Antecedents and Outcomes of Technology Licensing

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Abstract

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from the licensed knowledge will be limited. Finally, we suggest that financial resources at the discretion of the licensee may be an important catalyst unlocking benefits of licensing, even if aforementioned impediments for learning and recombining of in-licensed knowledge are present. We test our hypotheses using a longitudinal design tracking the licensing and innovation behavior of firms operating in the global biopharmaceutical industry.
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Introduction
The ability to tap into knowledge and technologies from outside the organization is considered critical for firms to be competitive (Cassiman & Veugelers, 2006; Chesbrough, 2003). Among many alternatives, technology-licensing is acknowledged as one of the most important contractual mechanisms through which firms exchange knowledge and complement internal R&D activities (Anand & Khanna, 2000; Cassiman & Veugelers, 2006; Contractor, 1990). The literature on licensing and markets for technology has predominantly covered the incentives and motives behind firms’ decisions to license-out their technologies (e.g., Teece, 1986). Yet, in contrast to other forms of accessing external knowledge (e.g., acquisitions or alliances), we know relatively little about how firms make licensing-in decisions and the consequences those decisions have for firm innovation.
In this paper, we aim to provide a more systematic understanding of the key conceptual underpinnings of firms’ decision to license-in external technologies and of how licensing-in shapes firms’ ability to innovate. In doing so we consider licensing as a process in which the decision to license-in a new technology and the possibility to learn and benefit from it are two distinct but inter-dependent activities. A process view opens the possibility not only to jointly model the licensing-in antecedents and outcomes, but also to understand how the factors that lead firms into licensing in the first place can have repercussions along the process of integrating licensed technologies. Adopting this approach, we define technology licensing-in as a two-stage process starting with (1) the antecedents leading firms to take licensing-in decisions and then moving into (2) the outcomes related to licensing decisions in terms of innovation.

Our theoretical framework draws on the literatures of markets for technology (Arora and Fosfuri, 2003; Fosfuri, 2006), competition (Chen, 1996; Aghion et al., 2005), and innovation (Laursen and Salter, 2006; Cassiman & Veugelers, 2006). We suggest that competitors’ R&D moves are an important antecedent to licensing-in decisions as licensing allows firms a speedy, specific and competitive response (Laursen, Leone, & Torrisi, 2010; Leone & Reichstein, 2011) to R&D actions emerging from competitors. Next, we take into account that licensing agreements increase a licensee’s potential to learn from external pockets of knowledge (Laursen et al., 2010), thus increasing a firm’s capacity to innovate. However, we also suggest that when used as a response to increasing competitive R&D pressures, firm’s capacity to learn and benefit from the licensed knowledge will be limited. In such cases, despite adding new knowledge to their repertoire through licensing, firms may not be able to realize their full potential to innovate. Finally, we take into account that learning benefits and possible impediments to learning are also shaped by the internal organizational context into which the licensed knowledge is added.
(Ceccagnoli & Jiang, 2013). Specifically, financial resources at the discretion of the licensee may unlock or mitigate the potential to learn from licensing-in.

Overall, our theoretical model of licensing as a process uncovers competitive pressure as an important antecedent to licensing-in new knowledge, and explicates how the relationship between licensing and innovation ultimately unfolds under both external and internal conditions, such as high competitive pressure and the presence of discretionary financial resources.

We test our theoretical model through a longitudinal design tracking the licensing and innovation behavior of 205 firms operating in the global bio-pharmaceutical industry. Using a large longitudinal sample makes it possible to observe the process capturing both antecedents and outcomes of licensing-in decisions. The final dataset used to test our predictions combines licensing data from the Deloitte Recap, product development data from Pharmaprojects to capture competitors R&D pressures, financial information from Compustat and patent data collected from the United States Patent and Trademark Office (USPTO) to capture firms’ innovation outcomes. Our findings indicate that R&D competitive pressure is an important antecedent to licensing-in decisions. With respect to licensing outcomes we find that licensing-in increases a firm’s capacity to create innovations. However, when licensing under increasing competitive pressure, the relationship between licensing and innovation is weaker. Finally, we find mixed evidence that financial resources are a key catalyst to benefit from licensing for firms but as a key moderator on how firms can benefit from licensing-in.

The paper makes three main contributions to research and literature on technology licensing and innovation. To the best of our knowledge, this is the first attempt to systematically look at the licensee perspective using a process model that takes into account the antecedents as well as the outcomes of technology licensing-in. The paper is also among the first to take into consideration external and internal organizational factors explaining the relationship between
licensing and innovation within the same analytical framework. Specifically, we connect the characteristics of technology licensing to the way firms react to R&D competitive pressures, which adds to the literature on competitive dynamics (Kaul, 2012), and to the availability of discretionary financial resources inside the firm (Jensen & Thursby, 2001). Finally, the paper contributes to the understanding of firms’ behaviors on the demand side of markets for technology (Arora & Gambardella, 2010), investigating the repercussions that licensing has on firm capacity to learn and, ultimately, to innovate (Johnson, 2002).

Theory

Technology Licensing – Process, Antecedents and Outcomes

In competitive environments, technological opportunities emerge rapidly and existing competencies are quickly rendered obsolete, requiring firms to continuously take knowledge-seeking actions (D'Aveni, Dagnino, & Smith, 2010). An important knowledge seeking action, which has grown substantially over the last decades is technology licensing, which enables firms to access existing knowledge and technologies developed outside its organizational boundaries (Leone & Reichstein, 2012). It means that under circumstances that require quick strategic reactions in response to changes in the industry technological landscape firms can rely on licensing deals to acquire the rights to exploit externally developed technologies (Agrawal, Cockburn, & Zhang, 2015; Arora & Gambardella, 2010).

Technology licensing differs from other forms of knowledge-sourcing activities such as alliances or outright acquisitions. A key distinctive feature of technology licensing lies in the nature of the technological knowledge being exchanged. While, in research alliances, two or more firms combine resources and capabilities to develop a new technology, in licensing contracts, the licensor agrees to transfer to the licensee the right to use or develop an existing technology for an up-front fee and/or royalties (Contractor, 1990; Jensen & Thursby, 2001).
Thus, through licensing, firms can decide the type and characteristics of the technology to be sourced \textit{ex-ante} (in contrast to an alliance) while the ownership of the technology is retained by the licensor (in contrast to an acquisition). These characteristics make licensing a highly flexible tool for firms to quickly access specific pieces of knowledge (Leone & Reichstein, 2011).

Yet, in spite of these distinctive characteristics of licensing, we know little about the underlying processes triggering firms to make the decision to license-in as well as its consequences for firm capacity to innovate. While researchers have examined similar questions in the context of alliances (e.g., Mowery, Oxley, & Silverman, 1996) and acquisitions (e.g., Colombo & Rabbiosi, 2014), little is known about the antecedents of technology licensing.

