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Schumpeterian Competition and the Dynamics of Spillover Pools

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Abstract

Spillover pools are often assumed to be exogenous. Under this assumption, the amount of external knowledge the focal firm can capture increases with its knowledge-based assets. However, this positive relation may not hold when spillover pools are endogenously determined by competitive positioning strategies. Indeed, the dual nature of knowledge-based assets ? competition and learning - challenges the exogeneity assumption of spillover pools. We investigate this issue in the context of market entry. While knowledge stocks may increase incumbents? learning ability, they also create competitive concerns for entrants, who bring innovative ideas into the industry. In the presence of market overlap, entrants may react to competitive threats by positioning in distant technological niches to differentiate their products, thus reducing their technical proximity to incumbents and, consequently, impoverishing the relevant spillover pool. Overall, we enrich the scholarly understanding of inter-organizational learning by showing that high investment levels in knowledge-based assets, which may be beneficial in a static environment, can be less effective in a Schumpeterian setting where entrants can apply novel knowledge in remote technological niches. Our paper further contributes to the recent development of the duality tenet of the RBV by identifying competitive concerns as a strategic source of within-market firm heterogeneity. We find support for our theoretical arguments in the cardiovascular medical device industry.

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ABSTRACT

Spillover pools are often assumed to be exogenous. Under this assumption, the amount of external knowledge the focal firm can capture increases with its knowledge-based assets. However, this positive relation may not hold when spillover pools are endogenously determined by competitive positioning strategies. Indeed, the dual nature of knowledge-based assets – competition and learning - challenges the exogeneity assumption of spillover pools. We investigate this issue in the context of market entry. While knowledge stocks may increase incumbents' learning ability, they also create competitive concerns for entrants, who bring innovative ideas into the industry. In the presence of market overlap, entrants may react to competitive threats by positioning in distant technological niches to differentiate their products, thus reducing their technical proximity to incumbents and, consequently, impoverishing the relevant spillover pool. Overall, we enrich the scholarly understanding of inter-organizational learning by showing that high investment levels in knowledge-based assets, which may be beneficial in a static environment, can be less effective in a Schumpeterian setting where entrants can apply novel knowledge in remote technological niches. Our paper further contributes to the recent development of the duality tenet of the RBV by identifying competitive concerns as a strategic source of within-market firm heterogeneity. We find support for our theoretical arguments in the cardiovascular medical device industry.

Keywords:

Spillovers; Knowledge Stocks; Competitive Positioning

INTRODUCTION

One of the central aspects of industry evolution is the creative destruction process, which results from the incessant attempts by entrants to displace industry incumbents (Schumpeter, 1942). Despite incumbents' preemptive efforts, entrants can circumvent barriers to entry by innovating, occupying a market niche or even disrupting incumbents eventually (Christensen, 1997). To stay abreast of such challenges and strategically renew themselves, incumbent firms must understand evolving competitive pressures by assimilating new external knowledge (Agarwal and Helfat, 2009). In this respect, knowledge-based investments are one of the tools available to incumbents to increase their absorptive capacity, that is, their ability to identify, assimilate and exploit knowledge from the environment (Cohen & Levinthal, 1990).

Perhaps because the absorptive capacity literature is a pivotal pillar of the capability-based view of the firm, whose theoretical thrust resides in its shift from the economics-oriented focus on product markets to firm-specific heterogeneity (Collis, 1994; Helfat, 1997), scholars of inter-organizational learning have primarily taken a firm-centric perspective too. While past contributions have gone great lengths to explore factors inside the firm that can explain differences in firms' exposure to extramural knowledge, stressing the importance of knowledge-based investments as determinants of knowledge inflows (Cohen & Levinthal, 1990), little analytical focus has been devoted to how external rivalry influences firms' technological trajectories and, in turn, their contribution to the spillover pool. Indeed, the external spillover pool is typically assumed to be constant by the standard approach, which takes within-industry R&D investments, weights them by a technical proximity measure, and treats them as an exogenous independent variable in the knowledge production function (Griliches, 1992; Hall, Mairesse, & Mohnen, 2009; Jaffe, 1986). Given this assumption, the amount of external knowledge the focal firm can capture increases with its knowledge-based assets.

However, the size of the spillover pool is likely to be the endogenous result of the competitive interactions among rivals. As recognized by the original article by Cohen and Levinthal (1989), there are "two faces" of R&D: while R&D increases one firm's absorptive capacity, it also fuels its competitive strength and makes the focal firm a concern to other firms (Dierickx & Cool, 1989; Grant, 1996). As a response, rivals may differentiate away from the neighborhood of the focal firm's technical expertise, depleting the technical locus where learning takes place (Rosenkopf & Nerkar, 2001). It is this dual nature of R&D - learning and competition - that challenges the exogeneity assumption of the spillover pool, demanding an attentive evaluation of how external-to-the-firm competition influences the focal firm's exposure to knowledge spillovers.

At the phenomenon level, market entry lends itself as a natural context in which to study the impact of the dual nature of R&D. On one hand, entrants are a valuable knowledge source. They update the spillover pool, bringing novel knowledge that could be beneficial to incumbents endowed with related knowledge stocks (Alcacer & Chung, 2007; Dushnitsky & Lenox, 2005; Dushnitsky & Shaver, 2009). On the other hand, because incumbents with deep knowledge stocks are also likely to display a more tenacious resistance to new sources of competition, entrants may react by differentiating, thus positioning remotely along the technical dimension. Consequently, since learning is easier when firms are technologically proximate, higher investment in knowledge-based assets may possibly reduce the effective size of the knowledge pool incumbents can draw from.

The above arguments show the importance for incumbents to take a balanced perspective in managing competition and absorbing external knowledge. To investigate the specific mechanisms at play, our analysis references the duality tenet of the resource-based view of the firm (RBV) as its main theoretical lens (Wernerfelt, 1984). According to the RBV, firms competing in the same product market could be endowed with heterogeneous resources (Lee, 2008, 2009; Polidoro & Toh, 2011). We leverage this significant variation to conceptualize competition as depending on both technical proximity and market overlap. Competitive considerations may induce entrants to minimize their technical similarity with strong rivals operating in the same product market, a differentiation choice allowed by the dual nature of resources and products.

We use the cardiovascular medical device industry for our empirical analysis for several reasons. First, entrants are a recurrent and significant phenomenon. Second, the FDA determines fine-grained categorizations of product markets and this allows the identification of firms' positioning along the market dimension. Third, patenting is a key strategic parameter in the industry. This abundance is instrumental in locating firms' positioning on the technological landscape. Finally, the science underlying the production of patents is cumulative and it benefits from the recombination of diverse knowledge bits. Accordingly, we are able to construct reasonable proxies for knowledge flows among firms, who can assimilate knowledge from various sources to generate original innovations, while not necessarily infringing existing intellectual property rights (Somaya, 2012). In this setting, we find support for the positive impact of technological proximity and market overlap on incumbents' ability to purposefully use entrants' knowledge to generate patents. However, when knowledge stocks are high, entrants are less likely to locate in the same technological niche as incumbents, especially in the presence of market overlap.

