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Industry Leaders’ Exploratory Innovations and Sales Growth of Competitors

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Abstract
This study suggests that one firm’s effort to further its interest can help other firms. We study this by looking at an industry leader’s degree of exploratory innovation and its effect on sales growth of its direct competitors (fringe firms). We argue that fringe firms grow because exploratory innovation of industry leaders create new submarkets that fringe firms can enter. However, not all fringe firms grow equally. Factors such as the number of participants in the industry, each firm’s financial slack, and its operational efficiency affect the extent of sales growth. The findings highlight that the joint study of heterogeneity across industries and that within each industry can yield valuable insights into which industries grow more as they evolve and which firms outgrow others.

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Industry Leaders' Exploratory Innovations and Sales Growth of Competitors

Abstract. This paper examines the effect of an industry leader’s degree of exploratory innovation on the growth of its direct competitors (fringe firms). Drawing on industry evolution and innovation literature, we argue that an industry leader’s degree of exploratory innovation can create new submarket(s) that both the leader and its competitors can appropriate to grow. The extent of growth, however, depends on the number of fringe firms present because increased competitive pressure reduces growth opportunities. We also argue that the level of fringe firms’ financial slack and operational efficiency affect whether fringe firms grow from their industry leader’s exploratory innovation. We empirically test and find support for our hypotheses in the context of the US computer sector. This study suggests that while an industry leader’s exploratory innovation is meant to further its own interests, it also exogenously affects fringe firms’ growth potential. The extent of growth from an industry leader’s exploratory innovation, however, depends also on the fringe firm’s own endogenous conditions, such as resource endowment and efficiency.

INTRODUCTION

Various scholars have long recognized that firm performance varies both across and within industries. We observe persistent difference in many aspects of firm performance such as innovation, profitability, and growth (Spithoven, Frantzen, and Clarysse, 2010). This is also true of vertically related industries, i.e. sectors, where firms in different industries are highly interdependent (Jacobides, Knudsen, and Augier, 2006). This study aims to examine how heterogeneity in innovative output across industry leaders is related to inter-industry growth differences in a sector. In addition, we investigate what enables or hinders participants within the same industry to benefit from such growth externalities.

The literature on industry evolution and technology innovation has shown that innovation plays an important role in industry dynamics (e.g. Abernathy and Utterback, 1978; Dosi, 1982; Klepper, 1996; Nelson and Winter, 1982). Prior studies have looked at how innovation can change competitive dynamics to the extent that some firms exit while others prosper (Adner and Zemsky, 2005; Bhaskarabhatla and Klepper, 2014) and/or enable new entrants to get a foothold in the established industry (Adner and Levinthal, 2001; Mitchell and Skrzypacz, 2015). Literature on endogenous growth theory has also identified innovation as an engine of growth by positively affecting other economic factors of growth (see, inter alia, Aghion and Howitt, 1992; Grossman and Helpman, 1994; Romer, 1990). One key mechanism that scholars identified between innovation and firm growth is the creation of submarkets (Mitchell and Skrzypacz, 2015; Sutton, 1998). That is, firms intentionally innovate and create new submarkets either to avoid competition and secure the lion’s share of...
the new market (Nerkar and Roberts, 2004) or to exploit their existing capabilities (Mitchell and Skrzypacz, 2015).

Industries evolve differently over time. We argue that firms in different industries have different incentives and capability to innovate, and that this heterogeneity affects growth and submarket dynamics. Such heterogeneity exists among a set of industries that are vertically related and exhibit high interdependence (e.g. Teece, 2010; von Hippel, 1988). Here, we explore how the proportion of exploratory innovation—defined as innovation that utilizes novel knowledge—of an industry leader (defined in terms of market share) can affect the sales growth of directly competing firms (hereafter referred to as fringe firms).

Exploratory innovation involves identifying and assimilating new knowledge, which can prevent overutilization of existing knowledge and provide hitherto unanswered solutions. This, in turn, is likely to lead to creation of new submarkets in the industry. As many studies have highlighted the role of large firms in influencing smaller firms (e.g., de Figueiredo and Silverman, 2007; Mudambi and Swift, 2014), we specifically investigate if an industry leader’s proportion of exploratory innovation helps fringe firms grow. Because it is highly unlikely that industry participants grow evenly, we also examine what other industry- and firm-level factors affect this leader exploratory innovation-sales growth relationship. We thus link two different levels of analysis in studying the effect of innovation on firm growth: Heterogeneity in innovation observed across vertically related industries and heterogeneity among firms within each industry.

Our central argument is that an industry leader’s proportion of exploratory innovation has positive effect on sales growth of fringe firms. We start by highlighting that industry leaders undertake exploratory innovation to maintain their competitive advantage. We then conjecture that industry leaders’ exploratory innovation creates new submarkets into which fringe firms can enter and subsequently grow their sales. We argue that the net effect of growth at the industry level is contingent on the number of firms in the industry, as it determines the competitive pressure among participants. We then argue firm-level characteristics such as available resources and the current level of operational efficiency moderate the leader exploratory innovation-sales growth relationship. In other words, we study growth heterogeneity across and within industries. We empirically test these

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1 We do not assume that industry leaders’ exploratory innovation will always lead to fringe firms’ sales growth: We show in our robustness checks that the more the industry leaders increase their sales due to exploratory innovation, the less growth fringe firms experience.
relationships in the US computer sector, which is characterized by constant innovation and dynamic changes in the fate of participants in different industries.

This study posits, consistent with studies on positive externality (e.g. Agarwal and Bayus, 2002; Jacobides and Tae, 2015) that one firm’s effort to further its interest can help other firms improve their performance. We find that a higher proportion of exploratory innovation by an industry leader is positively related to fringe firms’ sales growth, indicating externality or growth spillover. Due to competitive pressures, the number of firms in the industry negatively affects this relationship. Although these exogenous conditions influence growth opportunities for fringe firms, they do not equally share the net growth at the industry level. We find that endogenous conditions matter in fringe firms’ ability to appropriate the opportunities and grow: Whereas financial slack positively moderate the growth externality, operational efficiency does so negatively. Focusing on individual fringe firms’ growth as the dependent variable and the industry leaders’ proportion of exploratory innovation as the independent variable, our analysis complements the existing literature that has long recognized the positive role innovation plays on firm growth. In so doing, it highlights the role of industry leader and its propensity to conduct exploratory innovation on industry growth and competitive dynamics within.