Based on these distinct areas of inquiry, we model technology licensing as a two-stage process (see Figure 1). In the first stage of our process model, we focus on \textit{Licensing Antecedents} by explicitly considering the competitive landscape and the competitive pressures brought by other industry participants as important factors affecting firm choices to tap into external knowledge using licensing deals. We then move towards the second stage regarding the \textit{Licensing Outcomes}, specifically taking into account the mechanisms through which licensing affects a firm’s ability to learn and innovate to improve their competitive position.

[Insert Figure 1 here]

This approach allows us to shed light on the overall licensing-in process and explicate how learning mechanisms unfold when licensing decisions are taken under conditions of increasing R&D pressure from industry competitors. Finally, we take into account that the effective integration of external knowledge requires the allocation of dedicated resources, in particular, financial resources, at the discretion of the licensee firm (Bierly et al., 2009). We next move through these different stages, related to the antecedents and outcomes of the technology licensing processes, to detail our theoretical framework.
Antecedent to Licensing: Competitive Pressure

Extant research highlights that R&D competition in an industry gives rise to organizational decisions and actions (Chen, 1996; Scherer & Ross, 1990). In particular, firms increase R&D investments and corporate transactions (e.g., strategic alliances, M&As and hiring of skilled employees) as a response to competitive R&D moves from other industry players (Aghion, Bloom, Blundell, Griffith, & Howitt, 2005; Kaul, 2012). We argue that a notable response by firms to pressures from competitors’ R&D is to access external knowledge through licensing-in.

We focus on actions taken by competitors in the form of successfully pushing products on the market in which a focal firm actively invests in R&D. Such competitive R&D actions are a) highly visible and b) can objectively deteriorate the competitive position of a focal firm as competitors strengthen their competitive and technological position at the expense of other firms within the same industry (Aghion et al., 2005). Accordingly, such R&D actions lead to competitive pressures as firms fear the deterioration of their future position within an industry and experience greater uncertainty about their current markets (Ang, 2008; Dickson, 1992). Failure to react to a competitor’s R&D moves can lead a focal firm to eventually experience the obsolescence of its technological portfolio (Robertson & Gatignon, 1998), loss of product market (Aghion et al., 2005) and make it more difficult to access financial resources (Valta, 2012). These pressures are exacerbated as the competitor’s efforts in R&D also invoke negative reactions from the focal firm’s stakeholders, such as providers of capital or financial analysts who may demand a response to actions by competitors (Benner & Ranganathan, 2012; Florida & Kenney, 1988; Gompers & Lerner, 2004). In summary, R&D moves from competitors can have important implications for a firm’s capacity to remain competitive and for its long-term survival.

Extant research has suggested that firms can respond to competitive pressure by directly intensifying internal R&D efforts (Chen & Miller, 2007; Greve, 2003; Katila & Chen, 2008;
Scherer & Ross, 1990). Complementing this perspective, we suggest that a number of factors make licensing an important move for firms under conditions of R&D competitive pressure.

First, competitive actions tend to demand a timely response (Chen et al., 2007). For example, competitive pressures have been demonstrated to lead to fast decisions in product development (Schoonhoven et al., 1990). Licensing offers firms a way to rapidly access existing knowledge and technologies from outside the firm (Mowery et al., 1996) and has been shown to substantially accelerate innovation cycles in general (Laursen et al., 2010; Leone & Reichstein, 2011; Markman, Gianiodis, Phan, & Balkin, 2005). It follows that when firms want to offer a timely response to competitive R&D actions, licensing provides a flexible option to access readily available knowledge as compared to developing it from scratch through the substantial commitment of fixed assets as required through internal R&D (Swan & Allred, 2003). Licensing also has been shown to allow firms to refocus their actions when additional information (e.g., through competitors’ R&D actions) emerges. It stands to reason that when competitive pressure increases, firms more likely will respond by taking licensing-in decisions.

Second, competitive pressure may challenge a firm’s “conventional” way of approaching R&D problems (Luo, 2003). R&D actions taken by competitors reveal the type of knowledge and technologies which allowed the other firms to create a competitive advantage and exert competitive pressure in the first place. Extant work suggests that initial (successful) R&D actions by competitors can spur firms to learn more about the areas in which these successes have been achieved (Henderson & Clark, 1990). Licensing is unique as it allows a directed response towards competitive R&D actions as firms can define and select ex-ante the relevant pockets of knowledge and technologies to be acquired (Chen & Miller, 2007; Cyert & March, 1963; Greve, 2003). Licensing, thus, represents a unique form of problemistic search, in which firms seek for implementation of a solution for a specific performance problem (in our case competitive
pressures) that firms have at hand (Cyert & March, 1963). In the absence of competitive pressures, firms have lower incentives to directly identify and focus on filling the gaps between theirs and competitors’ knowledge bases.

Third, licensing by nature is a competitive move as by acquiring the rights to access and use the knowledge of another firm, licensees can preclude additional competitors from using the same technology\(^1\) (Anand & Khanna, 2000; Ziedonis, 2007). Indeed, by acquiring the right to exploit valuable technologies, firms can impose a deterrence barrier that precludes rivals from accessing and building competitive advantages on these technologies (Rivette & Kline, 2000). Not only does licensing allow to preclude possible competitors but it also presents a way to access external knowledge and technologies without reciprocation in terms of knowledge exchange (Arora, Fosfuri, & Gambardella, 2001; Mulotte, 2013). When reacting to competitive pressure firms may be reluctant to reveal their own internal R&D efforts. Licensing offers a way to access knowledge without fear that competitors appropriate a firm’s technological knowledge.

Taking all arguments together, the unique characteristics of licensing make it an important response for firms to competitive R&D pressures. We, hence, suggest:

**Hypothesis 1:** Firms are more likely to engage in technology licensing the greater R&D pressures from competitors.

We now move from the antecedents of licensing decisions to the consequences that they can have for firm outcomes. In line with our arguments regarding licensing-in antecedents, we expect that by licensing-in technologies and knowledge, firms generally have the intention to derive innovation benefits to improve their competitive position. Given that R&D investments

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1 Exclusivity is common in licensing contracts. Using a cross-industry sample, Somaya et al. (2011) report that, in their sample, around 80 percent of the licensing deals use an exclusivity clause.
and innovation are inextricably connected (Cassiman & Veugelers, 2006), one important way for firms to react and remEDIATE both short- and long-term competitive losses triggered by R&D moves from competitors is through becoming more innovative. Therefore, one should expect that by licensing-in, firms are not only aiming at neutralizing the immediate threat imposed by rivals, but are also trying to improve their own capacity to innovate more effectively, thus gaining future competitive advantages. As to the antecedents of the effects of licensing decisions on the consequences of licensing-in, we now examine how licensing-in, in general, shapes firm innovation. Then, we explore how competitive pressures affects licensing and innovation.