This study aims at enriching scholarly understanding of the growing literature on how competition influences inter-organizational learning (Alcacer & Chung, 2007; Dushnitsky & Lenox, 2005; Dushnitsky & Shaver, 2009; Polidoro & Toh, 2011). The existing literature has provided partial guidance on how competitive positioning choices influence spillover pools in dynamic settings. This research topic is important because the general wisdom is that firms undertaking costly investments in knowledge stocks build the potential to learn more. Yet, for firms with deep knowledge stocks, there may be less to learn from. Referencing the duality of resources from the RBV, our study highlights the dimensions to be taken into account when assessing the impact of investments in knowledge-based assets on the relevant spillover pool accessible to firms. In Schumpeterian settings, investments in knowledge stocks may reduce the effective size of the spillover pool available to incumbents. In the short-term, when the external knowledge pool is practically static and it can be treated as exogenous, some firms may benefit from high investments in related knowledge-based assets. In the long-term, however, multiple entry events consisting of entrants locating in distant technological niches may deplete the technological landscape in the proximity of the focal firm.

Our paper further contributes to the duality tenet of the RBV (Lee, 2008, 2009; Polidoro & Toh, 2011). Recent work on the duality tenet posits the existence of correspondence between resources and markets (Helfat & Lieberman, 2002; Lee, 2008, 2009). Such a characterization is reminiscent of the traditional IO view, which envisions a one-to-one correspondence between production functions and industries (Conner, 1991; Peteraf, 1993). While we also find corroborating evidence supporting the existence of such correspondence, we identify competitive dynamics as an important source of within-market firm heterogeneity. In our theory, within-market firm heterogeneity is not the result of the underlying scarcity of certain resources or of firms' differential locations along market-specific learning curves (Balasubramanian & Lieberman, 2010), but it is the outcome of positioning strategies to enhance the commercial viability of entrants' innovations. We discuss further implications of our study in the conclusion.

THEORY AND HYPOTHESES

Learning theory: Technical proximity and related knowledge stocks

As previously stated in the introduction, the scope of this paper is to examine the endogenous nature of spillover pools due to competitive dynamics. As such, our theory consists of two distinct but interdependent analyses. The first analysis concerns the determinants of inter-organizational learning in the context of incumbents learning from entrants. We refer to this analysis as "learning theory", whose formulation will be relatively succinct since it is built on well established theories. The second is a more detailed examination of the effect of competitive dynamics on the variables relevant for knowledge absorption. We refer to this analysis, which represent the main novelty of our work, as "positioning theory". In what follows, we develop our baseline hypotheses (i.e., H1 and H2).

New entrants are a useful knowledge source for incumbent learning (Dushnitsky & Lenox, 2005). To the extent inter-organizational learning is a response to technical problems, the tendency of firms to favor local search is likely to drive how incumbents absorb knowledge from entrants (Nelson & Winter, 1982). Organizationally, the sourcing of technical solutions through the recombination of related knowledge bits is simple and reliable and technical developments tend to occur within the neighborhood of firms' technological trajectories (Fleming, 2001; Nelson & Winter, 1982). Therefore, we propose that knowledge is more likely to flow to incumbents if entrants are proximate along the technological dimension.

Previous arguments focus on the technical proximity between entrants and incumbents, holding constant incumbents' knowledge stocks. In what follows, we analyze the impact of incumbents' investment depth in technological areas that relate to entrants' knowledge.

In a given technological niche, the accumulation of knowledge-based assets engenders a path dependent process that facilitates the repeated practice with a given set of knowledge bits (Cohen & Levinthal, 1990). This can lead to a deeper understanding of the cause-effects relationships underpinning a particular technological area and promote the identification of valuable knowledge elements in its proximity (Cohen & Levinthal, 1990; Katila & Ahuja, 2002). Consequently, we hypothesize:

Hypothesis 1: Ceteris paribus, the degree of learning by an incumbent with respect to an entrant's knowledge increases with the technical proximity between the two firms.

Hypothesis 2: Ceteris paribus, the degree of learning by an incumbent with respect to an entrant's knowledge increases with the incumbent's knowledge stocks that relate to the entrant's knowledge.

Learning theory: Market overlap

The above two hypotheses are derived from established theories on inter-organizational learning. Next we extend this literature by introducing the concept of market overlap, which is at the intersection of the learning theory discussed here (where market overlap facilitates learning) and the positioning theory to be discussed next (where market overlap causes competitive concerns).

Inter-organizational learning is facilitated when two conditions are met: the recipient firm is aware of the source and the source is understood as relevant in that the recipient expects to profit from learning (Cohen & Levinthal, 1990; Lieberman & Asaba, 2006). These conditions are more likely to be met in the presence of market overlap, that is, when the source (i.e., the entrant) and the recipient (i.e., the incumbent) compete in the same product market. Indeed, the entrant's product may serve the incumbent's customers in a new and superior fashion. As a consequence, the incumbent is likely to become aware of entry because it may cause the loss of some market share.

At the same time, the incumbent has accumulated market-specific complementary assets, such as sales forces, distribution channels, and customer service programs. When the entrant introduces an innovation in the same market where the incumbent is active, the incumbent has strong incentives to absorb the entrant's knowledge. Market-specific complementary assets are path dependent and difficult to imitate. The incumbent is in an advantageous position to profit from the entrant's innovation since it has a longer history of cumulative investments in market-specific complementary assets (Sosa, 2012). The incumbent may have an advantage even when it does not possess strong technical capabilities that relate to the entrant's knowledge and it can only imperfectly learn from the entrant. The incumbent's market-specific complementary assets may compensate for inferior technologies in the value-generating process (Lee, 2009; Tripsas, 1997). Consequently, we hypothesize the following:

Hypothesis 3: Ceteris paribus, the degree of learning by an incumbent with respect to an entrant's knowledge increases with the market overlap between the two firms.

Positioning theory

Previous work on inter-organizational learning has underlined the role played by technical proximity and knowledge-based assets on firms' exposure to extramural knowledge, which is generally assumed to be exogenous. However, the existing literature has provided partial guidance on the specific mechanisms by which the dual nature of knowledge stocks – competition and learning – influences the strategic behavior of rivals contributing to the spillover pool. Indeed, firms endowed with deep knowledge stocks may possess a competitive arsenal, engendering differentiating pressures on their rivals.

To explore the tension between competition and learning, the positing theory leverages the duality tenet of the RBV (Barney, 1991; Peteraf, 1993; Wernerfelt, 1984) as its main theoretical driver. According to the duality tenet of the RBV, firms competing in the same product market could be endowed with heterogeneous resources. In what follows, we first examine the impact of market overlap on the technical proximity between entrants and incumbents. Then, we look at how the incumbents' knowledge stocks impact their technical proximity to entrants.

Positioning theory: market overlap

According to the RBV, products and resources are two sides of the same coin (Wernerfelt, 1984). Products are a collection of attributes satisfying specific consumers' needs. In order to produce a set of attributes, firms may resort to the recombination of a bundle of resources (e.g., knowledge, physical equipment, capital) (Lee, 2008). In turn, each element in the bundle may be selected among a set of equifinal substitutes (e.g., the tip of a pacemaker electrode can be made of platinized platinum, titanium nitride, etc.).