The computer sector, our empirical setting, consists of industries that supply inputs such as semiconductors, softwares, and other peripherals, as shown in Table 1. According to gross domestic product (GDP)-by-industry data gathered by the US Bureau of Economic Analysis, the sector has steadily increased in importance in terms of the total manufacturing value added, from 9.4% in 2007 to 15% in 2014. It is a technology-intensive sector wherein innovation and imitation/improvement of existing products is the fundamental source of competitive advantage. Firms in the computer sector such as IBM, Microsoft, and Intel have consistently exhibited high patenting propensity (Cohen et al., 2000). Scholars have looked at the technological determinants of the evolution of this sector (Baldwin and Clark, 2000) and how firms use technology to increase their economic rents (Bresnahan and Greenstein, 1999). Yet, there is paucity in research that has looked at how innovations from firms such as IBM, Microsoft, and Intel affected their rivals and if the variations in the types of innovation among these industry leaders have any implications for other industry participants. Building on recent research by Jacobides and Tae (2015) that highlighted the role of industry leaders in shaping the evolution of the sector, this paper examines if and how the variance in a certain type of innovations undertaken by industry leaders affects the plight of their rivals.

INSERT TABLE 1 ABOUT HERE.
THE CONCEPTUAL FRAMEWORK AND HYPOTHESES

Innovation is important to industry evolution because it fuels growth. Klepper (1996) noted that it is because innovations introduce new submarkets. Researchers found that firms intentionally innovate and create new submarkets either to deter potential entry (Bhaskarabhatla, 2016; Uzunca and Cassiman, 2013) or to exploit/develop dynamic capabilities (Mitchell and Skrzypacz, 2015). Literature on endogenous growth theory has identified innovation as an engine of growth by positively affecting other economic factors of growth (e.g., Aghion and Howitt, 1992; Grossman and Helpman, 1994; Romer, 1990). In this line of literature, purposive, profit-seeking investments in knowledge (or R&D) for innovation is critical for growth. Agarwal and Bayus (2002), for example, found that sales takeoff, or market growth, for a new product (a new submarket created through innovation) happens as more firms start to participate in the submarket after the initial uncertainty about profitability and quality concerns subside. This is consistent with the argument that “firms invest in new technology in the hope that this investment will translate into more advantageous market positions (Nerkar and Roberts, 2004: 794).” Similarly, studies rooted in evolutionary economics have identified innovation and technological change as important drivers of economic growth (Nelson and Winter, 1982; Schumpeter, 1934). Because firms persistently differ in their R&D efforts and capabilities, the relationship between innovation and growth is one of the keys explaining the substantial differences in firm performance. In recent years, scholars have provided empirical evidence supporting this relationship (e.g. Audretsch, Coad, and Segarra, 2014; Coad and Rao, 2008; Spithoven et al., 2010).

Bottazzi et al. (2001) provided an overview of how innovation, growth, and industry evolution takes place using the pharmaceutical industry as an example. They argued that breakthrough innovations are few and far in between, but they introduce fast-growing submarkets. This, in turn, drives market growth because new submarkets partially substitute existing demand from other submarkets and other firms, upon realizing the potential of the new submarket, enter it (Agarwal and Bayus, 2002). Bottazzi et al. (2001) also noted that firms that introduce new submarkets through breakthrough innovations are a handful of firms such as Pfeizer, GlaxoSmithKline, and Merck, implying that some firms, through their innovations, may be more suited to affect other firms’ growth and evolution of their industries than others.

Industries evolve differently. We argue that firms in different industries have different incentives and capability to innovate, and that this heterogeneity affects growth and
submarket dynamics. In this study, we focus on a certain type of innovation that a current industry leader undertakes. We link this innovation to fringe firms’ sales growth. We also investigate if and how attribute differences among industry participants affect the leader innovation-fringe firm growth relationship. We thus link two different levels of analysis in studying the effect of innovation on firm growth: Heterogeneity in innovation observed across vertically related industries and heterogeneity among firms within each industry.

**Exploratory innovation and industry leader**

Some innovations create new markets while others enable future innovations or improve the efficiency of producing existing products. Because technological advancement is cumulative, innovations at a point in time i) enable later innovations that might otherwise have not been developed, ii) reduce the cost of later innovations, and/or iii) expedite the speed of technological advance (Scotchmer, 1991). Firms eventually reach local optima, i.e. exhaust their opportunities to innovate through recombination of a known set of knowledge. Nerkar and Roberts (2004) argued that firms need to search broadly and incorporate a more diverse set of knowledge elements into their efforts to reach global optima. Building on this, we argue that innovations most likely to create new submarkets by addressing unmet demand in the market (Levinthal and March, 1993) are those that embody novel knowledge, which enable firms to overcome inertia built into their existing knowledge base (Fleming and Sorenson, 2004; Katila and Ahuja, 2004). We refer to such innovations as exploratory innovations. Although exploratory innovations can help address problems that would otherwise remain unsolved, they do not necessarily depart from the existing technological regime. They often do not represent a real break from existing markets and products offered, but a change or improvement (de Figueiredo and Kyle, 2006; Helfat and Lieberman, 2002). Moreover, not every exploratory innovation results in a new submarket: The higher the amount of exploratory innovation by a firm, i.e. the number of ‘bets’ the firm places on the unknown solution, the more likely a submarket is introduced due to increasing odds of success with each subsequent bet (Leiponen and Helfat, 2010).