**Consequences of Technology Licensing: Learning & Innovation**

The link between licensing and innovation lies in firms learning and creating novel potential combinations using the licensed knowledge (Galunic & Rodan, 1998). The mechanisms that connect licensing-in and the creation of innovations have received little attention (notable exceptions are: Laursen et al., 2010; Oxley & Wada, 2009). We propose that licensing-in not only saves effort and resources that would otherwise have been spent on creating a totally new technology, but it also provides the licensee with a larger set of technological opportunities that firms can learn from, integrate and transform into innovations (Johnson, 2002).

We suggest that there are at least two distinct mechanisms through which licensing-in leads to organizational learning that increases a firm’s capacity to create innovations. The first involves a firm’s knowledge repertoire (Arora, 1995; Grindley & Teece, 1997). Through licensing, firms can learn about state-of-the-art technologies and then can experiment by linking newly licensed knowledge with knowledge already residing inside the firm (Bierly et al., 2009). In particular, licensing increases a firm’s pockets of available knowledge, which, in turn, increases the potential for recombination between new and existing elements (Galunic & Rodan,
1998; Katila & Ahuja, 2002). Accordingly, newly acquired pieces of knowledge provide the licensee with a context to create novel sets of combinations (Grant, 1996).

Beyond a quantitative increase in a firm’s knowledge pool, licensing allows firms to increase their knowledge variety by adding technologies about which they know very little or nothing (Laursen et al., 2010). Such variety is important as the process of innovation often requires firms to tap into knowledge from a range of disciplines or knowledge distant and different from their existing knowledge domains (Galunic & Rodan, 1998). This second mechanism connecting licensing-in to learning opportunities relates to the access that firms can have to unfamiliar and diverse knowledge. Importantly, licensing is often associated with the transfer of tacit knowledge (Arora, 1995) that goes beyond patents and blueprints and allows firms to acquire idiosyncratic knowledge embedded in the licensor’s routines and internal processes, information that would be difficult to access simply by observing competitors. These diverse pockets of knowledge will allow firms to learn about new ways of solving problems, processes and routines, all of which may substantially depart from how the firm has conducted research internally (Laursen et al., 2010). The result is that licensing enhances the potential for a firm to learn about diverse pieces of knowledge and recombine them in novel ways, thus enhancing a firm’s capacity to create innovations. In summary, we expect that licensing induces learning and creates greater potential for learning and recombination to unfold, thus enabling firms to increase their rate of innovation. We propose that:

Hypothesis 2: Engaging in technology licensing will be positively related to a firm’s subsequent capacity to innovate.
Licensing, Competitive Pressure & Innovation

We identified that competitive R&D actions are important antecedents to licensing activities (H1) and the creation of innovations is a significant and expected outcome from licensing-in (H2). Now we combine both arguments and explore the consequences of licensing under competitive pressure, i.e., at the time the licensing decision is made, the circumstances surrounding a competitive environment can have *ex-post* repercussions on firms’ capacity to innovate based on the newly acquired technologies. While our baseline case suggests that licensing should yield a positive innovation effect, there is reason to believe that licensing under increasing competition may have side effects on the ability of firms to innovate. In particular, we examine the key mechanisms that we identified to explain licensing-in decisions following competitive R&D pressures in the first place, i.e., a quick and short-term response, the directed and problemistic nature of licensing and the emphasis on licensing-in without having to reciprocate the knowledge flows, to suggest that these factors may prevent a firm from learning.

We started by highlighting that licensing under increasing competitive pressure can serve as a strategic and flexible response to competitive pressures as firms can reach existing technologies that provide an quick reaction. However, learning and recombination of knowledge is a time-consuming process (Galunic & Rodan, 1998) that requires firms to assume a long-term perspective as, for example, many possible applications for existing knowledge only reveal themselves over time (Helfat, Finkelstein, Mitchell, Teece, & Singh, 2007). It stands to reason that licensing under increasing competitive pressures may diminish subsequent learning, as firms licensing under these conditions are less likely to take a long-term perspective to envisioning the potential usefulness of external knowledge for solving future problems. In a similar vein, for learning to transpire in firms, it is required mindfulness and abstraction (Ghosh, Martin,
Pennings, & Wezel, 2013), but this may be challenging if licensing is deployed solely as an immediate and specific response to pressures emerging from competitors’ R&D actions.

Moreover, even though licensing-in allows firms adding variety, when responding to competitive pressure, the learning gained by such variety may be limited. We highlighted that when licensing-in under increasing competitive pressure, firms will be guided by competitors’ R&D actions and hence be drawn to acquire technological knowledge as an *ad hoc* and specific reaction to their competitor’s R&D moves (Aghion et al., 2005; Deephouse, 1999). This limits the scope of the knowledge that firms consider feasible for learning and recombination to a smaller subset among possible alternatives, as they attempt to remediate or imitate the strategic moves initiated by their competitors (Zander & Kogut, 1995). Thus, acquiring new knowledge and technologies through licensing as a specific response, may mute possible learning and recombination as compared to licensing-in decisions which are not guided to responding to competitor’s R&D actions in the first place. The problem is exacerbated as it is uncertain if the specific pockets of knowledge added when responding to competitors’ R&D actions are the adequate inputs for subsequent innovations as the technological landscape changes rapidly.

Finally, treating licensing predominantly as a competitive reaction may reduce potential bilateral knowledge flows between licensor and licensee. In particular, firms using licensing in this way (e.g., by focusing on the exclusion of other parties) may be unable to pay sufficient attention to learning opportunities not directly contracted in the licensing deals. We claimed that it is more likely that, following competitive pressure, licensing is used as a competitive response and that licensees would emphasize the unilateral flow of knowledge in such licensing deals to protect their own knowledge base from potential partner’s opportunism. However, learning is easier to induce under conditions of reciprocal interactions between licensor and licensee following such licensing agreements (Agrawal, 2006; Dyer & Singh, 1998; Galunic & Rodan,
1998) and it is particularly difficult to transfer tacit components of knowledge if both parts (i.e., licensor and licensee) are not committed to that process (Arora, 1995). The lack of willingness to engage in a reciprocal knowledge exchange with the licensor, thus, cannot only restrict the quantity of knowledge that licensees acquire, but also limit their understanding of how to recombine and apply it effectively to innovate. Given that we expect such reciprocity to be less salient when licensing is used under competitive pressure, we expect that the overall potential to learn and recombine knowledge following licensing is reduced.

Therefore, we propose that licensing leads to the potential to innovate but such potential may be affected by licensing as a response to increasing competitive R&D pressures.

Hypothesis 3: The positive relationship between technology licensing and a firm’s subsequent capacity to innovate will be attenuated by the intensity of competitive pressures the firm faces at the time of licensing-in.

