrid framework offers novel insights for research into the market for technology. First, current literature focuses on the determinants of out- and in-licensing, such as transaction costs, fear of competition, technology characteristics, and risk sharing (Anand and Khanna, 2000; Arora and Ceccagnoli, 2006; Arora *et al*., 2001; Fosfuri, 2006; Gans and Stern, 2003). We show that product strategy influences a firm's strategies in the market for technology and thereby identify another source of heterogeneity that can explain firms' varying technology strategies. Second, our analysis suggests that the existence of a thick market for technology (Gans and Stern, 2010) constitutes a mechanism that facilitates the exchange of complementary resources between generalists and specialists (Teece, 1986) and therefore their survival. An underdeveloped technology market forces generalists to divert resources from the accumulation of integrative knowledge to develop state-of-the-art technology, lowering their survival chances, because generalists need to appeal to their broad customer base (Carroll, 1985). Similarly, for specialists, the absence of a technology market means postponing the commercial exploitation of their technology, which reduces their chances to mitigate problems of scarce slack resources (Arora *et al*., 2001). The benefits of well-functioning markets for technology have been widely discussed (Arora and Gambardella, 2010), but this mechanism has not been revealed previously.

The joint consideration of both resource partitioning and markets for technology helps extend extant literature as well. Most prior research has investigated the intensity and type of competition in different resource spaces (Carroll and Swaminathan, 2000; Hannan and Freeman, 1989). According to ecology research, partitioning resources creates two groups of organizations (Carroll, 1985; Dobrev *et al*., 2001; Swaminathan, 2001); we show that it does not imply their complete isolation in impermeable spaces though. Not all resources are partitioned, because specialists' strategies and routines generate non-rival or abundant resources (e.g., technologies) that can be exchanged for another set of resources produced by generalists (e.g., liquidity, distribution channels). In short, an important contribution of our work is to underscore that relationships between generalists and specialists are more complex than suspected; these two organizational populations might compete in one resource space and be complementary in another, with a significant impact on survival rates. Although ecology literature already has emphasized that the lack of coherence creates a liability of middleness (Zuckerman *et al.*, 2003), our study is among the first to highlight the presence of this liability at a new level of analysis, between niche positioning and roles in technology trade.

We have focused on technology trade through arm's-length agreements, but extending our theoretical logic to trading or sharing resources other than technology (i.e., human resources) might provide novel insights while also confirming the generalizability of our framework. The evidence we present refers to a specific industry, with peculiar features, that matches our theory, so our study lacks cross-industry heterogeneity. Industries such as lasers, biotechnology, conversion coating, and battery chemistry offer good candidates for confirmatory studies.

Our results can be useful to managers. First, we show different paths for survival. A specialist organization should pay continuous attention to the demand side of the market for technology and quickly identify potential buyers that offer low product competition threats, then create updated technologies that appeal to this market. Generalists instead should scan the supply side of the market for technology and develop competences for identifying appropriate technologies to use, adapting quickly to their in-house knowledge and routines. For specialists, our results call for actions that make their technology more easily accessible and visible on the market; for generalists, they imply the creation of business intelligence that constantly scans and monitors the technology landscape.

Second, our findings encourage managers to recognize the importance of fine-tuning their product and technology strategies, especially when the technology can be disembodied from final products and provide a source of firm legitimacy and reputation. We have shown that mismatches can be detrimental to a firm's survival and that successful organizations must guarantee coherence in their product and technology strategies. The latter effort requires managers to adapt their product and licensing strategies; it also demands efficient coordination across the firm's product, marketing, and research divisions. A stand-alone licensing unit could help both types of organizations and might strengthen bridges across divisions, avoiding mismatch among strategy timing, steps, and decision order. This proposition is consistent with recent research that shows that firms with centralized licensing units tend to be more active in technology markets (Arora, Fosfuri, and Ronde, 2013).

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Table 1. Annual average number of firms and products per niche

	1989–1995				1996–2002			
	Number of Firms		Number of Products		Number of Firms		Number of Products	
Niche	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Authentication	5.6	2.9	5.8	3.3	5.6	3.4	6.4	4.2
Antivirus	3.7	2.0	4.7	2.7	29.5	33.8	38.1	45.0
Authentication digital signature	14.8	12.1	19.8	15.6	58.4	26.7	80.4	43.3
Firewalls	6	2.8	16.5	13.4	25.2	18.2	33.5	20.6
Network security and management	7	8.1	9.0	11.2	82.8	18.5	135.3	29.7
Utility software	5.0	2.2	5.0	2.2	69.3	74.0	95.0	105.7