However, not all the resources necessary to produce a product feature may have close substitutes (Barney, 1991; Peteraf, 1993; Polidoro & Toh, 2011). This implies that entrants may need to develop resource profiles around the crucial resources necessary to compete in the incumbent's product market. As a consequence, entrants' technological positions are likely to be correlated to those of the incumbents, who, by definition, already control the resources relevant to that market (Helfat & Lieberman, 2002; Lee, 2008; Silverman, 1999). In the case of implantable pacemakers, entrants are likely to develop an expertise in certain technical realms – e.g., computer science, electronic circuits, cardiac anatomy, etc. - typically mastered by firms operating in that market (Jeffrey, 2001). Consequently, we hypothesize:

Hypothesis 4: Ceteris paribus, the technological proximity between the entrant and the incumbent increases with the market overlap between the two firms.

Positioning theory: knowledge stocks and their interaction with market overlap

Strategy scholars have often claimed that knowledge is the one of the most important sources of competitive advantage (Grant, 1996). Indeed, the knowledge bits in the technological base are the intermediate outputs whose recombination allows for the introduction of innovations (Fleming, 2001). Firms with deep knowledge stocks are endowed with a wider combinative space and have a higher innovative potential. More fundamentally, accumulated knowledge stocks are likely to be the result of the underlying capability to generate knowledge and renovate the combinative space (Agarwal & Helfat, 2009; Collis, 1994). Therefore, in Schumpeterian settings, where market structure is in a state of flux and product-based advantages over rivals are at best temporary, incumbents with deep knowledge stocks may mount a better resistance to new sources of competition.

Given that the effects of direct competition between entrants and incumbents are exacerbated when firms attempt to serve the same customer pool with highly substitutable products, competitive considerations increase the entrants' incentive to differentiate from the dominant incumbents (d'Aspremont, Gabszewicz, & Thisse, 1979; Polidoro & Toh, 2011). In the presence of market overlap, incumbents are advantaged because they can rely on market-specific complementary assets to retain market share (Sosa, 2012). Therefore, direct competition with strong incumbents is likely to erode the economic rents available in the market. Entrants are better off offering products that differ in at least some dimensions from the incumbents'. Because product features are the outcome of the recombination of resource bundles, product differentiation within the same market category implies that firms are also differentiating in their resource profiles, increasing their technical distance to superior incumbents. In the absence of market overlap, competitive threats become less relevant because incumbents' products are only imperfect substitutes to the entrants', lowering differentiation incentives.

Anecdotal evidence supports our theoretical argumentations. The early lead developed by Medtronic in the circuit technology necessary for the production of implantable pacemakers made its products more reliable and durable than its rivals' for decades (Jeffrey, 2001). While other firms engaged in the production of implantable pacemakers, their inability to match Medtronic's reliability and durability obliged them to differentiate their products. Entrants started commercializing pacemakers offering different features, such as wider programmability options, diagnostics, telemetry, etc. (Jeffrey, 2001). Given that product features are underpinned by resources, this meant that Medtronic's rivals developed an expertise in technological realms that differed from Medtronic's areas of proficiency.[1] Consequently, we hypothesize: [2]

Hypothesis 5: Ceteris paribus, the technological proximity between the entrant and the incumbent decreases with the incumbent's knowledge stocks.

Hypothesis 6: Ceteris paribus, the negative relationship between the incumbent's knowledge stocks and its technological proximity to the entrant is stronger in presence of market overlap.

The overall picture resulting from of the above hypotheses is that the effectiveness of incumbents' investments in related knowledge-based assets is enhanced when entrants locate in the same market and in the same technological niche as the incumbents. However, such a contingency is not likely to arise when incumbents heavily invests in related knowledge-based assets, because entrants endogenize the incumbents' characteristics in their entry choice.

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[1] At the same time, it must be noted that in the absence of market overlap, Medtronic's expertise in drug-eluting electrodes for pacemakers may not have engendered competitive concerns for firms operating in the drug-eluting segment of the stent category.

[2] We do not deny the possibility that entrants may avoid altogether markets populated by incumbents with deep knowledge stocks. Our current derivation is only for ease of presentation. In any event, conditional on observing market overlap, our hypotheses and tests would not change.

Taken together, H3 and H4 complement the previous contributions on inter-organizational learning (summarized by H1 and H2). H3 posits that, on average, incumbents can more easily absorb knowledge in the presence of market overlap, controlling for technical proximity. H4 posits that incumbents are, on average, more technically proximate to entrants competing in the same product market. As argued in the learning theory, because technical proximity has a critical impact on incumbents' learning, one direct implication of H3 and H4 is that, on average, incumbents learn more from entrants in the presence of market overlap. Therefore, market overlap is instrumental in understanding which knowledge sources are relevant to the incumbent.

In this context, H5 and H6 are important because they imply that investments in knowledge stocks may reduce the incumbents' technical proximity to the relevant spillover pool. The positioning theory does not contradict the learning theory. By investing in knowledge stocks, incumbents build the potential to learn more. However, when incumbents do invest in knowledge stocks, there is less to learn from. The effect of knowledge-based assets on entrants' technical positioning reduces the pool of external knowledge from which incumbents can draw.

METHODS

Setting

The cardiovascular device industry in the United States provides a suitable setting to test our theory (see Figure 1 for the classification of this industry). Cardiovascular devices are constructed tools used to diagnose and treat heart diseases and related health problems. The commercialization of cardiovascular medical devices in the United States is regulated by the Food and Drug Administration (FDA). The FDA divides cardiovascular devices into eight independent horizontal categories: catheters, occluders, pace makers, heart valves, stents, defibrillators, grafts, and bypasses (Level 1 in Figure 1). Each horizontal category, in turn, is subdivided in product market segments, for a total of 70 product markets (Level 2 in Figure 1). This nested structure allows the analysis of how entry at the product market level (Level 2 in Figure 1) influences firms' technological trajectories within the independent horizontal categories (Level 1 in figure 1).

In a given product category, there are three FDA regulatory classifications of medical devices - Class I, Class II, and Class III - assigned according to the risk presented to patients (Kaplan et al., 2004). As the risk to patients increases, the classification level increases. Class III devices are those that support or sustain human life and whose adoption presents a potential risk of illness or injury. Because of their function, Class III devices are the most technologically advanced in the industry.

Since the focus of the analysis is on entrants updating the spillover pool with valuable innovations, attention is restricted to Class III product categories and Class II categories that used to be classified as Class III.[3] Because the adoption of Class III devices exposes patients to potential health hazards, new devices are granted market clearance if the increased benefit from their adoption compensates for the associated risk. Therefore, new Class III devices are required to be superior to existing ones in at least some dimensions (Kaplan et al., 2004). This provides a rare opportunity to test the learning tension between innovative entrants and incumbents in a quasi-natural experiment.

Another advantage associated with the setting consists in the presence of public records due to regulatory requirements, which provide a fine-grained categorization of product markets. The FDA, in fact, collects the complete history of firms' innovations and market entry. Accordingly, we can precisely identify firms' positioning along the market dimension.