The Role of Internal Financial Resources

We have discussed the ways in which both the decision to license-in and the consequences of licensing are influenced by external factors such as competitive pressures. However, it is also important to note the internal organizational context, which is also acknowledged to shape the knowledge transformation process of externally acquired knowledge (Bierly et al., 2009). The process of knowledge transfer, learning and recombination is directly dependent on the organizational capabilities and resources that the acquiring firm possesses that will allow it to integrate external knowledge (Ceccagnoli & Jiang, 2013; Grant, 1996). To illustrate this point, we next investigate the role of availability or lack of financial resources within the firm to explain why some firms are better able than others to benefit from licensing-in.
Since innovation is ultimately an uncertain task and often requires irreversible investments, prior research has stressed the importance of financial resources available inside an organization to support the innovation process (Teece, 1996). The pool of discretionary financial resources that are in excess of the resources that are needed for current operations (Cyert & March, 1963) often is referred to slack and can be observed in the form of excess financial resources such as free cash-flow (Cuervo-Cazurra & Annique Un, 2010; Cyert & March, 1963). Indeed, when firms have internal financial resources, they can divert or redeploy it to achieve organizational goals (George, 2005). While the direct role of such excess financial resources in innovation is subject to debate (Jensen & Ruback, 1983; Nohria & Gulati, 1996), we suggest that the availability of financial resources inside the organization can play an important part in realizing benefits from licensing-in, especially from licensing-in under competitive pressure.

Extant research suggests that learning from and recombination of external knowledge entail integration costs (Arora, 1995; Ceccagnoli & Jiang, 2013). Firms may only have a limited understanding of how the new technology can be applied and further developed and hence be dependent on the licensor to support the process of knowledge integration by dispersing resources in a timely manner. Accordingly, internal discretionary financial resources, within the firm may be particularly useful to such integration activities. Such discretionary internal funds are also easily and rapidly available, which is why they can be immediately utilized to support the integration of licensed-in technologies. The presence of financial resources ensures the resources necessary for licensees to go through a process of recombination, refinement and adaptation of licensed knowledge to their specific needs (Jensen & Thursby, 2001). Lacking discretionary financial resources, firms may face difficulties in the integration of the newly licensed-in technologies and those technologies may remain underutilized.
The presence of discretionary internal financial resources, also, allows firms to pay attention to very diverse pockets of knowledge simultaneously (Cyert & March, 1963). Integration costs are particularly high when licensed-in knowledge departs from the internal knowledge base of an organization (Wilcox King & Zeithaml, 2003). However, the availability of discretionary financial resources not only facilitates integration per se but also allows firms to experiment with new ways of solving problems (Nohria & Gulati, 1996). In contrast, when discretionary resources are absent, firms may focus on the development of projects with less uncertainty and ambiguity in terms of potential outcomes.

Given the importance of the availability of discretionary financial resources for the integration of licensed knowledge, we propose:

Hypothesis 4a: The relationship between licensing and innovation is positively moderated by the availability of discretionary financial resources inside the firm.

Using above arguments, we can derive implications of the presence or lack of financial resources for the relationship of licensing agreements and innovation when firms engage in licensing under competitive pressures.

Internally available financial resources provide firms a buffer, which likely allows them to move beyond simply deploying licensed knowledge as a short-term fix to the immediate problems emerging from R&D pressures to the consideration of long-term goals and targets. Hence, while licensing-in under competitive pressure reduces a firm’s ability to benefit from such licensed knowledge, these challenges may be attenuated in the presence of abundant financial resources. Also, when licensing-in under competitive pressure, discretionary financial resources could “provide a source of funds for actions that would not be approved in the face of scarcity” (Cyert & March, 1963:189), allowing firms to go beyond the directed and problemistic orientation we expect from them as they respond to R&D efforts by their competitors. Thus, in
the presence of internally available financial resources, firms are more likely to remain experimental even though competitive pressure is leading them towards a specific path. Finally, we argued that, when licensing is used predominantly as a competitive tool, it may minimize learning as firms will focus on receiving but not actively exchanging knowledge with the licensee. However, in the presence of discretionary financial resources, it is more likely that firms are able to manage multiple (often competing) goals and facilitate engagement in a true exchange versus a mere unidirectional transfer of knowledge between licensor and licensee.

Our arguments jointly suggest a key role of financial resources when licensing-in under competitive pressure. In relative terms, licensing-in under competitive pressures benefits more from the presence of discretionary financial resources than licensing in the absence of competitive pressures. This complements prior work suggesting that excess financial resources may be necessary to absorb competitive pressure (Singh, 1986). While, as a baseline, we identified that licensing under competitive pressure can limit firms in their learning compared to licensing in the absence of competitive pressures, these limitations can be attenuated when firms have the discretionary financial resources:

Hypothesis 4b: The negative effect of competitive pressure on the relationship of licensing and innovation is attenuated by the availability of discretionary financial resources inside the firm.

METHODS

Context: Bio-Pharmaceutical Industry

The bio-pharmaceutical industry offers an appropriate setting to test our hypotheses on the antecedents and outcomes of technology licensing-in. Over the last decades, this industry has been characterized by rapid technological change as exemplified by the emergence of new technologies (e.g., gene expression and gene sequencing) and therapeutic approaches such as monoclonal antibodies or stem cells (Nishimura & Okada, 2014). The industry is also highly
competitive as the earning potential for treatments diminishes over time, requiring firms to constantly innovate (Roberts, 1999). The competitive nature of the industry is amplified as firms compete in moving specific treatments towards regulatory approval and market access, which, in many cases, is characterized by competitive races (Cockburn & Henderson, 1994). The result is that bio-pharmaceutical firms tend to pay substantial attention to competitors’ R&D actions and often have dedicated resources to scan and observe the competitive external environment (Henderson & Cockburn, 1994; Klueter & Monteiro, 2016). Finally, over time, licensing-in has emerged as a key strategic mechanism for firms to tap into rapidly emerging knowledge, create innovations and build a competitive advantage within the industry (Nishimura & Okada, 2014; Roberts, 1999). All of the above characteristics create an appropriate context in which to test the antecedents of technology licensing-in and how it affects firm’s capacity to innovate.

Data and Sample

In order to test our hypotheses, we compile a novel database combining multiple data sources: Recap Deal Builder, Pharmaprojects, Compustat and the NBER patent project. The sampling of firms to be included in our analysis is based on the following criteria. First, we want to ensure that selected firms actually deploy technology licensing-in as a mechanism to acquire external knowledge. We used the Recap Deal Builder Database to examine the licensing deals listed in the period between 1989-2004 (15 years). Recap is acknowledged as one of the most accurate and comprehensive sources of information regarding partnerships and technology exchange involving pharmaceutical firms (Schilling, 2009). This database allows us to access detailed information regarding the licensing deals as well as to unambiguously identify the licensor and licensee for a given deal. To be included in our sample, we require a firm to have reported at least one licensing deal as licensee for the period used to construct our sample.
The second step is to ensure that we are able to obtain consistent longitudinal financial and licensing information for our sampled firms. Firms listed on the stock market have much more stringent disclosure requirements than their privately held counterparts. Hence, we focus on firms that are publicly listed on the North American stock market as this alleviates concerns of unreported deals and ensures that we have sufficient information about the firm’s financial activities. Recap is compiled based on press releases, Securities and Exchange Commission contracts, analysts’ reports, clinical trials, and requests under the Freedom of Information Act, these sources that are significantly more comprehensive in covering information from publicly listed firms. Thus, our sampling criteria reduces concern about unreported deals. We use the names identified in Recap licensing contracts and match licensees with the Compustat.