Figure 1. Firm and product density in SSI

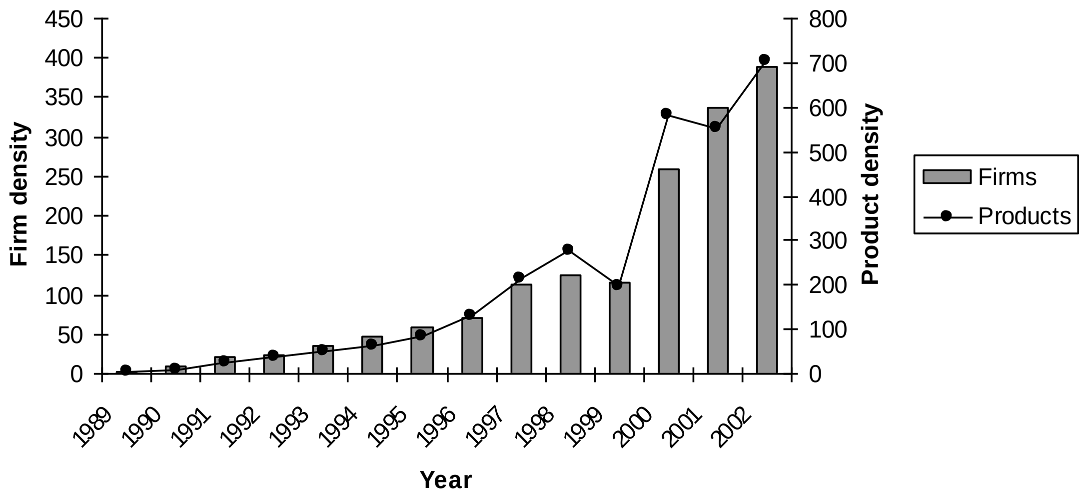

Table 2. Descriptive statistics

Independent Variables		Mean	SD	Min	Max
Dependent variables					
1	Technology sales	0.07	0.33	0	6
2	Technology acquisitions	0.10	0.58	0	13
Core variables					
3	Berry index	11.30	21.83	0	80
4	Versioning index	1.68	1.67	0	25
Time-invariant controls					
5	Density delay	135.84	113.60	3	388
6	Entry age	6.77	15.80	0	159
7	U.S. dummy	0.74	0.44	0	1
8	Entryseller	0.03	0.26	0	7
9	Entryacquirer	0.03	0.23	0	4
Time-variant controls					
10	Density	181.29	111.28	0	338
11	Age in market	2.74	2.71	0	13
12	Total products	1.54	1.64	1	29
13	Patents	5.81	46.76	0	771.24
14	Pat_Generality	1.63	0.52	0	2.99
15	Pat_Forward citations	0.54	3.07	0	45.33
16	NetTechAcquisition	0.02	0.65	-6	13
17	ThicknessMfT ♣	0.03	0.02	0	0.05
18	ThicknessMfT ♠	0.80	0.61	0	1.83

Source: These elaborations stem from various data sources, including Infotrac's General Business File ASAP and PROMPT, the U.S. Patent and Trademark Office, and Compustat.

♣ This *ThicknessMfT* variable refers to the ratio of the annual number of seller and buyer organizations to the cumulative number of patents.

♠ An alternative *ThicknessMfT* variable is the annual number of seller and buyer organizations divided by a Herfindhal measure, built on annual industrial products, which encompasses all six SSI niches (a lower value in the denominator implies a more fragmented product market, which then increases the thickness measure).

Table 3. Bivariate correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1																
2	0.04	1															
3	-0.09	0.33	1														
4	0.25	-0.03	-0.03	1													
5	0.19	0.02	-0.02	-0.01	1												
6	0.01	0.21	0.20	-0.02	0.14	1											
7	-0.01	0.04	0.00	0.03	-0.03	-0.10	1										
8	0.10	-0.02	-0.06	0.06	0.14	0.01	-0.02	1									
9	-0.03	0.09	0.12	-0.04	0.20	0.19	-0.02	-0.02	1								
10	0.06	-0.01	0.12	0.11	0.59	0.07	-0.02	0.08	0.11	1							
11	-0.11	0.02	0.14	0.13	-0.57	-0.08	0.04	-0.08	-0.10	0.16	1						
12	0.09	0.61	0.38	0.20	-0.01	0.16	0.06	0.00	0.04	0.01	0.04	1					
13	0.03	0.37	0.26	0.00	-0.09	0.29	0.06	-0.01	-0.02	-0.05	0.07	0.41	1				
14	-0.07	0.01	-0.09	-0.07	-0.44	-0.06	0.01	-0.07	-0.09	-0.71	-0.07	0.02	0.05	1			
15	0.09	0.18	0.19	0.25	-0.11	0.11	0.02	-0.02	-0.02	-0.07	0.05	0.29	0.33	0.08	1		
16	-0.47	0.87	0.34	-0.15	-0.08	0.19	0.03	-0.07	0.09	-0.04	0.07	0.49	0.31	0.04	0.11	1	
17	0.18	0.09	0.15	0.08	0.49	0.08	-0.02	0.08	0.10	0.58	0.12	0.06	-0.04	-0.55	-0.07	-0.01	1
18	0.19	0.12	0.13	0.07	0.39	0.07	-0.02	0.06	0.08	0.39	0.11	0.07	-0.03	-0.40	-0.06	0.01	0.97

Notes: Correlations with an absolute value of 0.04 or more are significant at $p < 0.05$.