Firms strive to innovate given the importance of innovation on growth and competition. However, because firms differ in their resource endowments, the outcome of innovative efforts differ. Scholars have observed that in general, firms with more experience, thus more established and with better capabilities, have more success (Mitchell and

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2 We are agnostic as to whether or not leaders’ innovations, regardless of the type, affect growth of non-leader firms. In this paper, we first examine the effect of a leader’s exploratory innovation that incorporates novel knowledge on growth of non-leader firms.
Skrzypacz, 2015; Nerker and Roberts, 2004). These firms are more likely to introduce innovation that can create new submarkets for several reasons. First, incorporation of novel knowledge or technology to existing knowledge base, i.e. exploratory innovation, requires large amount of resources with little assurance of future profit ex ante (March, 1991). Second, commercial exploitation of technological knowledge requires a substantial amount of resources (Grossman and Helpman, 1994; O’Conner and Rice, 2013). It is therefore only resource-rich and established firms with strong market position that can afford to engage in exploratory innovations. Third, having better quality information on potential developments that firms can gather through extensive market experience (Adner and Zemsky, 2006; Giarratana, 2004) is important for successful outcome in the future (Bhaskarabhatla, 2016). Finally, reputation and brand power, development or acquisition of which take time and resources, plays an important role in successful new product launch (de Figueiredo and Kyle, 2006). Taken together, firms with higher market share, which is a proxy of how much successful experience they have had in the past, are the ones likely to have the necessary resources to innovate successfully and create new submarkets. As such, firms with the highest market share in their industries, i.e. leaders, are the most likely to succeed with their innovative efforts than their rivals.

Leader’s exploratory innovation and other firms’ growth

We argue that exploratory innovation, by creating new submarket(s), affects the growth of the leader and other market participants. It is specifically industry leaders’ exploratory innovation that has positive effect on sales growth of other firms.

Industry leaders have little incentive to change the status quo because they already have competitive advantage (Christensen, 1997; Fleming and Sorenson, 2004). To sustain their competitive advantage over time, however, these firms need to remain at the technological frontier and set the course for future advancement to their advantage. Bhaskarabhatla (2016: 1052) noted that “… to the extent that incumbents pioneer new and independent submarkets that do not cannibalize the existing sources of revenue, they have as much, if not more, incentive to innovate as potential entrants.” Exploratory innovation and creation of submarkets help industry leaders to sustain their position in at least two ways.

First, leaders can pre-empt or at least delay entry and subsequent competition from other firms (Giarratana, 2004; Uzunca and Cassimian, 2013) by pioneering a new submarket that is close to their existing submarkets (Helfat, 1997; King and Tucci, 2002). They can then enjoy (temporary) first-mover advantage in those submarkets they create along the existing technology regime (Bottazzi et al., 2001). When competition ensues eventually, leaders can
have an advantage vis-à-vis late entrants due to accumulated experience (Mitchell and Skrzypacz, 2015; Nerkar and Roberts, 2004).

Second, creating new submarkets through exploratory innovation enables leaders to gain better quality information. Because there is time lapse between exploratory innovation and sales take-off in the corresponding submarket (Agarwal and Bayus, 2002; Bottazzi et al., 2001; Frattini et al., 2014), leaders straddle multiple submarkets rather than immediately substituting their existing submarkets with the new one. This multiple presence helps firms to gain better quality information about emerging demand (Giarratana, 2004). Having better quality information subsequently enable leaders to successfully address the emerging demand and capture more value in the future. That is, having better quality information and experience puts in motion a virtuous cycle where competitive advantage is reinforced over time.

The above seems to imply that leaders can sustain their dominant position to the detriment of fringe firms. However, this is only part of the story. Existing literature recognizes that actions taken by leading firms have implications for other industry participants. Researchers showed the behavior of dominant firms has significant effects on what other firms do and how they benefit (e.g. de Figuereido and Silverman, 2007; Jacobides and Tae, 2015). Following this line of thought, we argue that fringe firms can increase their sales from the industry leader’s exploratory innovation.

New submarkets do not pose immediate threat to firms. Scholars have noted that new submarkets take time to establish enough demand and credibility to affect competitive dynamics in existing submarkets (Agarwal and Bayus, 2002; Bottazzi et al., 2001; Frattini et al., 2014) even without substitution of the latter with the former. For example, de Figueiredo and Kyle (2006) found that innovative firms do not pull their older, yet profitable predecessor products off the market when they introduce new products. Because old and new submarkets co-exist, competitive dynamics within existing submarkets remain relatively unchanged in the short run. Fringe firms are thus able to explore the possibility of entering new submarkets to appropriate market opportunities (Breschi and Lissoni, 2001) with little concern for short-run performance implications.

An introduction of a new submarket from a leader’s exploratory innovation is more likely to trigger reactions, i.e. participation in that submarket, from other firms than when a new submarket is introduced by a non-leading firm. This is due to differences in salience between a leader and a non-leader (Bessen and Maskin, 2009; de Bruyne et al., 2002). Response to a competitor’s action is based on the interpretation and attention paid to the said
firm by observing firms. It is usually the case that more ‘visible’ firms, based on the track record and subsequent position or reputation within the existing market, receive more attention. Their actions are also likely to be viewed from a positive light, inducing an active response (de Bruyne et al., 2002; de Figueiredo and Silverman, 2007). The consequence of such response, i.e. entry, by fringe firms is the increase in the market size by serving new demand (Anderson and Tushman, 1990; Bottazzi et al., 2001; Harhoff, 1996). In industries like software or computers where innovation is both sequential and complementary, innovating firms have welcomed competition and the prospect of being imitated, as evidenced by Apple’s welcoming of IBM into the PC market in 1981 and Cisco and IBM’s donation of patents or patented technologies for free usage. The oft-cited rationale for this is to build the overall ‘ecosystem,’ i.e. increasing the size of the pie based on a set of knowledge (Bessen and Maskin, 2009). When followers into a newly created submarket serve a portion of the demand for it, ceteris paribus, they can expect to grow their sales. Therefore,

Hypothesis 1. An industry leader’s proportion of exploratory innovation is positively associated with its rivals’ sales growth.

The new submarket cannot accommodate many firms early on due to small demand. With increased entry, competition among participants will thus be fierce in the submarket. This can put downward pressure on price, resulting in fragmentation of total revenues among firms rather than the increase in total revenues (Ethiraj and Zhu, 2008). Firms that do not enter the new submarket, on the other hand, may try to compensate for the foregone opportunity by focusing all their efforts in the existing market (Jansen et al., 2006). This will result in fierce competition even within existing submarkets, resulting in the sales fragmentation and profit erosion. Therefore, when there are many firms in an industry, creation of submarkets can result in intensified competitive pressure in both the new and existing submarkets with little opportunity for growth. Although sales take-off can eventually take place (Agarwal and Bayus, 2002; Frattini et al., 2014) and relax the competitive pressure by sufficiently increasing the demand, this is unlikely in the short run. Therefore,

Hypothesis 2: The number of firms in an industry negatively moderates the relationship between a leader’s exploratory innovation and its rivals’ sales growth.