Furthermore, in this industry, patent-based measures provide a good representation of inter-organizational knowledge flows. Patenting is a key strategic parameter in the industry with thousands of patents issued to date, this being a consequence of the misappropriation hazards associated with not

[3] We include these Class II categories because some of the product classes may have changed from Class III to Class II over time as these product categories are shown to be less risky. To rectify this potential bias, we also include any Class II product categories that contain PMAs at any point in time, as this implies they contained innovative products.

patenting at all. The abundance of patents is also instrumental in locating entrants and incumbents along the technological dimension.

[Insert Figure 1 approximately here]

Data

Product approval data and the respective product categories from 1977-2004 for all firms in the cardiovascular devices area are obtained from the Center for Devices and Radiological Health (CDRH) of the FDA. Patent data during the sample period 1977-2004 are collected from the United States Patent and Trademark Office (USPTO), the National University of Singapore-Melbourne Business School patent database, and National Bureau of Economic Research (NBER), and manually matched to each firm. Following the prior literature, the attribution of patents to firms is based on the application year of the patent to reflect the actual innovation date (Rosenkopf & Nerkar, 2001).

We address ownership changes, name changes, mergers, acquisitions, and dissolutions by manually verifying firm information from sources including firms' annual reports (if publicly listed), their websites, SDC Platinum, Thomas' Register, Hoovers, Corptech, and HighBeam Research, as well as information providers specializing in this industry, such as Informagen and Medical Device Register: The Official Directory of Medical Suppliers Resource.

To test our hypotheses we construct an unbalanced panel consisting of 44,966 observations. Each observation represents an entrant-incumbent-category-year quadruple over the period 1977-2004. A category is defined as one of the eight broad horizontal categories identified by the FDA: catheters, occluders, pace makers, heart valves, stents, defibrillators, grafts, and bypasses (Level 1 in Figure 1). Following prior work, an entrant is defined as a firm which had been commercializing a product in the focal category for at most eight years (Boeker, 1989; Eisenhardt & Schoonhoven, 1990; Li & Atuahene-Gima, 2001; McCann, 1991). A firm enters our dataset at the moment it starts commercializing a product in one of the eight product categories identified by the FDA or at the beginning of the observation period, whichever comes later. It is then matched to any other incumbent already operating in the focal category. The dataset includes 226 entrants and 224 incumbents. In accordance with prior literature, our sample only covers firms to whom patents were successfully assigned by United States Patent and Trademark Office during the observation period (Rosenkopf & Nerkar, 2001).

Variables

To model the hypothesized relations we use two sets of regressions. The "learning regressions", which mirror the learning theory of our analysis, test the impact of market overlap, technical proximity and incumbents' related knowledge-based assets on the incumbent's ability to absorb knowledge from the entrant. The "positioning regressions", which parallel the positioning theory of our analysis, assess the impact of market overlap and incumbent's knowledge-based assets on the technical proximity between the entrant and the incumbent.

Because both analyses hinge on the identification of the technological positioning of entrants and incumbents along the relevant technological spaces, we map technological classes and subclasses into categories (Level 1 in Figure 1). Our approach follows the logic of Silverman (1999). The mapping consists of a frequency distribution that associates patents to categories. We look at the patent portfolios of firms operating in a given category and we count the frequency with which firms in a given category patent in a given class. Each patent class, then, is associated to the five categories or the number of categories that represents 90% of the total frequency, whichever is less.

CIT_{jimt} is the dependent variable in the learning regressions and indicates the number of patent citations that incumbent *j* makes to entrant *i* in category[4] *m* in year *t*. A citation is attributed to a category if the citing patent belongs to a patent class in the technological space mapped to said category. The variable CIT_{jimt} is deemed a good proxy for the learning undertaken by incumbent *j* with respect to entrant *i*'s knowledge, because it measures the instrumental and successful use of the knowledge introduced by *i*

[4] The term category refers to Level 1 in Figure 1.

in category *m* (Alcácer & Gittelman, 2006; Katila & Ahuja, 2002; Lampe, 2010; Rosenkopf & Nerkar, 2001)[5].

$TECHPROX_{jimt}$ is a dependent variable in the positioning regressions and an independent variable in the learning regressions. It measures the technical proximity between incumbent *j* and entrant *i* over the technological space mapped into category m in year *t*. $TECHPROX_{jimt}$, is Jaffe's angular separation coefficient (Jaffe, 1986), computed as follows:

$$TECHPROX_{jimt} = \frac{I_t J_t^{'}}{\sqrt{I_t I_t^{'} J_t J_t^{'}}}$$

where I_t and J_t are two column vectors whose dimension equals the number of patent classes associated with category *m*. Each individual component of I_t consists in the summation of patents that entrant *i* has in a determined patent class up to year *t*, where older patents are discounted by a yearly factor equal to 0.7.[6] The individual components of J_t are computed similarly to the ones in I_t, but they make reference to incumbent *j*'s patents. $TECHPROX_{jimt}$ can take values between 0 and 1. $TECHPROX_{jimt} > TECHPROX_{j'i'mt}$ means that the pair *i* and *j* is more proximate than the pair *i'* and *j'*.

$STOCK_{jmt}$ is an independent variable in both set of regressions. It is a proxy for incumbent *j*'s knowledge-based assets in category *m* in year *t*. $STOCK_{jmt}$ is measured as the discounted stock of patents that incumbent *j* filed in the patent classes mapped into category *m*. Its computation follows the formula:

$$STOCK_{jmt} = Patents_{jmt} + 0.7 \times STOCK_{jmt-1}$$

5 Alcacer and Gittelman (2006) and Lampe (2010) suggest that examiners' citations and applicants' strategic citations may be a potential source of noise in patent citations. However, both studies mention these sources of noise as less relevant in high-tech classes. Furthermore, neither study establishes a correlation between direct competition and the aforementioned disturbances. Lampe (2010) posits that a firm's patent stock is associated with a higher likelihood of withholding relevant citations, but this effect makes our estimates of the predicted positive effect of the incumbent's patent stock on learning more conservative.

6 We constructed the same proxy using different discount factors, obtaining results robust to different specifications.

We use a discount rate of 0.7, which has been previously applied in other studies (Dushnitsky & Lenox, 2005).[7] We divide the variable $STOCK_{jmt}$ by 1000 to facilitate the interpretation of the outputs of the empirical analysis.

$MARKOV_{ijmt}$ is an independent variable in both set of regressions. It is a proxy for market overlap. Within each of the eight horizontal categories identified by the FDA, it is possible to distinguish further subcategories (Figure 1). For example, within the defibrillator product category, it is possible to identify 11 product markets. $MARKOV_{ijmt}$ is a dummy which takes value 1 if two firms operating in the same category are also active in the same subcategory.

Controls

Jaffe's angular separation coefficient (Jaffe, 1986) can be interpreted as a measure of technical overlap (numerator) between two firms' patent portfolios weighted by the "size" of technological space that those two portfolios identify (denominator), which is a subset of universe of patent classes. This measure is not affected by the number of patents in the portfolios, because it is determined by the distribution of patents over the patent classes. However, firms active in multiple patent classes are more likely to have some patent classes in common with any other firm, thus increasing the numerator of the separation coefficient but not the denominator. Imagine a universe consisting of 100 patent classes. One incumbent is active in 30 patent classes, while another is active in 50 patent classes. If the patent classes each firm is active are randomly assigned to the 100 possible cells, the likelihood of overlap (the numerator of the separation coefficient) with an entrant active in 1 class is bigger for the second incumbent than for the first (Ren, Hu, Hu, & Hausman, 2011). However, the size of the space either pair can randomly indentify (the denominator of the separation coefficient) is constant and it is equal to 100, i.e., the universe of patent classes. Intuitively, any patent class in the universe has a positive probability of being selected by any firm in any pair.