Next, we ensure that the firms in our sample are subject to experience pressure from competitors R&D actions. We, hence restrict our sample to firms active in drug development by ensuring that a sampled firm had at least one therapeutic product in development using data from Pharmaprojects. This database has been used in prior bio-pharmaceutical studies to capture drug development activities (Kapoor & Klueter, 2015). We construct the drug development pipeline of each focal firm by tracking their reported activities related to the development and launch of new drugs. The pharmaceutical R&D process is characterized by races in which all firms compete to develop and launch drugs to enjoy periods of exclusivity (Macher & Boerner, 2012). Thus, firms engaging in drug development compete with each other to achieve market success, while those, which do not pursue active drug development most likely follow a different revenue model.

To account for the Mergers and Acquisitions (M&A) activities that are very common in this industry, we dynamically track changes in the ownership structure of the companies in our sample using the M&A information provided by Recap. This allows us to build a detailed history of each firm and ensures that our measures capture the given activity of a firm in a given year.
Next, we generate a panel with the firm-year observation serving as unit of analysis. Because not all financial information was available for all the firm-years, our dataset has different numbers of time series per firm, which translates to an unbalanced panel for 228 firms. We remove from the sample firms that appear for less than two years to increase the overall balance of the panel and ensure that we can add fixed effects in our econometric analysis. In the final sample, we observe 205 firms, with each firm appearing, on average, 7.7 times, with a minimum of two and a maximum of 14 observations. For these firms, we identify 3,604 licensing deals in the period 1989-2003. Overall, the dataset this study draws on includes 1,579 firm-year observations concerning the period 1989-2004 inclusive. We define 1989 as the starting year, based on the availability of consistent licensing and trials information from Recap and Pharmaprojects and 2004 as the ending year, based on the availability of patent data.

**Dependent variables**

**Licensing-in Decision.** To capture firms’ strategic use of licensing-in as a reaction to R&D competition, we create a dummy variable with the value of 1 if firm \( i \) has engaged in at least one licensing deal at year \( t \) and value 0 if no licensing-in activity has been observed. Recap includes several types of deals that are distinct from technology licensing-in. To ensure that this measure is aligned with our theoretical constructs, we only count “real” licensing deals in which the licensor agrees to grant the licensee access to specific knowledge in exchange of monetary compensation. This variable is intended to capture firm’s \( i \) propensity to license-in in year \( t \).

**Firm Innovation.** We measure firm innovation using counts of successful patent applications from firm \( i \) in year \( t \). Prior studies have shown that patents are strongly correlated with new product introductions as well as with non-patentable innovations (Trajtenberg, 1987). We capture patents by connecting our sampled firms with their patenting activity reported in the NBER patent database. This dataset is compiled based on information extracted from the United States...
Patent and Trademark Office-USPTO. The focus on a single patent office avoids noise produced by differences in evaluation procedures across patent offices. Given that the U.S. market represents the world’s largest market for high-tech products, global firms have large incentives to apply for patents at the USPTO as early as possible (Henderson & Cockburn, 1994). We use the patent application date because it is closely related to the timing of knowledge creation. The variable Firm Innovation captures the total number of patents firm $i$ applied for in year $t$.

**Independent Variables**

**Number of Licensing-in Deals.** To capture the effect of licensing-in on a firm’s subsequent innovation, we count the number of licensing deals in which firm $i$ has been involved in year $t$. While in *Hypothesis 1*, we are interested in the choice of licensing as a strategic reaction to R&D competition, in *Hypothesis 2*, we are examining the overall effect of licensing on innovation. Given that firms may differ in the intensity with which they license-in, we opt to capture the effect of licensing on innovation using a count variable. This is because a larger number of licensing deals can expose firms to more variety and quantity in terms of access to new knowledge that firms gain through licensing-in.

**R&D Competitive Pressure.** Next, we rely on the Pharmaprojects database to capture the R&D moves from firms in the Pharmaceutical Industry. In total, we scrutinize over 13,000 projects in development by the firms in our sample. Each drug development project in Pharmaprojects is associated with a broader therapeutic area such as Cancer, Neurology or Cardiovascular and we consider a firm to be actively competing in an area if they have drug development projects within a therapeutic area or a drug launched in prior 5 years.

We capture competitive R&D pressures by the number of global new drugs launched by competitors in a given year in the therapeutic areas in which a sample firm was active. Pharmaprojects documents the launch of a drug in the key event details, which is available for
each drug in the database. Launched drugs tend to be a) highly visible as they are exhaustively covered by the media and b) have the potential to deteriorate the competitive position of a focal firm either by affecting its existing revenues streams or by making it harder to capture value from future drug development activities in the respective therapeutic market (Cockburn & Henderson, 1994). Furthermore, the approval of new drugs is the outcome of substantial sunk investments in R&D activities with important repercussions the drug development pipeline for all firms in the industry active in the same therapeutic area or “market” (Ang, 2008). The measure Competitive R&D pressures counts the overall number of global drug launches reported in the therapeutic areas, in which each sample firm was active in a given year. A higher number of launched drugs suggests stronger competitive pressures on the focal firm as competitors are able to position themselves favorably within the respective therapeutic areas.²

**Discretionary Financial Resources.** In order to operationalize the availability of resources or financial constraints in line with our theoretical mechanisms, we examine the presence of free cash flow of firms using Compustat (Cuervo-Cazurra & Annique Un, 2010). We take into consideration that the absence and the presence of available cash flows are two important issues in the bio-pharmaceutical industry, in which firms require substantial financial resources to innovate. The fact that a firm has positive operating cash flow indicates that it is able to fund its operations from sales, as opposed to firms with a negative cash flow (Campello, Graham, & Harvey, 2010). Moreover, the lack of positive cash flow has been used as a proxy for financial constraints resources in the management and finance literatures to proxy firms’ access to financial resources that can be strategically allocated to achieving short- or long-term goals (e.g.,

² We exclude drugs launched by the focal firm in a given year when constructing the variable. As a robustness test we build a measure using the same methodology with newly initiated Phase 3 trials by competitiors as a proxy for competitive pressures. This measure is highly correlated with the one capturing drug launches and yields qualitatively similar results to the ones reported.
Allayannis & Mozumdar, 2004). We capture the availability of discretionary financial resources by using a dummy that takes value 1 if firm $i$ has presented positive operating cash flow in year $t$ and 0 otherwise. This measure can vary longitudinally for each firm in our sample.