Heterogeneity in sales growth among fringe firms

Even when there is net growth in an industry, not all firms grow. Firms need to strategically manage opportunities and successfully exploit them to their benefit (e.g. Agarwal et al., 2007; Klepper and Thompson, 2006; O’Conner and Rice, 2013). Since firms differ in their heritage, their ability to manage and exploit such opportunities also differ. Firms may also differ in
their motivation to take advantage of new opportunities for the fear of undermining their current operations, i.e. cannibalize. Because firms cannot know ex ante whether their investments in these opportunities will yield the expected return, a strategic dilemma arises. Firms can commit to the status quo, or they can take chances with new opportunities that may or may not prove fruitful. We argue that these differences in ability and motivation to exploit opportunities, determined by endogenous factors, are important in determining the extent of growth externality from leader’s exploratory innovation.

Amount of financial slack. Resource availability defines both the direction and limits of firm growth (Peteraf and Barney, 2003). Firms “take advantage of opportunities afforded by the environment (Thompson, 1967: 150)” when they have resources in excess. Because firms lack immediate access to external resources as needed, firms with internal slack resources are more likely to exploit the opportunities (Troilo, De Luca, and Atuahene-Gima, 2014). Slack resources are “a pool of resources in an organization in excess of the minimum necessary to produce a given level of organizational output (Nohria and Gulati, 1996: 1246).” Among various slack resources, financial slack has been identified as the most fungible and redeployable (George, 2005). Firms with better historical performance generally have higher levels of financial slack. Firms with comparable historical performance can also differ in their slack resources due to different accumulation processes (Dierickx and Cool, 1989) and/or managerial decisions in the past (Penrose, 1959; Mishina et al., 2004).

Studies have shown that how firms manage opportunities and the outcome from exploiting such opportunities depends on their budget constraints (Kaul 2012). For example, Natividad (2013) showed that financial slack is positively related to the increase in new product releases, but that their performance was not superior to other releases. Similarly, participation in the new submarket does not guarantee growth (Aaker and Day, 1986). Firms need to acquire specific assets, be it technological, market-related, or both, to facilitate growth in the new submarket. Such assets are developed through experience, which requires time and resource investment (Bessen and Maskin, 2009; Nerkar and Roberts, 2004; Troilo et al., 2014). Firms with more slack resources are thus more likely to develop those assets to exploit the new submarket’s opportunity whereas those with little or no slack may deem the opportunity cost of entry too high. In short, financial slack affects fringe firms’ ability to take advantage of new submarket opportunities coming from the leader’s exploratory innovations. Therefore,

*Hypothesis 3: A firm’s financial slack positively moderates the relationship between a leader’s exploratory innovation and its sales growth.*
The level of efficiency. Firms differ in what they consider the best course of action in a given situation. One of the factors affecting firms’ motivation to exploit opportunities is their degree of fit with the environment. The fit between firms’ heritage of routines and the current environment largely determines their fate (Nelson and Winter, 1982). Firms develop a unique set of routines through a repeated trial-and-error process whereby tasks become easier to perform and more efficient. Once developed, routines determine how firms utilize their resources. The differences in utilization of resources give rise to operational efficiency rents (Peteraf and Barney, 2003). Operational efficiency can thus be an indicator of how well firms “fit” the competitive environment (Jansen et al., 2006) and their future performance (Soliman, 2008). Operationally efficient firms are likely to maintain the status quo: Managers prefer to exploit operational efficiency within existing submarket(s) that provide predictable outcomes than pursue new submarket opportunity with uncertain outcomes (Benner and Tushman, 2002).

Routines that enable efficient operations also impede change (Abernathy and Utterback, 1978; Levinthal, 1991) because they are specialized for a specific task (Teece, 1986). Due to this specificity, it is questionable ex ante if existing routines will be as efficient when applied to tasks catering to the new submarket. Since firms with high operational efficiency are likely to get positive feedback from the environment, there is little motivation for them to risk making their existing routines be inefficient in the new submarket. Firms with greater efficiency and scale also find it difficult to deviate from existing submarkets due to fear of cannibalization (Christensen and Bower, 1996). That is, the opportunity cost of entering the new submarket is high for firms with high operational efficiency.

This results in firms continuing to exploit their existing routines for high operational efficiency at the expense of exploring new submarkets for growth potential. It also results in firms not having the necessary resources and routines to exploit opportunities, i.e. dynamic capabilities (Teece et al., 1997), as firms lack the experience to develop them (Burgelman, 1994). Thus, firms with high of operational efficiency not only lacks the motivation to exploit the opportunities coming from the new submarket, but they also lack the necessary routines and capabilities to benefit from entering the new submarket. Therefore,

*Hypothesis 4: A firm’s level of operational efficiency will negatively moderate the relationship between a leader’s exploratory innovation and its sales growth.*

Figure 1 summarizes our conceptual model.

**DATA AND METHODS**
Data overview
We created a panel of firms operating in the computer sector using three data sources—COMPUSAT (North America), Harvard Patent Network Dataverse, and the NBER Patent Project.

We constructed a firm-year panel (1978-2004 inclusive) by extracting information from COMPUSAT on firms reporting their main Standard Industrial Classification (SIC) codes in the Computer Sector (See Table 1). We removed data points with missing information about our variables of interest. Because we are interested in tracking firms’ performance over time, we also dropped firms that appear less than five times to increase the overall balance of the panel. We then verified that the remaining unbalance in the panel would not bias our results following Verbeek and Nijman (1992).

Next, we identified an Industry Leader for each SIC-year combination. We defined industry leaders as firms with the highest market share in each SIC-year combination. We also tried different identification methods by substituting sales with market capitalization and amount of R&D investments and obtained identical results.