[7] Different discount factors do not significantly change our findings.

In the positioning regressions, we are interested in firms' purposive efforts to differentiate. Only in that particular set of regressions, then, we control for this "random" component of technological proximity with $E[TECHPROX_{jimt}] = \frac{\sqrt{n_{jm}n_{im}}}{N_m}$, where N_m is the cardinality of the universe of patent classes mapped into category m, n_{jm} is the cardinality of the subset of patent classes in the universe in which incumbent j is active, and n_{im} is the cardinality of the subset of patent classes in the universe in which entrant i is active. [8]

Additionally, in both regressions, we use a set of controls relevant in establishing the effects of the variables of interests. Firm-specific controls for both entrants and incumbents include ENT_STOCK_{it}, $COUNT\_CLASS_{jt}$, $COUNT\_MKTS_{jt}$, $SIZE_{jt}$, and $PUBLIC_{jt}$.[9] ENT_STOCK_{it}, a proxy for the entrant's patent stock, is constructed similarly to $STOCK_{jmt}$. $COUNT\_CLASS_{jt}$ is a count of the relevant technical classes in which the focal firm is active. We also include the variable, $COUNT\_MKTS_{jt}$, which counts the number of categories (Level 1 in Figure 1) in which the focal firm operates. $SIZE_{jt}$ is categorical variable measuring firms' sales. We include a dummy for firms with sales of 0-1 million, 1-10 million, 10 million-1 billion, and 1 billion and above, respectively. Because data on firm sales are available only for public firms, we also include the dummy $PUBLIC_{jt}$, which takes the value of 1 if a firm is publicly traded.

Category-specific controls include $COMP_{mt}$ and $CATEGORY_t$. $COMP_{mt}$ is the count of the number of firms competing in the category where the incumbent is active. $CATEGORY_t$ is a set of dummy variables constructed for each of the broadly-defined horizontal product categories (Level 1 in Figure 1). It controls for time invariant unobserved heterogeneity across categories. We also included year, entrant, and incumbent dummies to control for fixed effects.

Table 1 presents sample means, standard deviations, and correlations for the main variables.

[8] A proof of the mathematical derivation of this formula can be provided by the authors upon request. We do not include it here for the sake of brevity.

[9] These variables are constructed both for the entrants and for the incumbents. We report them here only with the subscript *j*, which we generally use to identify variables referring to the incumbents, for the sake of brevity.

[Insert Table 1 approximately here]

Econometric Methods

We test our hypotheses using two different econometric methods, one for each set of regressions. In the learning regressions, which test H1, H2, and H3, the dependent variable (i.e., CIT_{ijmt}) is a citation count and it has non-negative integer values. Hence, a count model is used (Rosenkopf & Nerkar, 2001). To address the issue of over-dispersion, we estimate unconditional fixed-effects negative binomial models with the following mean specification: [10]

$$\log(CIT_{ijmt}) = \alpha + \beta X_{jmit-2} + \gamma Z_{ijjmt-2} + \varepsilon_{ijt-2}$$

where $E(CIT_{ijmt})$ is the expected number of citations, X_{ijmt-2} is a vector of independent variables of main interest, Z_{ijmt-2} is a vector of control variables, including firm dummies, year dummies, and category dummies, and ε_{ijt-2} is a random disturbance. All independent and control variables are lagged by two years to reflect the gestation period of innovations in the industry before the filing the patent application (Kaplan et al., 2004) and to prevent the most obvious form of reverse causality. We calculate robust standard errors clustered at the entrant-incumbent-category triple level to account for intra-triple non-independence of observations (Rogers, 1993; White, 1980).

In the positioning regression, which tests H4, H5, and H6, the dependent variable (i.e., $TECHPROX_{jimt}$) can take values between zero and one. Consequently, we opt for a corner solution application of the two-limit tobit with censoring of the dependent variable at zero and one. This estimation procedure has the desirable property of predicting values in the same range of the dependent

[10] Allison and Waterman (2002) suggest that the standard errors from an unconditional fixed-effects negative binomial regression (i.e., a negative binomial model with with dummies for fixed effects) may be underestimated. To address this issue, they propose a correction consisting in the multiplication of the estimated standard errors by the square root of the ratio between the deviance of the MLE estimator and its degrees of freedom. Given the sheer amount of degrees of freedom in our models (due to the number of observations), the aforementioned corrective multiplier is a number smaller than one, making the uncorrected estimates more conservative than the corrected ones. Hence, we avoid applying the correction.

variable. We include firm dummies, year dummies, and category dummies to control for fixed effects. The structural equation in the Tobit model is:

$$TECHPROX_{jimt}{}^{*} = \alpha + \theta X_{jmit-2} + \delta Z_{ijjmt-2} + u_{ijt-2}$$

Where $TECHPROX_{jimt}{}^{*}$ is a latent variable that is observed for values greater than zero and smaller than one and censored otherwise. $TECHPROX_{jimt}{}^{*}$ is assumed to be a linear function of Y_{ijmt-2}, a vector of independent variables of main interest, Z_{ijmt-2}, a vector of control variables, and u_{ijt-2}, the random disturbance. The observed $TECHPROX_{jimt}$ is defined by the following measurement equation:

$$TECHPROX_{jimt} = \begin{cases} TECHPROX_{jimt}{}^{*} & \text{if } 0 < TECHPROX_{jimt}{}^{*} < 1 \\ 0 & \text{if } 0 > TECHPROX_{jimt}{}^{*} \\ 1 & \text{if } 1 < TECHPROX_{jimt}{}^{*} \end{cases}$$

Because less than 13% of the observations in our sample are censored, the estimates in a tobit model are very close to those of a linear regression model. We exploit this resemblance by performing a Box-Cox transformation on $STOCK_{jmt-2}$ to identify the optimal monotonic transformation of the predictor of interest. Box and Cox (1964) introduced a family of power transformations such that the transformed values are a monotonic function of the observations over some admissible range and indexed by

$$x_i = \begin{cases} \dfrac{x_i{}^{\lambda} - 1}{\lambda} & if \;\; \lambda \neq 0 \\ log x_i & if \;\; \lambda = 0 \end{cases}$$

Such that for unknown λ, it is possible to identify

$$y_i = \theta x_i{}^{\lambda} + \varepsilon_i$$

Where x_i is a vector of independent variables, θ is a vector of unknown parameters associated with the transformed values, and $\varepsilon_i \sim N(0, \sigma_i)$ is the random error. The estimated λ for $STOCK_{jmt}$ is 0.9, implying the existence of diminishing returns of $STOCK_{jmt}$ on $TECHPROX_{jimt}$. As in the learning regressions, we estimate robust standard errors clustered at the entrant-incumbent-category triple level. Similarly, we lag independent and control variables by two years. However, in the positioning regression there is a fundamental difference. Here, we do not lag the proxy for market overlap. Such a modeling choice reflects the simultaneous nature of the technical and market positioning decisions before entry.[11] More precisely, we assume that the entrant, in anticipation of its future market positioning, is likely to decide in which technologies to invest as a response to the characteristics of the incumbents it will compete with.