**Control Variables**

**Firm Drug Pipeline.** Firms may vary in their reaction to the strategic R&D moves of competitors according to the strength of their own R&D efforts and internal pipeline. We control for the *Firm Drug Pipeline* using FDA data to count the number of *phase 3* drugs that the firms have in their pipeline as a stronger pipeline may make a firm less reactive to competitive R&D pressure through in-licensing.

**Organizational Myopia.** Previous studies have shown several facets of myopia related to organizational learning (Levinthal & March, 1993), lack of capacity to identify opportunities and threats and resistance to new technologies (Mezias & Glynn, 1993). We control for firms’ myopic behaviour related to the use of knowledge generated outside their boundaries. To operationalize this construct, we employ Agrawal, Cockburn, & Rosell’s (2010) measure of organizational myopia, which is computed on the basis of the backward citations of firms’ patents. Accordingly, we calculate this measure in the following way:

$$\text{Organizational Myopia } it = \frac{C_{it}^s}{C_{it}}$$

where $C_{it}^s$ represents the total number citations that firm $i$ made to its own patents, and $C_{it}$, the total number of citations, regardless of the ownership of the cited patent. We apply a seven-year moving window to allow for a sufficient number of patents to be produced and to account for knowledge depreciation over time.
**Patenting Experience.** We control for technological experience using the number of years that elapsed between the first time the firm applied for a patent and year $t$. We also expect this variable to be correlated with firm age, which affects innovation (e.g., Sørensen & Stuart, 2000).

**Firm R&D Intensity.** A firm’s expenditure in R&D activities is one of the main determinants of its capacity to absorb external knowledge and also to produce future innovations (Cohen & Levinthal, 1990). So, in order to control for firm differences in terms of absorptive capacity, we measure R&D intensity by dividing a firm’s R&D expenses by its sales at year $t$.

**Firm Size.** Larger firms may have a stronger propensity to license and innovate. To control for firm size, we use the natural log of the number of employees (thousands) for firm $i$ in year $t$.

**Technological Diversity.** Higher levels of diversity of a firm’s knowledge base may affect its ability to recombine knowledge and innovate (Cohen & Levinthal, 1990). We control for a firm’s technological diversity using the Herfindahl index applied to the technological classes of the patents that firm $i$ produced in the seven years prior to year $t$:

\[
\text{Technological Diversity } it = 1 - \sum_{j=1}^{N} \left( \frac{N_{ijt}}{N_{it}} \right)^2
\]

Where $N_{it}$ is the total number of patents that a firm accumulated in the previous seven years and $N_{ijt}$ represents the number of patents in technology class $j$. The final measure is obtained by subtracting 1 from the value reflecting the concentration of patent classes across the different technological domains.

**Evaluation Capacity.** Firms differ significantly in their capacity to evaluate external knowledge. On the basis of Arora and Gambardella (1994), we calculate the Evaluation Capacity variable using the average number of scientific references in the backward citations of patents accumulated in the seven years preceding year $t$. This measure captures firms’ in-house scientific capabilities, which reflect the extent to which inventors search the frontier of technological space.
**Technological Complexity.** We control for firms’ ability to handle technological complexity by computing the average number of claims on patents applied for firm \( i \) the seven years preceding year \( t \). Experience in dealing with complex bodies of knowledge makes it easier for firms to integrate the acquired technology into their own knowledge bases (Leone & Reichstein, 2012).

**M&A Activities.** Firms can use Mergers and Acquisitions to become more innovative and also to pre-empt technology competition (Grimpe & Hussinger, 2008). We construct the variable *M&A Activities* using RECAP. It tracks the yearly number of acquisitions in which the firms in our sample have been involved as the acquirer firm.

**Strategic Alliances.** Firms engage in strategic external collaborations to develop knowledge, technological capabilities and acquire new resources (Mowery et al., 1996). These activities have also been shown to be correlated with a firm’s innovation productivity and with licensing decisions (Sampson, 2007). We control for a firm’s strategic use of external collaboration using the yearly count of R&D co-development and collaboration agreements reported at RECAP.

**Industry Commercial Competition.** We control for commercial competition in order to avoid confounding effects between *R&D competition* and competition on commercial markets. The variable *Industry Commercial Competition* is based on a Herfindahl-Hirschman index (HHI) computed using firm sales data. In order to calculate this index, we take into account the sales of all firms operating in the same industry as the sample firm (4-Digit SIC code), regardless of their inclusion (or not) in our licensing sample. The HHI is calculated using the sum of an industry’s squared market share, according to the following formula:

\[
Industry \ Commercial \ Competition = 1 - \sum_{i=1}^{I} S_{i,j}^2
\]

Where \( S_{i,j} \) is the market share of firm \( i \) in industry \( j \). We perform the above calculations each year for each industry based on SIC codes. Since we are interested in the effect of increased
competition on licensing rates, we subtract the original index from 1 to generate a measure of
dispersion of sales, the greater the value, the stronger the competition in commercial markets.

Model Specification

Given that we have two distinct dependent variables; we employ an empirical strategy that takes
into account licensing as a two-stage process while incorporating the longitudinal structure of the
data. Because our first dependent variable is a dummy taking values 0 or 1 according to firms’
decisions to license-in during a given year, we model it using a random-effects Probit model.
This type of model allows dealing with firm-specific unobserved heterogeneity that is not
correlated with our independent variables.

The second dependent variable is measured using the count of patents that each firm $i$
successfully applied for in year $t$. Given the non-negative integer count values observed in patent
data, we model it using a conditional Negative Binomial specification (Hausman, Hall, &
Griliches, 1984), which is a generalization of the Poisson that is appropriate under conditions of
over-dispersion. The estimation of a Negative Binomial model in a longitudinal setting allows the
implementation of either fixed or random effects as an alternative to account for unobserved
characteristics regarding the subjects in the sample. We choose to use the fixed effects
specification as it allows for arbitrary correlation between unobserved time-constant factors and
the explanatory variables (Wooldridge, 2002), providing more conservative estimators. In the
case of this setting, we expect that not all relevant time invariant attributes simultaneously
affecting firm capacity to deal with licensed-in technologies and to innovate can be successfully
incorporated into the model.

To alleviate concerns regarding the use of fixed-effects in negative binomial models
(Allison & Waterman, 2002), we use the Pre-entry patent stock information approach of
Blundell et al. (1995) as an explanatory variable and include in the Probit Random effects models
and in the Negative Binomial with Fixed effects models. We expect this variable to control for a large portion of residual unobserved heterogeneity concerning firms’ differences in patenting propensity, which is relevant to both the firm’s decision to license-in and their creation of subsequent innovations. Finally, we employ year dummies to capture overall temporal trends in firms’ licensing-in and patenting activities. All our independent variables are lagged by one year.