Finally, we used industry leaders’ names and global company keys (GVKEYs) to link each firm to the Harvard Patent Network Dataverse and the NBER Patent Project. This enabled us to track the patents owned by each industry leader in our sample, including information on the characteristics of each patent successfully applied for at the USPTO. We used the qualitative information on patents to calculate industry leaders’ exploratory innovation. We dropped industry leaders from the COMPUSAT firm-year data after we created the variable on the industry leaders’ proportion of exploratory innovation as our study only concerns the performance effect on fringe firms. Our final sample comprises an unbalanced panel with the firms being observed 11.3 times on average (min= 5, max= 28) with the total number of firms at 10,288.

Dependent variable
Change in sales. We are interested in the market implications that an industry leader’s exploratory innovation brings to fringe firms. Our dependent variable thus moves away from prior studies that looked at innovation performance (e.g. Laursen et al., 2010). We computed our dependent variable based on the following formula:

\[
\text{Performance} = \ln(\text{sales})_t - \ln(\text{sales})_{t-1},
\]

3 We chose this time window for consistency as data on patents suffer from right censoring after 2004.
where \( \ln(\text{sales}) \) is the natural logarithm of firm i’s sales, computed for both periods t and t-1. The final variable represents the difference between the two periods. By doing so, we tried to address two potential issues arising from the use of sales data—skewness and small variations that can lead to serial correlation.

**Explanatory variables**

*Industry leader’s exploration.* We tracked all the USPTO patents that each industry leader successfully applied for in year t. With this yearly patent portfolio for each industry leader, we traced all backward citations related to those patents to determine if they were cited by the firm in the past (Katila and Ahuja, 2002) using a seven-year moving window. We then calculated the ratio of new citations to total citations (Katila and Ahuja, 2002) to capture the proportion of the industry leader’s exploratory innovation. The measure ranges from 0 to 1, with higher values indicating more exploratory innovation with new (unfamiliar) knowledge.

Number of firms in the same industry. This variable is the number of firms operating within the same four-digit SIC code as the industry leader in a given year.

Financial slack. Many studies have operationalized slack based on financial ratio measures (Bourgeois, 1981; Cheng and Kesner, 1997). We also measured financial slack using the ratio between current assets to current liabilities (Singh, 1986). This measure builds on the idea that unabsorbed financial resources can be used to take advantage of new submarket.

Operational efficiency. We used asset turnover ratio (total sales divided by total assets) as a proxy for operational efficiency. It reflects “efficient use of property, plants, and equipment; efficient inventory processes; and other forms of working capital management (Soliman, 2008: 824).” This ratio is appropriate to test the mechanisms of our interest, as it measures how efficient a firm is in deploying its assets to generate sales.

**Control variables**

Fragmentation. In order to control for qualitative dimensions of the industry leader’s innovation, we compute a version of the fragmentation index proposed by Ziedonis (2004). It controls for the degree of fragmentation of ownership in each industry leader’s patent portfolio. This measure captures the extent to which the industry leader builds on a large number of sources to create its own innovation. To calculate it, we use the following metric:

\[
Fragmentation = 1 - \sum_{j=1}^{N} \left( \frac{NBCITES_{ij}}{NBCITES_i} \right)^2, i \neq j,
\]

where \( j \) refers to the unique entities cited by the patents granted to industry leader \( i \) in a given year. Therefore, \( NBCITES_i \) refers to the total number of backward citations present in
industry leader i’s patents in year t, and $NBCITES_{ij}$ refers to the number of unique entities listed in those citations.

Industry leader’s number of patents. An industry leader’s total innovation output can affect the fringe firms’ ability to appropriate new submarket opportunities, as the sheer quantity can influence the number of newly created submarkets. To control for this effect, we used the industry leader’s total number of patents in year t.

Total sales. Each firms’ size can also affect the extent of growth externality, as suggested in the knowledge spillover literature (e.g., Knott, 2003). We controlled for firm size by including firm i’s total sales in year t. This variable also controls for the effect of previous performance on our dependent variable.

R&D intensity. Absorptive capacity is one of the main determinants of a firm’s ability to benefit from knowledge generated outside its boundaries (Cohen and Levinthal, 1990). As absorptive capacity is one of the firm-level factors known to enable firms to benefit from exploiting given opportunities, we consider this construct in our analysis. Following Cohen and Levinthal (1990), we proxied for absorptive capacity using a firm’s level of R&D intensity computed as the ratio between investments in R&D to sales at year t. Higher values indicate higher levels of absorptive capacity.

Share of R&D. We expect fringe firms with a larger share of the industry’s R&D investments are better able to benefit from new submarkets created through industry leader’s exploratory innovations. To isolate this effect, we used the fringe firm i’s share of the total industry R&D investments in year t.

Lost market share. Previous performance can affect a firm’s current sales, both relative to the past and in absolute amounts. To control for the confounding effect of prior performance, we used a dummy variable that takes the value 1 if the fringe firm has lost market share relative to the previous year and 0 otherwise. Finally, we incorporated year dummies to absorb trend effects shared by all firms in our sample in the same year.

**Statistical Method**

Timing is one of the empirical challenges in this study. One would not expect fringe firms to benefit instantaneously, but with time lapse given that exploratory innovation involves boundary spanning and non-local searching (Katila and Ahuja, 2004; Nerkar and Roberts, 2004). We also hypothesize the existence of heterogeneous effects across firms in the same industry and expect slack and efficiency to play a role in this regard. Restricting our analysis to a cross-sectional setting would limit our understanding of the role played by firm
heterogeneity. We therefore use two different lags for the dependent variable (Variables \( t+1 \) and Variables \( t+2 \)). This strategy is useful not only to capture both the main and moderation effects over time but also to reduce concerns regarding reverse causality (Angrist and Pischket, 2009).

We used an ordinary least squares (OLS) time series model with firm (within) fixed effects. The use of firm fixed effects helps to control unobserved time-invariant characteristics across firms (Wooldridge, 2009). In our setting, we want to control for some time-invariant firm characteristics, such as geographic location or industry affiliation, that can correlate unobserved fringe firms’ characteristics and change in sales. We also applied robust standard errors to our estimates to address potential heteroscedasticity concerns.

RESULTS

Table 2 reports descriptive statistics and pairwise correlation coefficients for the dependent variable and all independent variables used. For simplicity, we report the correlation coefficients within the same year as the dependent variable (t=t). To ensure any potential collinearity issues across the two lags, we computed the mean uncentered variance inflation factor (VIF) for the full model in each lag \( t+1: 2.51; t+2: 2.58 \).