RESULTS

Results for the learning regression

Table 2 shows the results for the learning regression. The first model (Model 2-1) contains only the control variables. Model 2-2 controls for the main effects of the variables of interests: knowledge stocks ($STOCK_{jmt-2}$), technical proximity ($TECHPROX_{jimt-2}$), and market overlap ($MARKOV_{jimt-2}$). Because the dependent variable in the learning regressions is log-transformed, the format for interpretation is that the dependent variable changes by $100 \times coefficient$ percent for a one unit increase in the independent variable while all other variable in the model are held constant. As predicted by H1, the effect of technical proximity on incumbents learning from entrants is positive and statistically significant. The effect of our proxy for market overlap is also positive and significant, providing supporting evidence for H3. When controlling for market overlap and technical proximity, the coefficient of $STOCK_{jmt-2}$, our proxy for the incumbent's knowledge stock, is negative but statistically insignificant. This does not necessarily provide conflicting evidence to H2, which posits that related knowledge stocks have a positive effect on knowledge absorption. $STOCK_{jmt-2}$ is a measure that includes both the knowledge-based assets which relate and the knowledge-based assets which do not relate to the entrant's

[11] We do not deny the possibility that certain innovators may first choose an attractive market and then produce an innovation suitable to that market or, vice versa. Our current derivation is only for ease of presentation and it can be regarded as a "reduced form" representation of the negative correlation between technical and market proximity. Our hypotheses and tests would not substantially change if different timelines were assumed.

knowledge. We construct a proxy for the incumbent's related knowledge stocks by interacting $STOCK_{jmt-2}$ and $TECHPROX_{jimt-2}$. We interpret $TECHPROX_{jimt-2}$ as an approximation for the percentage of the incumbent's knowledge stocks that relate to the entrant's knowledge.

Model 2-3 controls for the main effects of $STOCK_{jmt-2}$, $TECHPROX_{jimt-2}$, $MARKOV_{jimt-2}$, and for the interaction term between $STOCK_{jmt-2}$ and $TECHPROX_{jimt-2}$. The coefficient of $MARKOV_{jimt-2}$ is practically unchanged across Model 2-2 and Model 2-3. In our sample, market overlap is associated with a 22.3% increase on the expected number of citations made by the incumbent. The coefficient of $TECHPROX_{jimt-2}$ is substantially reduced by the inclusion of the interaction term $TECHPROX_{jimt-2} \times STOCK_{jmt-2}$. In this model, when the incumbent's knowledge stock is small, a one-standard-deviation increase of technical proximity (i.e., 0.27) is approximately correlated with a 66.7% increase (i.e.,0.27×2.47) on the expected number of citations made by the incumbent. Consequently, Model 3-3 also supports H1 and H3.

The coefficient of the interaction term between $STOCK_{jmt-2}$ and $TECHPROX_{jimt-2}$ is also positive and significant, suggesting that deep investments in knowledge-based assets that relate to the entrant's knowledge facilitate learning. Hence, H2 is supported. In model Model 3-3, a one-standard-deviation increase in $STOCK_{jmt-2}$ (i.e., 0.392, which corresponds to 392 patents) when technical proximity is equal to one is approximately associated with a 96% increase (i.e., 0.39×2.45) in the expected number of citations made by the incumbent. In this regression, the main effect of $STOCK_{jmt-2}$ captures the effect of the incumbent's investment in knowledge-based assets that do not relate to the entrant's knowledge, which has a negative and significant effect on the incumbent's absorptive capacity. In model Model 3-3, a one-standard-deviation increase in $STOCK_{jmt-2}$ (i.e., 0.392) when technical proximity is equal to zero is approximately associated with an 0.31% reduction (i.e., -0.39×0.80) in the expected number of citations made by the incumbent.

Interestingly, from the coefficients reported in Table 3 in the column associated to model 3-3, it is also possible to note that the effect of $TECHPROX_{jimt-2} \times STOCK_{jmt-2}$ dominates the effect of $STOCK_{jmt-2}$ only if $TECHPROX_{jimt-2}$ is bigger than 0.32, which is very close to the average $TECHPROX_{jimt-2}$ in the presence of market overlap (without market overlap, the average proximity is lower, i.e., 0.22). This implies that investments in knowledge stocks are beneficial to the incumbent's absorptive capacity only if the entrant locates more proximately along the technical dimension than the average entrant.

These results are remarkable because, in the presence of market overlap, knowledge stocks seem to have no average impact on the amount of knowledge the incumbent can absorb from the entrant. Additionally, without market overlap, firms tend to be less technologically proximate on average and investments in knowledge stocks may reduce the incumbent ability to absorb extramural knowledge. It is then likely that entrants operating in other markets play a marginal role in defining the incumbent's relevant spillover pool.

To sum up, at the aggregate level (i.e., summing the expected citations made by the incumbent), the amount of knowledge absorbed by the incumbent depends mainly from its technological proximity to entrants. When the average proximity is high, the incumbent absorbs substantial amounts of knowledge. When the average proximity is low, independent of the incumbent's investments in knowledge stocks, the relevant spillover pool is depleted. Overall, Model 2-3, highlights the importance of technical proximity and market overlap as key predictors for knowledge absorption. For the incumbent, the relevant spillover pool is determined by economic agents that are proximate along both the market and the technical dimension.

[Insert Table 2 approximately here]

Results for the positioning regression

The results from the two-limit Tobit regressions are summarized in Table 3.[12] The first model (Model 3-1) includes only the control variables. The second model (Model 3-2) includes the main effects of $STOCK_{jmt-2}$ and $MARKOV_{jimt-2}$ on the entrant's technological positioning choice. As predicted by H4, the effect of market overlap on technological proximity is positive and significant. We can interpret this result as supporting the RBV tenet by which firms with similar resources tend to enter similar markets (Helfat & Lieberman, 2002; Lee, 2008). The impact of $STOCK_{jmt-2}$ on $TECHPROX_{jimt}$ is negative and significant at the 10% level. Hence, H5 is only partly supported.

However, according to H6, competitive dynamics and differentiating pressures are likely to be salient mainly in the presence of market overlap. To accommodate our theory, Model 3-3 includes an interaction term between $STOCK_{jmt-2}$ and $MARKOV_{jimt-2}$, which is negative and statistically significant at the 0.1% level. In the presence of market overlap, a one-standard-deviation increase in $STOCK_{jmt-2}$ (i.e., 0.392) from the mean (i.e., 0.172) is approximately correlated with a 5% decrease (i.e., $\left[(0.392 + 0.172)^{\frac{9}{10}} - (0.172)^{\frac{9}{10}}\right] \times (10.5\% + 1.7\%)$)[13] in technical proximity. In model 3-3, the main effect of market overlap is positive and significant. The presence of market overlap is correlated with a 4.1% increase in the expected technical proximity between the entrant and the incumbent. The main effect of $STOCK_{jmt-2}$ is not significant and it is of a lesser magnitude than its counterpart in Model 3-2.