**Results**

Table I reports descriptive statistics and simple pairwise correlations between the dependent and the independent variables used in the regression analyses. We start by reporting the two dependent variables following a one-year lag structure and then move into the main explanatory and control variables. Results of the pairwise correlation raised no concerns regarding multicollinearity. Particularly, the explanatory variables concerning the hypothesized effects do not present any strong correlations among themselves or with the control variables. Additionally, the maximum variance inflation factor (VIF) associated with any of the independent variables was 5.10 (mean VIF = 2.51), which is well below the rule-of-thumb value of ten (Gujarati & Porter, 2003). On average, 52% of the firm-year observations in the sample involve at least one Technology Licensing deal over the period of the analyses.

Restricting the sample only to public firms could raise concerns that the observations in our sample would rarely exhibit negative cash flow. The descriptive statistics on Table 1 show that this is not the case as 41% of the firm-year observations in our sample take value 1 for the variable *Discretionary Financial Resources*. We also observe that around 42% of the firms in our sample change status (either from 0 to 1 or vice versa) for the variable *Discretionary Financial Resources* during the period they are tracked in our analyses.
We also look at the distribution of the 3,604 licensing deals from RECAP over the years to ensure that there is no overrepresentation of licensing activity in certain periods. We observe that the highest number of licensing deals for all the firms in our sample in a single year was 472 in 2001, which represents 12.55% of the total number of deals observed in the total sample. Furthermore, the average number of licensing-in deals per firm was 1.98 (SD: 3.69), with a minimum of 1 and a maximum of 184. The firms with the largest number of deals in our sample are GlaxoSmithKline (184), Wyeth (153), Pfizer (152), Roche (52), and Merck & Co (141).

Table II reports the regression results. Models 1-4 show the Probit Models with firm Random Effects, with the Licensing-In decision as dependent variable. Models 5-9 show the Negative Binomial Models with firm-Fixed Effects with the dependent variable Firm Innovation. We start by adding each of the main explanatory variables in a step-wise fashion. For each of the two dependent variables, the first models (Models 1 and 5 respectively) include only the control variables and then the variables of interest enter the models subsequently. We observe that the presence of financial resources is conducive for licensing-in and that the strength of the current pipeline both predicts licensing-in as well as firm innovation. Licensing-in is also predicted by a firm’s R&D intensity, its evaluation capacity as well prior M&A and collaborative agreements. As expected, firm innovation increases with technological diversity and patenting experience.

Model 2 enters the variable R&D Competitive Pressure. The results provide support for Hypothesis 1. In Model 2, the coefficient for the variable R&D Competitive Pressure is positive and statistically significant (p < 0.01). We estimated the marginal effects for the coefficient regarding R&D Competitive Pressure to assess how much an increase of one standard deviation in competitive pressure affects the likelihood of firms moving into licensing-in. In economic
terms, it implies an observed change in the rate of new drugs being brought into the market from around 40 to 70 new drugs a year. This change in *R&D Competitive Pressure* leads to an increase in the likelihood of licensing-in to the order of 25%.

Now we turn to the *Negative Binomial Model with Firm-Fixed Effects* that examines the effect of licensing-in deals on firm innovation. Model 6 enters the variable *Number of Licensing-in Deals*. The coefficient for the variable *Number of Licensing-in Deals* is positive and statistically significant (p < 0.01). This result suggests that, as firms engage in licensing-in deals, they improve their subsequent capacity to produce innovations. This is in line with our expectations, lending support to *Hypothesis 2*. Computing the marginal effects for *Number of Licensing-in Deals*, we observe that when the number of licensing-in deals changes from around 2 to 5.7, firms increase their subsequent capacity to produce innovations in 8.74%.

We then enter the interaction of *R&D Competitive Pressure* and *Number of Licensing-in Deals* in Model 7. The empirical results also provide support to the idea proposed in *Hypothesis 3*. The coefficient for the interaction terms *R&D Competitive Pressure x Number of Licensing-in Deals* is negative and statistically significant (p < 0.05). This result suggests that, with an increase in R&D competitive pressure at the time of licensing-in, firms are likely to benefit less from licensing-in deals in terms of their capacity to innovate. Additionally, we use a Wald test to verify whether the combined effect of this interaction term is simultaneously equal to zero when compared to the *Number of Licensing-in Deals* and to *R&D Competitive Pressure*, which would suggest that removing the interaction term would not significantly reduce the model fit. The results for the Wald test rejected the hypothesis that both terms are jointly equal to zero.

Figure 2 shows the average elasticity of firm innovation and the number of licensing-in deals, conditional on different levels of *R&D Competitive pressure*. In line with our prediction in
Hypothesis 3, the graph indicates that, as competitive pressure gradually increases, the marginal increment of licensing deals on firm innovation decreases.

[Insert Figure 2 here]

Next, we test the role of financial constraints in the relationship of licensing, competitive pressures and innovation. The variable Financial Resources is binary and we test the moderation effect for this variable by employing a split sample technique in which we create two sub-samples based on the availability or absence of discretionary financial resources. Model 8 shows the subsample of observations that have financial resources and, Model 9, the subsample of observations with financial constraints. Models 8 and 9 show that the coefficient for Number of Licensing-in Deals is positive and significant (p<0.01) when there are no financial constraints, while it is not statistically significant for the group of observations that are financially constrained. We use a seemingly unrelated estimation technique to examine if the difference we observe between the two groups is statistically significant. The statistical comparison of the two coefficients indicates that the difference between them is different from zero (Chi2=4.05 p<0.05). This finding is in line with Hypothesis 4a given it indicates that financially constrained firms do not benefit, or benefit less than unconstrained firms, in terms of innovation from engaging in technology licensing-in. This is in line with the idea that the process of integrating external knowledge requires organizational efforts and, in particular, financial resources.

To better understand the moderating effects of Discretionary Financial Resources on the relationship between licensing-in and innovation, we graph these effects. Figure 3 provides an illustration of the effect that the Number of Licensing-in Deals has on Firm Innovation, conditional on the focal firms having discretionary financial resources or being financially constrained. As is possible to observe, for a low number of licensing-in deals, both sub-samples that are financially constrained and financially unconstrained exhibit similar levels of innovation.
However, as the number of licensing-in deals increase, only financially unconstrained firms (i.e. with discretionary resources) observe a steep increase in their capacity to innovate while, for constrained firms, the licensing-in curve remains flat.

[Insert Figure 3 here]

Finally, Hypothesis 4b argues that the negative effect of competitive pressure on the relationship of licensing and innovation is attenuated by the availability of discretionary financial resources inside the firm. We observe in Models 8 and 9 that, contrary to our expectations, the coefficient for the interaction term \( R&D \text{ Competitive Pressure} \times \text{Number of Licensing-in Deals} \) is statistically insignificant for both subsamples. The absence of statistical significance in these models suggests that the effect of the interaction of the terms \( R&D \text{ Competitive Pressure} \times \text{Number of Licensing-in Deals} \) and \( \text{Firm Innovation} \) is not conditional on the amount of Discretionary Financial Resources that firms possess at the time of licensing-in. We will examine further this observation when discussing our supplementary analysis.