Table 3 reports the OLS time series model with firm fixed effects for the dependent variable Change in ln(Sales) with the two different lags \( t+1; t+2 \). Models 1, 2, 3, 4, and 5 indicate the results for all control and independent variables lagged for one year relative to the dependent variable. Models 6, 7, 8, 9, and 10 report the results for the two-year lag. We enter the explanatory variables in the models in a step-wise manner. Models 1 and 6 only included the control variables. We introduced the variable Industry Leader Exploration (Hypothesis 1) in Models 2 and 7. The first interaction Industry Leader Exploration x Number of Firms in the Same Industry (Hypothesis 2) is introduced in Models 3 and 8. The interaction terms Financial Slack x Industry Leader Exploration (Hypothesis 3) was introduced in Models 4 and 9. Finally, Models 5 and 10 present the full model with the inclusion of the interaction term Industry Leader Exploration x Operational Efficiency (Hypothesis 4). Because the results in restricted and full models are identical in directions, we only interpret the results in the full model estimated for each lag.

Results in Models 1 and 6 reveal that, as expected, R&D Intensity is positive and statistically significant \( (p<0.01) \). This implies that firms investing more in R&D tend to increase their sales in subsequent periods. The direct effect of the Number of Firms within the Same Industry is significant only for \( t+1 \). We also observe that the direct effect of the
Financial Slack and Operational Efficiency are negative and significant for t+1 and positive for t+2. Our results suggest that having too much slack in the short run can signal inefficiencies associated with resource allocation and adaptation processes (Nohria and Gulati 1996), thus showing a negative association with performance in t+1. However, slack enables pursuing “opportunities” that can bear fruit over time, resulting in positive association in t+2.

Hypothesis 1 predicted that the proportion of exploratory innovation by an Industry Leader is positively associated with fringe firms’ sales growth. In line with our expectations, we observe the positive effect of an Industry leader exploratory innovation on fringe firms’ performance in both Models 2 and 6. Hypothesis 1 is therefore supported. Hypothesis 2 predicted that the relationship predicted in Hypothesis 1 is negatively moderated by the number of firms in the same industry. We find strong support for this hypothesis in period t+1, but this effect becomes weaker in t+2. Concerning Hypothesis 3, we find mixed results. Whereas the sign of the coefficient is the opposite (negative) and without statistical significance in one-year lag, the coefficient for two-year lag is in the expected direction (b=0.02) and is statistically significant (p<0.01). Therefore, we find partial support for Hypothesis 3. The reason financial slack does not affect sales growth due to an Industry Leader Exploratory Innovation in a one-year lag model may be because of the time needed for fringe firms to “learn” (March, 1991) through trial and error, which is required in addition to the availability and commitment of necessary resources. In contrast, Hypothesis 4 predicted that the current level of operational efficiency negatively moderates the relationship in Hypothesis 1. We find consistent results in both Models 4 and 8. The signs of the coefficients are both negative (b=-0.119 and -0.107 respectively) and statistically significant (p<0.10 and p<0.01). Therefore, Hypothesis 4 is supported. This is consistent with our argument that firms with higher efficiency may not be willing or able to disturb the status quo of their operations.

To test if the inclusion of our explanatory variables provided a statistically significant improvement in model fit, we performed a likelihood ratio test. This test is run under the null hypothesis that constraining the parameter of the additional predictor to zero will not significantly reduce the model fit. Because our variables enter the model in a step-wise manner, we assume that each model is nested in the previous one for each lag. The log-likelihood comparison statistics at the bottom of Table 3 show that the inclusion of Industry Leader Exploration, Industry Leader Exploration x Number of Firms in the Same Industry,
Industry Leader Exploration x Financial Slack, and Industry Leader Exploration x Operational Efficiency all improved the overall model fit.

To interpret the size effects of the relevant explanatory variables, we estimate the conditional marginal effects computing the elasticity of Industry Leader Exploration with respect to the change in sales of fringe firms. We first predicted the values for the dependent variable with Industry Leader Exploration set at its mean. The results indicate that when Industry Leader Exploration increases by one standard deviation from its mean, fringe firms’ sales increase by 19% (p-value<0.01). Examining the moderators, we observe that when the Number of Firms in the same industry increases by one standard deviation from its mean, the effect of Industry Leader Exploration on the changes in fringe firms’ sales decrease by 18% (p-value<0.01). When Financial Slack increases one standard deviation from its mean, the effect of Industry Leader Exploration on fringe firms’ sales increase by 20% (p-value<0.05). Finally, the increase of a one standard deviation in Operational Efficiency leads to a decrease in fringe firms’ sales by 33% (p-value<0.05).

To help visualize the magnitude and direction of the moderating effects proposed in our hypotheses, we graph the conditional probabilities of Industry Leader Exploration on the dependent variable according to the different levels of our moderating variables. We graph the moderating effects using five levels for each moderator, represented by separate slopes. Figure 2 indicates that for a fixed level of Industry Leader Exploration an increase in the Number of Firms in the Same Industry will lead to a proportional reduction in the predicted values of the dependent variable. In Figure 2, we observe the opposite effect for Financial Slack, with increasing values of moderators leading to a stronger increase in the predicted values of our dependent variable. Finally, Figure 3 illustrates the negative moderating effect of Operational Efficiency on the relationship between Industry Leader Exploration and the predicted values of change in sales.

INSERT FIGURES 2, 3, AND 4 ABOUT HERE.