Table 4. GEE/Poisson regressions of the determinants of technology sales for SSI firms, 1989–2002

	Technology Sales							
	Baseline		Model 1		Model 2		Model 3	
Constant	-7.303**	(0.503)	-3.248**	(0.368)	-0.556**	(0.353)	2.739**	(0.431)
Core variables								
Berry index			-0.089**	(0.013)			-0.054**	(0.010)
Versioning index					0.291**	(0.039)	0.232**	(0.039)
Time-invariant controls								
Density delay	0.003	(0.004)	0.010**	(0.002)	0.008**	(0.002)	0.002	(0.003)
Entry age	-0.010†	(0.005)	-0.056**	(0.019)	-0.005	(0.005)	-0.005	(0.006)
U.S. dummy	-0.166	(0.168)	-0.011	(0.181)	-0.188	(0.148)	-0.099	(0.406)
Entryseller	0.222†	(0.134)	0.124	(0.127)	0.167	(0.124)	0.131	(0.122)
Time-variant controls								
Density	0.012	(0.012)	0.024*	(0.010)	0.006	(0.010)	0.003	(0.010)
Density2	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Age in market	-0.189	(0.213)	0.041	(0.151)	-0.187	(0.125)	-0.326*	(0.147)
Total products	0.006	(0.025)	0.552**	(0.083)	-0.005	(0.038)	0.055**	(0.020)
Patents	0.004†	(0.003)	0.006*	(0.003)	0.005*	(0.002)	0.011**	(0.002)
Pat_Generality	0.348†	(0.199)	-1.336**	(0.176)	-2.269**	(0.331)	-4.487**	(0.335)
Pat_Forward citations	0.091**	(0.014)	0.064**	(0.009)	0.042**	(0.011)	0.035*	(0.014)
Year dummies	Yes		Yes		Yes		Yes	
Scale parameter	1.27		4.02		0.83		1.25	
Number of firms	736		736		736		736	
Number of observations	3152		3152		3152		3152	
Wald test (χ2)	415.86		659.30		484.38		726.04	
Prob > χ2	0.000		0.000		0.000		0.000	

† $p < 0.1$. * $p < 0.05$. ** $p < 0.01$.

Notes: Values in parentheses are heteroskedastic consistent standard errors.

Table 5. GEE/Poisson regressions of the determinants of technology acquisitions for SSI firms, 1989–2002

	Technology Acquisitions							
	Baseline		Model 1		Model 2		Model 3	
Constant	-9.302**	(1.554)	-10.446**	(1.237)	-6.441**	(0.713)	-10.394**	(1.432)
Core variables								
Berry index			0.056**	(0.005)			0.054**	(0.005)
Versioning index					-0.232	(0.157)	-0.070	(0.115)
Time-invariant controls								
Density delay	0.006*	(0.002)	0.004*	(0.002)	0.006**	(0.002)	0.005*	(0.002)
Entry age	0.017**	(0.003)	0.009**	(0.002)	0.015**	(0.003)	0.008**	(0.002)
U.S. dummy	0.548*	(0.272)	0.278	(0.208)	0.507†	(0.295)	0.138	(0.233)
Entryacquirer	0.640**	(0.145)	0.330**	(0.126)	0.650**	(0.149)	0.321*	(0.124)
Time-variant controls								
Density	0.065**	(0.017)	0.065**	(0.018)	0.041**	(0.013)	0.063**	(0.019)
Density2	-0.0003**	(0.000)	-0.0003**	(0.000)	-0.0003**	(0.000)	-0.0003**	(0.000)
Age in market	0.165†	(0.092)	-0.005	(0.057)	0.202**	(0.070)	0.053	(0.068)
Total products	0.147**	(0.050)	0.113**	(0.025)	0.110†	(0.061)	0.120**	(0.029)
Patents	0.000	(0.002)	0.000	(0.001)	0.000	(0.002)	0.000	(0.001)
Pat_Generality	1.192*	(0.482)	1.192**	(0.275)	0.582*	(0.234)	1.172**	(0.399)
Pat_Forward citations	0.070**	(0.025)	0.037	(0.023)	0.077**	(0.028)	0.034	(0.027)
Year dummies	Yes		Yes		Yes		Yes	
Scale parameter	1.18		0.88		1.22		0.95	
Number of firms	736		736		736		736	
Number of observations	3152		3152		3152		3152	
Wald test ($\chi 2$)	518.43		793.66		613.67		917.73	
Prob > $\chi 2$	0.000		0.000		0.000		0.000	

† $p < 0.1$. * $p < 0.05$. ** $p < 0.01$.