Taken as a whole, we can interpret the results in Model 3-3 as strongly supporting our theory. The significant change in the coefficient of the variable $STOCK_{jmt-2}$ in the subsample characterized by market overlap, which is captured by the interaction term between $STOCK_{jmt-2}$ and $MARKOV_{jimt-2}$,

[12] The reported coefficients are the marginal effects of the independent and control variables on $TECHPROX_{jimt}{}^{*}$, the latent variable. Because less than 15% of the observations are censored, the average marginal effects of the predictors are practically equivalent to those reported in Table 3.

[13] Note that the variable $STOCK_{jmt-2}$ underwent a Box-Cox transformation, where λ was set equal to $\frac{9}{10}$.

may be likely due to differentiation incentives that induce entrants not to position in the neighborhood of the incumbents' technical expertise.

Furthermore, because the learning regressions highlight the positive impact of technological proximity on knowledge absorption, the results of the positioning regressions have strong implications also in the context of incumbents learning from entrants. While a detailed analysis reconciling the marginal effects in the learning regressions and in the positioning regressions is available from the authors,[14] here it is worth mentioning that, by negatively influencing technological proximity, which moderates the effect of knowledge stocks on learning, differentiation strategies may impoverish the spillover pool in which incumbents are immersed. Ultimately, knowledge-based assets may have a negative impact on incumbents' exposure to extramural knowledge, especially in the presence of market overlap. In fact, one-standard-deviation increase in $STOCK_{jmt-2}$ (i.e., 0.392) from the mean (i.e., 0.172) may reduce long-term learning (i.e., CIT_{ijmt+2} – please, note the four-year lag) from the focal market by 7.5%.

[Insert Table 3 approximately here]

DISCUSSION AND CONCLUSION

This study develops a theoretical framework to introduce the impact of positioning strategies on the characteristics of the spillover pool available to firms. With a focus on the focal firm's ability to learn, previous studies often assume the exogeneity of the external spillover pool. Under this assumption, the amount of external knowledge the focal firm can capture may possibly increase with its knowledge-based assets.[15] However, this positive relation might not hold when the spillover pool is endogenously determined by the focal firm's investment in knowledge stocks. The picture emerging from our theory and tests is that, at the level of the individual incumbent, the overall effectiveness of investment in knowledge stocks depends on the incumbent's average proximity to the entrants in the pool. When

[14] We do not report it for the sake of brevity.
[15] Note that the learning regressions support this notion only when the average technical proximity to the pool is high.

entrants are proximate, the spillover pool is rich and investments in knowledge stocks facilitate learning. When entrants are remote, the spillover pool is impoverished and investments in knowledge stocks are less effective. Therefore, in settings in which knowledge-based investments induce rivals to differentiate away, deep knowledge stocks may actually have a negative impact on firms' ability to absorb external knowledge.

Alternative mechanisms may explain the observed regularities. Entrants may position in distant technological niches not because they intend to differentiate their products, but simply to curtail misappropriation hazards. In fact, incumbents with related knowledge stocks are not only better competitors, but also more likely to absorb entrants' knowledge. However, misappropriation concerns may be constant across product markets to the extent that technically proximate incumbents with deep knowledge stocks, independent of their market positioning, may be equally capable to absorb and exploit entrants' knowledge.[16] In this case, the negative effect of knowledge stocks on technical proximity that we observe only in the presence of market overlap can be likely attributed to differentiation strategies.

Because we focus on a single industry, these findings may not be generalizable to other empirical settings. In addition, we examine only the effectiveness of learning, not its impact on overall profitability. It is possible that fending off entrants is always beneficial for profitability, at least in the short run, although it may prevent gaining new knowledge in the long run. Future research could address these shortcomings.

Despite these caveats, this paper makes a number of contributions to existing streams of research. First, we highlight positioning strategies as another important, yet under-studied, analytical dimension influencing the endogeneity of spillover pools. In particular, as one of Porter's (1980) five competitive forces, entrants pose competitive threat to industry incumbents. Sometimes they may displace industry incumbents with radical or disruptive innovations, leading to creative destruction (Schumpeter, 1942).

[16] Note that entrants do not control market-specific complementary assets that could facilitate the retention of market share in the face of imitation. For entrants, unintended knowledge leakages to any type of incumbent, even those who do not control complementary assets specific to the entrant's market, could be extremely dangerous.

Therefore, it is important for industry incumbents to cope with the competitive threat of entry. While incumbents can certainly establish barriers to preempt entry, they can also try to learn from the fresh knowledge brought into the industry by entrants. Incumbents must manage the tension between knowledge absorption and competition. On one hand, they need to be responsive and proactive in the face of a competitive threat, because ignoring an emerging rival can have fatal consequences. On the other hand, industry incumbents can leverage the new knowledge to enhance their own technologies or strategically renew themselves.

Second, we show the theoretical and empirical relevance of a classical RBV tenet - the duality between resources and products. Similarly to previous contributions (Lee, 2008; Silverman, 1999), we also find supportive evidence of the tendency of similar firms to compete in similar markets. However, we also identify competitive concerns engendered by dominant incumbents as an important source of within-market firm heterogeneity (Helfat & Lieberman, 2002; Lee, 2008, 2009). In our context, firm heterogeneity is not simply due to imperfections in the economic system, such as the underlying scarcity of certain resources and firms' different levels of expertise over certain activities (Balasubramanian & Lieberman, 2010), but it is a rational choice by firms which decide to differentiate to increase the commercial viability of their innovations.

Third, our study highlights the downside of ignoring entrants' knowledge applied in alternative product markets or in remote technological niches. Consistent with Christensen and Bower (1996), we show that incumbents pay less attention to entrants that are remote in the market and technical space. This may be harmful to the incumbents when hiding on the market and technical dimensions provides the entrants with enough time to build up the competence necessary to penetrate the incumbents' main niches. Thus, incumbents' success in fending off entrants in the short run may motivate entrants to develop disruptive innovations in the long run.

The results also have implications for managers, who should consider not only internal firm characteristics but also external competitive conditions when determining the optimal amount of knowledge-based investments. Our results show that more is not always better. Our findings also suggest that incumbent firms can choose a balance between market scope and knowledge-based investment to enhance learning. If high levels of knowledge-based investments lose their effectiveness by pushing entrants to alternative technological niches, the incumbent can purposefully reduce investment but increase market coverage. This may increase the chance of encountering entrants, learning about, and absorbing their knowledge through a common understanding of market needs.