Supplementary Analysis

We performed a series of additional tests to verify if the assumptions leading to our hypotheses hold against alternative explanations. We ran the supplementary analysis using the dependent variable Change in Ln(Sales)_{t+2} because two lags are more aligned with our expectations regarding the timing effect between the Industry Leader investments in exploration and its effects on fringe firms’ sales. First, we expect that fringe firms’ sales growth will be limited when an Industry Leader increases its own sales due to its exploratory
innovation. To test this idea, we estimated a different model in which we interact Industry Leaders Exploratory Innovation x Industry Leader Change in Sales. The results of Model 1 in Table 3 show that the coefficient for the interaction term is negative and significant, implying that if the Industry Leader takes over the submarket created by its investments in exploratory innovation itself, there will be fewer opportunities for fringe firms to grow their sales in that submarket. Second, given that our dependent variable concerns changes in sales, we did not restrict the sample of fringe firms to the ones that actively innovate. To verify if fringe firms that are more innovative are also more likely to increase their sales from Industry Leader Exploration, we computed the yearly patent stock for all fringe firms in our sample and split the sample between firms that had at least one patent in the focal year and those that had none. The comparison of the coefficients in Model 2 and Model 3 indicate that innovative firms are significantly (p<0.05) more likely to grow their sales due to Industry Leader’s exploratory innovation. Finally, we also examined if the extent of an Industry Leader dominance within the industry affects sales growth of fringe firms. We computed the variable Industry Leader dominance based on the ratio between the Industry Leader’s sales and the total sales of fringe firms within a segment in a given year and split the sample into two based on whether the ratio is greater than one. It indicates whether the Industry Leader has more than half the market share in the segment. Model 4 reports the observation within segments in which Industry Leaders have less than half the market share and Model 5 the cases in which Industry Leaders have more than half the market share. The coefficient for Industry Leader Exploration is statistically significant for both models (p<0.05). However, the comparison of the coefficients across the different models indicates that in industries with stronger Industry Leader dominance, the investments in exploration have a stronger positive effect on the change in sales for fringe firms. In other words, Industry Leaders exert smaller positive externality on their fringe firms when they are relatively less dominant over close competitors. This finding is consistent with the findings of Jacobides and Tae (2015), who highlighted that greater inequality within an industry benefits the industry as a whole vis-à-vis other industries in the sector.

DISCUSSION
We find that, at least in our setting, an industry leader’s innovative output can fuel growth among fringe firms, independent of their own innovative endeavor. Industry leaders’ exploratory innovation and the number of competitors in the industry “exogenously”
influences fringe firms’ growth on average. It is, however, fringe firms’ own attributes such
as availability of financial slack and degree of operational efficiency, that “endogenously”
determine the extent of growth from exogenous factors.

This paper builds on and expands the literature on industry evolution (Klepper, 1997),
in particular how innovation fuels growth of an industry as a whole. We show that
exploratory innovation, which can be either product- or process-based, drive growth for
industry participants (Nelson and Winter, 1982). Heterogeneity in industry leaders’ extent of
exploratory innovation can, all else equal, promote or constrain the industry’s relative growth
within a sector comprising vertically related industries. Through their exploratory innovations,
industry leaders can grow the size of the pie even after the emergence of a dominant design
and without disrupting it. Consistent with this, Baumol (2002: 3) noted:

“In this one should not undervalue the incremental contribution of the routine
activity (exploratory innovations in our parlance) that at least sometimes
arguably adds more to growth than do the more revolutionary prototype
innovations.” (Parentheses added by the authors)

Focusing more on innovations with novel knowledge contributes to growing the
industry’s market size, even when firms may reduce their overall innovative output. It
is the proportion of exploratory innovation to total innovation undertaken by industry
leaders that showed positive relationship with fringe firms’ growth. This adds a twist
to the existing industry lifecycle literature. Our results indicate that so long as industry
leaders keep the proportion of their exploratory innovations relatively high, they can
grow the industry. In other words, what matters more is the composition of different
types of innovations rather than the absolute amount of innovations.

Our findings also complement prior literature on the positive role of a few large,
dominant firms, i.e. industry leaders, on the plight of their competitors. We show that
industry leaders enable fringe firms to grow by creating submarkets through their exploratory
innovation, just as their market churns signal emerging product categories (de Figueiredo and
Silverman, 2007) and their superior capabilities and technological prowess set up favorable
templates of transactions across industries (Jacobides and Tae, 2015). Our finding is
consistent with what Agarwal and Bayus (2002) found in their studies that entry by firms into
a new market, pioneered by another firm, leads to growth in demand overall for mutual
benefit. This positive ramification is, however, a by-product of industry leaders’ pursuit of
self-interest (Bhaskarabhatla, 2016).
By showing the moderating roles of financial slack and operational efficiency, we highlight how attribute differences among industry participants affect the leader innovation-fringe firm growth relationship. Underneath the industry-level positive externality in aggregate lies its uneven distribution at the firm level due to firm heterogeneity. Interestingly, we find that what is often considered as a bad or good sign in isolation has the opposite effect on the leader’s exploratory innovation and sales growth relationship. Resource underutilization is manifest in too much slack (Nohria and Gulati, 1996) with forgone profit-generating opportunities, making higher level of available financial slack a bad sign. On the other hand, high operational efficiency implies full exploitation of available resources to generate income with little or no waste (Soliman 2008), thus a good sign. Our findings, however, indicate that such inefficient resource utilization and incomplete exploitation of resources is necessary for fringe firms to grow sales from industry leaders’ exploratory innovations. We thus link two different levels of analysis in studying the effect of innovation on firm growth: Heterogeneity in leaders’ innovation observed across vertically related industries and heterogeneity among firms within each industry.

The above findings on the effect of heterogeneity across industry leaders and among industry participants on growth illustrates how this joint analysis can enhance our understanding of industry evolution and growth dynamics. It also opens up new avenues of research. While we focused on industry leaders’ exploratory innovation and their competitors’ growth, other characteristics of industry leaders can also influence fringe firms’ growth. Identifying those characteristics and examining which characteristic dominates in explaining fringe firms’ sales growth will deepen our understanding of industry leaders’ positive externality. Our data indicate that industry leaders exhibit varying proportions of exploratory innovation, leading to differences in sales growth experienced by their competitors. We took this heterogeneity as a given and did not explore why some industry leaders exhibit higher proportion of exploratory innovation than others. Understanding what factors affect the propensity to produce more exploratory innovation can further our understanding of the dynamics between innovation and growth. It would also be worthwhile to explore other factors, such as scope, that can lead to uneven distribution of positive externality among fringe firms. In addition, examining the effect of a new industry leader, i.e. change in firm ranking, can be a fruitful avenue for future research.