Notes: Values in parentheses are heteroskedastic consistent standard errors.

Table 6. Piecewise exponential models of market exit for security software firms

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Core variables						
Berry index		-0.0258**	-0.0231**	-0.0234**	-0.0252**	-0.0248**
		(0.0058)	(0.0057)	(0.0057)	(0.0058)	(0.0058)
Berry index×NetTechAcquisition			-0.0433**	-0.0436**	-0.0441**	-0.0438**
			(0.0075)	(0.0075)	(0.0075)	(0.0077)
Versioning index		-0.2533**	-0.2296**	-0.2304**	-0.2381**	-0.2463**
		(0.0845)	(0.0805)	(0.0808)	(0.0832)	(0.0852)
Versioning index×NetTechAcquisition			0.5780**	0.5741**	0.5731**	0.5339**
			(0.1505)	(0.1507)	(0.1640)	(0.1591)
Time-invariant controls						
Density delay	-0.0204*	-0.0215**	-0.0189**	-0.0194**	-0.0214**	-0.0208*
	(0.0015)	(0.0016)	(0.0018)	(0.0017)	(0.0016)	(0.0017)
Entry age	-0.0121	-0.0101	-0.0149	-0.0148	-0.0150	-0.0157
	(0.0076)	(0.0078)	(0.0094)	(0.0094)	(0.0095)	(0.0098)
Non-U.S. dummy	-0.0367	-0.0575	-0.0687	-0.0752	-0.0834	-0.0661
	(0.1281)	(0.1247)	(0.1152)	(0.1157)	(0.1208)	(0.1196)
Time-variant controls						
Density	-0.0253**	-0.0173**	-0.0128*	-0.0131*	-0.0173**	-0.0320**
	(0.0054)	(0.0057)	(0.0053)	(0.0053)	(0.0056)	(0.0072)
Density^2	0.0002**	0.0001*	0.0001*	0.0001*	0.0001*	0.0002**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age in market	-0.2950**	-0.2117**	-0.1572*	-0.1670*	-0.2021**	-0.1925**
	(0.0573)	(0.0697)	(0.0708)	(0.0704)	(0.0703)	(0.0690)
Total products	-0.3983**	-0.2198*	-0.1660†	-0.1686†	-0.1887*	-0.2483*
	(0.0982)	(0.0929)	(0.0853)	(0.0860)	(0.0925)	(0.1075)
Patents	-0.1805*	-0.1735†	-0.1171†	-0.1195†	-0.1282	-0.1298
	(0.0822)	(0.0959)	(0.0709)	(0.0722)	(0.0804)	(0.0800)
Pat_Generality	-0.3570**	-0.4001**	-0.5077**	-0.4379**	-0.3979**	-0.3592**
	(0.0851)	(0.0867)	(0.1054)	(0.1008)	(0.0884)	(0.0845)
Pat_Forward citations	-0.1202†	-0.0683	-0.1549*	-0.1525*	-0.1626*	-0.1497*
	(0.0688)	(0.0465)	(0.0716)	(0.0716)	(0.0774)	(0.0752)
NetTechAcquisition			-0.8292**	-0.8218**	-0.7120**	-0.6299*
			(0.2761)	(0.2765)	(0.2696)	(0.2628)
ThicknessMfT ♣♠			-1.7217**	-3.0675**	0.4002**	-0.0567*
			(0.2417)	(0.3188)	(0.1227)	(0.0231)
Log-likelihood	1338.16	1357.04	1392.30	1389.86	1373.50	1381.78
d.f.	9	11	15	15	15	15

† $p < 0.1$. * $p < 0.05$. ** $p < 0.01$.

Notes: Values in parentheses are heteroskedastic consistent standard errors. This sample includes 278 exits and 1,505 organization-years (mortality rate models refer to 1989–2002).

♣ The *ThicknessMfT* variable in M3 refers to the ratio of the annual number of seller and buyer organizations over the cumulative number of patents; in M4, it is the annual number of seller and buyer organizations divided by a Herfindhal measure, built on the firm's annual share of products embracing all the six SSI niches; in M5, it is an annual Herfindhal index of each firm's annual share in technology sales; and in M6, it is the annual share of technology sales in SSI (out of the total number of technology sales in SSI), divided by the share of firms in SSI out of the total firms that release a product.

♠ To obtain coefficient and standard error estimates of comparable size, the values of the *ThicknessMfT* variable in Model 3 were divided by 100.