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Figure 1: Product market classifications

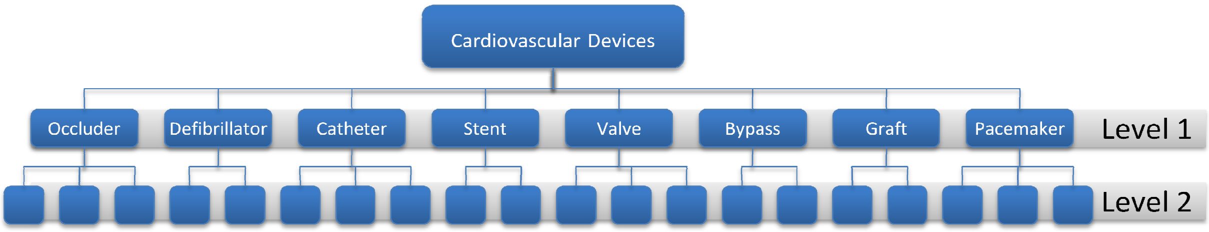

Table 1: Summary Statistics and Correlations for Selected Variables

	Variables	Mean	s. d.	1	2	3	4	5	6	7	8	9	10	11
1.	CIT_{ijmt}	0.59	5.53	1										
2.	$STOCK_{jmt}$	0.17	0.39	0.09	1									
3.	$MARKOV_{jmt}$	0.30	0.46	0.06	0.05	1								
4.	$TECHPROX_{jimt}$	0.25	0.27	0.13	-0.09	0.12	1							
5.	$E[TECHPROX_{jimt}]$	0.09	0.11	0.20	0.39	0.10	-0.03	1						
6.	ENT_STOCK_{imt}	0.10	0.37	0.10	0.01	0.02	-0.06	0.40	1					
7.	$COUNT\_CLASS_{jt}$ (incumbent)	63.10	74.60	0.07	0.79	0.07	-0.13	0.51	-0.01	1				
8.	$COUNT\_CLASS_{jt}$ (entrant)	36.00	61.23	0.12	0.02	0.06	-0.09	0.61	0.82	0.00	1			
9.	$COUNT\_MKTS_{jt}$ (incumbent)	2.30	1.66	0.12	0.20	0.15	0.18	0.24	-0.01	0.34	-0.00	1		
10.	$COUNT\_MKTS_{it}$ (entrant)	1.47	1.46	0.14	0.07	0.24	0.09	0.32	0.13	0.06	0.28	0.08	1	
11.	$COMP_{mt}$	55.36	23.22	-0.06	-0.07	-0.09	-0.01	-0.25	-0.01	-0.02	-0.10	-0.08	-0.19	1

Table 2: Results Learning Regressions
Negative Binomial Models with Unconditional Fixed Effects and Cluster-Robust SE

Independent Variables	Model 2-1	Model 2-2	Model 2-3
$STOCK_{jmt-2}$		-0.212	-0.805***
		(0.182)	(0.207)
$MARKOV_{jmt-2}$		0.222***	0.220***
		(0.0696)	(0.0679)
$TECHPROX_{jimt-2}$		3.201***	2.469***
		(0.126)	(0.148)
$TECHPROX_{jimt-2} \times STOCK_{jmt-2}$			2.453***
			(0.329)
ENT_STOCK_{imt-2}	1.252***	0.722†	0.725†
	(0.442)	(0.399)	(0.403)
$COUNT\_CLASS_{jt-2}$ (incumbent)	0.00611*	0.00952***	0.00823***
	(0.00265)	(0.00266)	(0.00264)
$COUNT\_CLASS_{jt-2}$ (entrant)	0.00682*	0.00738*	0.00737*
	(0.00333)	(0.00311)	(0.00311)
$COUNT\_MKTS_{jt-2}$ (incumbent)	0.423***	0.294***	0.251***
	(0.0585)	(0.0488)	(0.0478)
$COUNT\_MKTS_{it-2}$ (entrant)	0.0509	-0.0579	-0.0574
	(0.0409)	(0.0431)	(0.0424)
Dummy for publicly traded incumbents	0.842**	0.595*	0.447*
	(0.305)	(0.235)	(0.220)
Dummy for publicly traded entrants	0.389**	0.412**	0.422**
	(0.146)	(0.146)	(0.148)
Number of competitors in the category (LEVEL 1)	-0.0132*	-0.0117*	-0.0118*
	(0.00647)	(0.00553)	(0.00549)
$SIZE_{jt-2}$ (incumbent) (3)	Included	Included	Included
$SIZE_{it-2}$ (entrant) (3)	Included	Included	Included
Category dummies (7)	Included	Included	Included
Year dummies (26)	Included	Included	Included
Incumbent dummies (224)	Included	Included	Included
Entrant dummies (226)	Included	Included	Included
Constant	-4.733***	-4.091***	-3.866***
	(1.158)	(1.026)	(1.035)
$log(\alpha)$	1.069***	0.696***	0.650***
	(0.0489)	(0.0530)	(0.0537)
McFadden's pseudo R-squared	33.00%	36.30%	36.60%
Observations	44,966	44,966	44,966

Robust standard errors in parentheses
*** $p<0.001$, ** $p<0.01$, * $p<0.05$, † $p<0.1$

Table 3: Results Positioning Regressions
Two-limit Tobit Models with Unconditional Fixed Effects and Cluster-Robust SE

Independent variables	Model 2-1	Model 2-2	Model 2-3
$STOCK_{jmt-2}$		-0.0505†	-0.0174
		(0.0276)	(0.0292)
$MARKOV_{jmt}$		0.0308***	0.0411***
		(0.00615)	(0.00678)
$STOCK_{jmt-2} \times MARKOV_{jmt}$			-0.104***
			(0.0231)
$E[TECHPROX_{jimt-2}]$	0.614***	0.613***	0.625***
	(0.0499)	(0.0501)	(0.0499)
ENT_STOCK_{imt-2}	-0.00089***	-0.00074***	-0.00071***
	(0.000184)	(0.000209)	(0.000209)
$COUNT\_CLASS_{jt-2}$ (incumbent)	-0.00067***	-0.00064***	-0.00065***
	(0.000205)	(0.000207)	(0.000207)
$COUNT\_CLASS_{jt-2}$ (entrant)	0.0157***	0.0157***	0.0158***
	(0.00303)	(0.00304)	(0.00304)
$COUNT\_MKTS_{jt-2}$ (incumbent)	-0.00241***	-0.00251***	-0.00252***
	(0.000506)	(0.000507)	(0.000507)
$COUNT\_MKTS_{it-2}$ (entrant)	0.0147	0.0187	0.0152
	(0.0132)	(0.0132)	(0.0131)
Dummy for publicly traded incumbents	-0.0150*	-0.0155*	-0.0156*
	(0.00608)	(0.00608)	(0.00609)
Dummy for publicly traded entrants	0.0254***	0.0252***	0.0258***
	(0.00492)	(0.00490)	(0.00490)
Number of competitors in the category (LEVEL 1)	-0.0211	-0.0251†	-0.0245†
	(0.0138)	(0.0140)	(0.0140)
$SIZE_{jt-2}$ (incumbent) (3)	Included	Included	Included
$SIZE_{it-2}$ (entrant) (3)	Included	Included	Included
Category dummies (7)	Included	Included	Included
Year dummies (26)	Included	Included	Included
Incumbent dummies (224)	Included	Included	Included
Entrant dummies (226)	Included	Included	Included
ENT_STOCK_{imt-2}			
Constant	-0.222**	-0.246***	-0.264***
	(0.0884)	(0.0921)	(0.0928)
σ	0.215***	0.214***	0.214***
	(0.00227)	(0.00227)	(0.00227)
chi-squared	29,304***	29,445***	29,515***
Obs. summary	4277 left-censored, 12 right-censored	4277 left-censored, 12 right-censored	4277 left-censored, 12 right-censored
Observations	44,966	44,966	44,966

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.5, †p<0.1