This study has several limitations. First, while we argue that industry leaders’ exploratory innovation is likely to create new submarkets, through which their competitors grow, we do not directly observe if exploratory innovation results in new submarket creation.
Our comprehensive data comprise all participants in multiple SIC codes and their various performance and innovation measures, but we were unable to gather product-level data for each industry for the period we cover. The combined use of industry and patent data was constraining as it neither directly reflects the link between exploratory innovation and submarket creation nor allowed us to directly test the specific mechanisms. We thus chose to articulate the mechanisms that link industry leaders’ exploratory innovation with sales growth of fringe firms and then tested their “reduced-form,” instead of their “structural,” implications. As noted in other sector-level studies, there is no easy way to remedy the problem, but the shortcoming must be noted. Second, we only include publicly traded firms in our sample, as we did not have information on private firms whose inclusion might have changed the results. Because well-known industry leaders in the computer sector, such as IBM, Microsoft, and Intel, have been public for a long period of time, we believe omitting private fringe firms from our data provides conservative results rather than biased results. Regarding the analysis, we do not hypothesize or test the joint effect of slack resources and operational efficiency in tandem, although the two may be closely related. Because our primary interest here was to understand if exploratory innovations of industry leaders leads to sales growth among fringe firms, we opted not to explore the complexity observed within each fringe firm or its effect on sales growth.

This study suggests that one firm’s effort to further its interest can help other firms with their interests. We study this in the context of industry leader’s proportion of exploratory innovation and its effect on its direct competitors’ sales growth. We argue that fringe firms can grow because exploratory innovation of industry leaders create new submarkets that fringe firms can enter. However, not all fringe firms grow equally within each industry. Factors such as the number of participants in the industry, each firm’s financial slack, and its operational efficiency all affect the extent of each fringe firm’s growth. The findings of this study highlight that the joint study of heterogeneity across vertically related industries and that among firms within each industry can yield valuable insights into which industries grow more as they evolve and which firms outgrow others.
REFERENCES


Figure 1. Conceptual model

Creation of new submarkets within the industry

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Increased competitive pressure

The degree of leader’s exploratory innovation

H1: +

H2: -

Growth of fringe firms in the industry (as a whole)

The number of firms in a segment

Ability to undertake repeated endeavor

The level of fringe firm’s financial slack

H3a: +

H3b: -

Growth of individual fringe firms in the industry

The level of fringe firm’s operational efficiency

Inertia stemming from efficiency concerns
Figure 2. Conditional marginal effects of Industry Leader exploratory innovations: Moderating effect of the number of firms in an industry

Figure 3. Conditional marginal effects of Industry Leader exploratory innovations: Moderating effect of fringe firms’ financial slack

Figure 4. Conditional marginal effects of Industry Leader exploratory innovations: Moderating effect of fringe firms’ operational efficiency
### Table 1: Computer Sector Industries

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<th>Description</th>
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<td>3571</td>
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<tr>
<td>3572</td>
<td>Computer Storage Devices</td>
</tr>
<tr>
<td>3575</td>
<td>Computer Terminals</td>
</tr>
<tr>
<td>3577</td>
<td>Computer Peripheral Equipment, Not Elsewhere</td>
</tr>
<tr>
<td></td>
<td>Classified</td>
</tr>
<tr>
<td>3674</td>
<td>Semiconductors and Related Devices</td>
</tr>
<tr>
<td>7372</td>
<td>Pre-packaged Software</td>
</tr>
<tr>
<td>7373</td>
<td>Computer Integrated Systems Design</td>
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### Table 2: Descriptive Statistics and Correlation Coefficients

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<td>Number of Firms in the Same Industry</td>
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<td>0.03</td>
<td>0.00</td>
<td>0.43</td>
<td>0.000</td>
<td>0.147</td>
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<td>-0.070</td>
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<td>0.50</td>
<td>0.00</td>
<td>1.00</td>
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<td>0.032</td>
<td>-0.018</td>
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<td>Sales t-1</td>
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<td>R&amp;D Intensity</td>
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<td>61.67</td>
<td>0.022</td>
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<td>0.03</td>
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<td>Lost Market-share</td>
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<td>-0.036</td>
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Table 3: Fixed-effects Regression Coefficients

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<th>Change in ln(Sales) t+2</th>
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<td>Industry Leader Exploration</td>
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<td>0.232***</td>
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<td>(0.053)</td>
<td>(0.087)</td>
<td>(0.087)</td>
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<td>-0.045***</td>
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<td>(0.024)</td>
<td>(0.024)</td>
<td>(0.024)</td>
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<td>Industry Leader Exploration x Financial Slack</td>
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<td>(0.011)</td>
<td>(0.014)</td>
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<td>Industry Leader Exploration x Operational Efficiency</td>
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<td>Number of Firms in the Same Industry</td>
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<td>Sales</td>
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<td>(0.612)</td>
<td>(0.620)</td>
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</tr>
<tr>
<td>Industry Leader Exploration x Financial Slack</td>
<td>0.024**</td>
<td>0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Industry Leader Exploration x Operational Efficiency</td>
<td>-0.073</td>
<td>-0.056</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Industry Leader Increase in Sales</td>
<td>-0.000</td>
<td>-0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Number of Firms</td>
<td>0.000**</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Financial Slack</td>
<td>0.006***</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Operational Efficiency</td>
<td>0.061**</td>
<td>0.070***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Fragmentation</td>
<td>-0.115</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>(0.206)</td>
<td>(0.247)</td>
</tr>
<tr>
<td>Industry Leader Patents</td>
<td>0.000+</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Sales t-1</td>
<td>-0.000***</td>
<td>-0.000**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>R&amp;D Intensity</td>
<td>0.040***</td>
<td>0.032***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Share of R&amp;D</td>
<td>-1.673***</td>
<td>-5.462***</td>
</tr>
<tr>
<td></td>
<td>(0.602)</td>
<td>(1.835)</td>
</tr>
<tr>
<td>Lost Market-share</td>
<td>0.026***</td>
<td>0.024**</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Constant</td>
<td>0.107+</td>
<td>0.164+</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>9,382</td>
<td>6,271</td>
</tr>
<tr>
<td>Groups</td>
<td>906</td>
<td>820</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-3,713.192</td>
<td>-2,650.197</td>
</tr>
</tbody>
</table>

* p<0.10, ** p<0.05, *** p<0.01 (one-tailed test)