While we do not explicitly theorize about the moderating effect of financial constraints on the relationship between competitive pressure and licensing-in, Models 3 and 4 mirror the split sample analysis which we previously discussed. Model 3 shows the subsample of observations with financial resources, while Model 4 shows the subsample with financial constraints. We find that, in the presence of financial resources, the effect of competitive pressure is around 9.24% stronger. We also used a seemingly unrelated estimation technique to compare the coefficients of Model 3 and Model 4; we find that they are statistically different from zero (\( \chi^2 = 3.03, p < 0.10 \)).

In order to visualize the effect of different levels of competitive pressure on firms’ propensity to license-in, we graph the effect of \( R&D \text{ Competitive Pressure} \) conditional on financial resources. Figure 4 shows a positive relationship between \( R&D \text{ Competitive Pressure} \) and firm propensity to license-in. However, this effect appears significantly stronger for
financially unconstrained firms. Thus, while we do not find clear evidence that financial constraints moderate the interaction of competitive pressures and the number of licensing deals on innovation, financial resources may be an important enabler for firms to respond to competitive pressures through licensing.

Discussion and Limitations

This study provides a process model connecting the antecedents and the outcomes of technology licensing-in from the licensee’s perspective. By doing this, it holds important theoretical and empirical contributions to the literature on licensing, competition and innovation.

Importantly, we investigate and analyze the connections between licensing and innovation looking at both external and internal conditions, such as competitive pressures and discretionary financial resources, as possible contingencies explaining the antecedents and outcomes of licensing-in. In the process model that we develop, we conceptually distinguish licensing-in from alternative strategies firms pursue to develop innovation, including other forms of sourcing external knowledge or developing knowledge internally. We reveal that the unique characteristics of licensing-in make it an important response to R&D pressures. In doing so, we contribute to research on competitive dynamics, as to how firms respond to competitive pressures through R&D actions, including licensing-in decisions (Chen, 1996; Kaul, 2012).

Specifically, our emphasis on external (competitive R&D pressures) and internal contingencies (discretionary financial resources) in relation to licensing-in sheds new light on previous research on external knowledge sources (Cassiman & Veugelers, 2006; Chesbrough, 2003) and on the role of financial resources in benefiting from external knowledge (Cecagnoli & Jiang, 2013). By exploring contingencies that make firms better or worse off in drawing from licensed-in knowledge, we add to previous studies on how different forms of external knowledge
sourcing may distinctively shape a firm’s innovative outcomes (e.g., Van de Vrande, 2013). Moreover, the paper connects to those studies, which have highlighted that licensing as a “hand-off” from one organization to another may ultimately not be able to lead to innovative benefits for firms (Fey & Birkinshaw, 2005). Our paper partially confirms such assertion by showing that simply adding new knowledge into the firm may not be always sufficient to innovate and that these limitations are particularly salient under competitive pressures.

At the same time, our paper also reveals the importance of the organizational context into which licensed knowledge is added. In particular, we reveal the role of discretionary internal financial resources as catalyst for innovation to unfold following licensing, which adds to previous research examining the relationship of excess financial resources on innovation (Ceccagnoli & Jiang, 2013; Nohria & Gulati, 1996). Our results reveal that benefits from licensing knowledge are particularly strong in the presence of financial resources, which illuminates the role of such resources for the learning and recombination process to unfold.

Relatedly, we contribute to the literature on markets for technology and their relationship with external competition (Arora & Gambardella, 2010). We acknowledge that previous research in this stream has predominantly considered competitive forces through the lens of the licensor, which calculates net benefits of licensing-out under competitive threats (Fosfuri, 2006). This literature has substantially neglected the role of the licensee in reacting to competitive pressures in the industry. In this paper, we show that competitive forces are also an important trigger for licensees to license-in new technologies as a way to improve a firm’s capacity to innovate.

The findings in this paper entail relevant managerial implications. Considering that the relationship between licensing-in and innovation can be significantly affected by financial discretionary resources and R&D competition, these are two factors to which managers should pay attention when deciding to use licensing agreements as a reaction to competitors’ moves. Our
findings indicate that managers may find licensing a way to immediately react to competitive moves from other firms, but we also uncover that, when deciding to license-in, firms should examine the way that the acquired knowledge can be integrated into its existing knowledge base. Given that licensing deals can require the licensee to pay significant amounts in terms of up-front fees and royalties, it is in firms’ best interest that licensed technologies will not be underutilized.

We acknowledge that our study has several limitations, which provide opportunities for future research. First, we use the bio-pharmaceutical industry as the empirical context to test our hypotheses. This is the ideal setting for our study as R&D competitive pressure from competitors is part of this industry dynamics and licensing is a common mechanism for firms to acquire external knowledge. However, it also creates concerns regarding the generalizability of our findings. Future research should aim at extending this study into different empirical settings in which the acquisition of external knowledge plays a key role, including semiconductor and electronics industry.

Second, in our theoretical and empirical models, we only consider the effect of licensing on firms’ total innovation output. However, we already know that licensing has unique implications (e.g., relative to joint ventures) as firms may be able to learn in knowledge areas which are unrelated to a licensing agreement (Oxley & Wada, 2009) and allows tapping into exploratory knowledge (Laursen et al., 2010). We hope that future studies will take use of our proposed licensing model and explicitly consider implications of licensing on different dimensions of firms’ innovation outputs, such as its breadth, complexity, and radicalness.

Finally, we believe that using the licensing-in decision, not only as a theoretical point of departure, but also as part of our empirical strategy to deal with selection, creates a promising venue for future studies aimed at connecting the antecedents and outcomes related to firm innovation. The present paper constitutes a first step towards exploring this research agenda.
References


Figures

Figure 1: Antecedents and Outcomes of the Licensing-in Process

Figure 1: Conditional Average Marginal Effects of Number of Licensing-in Deals on Firm Innovation

Figure 2: Conditional Average Marginal Effects of the Number of Licensing-in Deals on Firm Innovation

Figure 3: Conditional Average Marginal Effects of R&D Competitive Pressure on the Licensing Decision
## Tables

**Table I. Descriptive Statistics and Correlation Coefficients (N = 1,605)**

<table>
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<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
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<td>0.52</td>
<td>0.50</td>
<td>1.00</td>
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<td></td>
<td></td>
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<td>(2) Firm Innovation</td>
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<td>0.11</td>
<td>1.00</td>
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<tr>
<td>(3) Number of Licensing-in Deals</td>
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<td>1.00</td>
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### Table 2. Antecedents and Outcomes of the Licensing-in Process

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Note: Standard errors are in parentheses.

*p < 0.10, **p < 0.05, ***p < 0.01 (two-tailed tests for all variables)